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Peer effects and school design: An analysis of efficiency and equity

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Abstract

This paper estimates educational peer effects in Swiss lower secondary schools where different ability tracking designs coexist. Using a cross-sectional survey based on standardized questionnaires, the structure and magnitude of peer effects among classmates are analyzed. The identification strategy relies on ability track fixed effects to find exogenous variation in peer group composition. Results indicate positive, small but significant average peer effects in reading and sciences whereas the average peer coefficient in mathematics is not significant. In reading and sciences, non-linear peer effects suggest that low-achieving students benefit most from peer effects whereas high-achieving students in mathematics obtain better school performances when they are placed together with similar peers. Class diversity does not affect the overall performance of the classmates but reduces the family background effect on school performances, whatever the field considered. These empirical findings show that mixing students in reading and sciences classes could enhance efficiency and equity while a similar practice in mathematics courses could only improve equity without any gain in efficiency.

JEL classification: I21, J24

Keywords: peer effects, ability tracking, PISA, equality of opportunity, quantile regressions.

1 Introduction

The magnitude and nature of peer effects are a prominent argument when defining educational policy such as ability tracking, anti-poverty programs, or classroom organization. Since the seminal Coleman report (1966), a growing literature has documented the importance of social interactions on educational outcomes (Hoxby, 2000; Sacerdote, 2001; McEwan, 2003; Vigdor and Nechyba, 2007; Burke and Sass, 2008; Ammermueller and Pischke, 2009; De Paola and Scoppa, 2010). The relationship between class composition variables and scholastic achievement can provide valuable insights regarding the optimal school design which generally boils down to choosing between two opposite systems: the *selective* (or *tracking*) system where students are separated into different ability groups and the *comprehensive* (or *mixing*) system where students follow ability-mixed classes.

Researches on peer effects and ability tracking are closely related because the existence of social interactions is a crucial element when discussing students' reallocation and the productivity of educational processes. Proponents of a selective system consider that tracking students maximizes student outcomes (measured through the accumulation of cognitive aptitudes) by forming more homogenous classes where the teacher can adapt his or her program to different kinds of students by focusing on their specific needs. Maximizing efficiency, however, is not the only concern of schooling policy. Other objectives like increasing life chances and social cohesion have to be satisfied too. Advocates of a comprehensive system insist on the fact that mixing students increases educational opportunities by giving the possibility to less-endowed students to benefit from high-achieving peers through direct learning, identification mechanisms or free-riding behaviors. At the same time, disruptive students may affect adversely student's behavior and test performances (Lazear, 2001; Figlio, 2005).

There is no clear evidence on which system is definitively the best in terms of efficiency or equity. On the one hand, a comprehensive system might enhance efficiency if students with learning difficulties benefit more from being placed together with more endowed peers while there are no adverse effects on the overall performance of the classroom. On the other hand, even if we expect a mixing system to increase the intergenerational transmission of human capital, ability tracking might improve equity if mobility across ability tracks is encouraged.

The estimation of peer effects, however, entails a number of econometric difficulties, including the endogeneity of the school or class choice (*selection* bias), the reciprocal influence between classmates' behavior (*simultaneity* bias), and the fact that common unobserved factors (e.g., teacher quality or spatial segregation) jointly determine individual and classmates' performances (*omitted variable* bias). These methodological constraints explain why empirical evidence on peer effects is rather mixed, and their potential to inform policy limited. Various definitions of the school outcomes, choices of peer reference groups, and data limitations further complicate the task of finding a consensus.

The main objective of this research is to find out if grouping students in a completely non-selective way at the Swiss lower secondary level could improve efficiency and equality of opportunity. During the past few years, tracking policies in Switzerland have been subject to several criticisms regarding equity, efficiency, or labor market needs (CSRE, 2010). In order to facilitate mobility across ability tracks, *partial tracking* policies based on within-school sorting have over time replaced *full tracking* policies which consist in separating students in different school types. Exploiting data from the PISA Swiss national sample 2006, the main contribution of this paper is to account explicitly for ability tracking within the school through the inclusion of ability track fixed effects. It is an improvement compared to previous literature where data limitations often do not allow the researchers to control directly for selective procedures within the school (Mc Ewan, 2003; Vigdor and Nechyba, 2007). Moreover, data at hand gives the possibility to distinguish between ability grouping (i.e., tracking at the class level) and level grouping (i.e., tracking within the class) and to lead such an analysis in three fields, namely reading, mathematics and sciences.

Empirical findings report that accounting for endogeneity issues is primordial to obtain unbiased peer estimates. In comparison with the traditional OLS model where I obtain positive, strong and significant peer effects in all fields considered, the introduction of ability track fixed effects reduces the magnitude of the peer coefficients in reading and sciences while the peer coefficient in mathematics loses its significance. In reading and sciences, non-linear peer effects suggest that low-achieving students benefit more from peer effects whereas high-achieving students in mathematics obtain better school performances when they are placed together with similar peers. Class diversity does not affect the overall performance of the classmates but reduces the family background effect on school performances, whatever the field considered. These empirical findings show that mixing students in reading and sciences classes could enhance efficiency and equity while a similar practice in mathematics courses could only improve equity without any gain in efficiency.

The rest of the paper is structured as follows. Analytical background and empirical evidence are reviewed in the second part. Data are presented in part three. I discuss the empirical framework in part four. The fifth part reports the results and the last part is devoted to the conclusion.

2 Background and literature review

The demarcation of the peer reference group, the nature of the social interactions, and the econometric difficulties are the three most important challenges in peer effect analysis. This part summarizes how literature deals with these issues and reports some empirical findings on educational peer effects.

2.1 Peer reference group

The level at which a peer group is defined depends essentially on the survey design. Studies working with PISA international data, which do not include class identifiers, assess the influence of schoolmates on student outcomes. While Fertig (2003) identifies peers as schoolmates, Rangvid (2004) and Schneeweis and Winter-Ebmer (2007) determine peers as pupils who are in the same school and grade. When data provide information at a more disaggregated level, some researchers estimate peer effects at the class level (Hoxby, 2000; Hanushek et al., 2003; Burke and Sass, 2008; Sund, 2007; Ammermueller and Pischke, 2009) while some others are interested in the influence of subgroups within the classroom, e.g., the share of pupils from dissolved families (Bonesronning, 2008) or the share of repeaters (Lavy et al., 2009). However, literature is inconclusive regarding the group level at which peer effects are the strongest (Betts and Zau, 2004; Vigdor and Nechyba, 2007; Burke and Sass, 2008).

2.2 Identification of peer effects

When we discuss peer effects, it is crucial to determine which kinds of social interactions we are talking about and separate them from non-social influences. According to the conceptual framework of Manski (1993, 1995, 2000), there are three arguments that may explain why students belonging to the same peer reference group tend to behave similarly:

- *Endogenous effects* exist when the behavior of one's peers (e.g., effort, motivation, inspiration, or commitment) influences personal behavior. Such contemporaneous interactions generate a social multiplier effect because the consequences of introducing a schooling policy not only affect the behavior of the students of interest but also affect the behavior of all school- or classmates through their reciprocal influences.

- *Contextual effects* occur when the exogenous characteristics of the peer group (e.g., ability[1], socioeconomic status, or gender) influence the individual's behavior. Here, however, policy interventions do not create a multiplier effect because these social interactions rely on attributes unaffected by the current behavior of the individuals.

- *Correlated effects* arise if individuals in the same reference group behave similarly because they face similar environments or share similar characteristics (e.g., teacher quality, living in the same socioeconomic area). Whereas endogenous and contextual effects result from social interactions, correlated effects are not a social phenomenon.

The estimation of peer effects is complicated by strong econometric constraints. Endogenous effects induce a simultaneity bias because individual and peers' outcomes influence each other. The usual way to reduce this *reflection* bias (Manski, 1993) consists in using a lagged peer outcome as instrument (Hanushek et al., 2003; Betts and Zau, 2004; Vigdor and Nechyba, 2007; Burke and Sass, 2008; De Paola and Scoppa, 2010). However, this strategy entails two main problems, i.e., the lagged achievement of peers ignores the impact of current peer effort and the presence of serial correlation may still affect the parameter estimates.

A second concern lies in the fact that peer background itself affects peer outcome. Consequently, *collinearity* problems may arise and the related coefficients cannot be identified. Whereas some authors make the assumption that only one form of peer effect exists (Gaviria and Raphael, 2001; Entorf and Lauk, 2006; Schneeweis and Winter-Ebmer, 2007), an alternative approach consists in assuming that the peer reference group is individual-specific, i.e., some of the peer groups overlap with one other (De Giorgi et al., 2009; Bramoullé et al., 2009). Expressed differently, individuals interact no longer in defined groups (where individuals are affected by all other members but by none outside it) but within a social network (where interactions are interdependent). As a result, we can use the educational outcome of the excluded school- or classmates as an instrumental variable for peer achievement[2], implying that both endogenous and contextual effects can be identified. However, such an approach, which may require the use of spatial econometrics, is beyond the scope of this paper, especially due to the data at hand.

[1]When ability is measured before the peer group formation, we can define ability as a contextual (or pretreatment) characteristic. However, when ability is measured after the peer group formation, we can use the test score information as a proxy for peers' performances. In other words, it allows for measuring endogenous (or during treatment) effects.

[2]This is a story of triangularization. Suppose that students A and B study languages together and B studies mathematics with C but not with A. This means that A is excluded from the reference group of C and inversely. In this example, for the student C, the perfomances of the excluded group (i.e., student A) will serve as instrument for the performances of its own peer reference group (i.e., student B).

The difficulty to identify separately the exogenous and endogenous peer effects explains why the main bulk of the literature relies on a *reduced form* model that incorporates a total social effect which does not account for the precise nature of social interactions (Sacerdote, 2001; Ammermueller and Pischke, 2009; De Paola and Scoppa, 2010). In this context, the choice of the peer variable is mainly determined by the survey design. While longitudinal data often contain a measure of prior ability (e.g., prior test scores), cross-sectional datasets generally do not include such information. As a result, studies using one-dimensional data rely rather on peer background attributes which serve as proxy for peer quality, e.g., the educational level of the mother (McEwan, 2003; Rangvid, 2004), the number of books at home (Raitano and Vona, 2011), the highest parental occupational status (Schneeweis and Winter-Ebmer, 2007), the number of students from dissolved families (Bonesronning, 2008), or the proportion of students with working parents (Fertig, 2003).

Correlated effects are not modeled directly in the econometric model. However, they play an important role if peer group composition is also determined by unobserved factors. For example, if students with higher unobserved abilities or resources are more prone to be oriented towards higher-ability tracks or better schools, peer group composition is not random and peer effect estimates cannot be interpreted in causal terms. Moreover, we need to separate out peer effects from other confounding factors such as teacher quality. The selection and omitted variable biases represent the main challenges in peer effect estimation, and this explains why recent literature focuses essentially on these issues. Because natural experiments are still in short supply, different strategies are possible to eliminate these two kinds of bias. Analyzing the case of Denmark where students are mixed during compulsory schooling, Rangvid (2004) estimates a regression model including numerous background attributes and school characteristics to reduce as much as possible the endogeneity problem. The author takes advantage of a large set of data that combines both PISA 2000 and additional register data. An alternative approach to address the problem of unobserved characteristics is to adopt an instrumental variable strategy to explicitly model the enrollment process (Fertig, 2003; Lefgren, 2004; Hoxby and Weingarth, 2005; Gibbons and Telhaj, 2008; Atkinson et al., 2008; De Paola and Scoppa, 2010). The other common strategy is to use fixed effects methods. Many researchers have employed school fixed effects to control for school differences, especially when tracking occurs at the school level (Lefgren, 2004; Schneeweis and Winter-Ebmer, 2007; Gibbons and Telhaj, 2008). This is an appropriate strategy as long as students are not sorted by ability within the school. If this is the case, school fixed effect estimates could be still biased by uncontrolled within-school ability sorting (Mc Ewan, 2003; Vigdor and Nechyba, 2007; Zabel, 2008). A better solution to rule out selection consists in combining school fixed effects with teacher and student fixed effects (Sund, 2007; Carman and Zhang, 2008, Burke and Sass, 2008).

2.3 Empirical evidence

The heterogeneous ways to identify the peer reference group (e.g., school, grade, or class), to measure social interactions (i.e., endogenous or contextual effects) and to solve the problem of endogeneity (e.g., large set of covariates, IV or fixed effects) explain why empirical evidence on peer effects is rather inconclusive. Overall, peer effects estimates are positive, relatively small, but often significant. An increase of one standard deviation in the peer group variable is, on average, associated with an increase by less than 10% of standard deviation in student achievement. Linear and average peer effects, however, are not informative regarding policy recommendations. For that purpose, nonlinear peer effects and measures of peer diversity are more prone to detect which kinds of students benefit more from social interactions and therefore allow to assess the relevance of the school design in force, especially with regards to efficiency considerations. A comprehensive system can be defined as *Pareto improving* if students with learning difficulties benefit most from peer effects (decreasing returns in peer effects) without penalizing the school performances of their classmates (no negative impact of peer diversity on the peer group's educational performances).

Table 1, largely inspired by the tables presented in Gibbons and Telhaj (2008) and Sacerdote (2011), summarizes the main findings obtained by some important papers closely related to this study. Considering OECD countries and Austria, respectively, Vandenberghe (2002) and Schneeweis and Winter-Ebmer (2007) find that peer effects are stronger for less gifted students, but that an increase in peer heterogeneity leads to some adverse effects on student performances. Consequently, these results cannot give clear recommendations concerning the optimal allocation of students. Analyzing the non-selective Danish school system, Rangvid (2004) shows that low-achieving pupils benefit most from schoolmates' interactions, while high-ability students lose nothing from the diversity in the student body. Relying on a rich dataset from Swedisch high schools, Sund (2007) finds that low-achieving students benefit most from an increase in both peer average and peer heterogeneity. Theses findings satisfy the Pareto improving condition and indicate that a comprehensive school design is an appropriate system to enhance efficiency. On the contrary, some findings reveal that high-achieving pupils benefit most from the presence of other high-ability students (Hoxby, 2000; Hanushek et al., 2003; Hoxby and Weingarth, 2005; Gibbons and Telhaj, 2008; Burke and Sass, 2008; Lavy et al., 2009). In such a case, ability tracking appears as the optimal policy to increase efficiency given that individuals perform better when they are sorted with similar peers.

In the context of equality of opportunity, mixing policies are relevant when the impact of class heterogeneity offsets the impact of family background on school performances. Using PISA 2006 survey for OECD countries, the contribution of Raitano and Vona (2011) shows that increasing peer diversity would reduce the parental background effect and therefore would improve equality of opportunity. In their preferred specification which includes country fixed effects, the authors find that an increase in one standard deviation of peer heterogeneity is associated with a reduction of 8.4% in the average family background effect.

3 Data

3.1 PISA national sample

Initiated by the OECD in 2000, the Program for International Student Assessment (PISA) is an internationally standardized assessment of knowledge and skills acquired by students at the end of compulsory education. Until now, four assessments have been carried out, i.e., every three years. At each wave, a major field (reading, mathematics, or sciences) is

Table 1: A selective review of closely related papers

Studies	Context	Outcome	Peer measure	Peer group	Methodology	Magnitude of average peer effects	Non-linearity and Peer Heterogeneity (PH)
Vandenbergue (2002)	Secondary schools, OECD countries	Test scores (maths and sciences)	Family SES	Class	Country FE and classroom RE	Significant evidence	Diminishing returns in peer effects and negative impact of PH
Mc Ewan (2003)	Secondary schools, Chile	Test scores (Spanish)	Mother's education	Class	School FE	1sd $\rightarrow$ 0.27sd	Diminishing returns in peer effects
Fertig (2003)	Secondary schools, US	Test scores (reading)	Test scores heterogeneity	School	IV strategy	-	Negative impact of PH
Lefgren (2004)	Chicago public schools, US	Test scores (reading and maths)	Prior test scores	Class	School-year FE and IV strategy	1sd $\rightarrow$ 0.024sd	-
Rangvid (2004)	Secondary schools, Denmark	Test scores (reading)	Mother's education	School-grade	Additional controls	1sd $\rightarrow$ 0.08sd	Diminishing returns in peer effects and no detrimental impact of PH
Schneeweis and Winter-Ebmer (2007)	Lower secondary schools, Austria	Test scores (reading and maths)	Parental occupational status	School-grade	School type FE and school FE	No evidence with school FE	Diminishing returns in peers effects for reading and mixed impact of PH
Vigdor and Nechyba (2007)	North Carolina 5th graders, US	Test scores (reading and maths)	Prior test scores	Class	School FE/apparent random assignment	1sd $\rightarrow$ 0.03sd	-
Sund (2007)	High schools, Sweden	Test scores (GPA)	Prior test scores	Class	School, teacher and student FE	1sd $\rightarrow$ 0.08sd	Diminishing returns in peer effects and positive effects of PH
Carman and Zhang (2008)	Middle schools, China	Course grade	Prior subject grade	Class	Teacher and student FE	0.1sd $\rightarrow$ 0.04 sd (maths)	Mixed evidence for non-linearity but no detrimental impact of PH
Gibbons and Thelaj (2008)	State secondary schools, England	Average test scores	Prior test scores	School-grade	Year-to-year changes in school composition	No evidence	Increasing returns in peer effects
Burke and Sass (2008)	Florida public schools, US	Test score gains	Fixed characteristics	Class	Student and teacher FE	1pt $\rightarrow$ 0.044pt	Increasing returns in peer effects and negative impact of PH
Ammermueller and Pischke (2009)	Europe primary schools	Test scores (reading)	Average peer characteristics	Class	School FE	1sd $\rightarrow$ 0.07sd	-
De Paola M. and V. Scoppa (2010)	Calabria University, Italy	Secon Level grade	First level grade	Class	2SLS	1sd $\rightarrow$ 0.19sd	-
Raitano and Vona (2011)	OECD countries	Test score (sciences)	Books at home	School	Country FE and pseudo school FE	-	Decreasing returns in peer effects and PH reduces family background effect

examined in depth. Moreover, OECD allows each participating country to generate complementary samples. Consequently, since PISA 2000, Switzerland has taken advantage of this opportunity to generate a PISA *national* sample. In contrast to the international sample that focuses only on 15-year-old students, the PISA Swiss sample is exclusively composed of students attending the ninth grade (i.e., the last year of compulsory education) and additional variables are available to lead a regional analysis.

This study uses the supplementary PISA 2006 data provided by the Swiss Federal Statistical Office (SFSO)[3]. Compared to the PISA international sample, the Swiss national sample allows a peer effects analysis within the school. First, it contains the name of the class in which the student is enrolled. As some cantons have not opted for a class-based sampling, only 15 cantons are considered in the empirical analysis[4]. Second, I can identify tracking within school because data indicates the school, the ability track and the class the students attends. Finally, I have some information on the differentiated-ability level courses the student follows when ability tracking occurs within the class. Initially composed of 20,456 pupils, the analytical sample size was reduced for satisfying the fixed effects specification that exploits a variation in the subgroup composition (i.e., class level) within the fixed effects group (i.e., ability track level). To avoid fixed effect methods absorbing any variation at the fixed effects group level, I have to ensure that there are at least two classes per ability track. At the end, the final sample consists in 14,081 students. The following sections define the variables used for the empirical analysis. Summary statistics are presented in Table 2.

3.2 Educational outcomes

Educational performances in reading, mathematics, and sciences are measured through PISA test scores. As it is common in the literature using PISA or TIMSS (Trends in International Mathematics and sciences Study) data, I use the first plausible value for the students' actual score[5]. The scale of these variables has been standardized at the OECD level with an average of 500 points and a standard deviation of 100 points.

3.3 School track design and ability tracks

The Swiss educational system is organized in a federalist way and therefore involves different actors: Confederation (i.e., central government), cantons (i.e., sub-national governments) and communes (i.e., municipalities). Based on the subsidiarity principle, cantonal and communal authorities enjoy a large degree of autonomy regarding the structure of their schooling system, especially at the lower secondary level. As a result, ability tracking practices differ between and within cantons. If we regroup these heterogeneous practices on the basis of unified criteria, we can distinguish between three school track designs:

- The *separated* system tracks students in different school types according to the school performances, i.e., ability tracking occurs at the school level. Consequently,

[3] "Base de données suisse PISA 2006 pour la $9^{ème}$ année" (OFS/CDIP).

[4] Participating cantons are Aargau, Bern, Basel Land, St. Gallen, Schauffhausen, Thurgau, Zürich, Valais, Vaud, Genève, Neuchâtel, Jura, Fribourg, Tessin and Graubünden.

[5] PISA test scores are based on too few items to give a realistic estimation of students' ability. For that purpose, a probability distribution for identifying students' ability is estimated. Plausible values represent random draws from this empirically derived distribution of proficiency values that are conditional on the observed values of the assessment items and the background variables.

each school has its own curricula and teaching staff. Some schools prepare pupils for university entrance, other for vocational formation (e.g., apprenticeship or professional matura). Expressed differently, the pupils enrolled in the same school follow the same ability track.

- The *cooperative* system sorts students into different ability tracks within a given school, i.e., ability tracking occurs between classes within the same building. As in the separated system, each ability track prepares pupils for different schooling pathways. The advantage of such system is to facilitate the mobility between ability groups which are so-defined located in the same school.

- The *integrative* system mixed pupils in a comprehensive way, except for core subjects like reading and mathematics where pupils from the same class are sent to different level groups on the basis of their aptitudes, i.e., ability tracking occurs within the classroom. Students following high-ability classes are prepared for an academic matura while those following middle- and low-ability classes are more prone to attend a vocational formation.

The separated and cooperative systems are defined as homogenous given that all students from the same class belong to the same ability track. In such a case, we refer to the concept of *ability grouping*. In opposition to the two former designs, the integrative system is defined as heterogeneous on the grounds that it combines both mixed-ability classes (e.g., sciences) and *level grouping* (e.g., mathematics and reading). Level grouping occurs when students from the same class can belong to different ability tracks regarding the subject of differentiation, e.g., higher-ability track in mathematics but lower-ability track in language instruction. A combination of ability grouping with level grouping also exists in some cantons.

For the empirical analysis, the school track design is accounted for with a dummy variable taking the value 0 if the student belongs to the homogenous system and the value 1 if she belongs to the heterogeneous system. Unfortunately, due to data limitations, I cannot make a distinction between the separated and the cooperative system. Ability track level is divided into three categories, i.e., high-, middle-, and low-ability track. For sciences, this variable contains a fourth category called "mixed-ability track" given that this field is not subject to level grouping in the integrated system.

3.4 Peer characteristics variables

In the homogeneous system, the peer reference group consists of pupils who are in the same class and - by definition - on the same ability track whatever the field considered. For the integrative system, the peer reference group refers to pupils who are in the same level group (reading and/or mathematics) or in the same class (sciences). For that purpose, I have to create field-specific peer groups on the grounds that a student in the integrated system does not necessarily have the same classmates in mathematics or reading. The advantage of such a strategy is to have a relevant set of peers for each situation.

The peer quality variable is measured by the mean parental economic, social, and cultural status in the reference group. This index which serves as proxy for parental background is derived from variables related to parental education, parental occupational status, and an index of home possessions (desk for study, educational software, books, computer, calculator, etc.). Similarly, peer heterogeneity is measured by the standard deviation of the peer variable in the reference group.

3.5 Control variables

At the individual level, I control for gender, age, migration background, and own parental background. I add a variable reporting if the language spoken at home is a Swiss national language or not. Parental expectations and the importance attached by parents to the field considered are included in the regression model to reduce the unobserved heterogeneity related to parents' educational preferences.

At the school level, I include a set of school characteristics and a measure of school selection procedure. The former are represented by school size, school location and the proportion of teachers with a university degree in pedagogy while the latter is a school admittance variable based on student's prior records. Finally, I control for the size of the class[6] where classes with less than six students are excluded from my analysis.

Table 2: Variables description and summary statistics

Variables	**Description**	**Mean**	**s.d.**
Test scores			
Reading	Standardized test scores (mean of 500pts and sd of 100pts)	506.608	81.428
Mathematics	Standardized test scores (mean of 500pts and sd of 100pts)	540.273	85.203
Sciences	Standardized test scores (mean of 500pts and sd of 100pts)	516.920	86.212
Peer characteristics			
Peer quality (reading)	Mean parental economic, social and cultural status in the peer reference group	0.170	0.435
Peer quality (mathematics)	Mean parental economic, social and cultural status in the peer reference group	0.171	0.435
Peer quality (sciences)	Mean parental economic, social and cultural status in the peer reference group	0.169	0.432
Peer heterogeneity (reading)	Standard deviation of parental economic, social and cultural status in the peer reference group	0.813	0.190
Peer heterogeneity (mathematics)	Standard deviation of parental economic, social and cultural status in the peer reference group	0.813	0.191
Peer heterogeneity (sciences)	Standard deviation of parental economic, social and cultural status in the peer reference group	0.812	0.186
Parental background			
Parental background	Parental economic, social and cultural status (index with mean of 0 and sd of 1)	0.171	0.872
Background characteristics			
Parental expectation	=1 if expectation is higher education graduated, =0 otherwise	0.172	0.378
	=2 if missing	0.107	0.308
Parental value	=1 if important	0.904	0.295
(reading)	=2 if missing	0.020	0.141
Parental value	=1 if important	0.900	0.300
(mathematics)	=2 if missing	0.020	0.140
Parental value	=1 if important	0.532	0.499
(sciences)	=2 if missing	0.027	0.162
Other language at home	=1 if none of Swiss official language is spoken at home	0.134	0.340
	=2 if missing	0.036	0.187
Migration background	Ref. cat.= natives		
	=1 if immigrant	0.122	0.327

[6] In the integrated system, class size refers to number of students following the same differentiated-level course.

	=2 if immigrant parents	0.095	0.294
	=3 if missing	0.015	0.122
Age	Student's age in years	15.695	0.625
Female	=1 if female	0.504	0.500
School track design			
Heterogenous system	=1 if heterogenous system , =0 if homogenous system	0.126	0.332
Ability tracks characteristics			
Ability track level (reading)	Ref. cat.= low-ability track		
	=1 if middle-ability track	0.306	0.460
	=2 if high-ability track	0.397	0.489
Ability track level (mathematics)	Ref. cat.= low-ability track		
	=1 if middle-ability track	0.307	0.461
	=2 if high-ability track	0.403	0.491
Ability track level (sciences)	Ref. cat.= mixed-ability track		
	=1 if low-ability track	0.218	0.413
	=2 if middle-ability track	0.297	0.457
	=3 if high-ability track	0.359	0.480
Class size			
Classe size (reading)	Number of students in the class	15.560	8.983
Classe size (mathematics)	Number of students in the class	15.607	8.941
Classe size (sciences)	Number of students in the class (sciencess) or in the differentiated-level course (reading and mathematics)	15.730	8.851
Schools characteristics			
Teacher quality	=1 if more than 50% of teachers held a university degree in pedagogy, =0 otherwise	0.556	0.497
	=2 if missing	0.200	0.399
School size	Ref. cat.= less than 500 students		
	=1 if between 500 and 1000 students	0.444	0.497
	=2 if more than 1000 students	0.085	0.279
	=3 if missing	0.035	0.183
School location	Ref. cat.= village		
	=1 if small town	0.480	0.500
	=2 if town	0.299	0.458
	=3 if city	0.078	0.268
	=4 if missing	0.010	0.100
School admittance			
Admission procedure	=1 if based on prior student's records, =0 otherwise	0.353	0.478
	=2 if missing	0.022	0.145
	Nb of schools	297	
	Nb of classes	893	
	Nb of students in the homogenous system	12,309	
	Nb of students in the heterogeneous system	1,772	
	Nb of students (total)	14,081	

4 Empirical analysis

This section is organized as follows. First, I propose a reduced form model that estimates the mean impact of classmates' quality on educational achievement by using OLS and ability track fixed effects, respectively. Second, I account for non-linearity in peer effects and peer heterogeneity to determine if mixing students can be an efficiency-enhancing policy. Finally, I move to the equity effect by investigating if class heterogeneity has an equalizing impact on student's performances with regards to their parental background.

4.1 Identification of mean peer effects

The OLS specification serves as baseline model. The basic linear-in-means model can be represented as follows:

$$\begin{aligned} Y_{ics} &= \beta_0 + \beta_1 \bar{PB}_{(-i)cs} + \beta_2 PB_{ics} + \beta_3 X_{ics} + \beta_4 C_{cs} \\ &+ \beta_5 A_{ics} + \beta_6 SD_s + \beta_7 S_s + \beta_8 SP_s + \epsilon_{ics} \end{aligned} \quad (1)$$

where Y_{ics} is the test performance of student i in class c and school s, $\bar{PB}_{(-i)cs}$ is the parental background of classmates, excluding the contribution of student i, PB_{ics} is the parental background of student i, X_{ics} is a vector of individual and other background characteristics (i.e., gender, age, immigration status, language at home, parental taste for schooling and parental expectations), C_{cs} is the size of the class, A_{ics} represents the ability track level the student follows, SD_s is the type of school design (i.e., homogenous or heterogenous), S_s are school characteristics, SP_s is a measure of school selection procedure and ϵ_{ics} is an error term. Equation (1), however, might suffer from selectivity problems, i.e.,

$$Cov(\bar{PB}_{(-i)cs}, \epsilon_{ics}) \neq 0$$

Consequently, estimates of β_1 can be biased. Indeed, even with a rich set of background variables, unobserved factors may still influence the peer group composition. In Switzerland, ability track assignment is based on different criteria such as prior test performances, teacher recommendations, or parental endorsement which are generally not observed by the researcher. In order to reduce selectivity issues, I introduced ability track fixed effects in equation (1). This identification strategy allows to find exogenous variation in peer group composition because it accounts for both between- and within-school sorting. My preferred specification is then:

$$\begin{aligned} Y_{ics} &= \beta_0 + \beta_1 \bar{PB}_{(-i)cs} + \beta_2 PB_{ics} + \beta_3 X_{ics} + \beta_4 C_{cs} \\ &+ \underbrace{\mu_k + \nu_{ics}}_{\epsilon_{ics}} \end{aligned} \tag{2}$$

where μ_k is an ability track specific component and ν_{ics} is an idiosyncratic error term.

4.2 Efficiency analysis

A comprehensive system needs to meet two conditions to enhance efficiency, i.e., decreasing returns in peer effects and no negative impact of peer diversity on student's achievement. I consider two strategies to account for non-linearity in peer effects.

The first approach interacts the peer variable with the parental background to detect if peer effects are stronger for pupils with disadvantaged parental background. I also introduce the standard deviation of the peer variable to explicitly control for class diversity because average peer effects can reflect either homogeneous or heterogeneous groups of pupils. I have then:

$$\begin{aligned} Y_{ics} &= \alpha_0 + \alpha_1 \bar{PB}_{(-i)cs} + \alpha_2 PB_{ics} + \alpha_3 X_{ics} + \alpha_4 C_{cs} \\ &+ \alpha_5 (\bar{PB}_{(-i)cs} \cdot PB_{ics}) + \alpha_6 \tilde{PB}_{(-i)cs} + \mu_k + \nu_{ics} \end{aligned} \tag{3}$$

where $\tilde{PB}_{(-i)cs}$ represents the standard deviation of the peer variable, i.e., heterogeneity in the peer reference group. This specification, however, only reports the effect of the class compositional variables on the average student whereas the most important question is to find for which kind of students does the peer group matter.

The second approach considers the same set of covariates and fixed components but within a quantile regression framework which analyzes peer effects for different subgroups of pupils, hierarchically structured by school performances. The quantile regression method has several advantages such as the reduced weight attached to outliers, the robustness to potential heteroscedasticity and the semi-parametric form of the model. I obtain the following specification:

$$\begin{aligned} Q_{\theta}(Y_{ics}) &= \alpha_{\theta 0} + \alpha_{\theta 1}\bar{PB}_{(-i)cs} + \alpha_{\theta 2}PB_{ics} + \alpha_{\theta 3}X_{ics} + \alpha_{\theta 4}C_{cs} \\ &+ \alpha_{\theta 5}(\bar{PB}_{(-i)cs} \cdot PB_{ics}) + \alpha_{\theta 6}\tilde{PB}_{(-i)cs} + \mu_k + \nu_{ics} \end{aligned} \tag{4}$$

where θ represents the θ^{th} quantile of the considered variables.

4.3 Equity analysis

In parallel of efficiency considerations whose objective is to maximize the accumulation of cognitive skills, the schooling system should also offer an equal access in schooling opportunities. On the basis of the contributions of Benabou (1996) and Hanushek and Woessman (2006), we expect a heterogeneous system to increase equity in the school environment. Some previous research, however, leads to contrasting results (Argys et al., 1996; Rees et al., 2000; Figlio and Page, 2002; Hidalgo-Hidalgo, 2009). To account for equality of opportunity, I consider a model inspired by the contributions of Schuetz et al. (2008) and Raitano and Vona (2011) which analyzes the relationship between student's test scores, parental background and sorting policies. The main objective is to assess how school selection procedures reinforce or weaken the parental background effect. However, assuming that the traditional observed school selection variables (e.g., student's prior records or teacher recommendations) can perfectly predict *ex-ante* the peer group formation is unrealistic. Other considerations (residential segregation or idiosyncratic preferences) can also constrain students choices. For that purpose, scholars consider that accounting for peer variables, which are an *ex-post* measure of peer group formation, can provide reliable information on how class composition and parental background interact each other.

The empirical model regresses the individual test's score on parental background, peer heterogeneity, school admittance procedure, school track design, individual background characteristics and a set of interaction terms between parental background and the variables of interest. I deliberately do not control for ability track fixed effects on the grounds that ability track enrollment is assumed to be strongly correlated with parental background and therefore may falsify the magnitude of the parental background gradient. I have then:

$$\begin{aligned} Y_{ics} &= \gamma_0 + \gamma_1 PB_{ics} + \gamma_2(PB_{ics} \cdot \tilde{PB}_{(-i)cs}) + \gamma_3(PB_{ics} \cdot SD_s) \\ &+ \gamma_4(PB_{ics} \cdot SP_s) + \gamma_5\tilde{PB}_{(-i)cs} + \gamma_6 X_{ics} + \gamma_7 SD_s + \gamma_8 SP_s \\ &+ \vartheta_{ics} \end{aligned} \tag{5}$$

The objective is to determine on the basis of the interaction variables mentioned in equation (2.5) if peer heterogeneity, the school admittance procedure and the school track design reinforce or weaken the impact of parental background on student's performances. The main focus is on the interaction term between peer heterogeneity and parental background to know if the former reinforce or weaken the effect of the latter on school performances. As before, I also consider a quantile regression approach to detect the potential differences along the test score distribution.

5 Results

5.1 Mean peer effects

Results from the baseline OLS regressions (ref. equation (1)) are presented in Table 3. The estimations report positive, strong, and significant average peer effects in all fields. Coefficients related to parental background, parental expectation, and language at home follow the expected signs. The value attached by parents to the field of interest influences positively and significantly the score obtained by their offspring in reading and sciences whereas the inverse holds for mathematics. A potential explanation may reside in the fact that parental interest for literacy or environmental issues can be more easily transmitted to children than their interest for mathematics. My results show that natives obtain higher test scores than pupils with migration backgrounds and that males perform better in mathematics and sciences, whereas females obtain better results in reading. As all students are in the ninth grade, the negative impact of age on school performances may be explained in the fact that older students generally reflect repeaters. Concerning the school track design, an integrative system seems to reduce reading's performances while having no significant effect on mathematics' performances[7]. In sciences, students who are grouped in a comprehensive way perform better than pupils who are enrolled in low ability tracks but worse than pupils from middle and high ability tracks. Overall, pupils in higher-ability tracks obtain better results in all fields considered. The coefficients related to class size are negative, small, and significant in each field excepted in mathematics where coefficient is not significant. Finally, I notice that PISA test scores are higher in schools whose enrollment process is based on prior student's ability. However, OLS estimation may be problematic regarding endogeneity biases and the coefficients need to be interpreted carefully.

Results from fixed effects regressions (ref. equation (2)) are presented in Table 4. Compared to the OLS regressions, the introduction of school track fixed reduces significantly the magnitude of peer effects in the three fiels considered. Moreover, the peer effect coefficient in mathematics is no longer significant. These results traduce the existence of strong selection effects in the peer group composition. By interpreting my peer estimates in terms of standard deviation, I obtain that a one-standard-deviation increase in peer quality produces an significant increase of 0.042 and 0.035 of a standard deviation in reading and sciences test scores, respectively. Concerning the other control variables, minor differences exist between OLS and fixed effects regressions. Only two coefficients (related to parental value in mathematics and class size) lose their significance.

5.2 Efficiency

The policy relevance of mean peer effects is limited because it is crucial for policy makers to know which subgroup of pupils is most affected by peer effects and what is the potential impact of heterogeneous classes on educational outcomes. The first strategy consists in including two additional peer variables in the regression model. First, I introduce the interaction between the peers' parental background and the own parental background. A negative (positive) coefficient for the interaction term would indicate that pupils with low (high) parental background are more sensitive to the peer group's influence. Second,

[7] The variable *Heterogenous system* is not included in the regression model for sciences because it is perfectly collinear with the variable *Ability track* given that mixed-ability classes correspond by definition to the integrated system.

Table 3: Mean peer effets, OLS estimation

Dependent variable	**Reading test score**	**Mathematics test score**	**Sciences test score**
Explanatory variables	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**
Peer characteristics			
Peer quality	21.338***	14.623***	17.533***
	(3.549)	(3.592)	(3.569)
Parental background			
Parental background	6.654***	6.629***	8.124***
	(0.766)	(0.727)	(0.760)
Background characteristics			
Natives (reference category)			
Immigrant	-16.090***	-21.199***	-26.635***
	(2.186)	(2.096)	(2.137)
Immigrant parents	-22.207***	-25.454***	-31.578***
	(2.328)	(2.496)	(2.370)
Age	-5.119***	-9.585***	-2.903***
	(1.147)	(1.164)	(1.139)
Female	15.083***	-27.039***	-20.329***
	(1.185)	(1.238)	(1.207)
Other language at home	-16.144***	-12.471***	-18.667***
	(2.204)	(2.148)	(2.148)
Parental expectation	7.947***	8.588***	12.524***
	(1.686)	(1.707)	(1.744)
Parental value	4.898**	-5.718**	17.869***
	(2.200)	(2.207)	(1.323)
Ability tracks characteristics			
Ability track: mixed			(ref. cat)
Ability track: low	(ref. cat)	(ref. cat)	-39.421***
			(3.974)
Ability track: middle	46.642***	52.148***	16.035***
	(3.278)	(3.119)	(3.586)
Ability track: high	73.887***	88.324***	50.007***
	(4.134)	(4.162)	(4.153)
Class size			
Class size	-0.203*	-0.145	-0.381***
	(0.121)	(0.115)	(0.137)
School track design			
Heterogenous system	-7.428**	-5.414	
	(3.622)	(3.301)	
School characteristics			
Teacher quality	8.206***	16.026***	9.365***
	(2.576)	(2.685)	(2.432)
School size: low (reference category)			
School size: middle	-10.017***	-12.785***	-14.728***
	(2.713)	(2.618)	(2.588)
School size: high	-5.231	-5.947	-9.734**
	(4.136)	(3.930)	(3.863)
School location: village (reference category)			
School location: small town	7.997**	10.236***	2.205
	(3.237)	(3.420)	(3.223)
School location: town	7.958**	7.788**	2.404
	(3.740)	(3.861)	(3.680)
School location: city	-0.140	-22.124***	-12.436**
	(5.150)	(5.540)	(5.102)
School sorting policies			
Admission procedure	16.457***	14.488***	19.432***
	(2.302)	(2.399)	(2.181)
Constant	524.419***	649.140***	554.680***
	(18.911)	(18.962)	(17.893)
R-squared	0.356	0.398	0.414
N	14,081	14,081	14,081

Standard errors clustered at the class level.
*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 4: Mean peer effects, ability track FE estimation

Dependent variable	**Reading test score**	**Mathematics test score**	**Sciences test score**
Explanatory variables	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**
Peer characteristics			
Peer quality	8.020***	3.476	6.994**
	(3.030)	(2.888)	(3.084)
Parental background			
Parental background	5.486***	5.782***	7.461***
	(0.776)	(0.719)	(0.754)
Background characteristics			
Natives (reference category)			
Immigrant	-12.045***	-15.408***	-20.110***
	(1.941)	(1.854)	(1.923)
Immigrant parents	-18.553***	-20.880***	-24.948***
	(2.097)	(2.178)	(2.171)
Age	-10.939***	-18.074***	-10.987***
	(1.011)	(0.999)	(1.006)
Female	13.315***	-28.906***	-21.858***
	(1.086)	(1.112)	(1.111)
Other language at home	-15.739***	-10.890***	-17.777***
	(2.141)	(2.006)	(2.108)
Parental expectation	11.966***	12.649***	15.608***
	(1.589)	(1.531)	(1.569)
Parental value	8.884***	-2.709	13.556***
	(2.074)	(2.133)	(1.168)
Class size			
Class size	-0.032	-0.038	-0.094
	(0.111)	(0.120)	(0.127)
Constant	729.414***	905.462***	763.731***
	(18.598)	(23.999)	(21.635)
Ability track FE	Yes	Yes	Yes
R-squared	0.462	0.507	0.509
N	14,081	14,081	14,081

Standard errors clustered at the class level.
*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

I consider the standard deviation of the peer variable. Both variables can give valuable information regarding the potential gains in efficiency that one could obtain by adopting mixed-ability classes.

All interactions terms between peer effects and parental background reported in Table 5 are non-significant. More interestingly, an increase in class heterogeneity does not decrease significantly the school performances of the average student, whatever the field considered. These findings do not allow to consider a comprehensive system as efficiency-enhancing on the grounds that the Pareto conditions are not fully satisfied, i.e., there is no dimishing returns in peer effects according to family background.

The second strategy (ref. equation (4)) gives the possibility to focus on the evolution of peer quality, the interaction between peer quality and parental background, and class heterogeneity along the ability distribution. Empirical findings from Table 6[8] report very interesting information concerning non-linearities in peer effects. For reading, we see a clear decrease in the peer coefficients along the ability distribution. In sciences, we can see that only pupils in the two first percentiles of the ability distribution benefit significantly from a higher peer average. On the contrary, high-achieving students in mathematics perform better when they are surrounded by similar peers given that peer effects estimates are only significant in the two last percentiles of the ability distribution. In all fields, class heterogeneity does not decrease significantly student's own achievement.

[8]Detailled results are presented in Table 9 to 11 in the Appendix.

Table 5: Nonlinear peer effects and peer heterogeneity, ability track FE estimation

Dependent variable	**Reading test score**	**Mathematics test score**	**Sciences test score**
Explanatory variables	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**
Peer characteristics			
Peer quality	7.803***	3.288	6.692**
	(3.023)	(2.887)	(3.083)
Peer quality*PB	-0.264	0.620	1.474
	(1.597)	(1.523)	(1.622)
Peer heterogeneity	-2.841	-1.157	-0.664
	(3.700)	(3.645)	(3.790)
Parental background			
Parental background	5.315***	5.581***	7.148***
	(0.860)	(0.808)	(0.848)
Background characteristics			
Natives (reference category)			
Immigrant	-12.024***	-15.412***	-20.121***
	(1.943)	(1.855)	(1.923)
Immigrant parents	-18.500***	-20.941***	-25.097***
	(2.108)	(2.192)	(2.178)
Age	-10.937***	-18.064***	-10.967***
	(1.011)	(1.000)	(1.007)
Female	13.310***	-28.912***	-21.864***
	(1.086)	(1.112)	(1.111)
Other language at home	-15.709***	-10.887***	-17.795***
	(2.089)	(2.004)	(2.105)
Parental expectation	12.005***	12.620***	15.519***
	(1.591)	(1.530)	(1.574)
Parental value	8.888***	-2.698	13.542***
	(2.072)	(2.134)	(1.167)
Class size			
Class size	-0.030	-0.039	-0.093
	(0.111)	(0.120)	(0.127)
Constant	732.336***	906.255***	763.616***
	(18.933)	(24.353)	(21.960)
Ability track FE	Yes	Yes	Yes
R-squared	0.462	0.507	0.509
N	14,081	14,081	14,081

Standard errors clustered at the class level.
*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

These results argue in favor of adopting comprehensive classes in reading and sciences because the conditions to be Pareto-improving are now met: low-ability students turn out to be most affected by a higher peer average without affecting the overall performance of the classroom. For mathematics, however, maintaining ability tracking turns out to be the best way to ensure school efficiency because only pupils at the top of the ability distribution obtain positive and significant peer effects estimates.

5.3 Equity

To determine if class heterogeneity reinforces or weakens the impact of parental background on student's performances, I focus on the interaction term between peer heterogeneity and parental background (ref. equation (5)). A negative (positive) coefficient would indicate that class heterogeneity reduces (increases) the impact of parental background on schooling performances.

Results from Table 7 show that class heterogeneity reduces the family background effect whatever the field considered. Moreover, we can see that a school admission procedure based on prior school performances reinforces the parental background effect and that the integrated system decreases it. To summarize, these findings speak in favor of

Table 6: Nonlinear peer effects and peer heterogeneity, Quantile regression with ability track FE

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Reading					
Peer characteristics					
Peer quality	10.777*	9.163***	8.412**	6.826**	1.560
	(6.006)	(3.382)	(3.472)	(2.995)	(3.606)
Peer quality*PB	0.199	-1.505	-0.134	0.909	-1.180
	(2.018)	(2.001)	(2.258)	(1.509)	(1.925)
Peer heterogeneity	-4.852	-5.194	-5.050	1.686	7.106
	(4.535)	(3.252)	(5.809)	(4.502)	(5.304)
Pseudo r-squared	0.303	0.295	0.274	0.257	0.252
Mathematics					
Peer characteristics					
Peer quality	0.791	1.458	3.997	7.401***	5.981*
	(4.302)	(3.390)	(3.424)	(2.859)	(3.911)
Peer quality*PB	-1.399	-0.871	1.008	0.158	1.553
	(3.020)	(2.158)	(1.980)	(1.588)	(1.521)
Peer heterogeneity	-2.956	0.546	-0.676	-5.615	-1.973
	(6.223)	(3.928)	(3.682)	(3.936)	(4.524)
Pseudo r-squared	0.321	0.317	0.310	0.301	0.296
Sciences					
Peer characteristics					
Peer quality	8.341***	9.638***	6.327	3.674	-1.019
	(2.394)	(2.688)	(4.080)	(3.540)	(3.646)
Peer quality*PB	0.143	0.335	0.757	0.892	1.367
	(1.860)	(1.747)	(1.960)	(1.611)	(2.339)
Peer heterogeneity	-2.113	-6.186	-3.027	0.510	-0.702
	(6.712)	(6.555)	(5.201)	(6.355)	(7.161)
Pseudo r-squared	0.327	0.325	0.311	0.295	0.289
Ability track FE	Yes	Yes	Yes	Yes	Yes
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively. The model also controls for migration status, age, gender, language at home, parental expectation, parental value for the field considered and class size.

adopting comprehensive classes to improve equality of opportunity at the lower secondary level, irrespective of the field analyzed. It is worth to point out, however, that such conclusions cannot definitively interpreted as causal because I do not control for unobserved characteristics in this specification.

As for efficiency, I estimate quantile regressions whose results are presented in Table 8[9]. First, interactions terms between peer heterogeneity and parental background reveal that mixing pupils with different parental economic, social, and cultural status reduces the parental background effect on schooling performances along the entire ability distribution in reading and mathematics whereas this reduction is only significant at the top of the ability distribution in sciences. The integrative system reduces the parental background effect in reading and sciences whereas results for mathematics are inconclusive. Finally, the variable related to the school admission procedure based on prior student's records is positively correlated with family background in the different field considered. On the basis of these findings, we see that most of variables analyzed here have a homogenous impact on student's performances, whatever the level of cognitive skills considered.

[9]Detailed results are presented in Tables 12 to 14 in the Appendix.

Table 7: Peer heterogeneity and educational opportunities, OLS estimation

Dependent variable	**Reading test score**	**Mathematics test score**	**Sciences test score**
Explanatory variables	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**	**Coefficients (Robust s.e.)**
Parental background			
Parental background	23.860***	28.652***	27.257***
	(3.614)	(3.787)	(3.966)
Interactions variables			
Peer heterogeneity*PB	-8.292**	-13.852***	-10.752**
	(3.875)	(4.095)	(4.371)
Heterogenous system*PB	-10.001***	-6.917***	-10.691***
	(2.408)	(2.478)	(2.344)
Admission procedure*PB	5.977***	5.823***	6.025***
	(1.916)	(2.074)	(1.925)
Main effects			
Peer heterogeneity	-6.529	-7.429	-6.049
	(6.917)	(7.602)	(7.648)
Heterogenous system	-12.571**	-10.412***	-10.291***
	(3.184)	(3.660)	(3.304)
Admission procedure	17.517***	20.233***	23.261***
	(2.778)	(2.984)	(2.758)
Background characteristics			
Natives (reference category)			
Immigrant	-20.763***	-28.675***	-32.475***
	(2.312)	(2.335)	(2.351)
Immigrant parents	-31.707***	-37.581***	-42.036***
	(2.619)	(2.788)	(2.722)
Age	-12.450***	-16.771***	-10.753***
	(1.302)	(1.317)	(1.277)
Female	19.120***	-23.219***	-16.181***
	(1.348)	(1.427)	(1.364)
Other language	-18.396***	-14.649***	-20.959***
	(2.452)	(2.457)	(2.448)
Parental expectation	25.261***	27.378***	27.437***
	(1.820)	(1.875)	(1.834)
Parental value	2.781	-6.693**	24.536***
	(2.472)	(2.554)	(1.531)
Constant	693.936***	825.570***	684.100***
	(20.785)	(21.478)	(20.818)
R-squared	0.207	0.229	0.269
N	14,081	14,081	14,081

Standard errors clustered at the class level.
*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

6 Conclusion

Revisiting the organizational design at the Swiss lower secondary level is relevant on the grounds that ability tracking seems to be positively associated with social inequalities, does not manage to form homogeneous classes in terms of students' skills, and is not well-adapted to the current labor market needs. Moreover, school segregation prevents low-achieving students to glean positive peer effects from a regular contact with more advanced students. However, most parents have concerns that creating ability-mixed classes can affect the quality of instruction in the classroom and reduce the motivation of brighter students.

On the basis of peer effect theory that analyzes the magnitude and nature of social interactions between classmates, this study investigates which kind of effects in terms of efficiency and equity we could expect from introducing a completely non-selective system in the Swiss educational landscape. This research question is addressed by exploiting the relevant resources available in the PISA 2006 Swiss national sample which allows to estimate peer effects at the class level and control for both between- and within-school

Table 8: Peer heterogeneity and educational opportunities, Quantile regressions

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Reading					
Parental background	25.350***	25.475***	24.588***	23.381***	20.055***
	(6.491)	(3.190)	(2.649)	(2.634)	(2.862)
Peer heterogeneity *PB	-7.717	-8.603***	-9.599**	-8.898**	-7.637*
	(6.209)	(2.896)	(4.054)	(4.169)	(4.639)
Heterogenous system*PB	-14.083***	-12.601***	-9.547***	-8.256***	-4.580***
	(3.357)	(2.290)	(1.142)	(0.968)	(1.570)
Admission procedure*PB	5.161**	6.270***	6.962***	5.184**	8.288**
	(2.461)	(2.058)	(1.988)	(2.502)	(4.212)
Pseudo r-squared	0.129	0.126	0.114	0.099	0.094
Mathematics					
Parental background	29.830***	29.850***	27.089***	28.609***	28.540***
	(6.998)	(5.455)	(2.291)	(2.278)	(7.426)
Peer heterogeneity*PB	-14.908*	-15.171**	-11.279***	-15.675***	-16.033**
	(8.661)	(6.673)	(2.863)	(3.464)	(7.895)
Heterogenous system*PB	-5.192	-6.088	-7.037***	-2.864	-2.967
	(4.878)	(4.173)	(1.858)	(3.993)	(3.079)
Admission procedure*PB	6.586***	6.879***	4.770***	7.224*	6.547**
	(0.510)	(1.148)	(0.407)	(3.697)	(3.053)
Pseudo r-squared	0.127	0.129	0.130	0.120	0.112
Sciences					
Parental background	24.138***	30.947***	28.281***	27.549***	30.079***
	(9.006)	(11.533)	(7.072)	(5.506)	(8.157)
Peer heterogeneity*PB	-6.502	-14.242	-11.484	-12.283***	-15.130***
	(11.078)	(13.978)	(9.201)	(5.832)	(7.479)
Heterogenous system*PB	-15.356***	-12.577***	-12.226***	-6.967	-7.579
	(5.735)	(3.664)	(3.114)	(4.709)	(4.630)
Admission procedure*PB	6.660***	5.837***	6.447***	6.796***	6.277***
	(1.517)	(2.157)	(1.728)	(1.646)	(1.611)
Pseudo r-squared	0.150	0.157	0.150	0.137	0.132
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.
The model also controls for migration status, age, gender, language at home, parental expectation and parental value for the field considered.

sorting. The peer quality variable is represented by the average parental socioeconomic background within the classroom and ability track fixed effects are introduced in the linear-in-means model to reduce correlated effects. Non-linear peer effects are estimated with quantiles regressions in order to analyze which kinds of pupils benefit most from peer effects along the ability distribution.

OLS results show that peer effects are sizeable and that classmates' quality represents a strong predictor of student's performances. The magnitude of peer effects estimates, however, decreases when ability track fixed effects are included in the model but they remain positive and significant in reading and sciences. I account for non-linearities in peer effects by using a quantile regression framework which analyzes peer effects for different types of pupils ranked according to their schooling performances. In reading, results report positive, significant and decreasing peer coefficients along the entire ability distribution. In sciences, only students at the bottom of the ability distribition benefit significantly from peer effects whereas it is the opposite for mathematics. Class diversity in terms of parental background has no adverse effects on school performances, whatever the field and percentiles considered. Finally, the specification measuring equality of opportunity indicates that peer heterogeneity reduces the impact of the family background on school performances in all fields considered. Main findings suggest that adopting mixed-ability classes in reading and sciences could lead to Pareto-improving redistributions of students across classes and/or schools. In mathematics, however, maintaining ability tracking seems to be the best practice to ensure school efficiency but does not lead to any gains in terms of equality opportunity.

The main caveat of this study is that we cannot control for teacher fixed effects while teacher behaviour can change with the peer group composition, especially when peer effects are measured at the class level. Indeed, the teacher adapts his or her teaching in a different way, if the average ability changes in a class. A second caveat is that the PISA dataset does not offer the possibility to distinguish between endogeneous and contextual peer effects, which explains why I rely on a reduced form model estimating a total peer effect.

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8 Appendices

Table 9: Nonlinear peer effects and peer heterogeneity, Quantile regression with ability track FE, Reading

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Peer characteristics					
Peer quality	10.777*	9.163***	8.412**	6.826**	1.560
	(6.006)	(3.382)	(3.472)	(2.995)	(3.606)
Peer quality*PB	0.199	-1.505	-0.134	0.909	-1.180
	(2.018)	(2.001)	(2.258)	(1.509)	(1.925)
Peer heterogeneity	-4.852	-5.194	-5.050	1.686	7.106
	(4.535)	(3.252)	(5.809)	(4.502)	(5.304)
Parental background					
Parental background	4.470***	4.919***	4.630***	4.479***	6.006***
	(1.061)	(0.805)	(0.745)	(0.571)	(1.165)
Background characteristics					
Natives (reference category)					
Immigrant	-10.673**	-10.175***	-12.950***	-14.546***	-15.533***
	(4.321)	(2.944)	(2.210)	(2.925)	(3.572)
Immigrant parents	-17.689***	-20.218***	-21.902***	-19.077***	-17.015***
	(3.969)	(2.768)	(3.339)	(4.069)	(4.639)
Age	-12.537***	-12.195***	-11.091***	-8.017***	-9.129***
	(1.328)	(1.359)	(0.868)	(0.921)	(0.858)
Female	15.220***	14.229***	11.758***	11.093***	11.474***
	(2.029)	(1.611)	(1.101)	(1.620)	(1.263)
Other language at home	-18.055***	-16.624***	-14.270***	-16.875***	-12.658***
	(3.490)	(3.604)	(3.789)	(3.029)	(3.617)
Parental expectation	12.154***	12.183***	11.653***	12.935***	13.474***
	(2.793)	(2.371)	(1.850)	(1.496)	(2.847)
Parental value	13.572***	10.028***	8.806**	7.958***	5.007*
	(3.773)	(3.877)	(3.441)	(2.765)	(2.666)
Class size					
Class size	-0.093	-0.20	0.001	0.108	0.170
	(0.168)	(0.198)	(0.165)	(0.181)	(0.210)
Constant	674.985***	705.449***	732.642***	729.148***	798.108***
	(36.081)	(28.693)	(20.812)	(22.674)	(25.933)
Ability track FE	Yes	Yes	Yes	Yes	Yes
Pseudo r-squared	0.303	0.295	0.274	0.257	0.252
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 10: Nonlinear peer effects and peer heterogeneity, Quantile regression with ability track FE, Mathematics

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Peer characteristics					
Peer quality	0.791	1.458	3.997	7.401***	5.981*
	(4.302)	(3.390)	(3.424)	(2.859)	(3.911)
Peer quality*PB	-1.399	-0.871	1.008	0.158	1.553
	(3.020)	(2.158)	(1.980)	(1.588)	(1.521)
Peer heterogeneity	-2.956	0.546	-0.676	-5.615	-1.973
	(6.223)	(3.928)	(3.682)	(3.936)	(4.524)
Parental background					
Parental background	4.717***	5.686***	5.024***	5.843***	4.080***
	(1.044)	(0.588)	(0.915)	(0.614)	(1.139)
Background characteristics					
Natives (reference category)					
Immigrant	-12.656***	-14.436***	-13.787***	-15.493***	-18.518***
	(2.035)	(2.501)	(1.321)	(2.263)	(2.810)
Immigrant parents	-21.083***	-21.624***	-17.370***	-18.604***	-20.703***
	(3.816)	(3.886)	(3.693)	(4.047)	(4.818)
Age	-19.929***	-17.838***	-17.671***	-17.760***	-16.514***
	(1.262)	(1.244)	(1.558)	(1.426)	(1.535)
Female	-27.176***	-28.465***	-30.649***	-30.247***	-29.762***
	(2.269)	(2.347)	(1.616)	(1.500)	(1.459)
Other language at home	-11.267***	-10.716***	-13.592***	-12.249***	-9.172***
	(2.680)	(2.073)	(3.255)	(2.786)	(3.131)
Parental expectation	12.488***	12.414***	11.676***	12.660***	13.488***
	(2.419)	(2.437)	(2.148)	(2.034)	(1.850)
Parental value	-2.115	-3.668	-4.221	-2.587	-3.131
	(2.396)	(2.399)	(2.781)	(2.050)	(2.264)
Class size					
Class size	-0.485***	-0.199	0.012	0.377*	0.376
	(0.162)	(0.146)	(0.227)	(0.199)	(0.145)
Constant	866.860***	856.034***	895.550***	943.242***	944.788***
	(19.581)	(38.048)	(26.071)	(18.738)	(26.300)
Ability track FE	Yes	Yes	Yes	Yes	Yes
Pseudo r-squared	0.321	0.317	0.310	0.301	0.296
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 11: Nonlinear peer effects and peer heterogeneity, Quantile regression with ability track FE, Sciences

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Peer characteristics					
Peer quality	8.341***	9.638***	6.327	3.674	-1.019
	(2.394)	(2.688)	(4.080)	(3.540)	(3.646)
Peer quality*PB	0.143	0.335	0.757	0.892	1.367
	(1.860)	(1.747)	(1.960)	(1.611)	(2.339)
Peer heterogeneity	-2.113	-6.186	-3.027	0.510	-0.702
	(6.712)	(6.555)	(5.201)	(6.355)	(7.161)
Parental background					
Parental background	7.438***	6.838***	6.873***	7.518***	7.026***
	(1.178)	(0.969)	(0.717)	(1.080)	(0.780)
Background characteristics					
Natives (reference category)					
Immigrant	-18.858***	-18.943***	-20.645***	-19.577***	-21.257***
	(1.596)	(1.895)	(1.859)	(2.380)	(1.763)
Immigrant parents	-27.958***	-26.910***	-23.765***	-25.031***	-24.595***
	(3.823)	(3.458)	(2.728)	(2.567)	(3.150)
Age	-12.280***	-11.046***	-10.442***	-10.156***	-9.307***
	(1.381)	(1.197)	(1.560)	(1.475)	(1.391)
Female	-18.729***	-20.081***	-22.796***	-23.724***	-24.726***
	(1.108)	(1.278)	(1.279)	(1.590)	(1.445)
Other language at home	-18.210***	-19.083***	-16.858***	-17.957***	-15.973***
	(3.961)	(3.066)	(3.236)	(1.763)	(2.500)
Parental expectation	16.064***	15.732***	14.815***	16.143***	15.119***
	(2.687)	(2.002)	(1.068)	(1.691)	(2.062)
Parental value	12.238***	11.844***	12.952***	14.412***	16.677***
	(1.496)	(0.868)	(0.908)	(1.460)	(1.768)
Class size					
Class size	-0.110	-0.120	-0.133	-0.126	-0.082
	(0.166)	(0.107)	(0.171)	(0.107)	(0.127)
Constant	729.333***	736.066***	750.190***	770.483***	805.358***
	(29.197)	(18.585)	(26.348)	(36.571)	(59.203)
Ability track FE	Yes	Yes	Yes	Yes	Yes
Pseudo r-squared	0.327	0.325	0.311	0.295	0.289
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 12: Peer heterogeneity and educational opportunities, Quantile regression, Reading

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Parental background					
Parental background	25.350***	25.475***	24.588***	23.381***	20.055***
	(6.491)	(3.190)	(2.649)	(2.634)	(2.862)
Interactions variables					
Peer heterogeneity *PB	-7.717	-8.603***	-9.599**	-8.898**	-7.637*
	(6.209)	(2.896)	(4.054)	(4.169)	(4.639)
Heterogenous system*PB	-14.083***	-12.601***	-9.547***	-8.256***	-4.580***
	(3.357)	(2.290)	(1.142)	(0.968)	(1.570)
Admission procedure*PB	5.161**	6.270***	6.962***	5.184**	8.288**
	(2.461)	(2.058)	(1.988)	(2.502)	(4.212)
Main effects					
Peer heterogeneity	-13.747***	-16.356***	-4.138	-2.415***	-0.050
	(1.954)	(3.864)	(2.937)	(0.630)	(2.537)
Heterogenous system	-5.917***	-10.318***	-14.499***	-16.240***	-16.269***
	(1.567)	(2.655)	(1.105)	(1.345)	(1.337)
Admission procedure	15.147***	15.177***	16.836***	19.930***	18.417***
	(2.081)	(1.639)	(0.709)	(0.633)	(2.075)
Background characteristics					
Natives (reference category)					
Immigrant	-15.255***	-19.416***	-23.180***	-25.245***	-26.119***
	(5.220)	(5.828)	(1.509)	(1.407)	(1.815)
Immigrant parents	-30.041***	-33.640***	-34.459***	-32.005***	-29.098***
	(2.982)	(3.051)	(2.755)	(1.994)	(1.322)
Age	-16.749***	-14.565***	-11.771***	-10.238***	-9.395***
	(1.786))	(1.383)	(1.394)	(1.198)	(1.156)
Female	23.342***	22.491***	16.641***	16.146***	15.593***
	(0.376)	(2.022)	(0.431)	(0.605)	(0.792)
Other language	-18.270***	-18.662***	-20.106***	-14.708***	-17.490***
	(0.971)	(1.938)	(3.190)	(2.172)	(2.030)
Parental expectation	28.978***	28.946***	25.176***	22.754***	21.768***
	(1.780)	(1.253)	(0.905)	(1.944)	(1.616)
Parental value	6.297	4.501	1.662	-0.393	-1.661
	(6.850)	(8.257)	(7.636)	(3.392)	(1.076)
Constant	685.365***	684.059***	687.696***	710.103***	722.697***
	(22.064)	(18.128)	(15.641)	(16.841)	(14.447)
Pseudo r-squared	0.129	0.126	0.114	0.099	0.094
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 13: Peer heterogeneity and educational opportunities, Quantile regression, Mathematics

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Parental background					
Parental background	29.830***	29.850***	27.089***	28.609***	28.540***
	(6.998)	(5.455)	(2.291)	(2.278)	(7.426)
Interactions variables					
Peer heterogeneity*PB	-14.908*	-15.171**	-11.279***	-15.675***	-16.033**
	(8.661)	(6.673)	(2.863)	(3.464)	(7.895)
Heterogenous system*PB	-5.192	-6.088	-7.037***	-2.864	-2.967
	(4.878)	(4.173)	(1.858)	(3.993)	(3.079)
Admission procedure*PB	6.586***	6.879***	4.770***	7.224*	6.547**
	(0.510)	(1.148)	(0.407)	(3.697)	(3.053)
Main effects					
Peer heterogeneity	-18.611**	-16.099**	-10.410***	2.451	6.077*
	(7.858)	(6.581)	(3.884)	(4.295)	(3.405)
Heterogenous system	-5.683	-7.510***	-10.379***	-14.116***	-13.634***
	(3.506)	(2.179)	(3.371)	(4.848)	(0.766)
Admission procedure	16.821***	18.442***	21.615***	21.142***	22.665***
	(1.095)	(1.610)	(1.624)	(1.348)	(1.625)
Background characteristics					
Immigrant	-23.778***	-23.910***	-32.242***	-31.182***	-32.472***
	(3.531)	(1.969)	(3.462)	(6.063)	(4.854)
Immigrant parents	-33.911***	-35.191***	-38.239***	-39.925***	-40.183***
	(5.273)	(3.287)	(4.152)	(3.987)	(5.845)
Age	-18.008***	-17.306***	-16.598***	-15.620***	-12.722***
	(0.339)	(1.717)	(0.501)	(0.576)	(0.911)
Female	-23.414***	-23.117***	-25.061***	-24.492***	-23.373***
	(1.885)	(3.356)	(1.591)	(1.177)	(1.539)
Other language	-12.740*	-13.221***	-16.195***	-14.997***	-15.475***
	(7.269)	(2.146)	(0.754)	(0.748)	(2.684)
Parental expectation	30.746***	30.790***	29.634***	27.928***	25.443***
	(4.229)	(0.565)	(3.282)	(0.377)	(1.056)
Parental value	-3.611	-5.004**	-5.999**	-11.335***	-5.714**
	(3.968)	(2.522)	(2.859)	(1.108)	(2.562)
Constant	771.022***	787.382***	826.349***	856.277***	828.686***
	(11.418)	(31.620)	(4.621)	(7.252)	(17.701)
Pseudo r-squared	0.127	0.129	0.130	0.120	0.112
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.

Table 14: Peer heterogeneity and educational opportunities, Quantile regression, Sciences

	Quantile				
	0.15	**0.25**	**0.50**	**0.75**	**0.85**
Parental background					
Parental background	24.138***	30.947***	28.281***	27.549***	30.079***
	(9.006)	(11.533)	(7.072)	(5.506)	(8.157)
Interactions variables					
Peer heterogeneity*PB	-6.502	-14.242	-11.484	-12.283***	-15.130***
	(11.078)	(13.978)	(9.201)	(5.832)	(7.479)
Heterogenous system*PB	-15.356***	-12.577***	-12.226***	-6.967	-7.579
	(5.735)	(3.664)	(3.114)	(4.709)	(4.630)
Admission procedure*PB	6.660***	5.837***	6.447***	6.796***	6.277***
	(1.517)	(2.157)	(1.728)	(1.646)	(1.611)
Main effects					
Peer heterogeneity	-13.965***	-10.870***	-9.749**	2.110	6.130
	(4.710)	(3.685)	(3.931)	(5.538)	(4.620)
Heterogenous system	-7.381***	-10.257***	-11.698***	-11.704***	-15.057***
	(1.750)	(1.060)	(3.916)	(0.960)	(2.647)
Admission procedure	21.622***	23.803***	22.911***	23.090***	24.159***
	(0.075)	(0.383)	(0.653)	(0.291)	(1.569)
Background characteristics					
Immigrant	-29.767***	-33.258***	-33.556***	-36.079***	-32.773***
	(3.240)	(6.368)	(3.327)	(3.992)	(2.073)
Immigrant parents	-44.527***	-46.246***	-44.047***	-39.832***	-39.851***
	(6.782)	(3.330)	(1.543)	(2.576)	(3.618)
Age	-14.122***	-11.852***	-9.751***	-9.050***	-8.837***
	(1.476)	(1.513)	(0.610)	(0.586)	(1.232)
Female	-11.610***	-14.172***	-17.624***	-18.283***	-19.886***
	(1.364)	(2.401)	(1.884)	(0.582)	(1.666)
Other language	-21.846***	-19.280***	-22.289***	-19.939***	-19.371***
	(3.018)	(2.626)	(4.096)	(4.706)	(4.908)
Parental expectation	31.511***	32.081***	29.712***	26.083***	25.501***
	(3.103)	(0.311)	(1.430)	(2.305)	(0.915)
Parental value	21.914***	23.989***	26.216***	25.524***	25.501***
	(1.090)	(0.984)	(2.634)	(1.018)	(0.915)
Constant	665.618***	653.217***	671.923***	702.664***	722.117***
	(26.579)	(28.252)	(7.043)	(10.388)	(20.410)
Pseudo r-squared	0.150	0.157	0.150	0.137	0.132
N=14,081					

*, **and*** indicate a statistical significance at 10%, 5% and 1% level, respectively.