

Teachers' Training, Class Size and Students' Outcomes: Evidence from Third Grade Classes in France

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Abstract

This paper studies the impact of different teacher and class characteristics on third graders' outcomes. It uses a feature of the French system in which some novice teachers start their jobs before receiving any training. Three categories of teachers are included in the sample: experienced teachers, trained novice teachers and untrained novice teachers. We find that trained and untrained novice teachers are assigned to similar classes, whereas experienced teachers have better students located in better environments. Hence, in order to match similar students and classes, we focus on pupils with novice teachers and discard those with experienced teachers. In addition, we show that the same sample can be used to estimate the causal effect of class size on students' outcomes. Our findings are: (1) the effect of teachers' training is substantial in mathematics; in reading, the effect is significant only in classes with a low proportion of low-achieving students; (2) teachers' education background has a significant impact since untrained teachers who majored in sciences at university compensate for their lack of training, they have the same effect as trained teachers; (3) the effect of class size is substantial and significant, class size affects similarly all students within a class, but the effect is larger in those classes with a high proportion of low-achieving students.

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Introduction

The literature on the effects of class size on student learning is huge. Yet there is no consensus on the impact of class size and the debate is still impassioned. Some economists, who do not believe much that smaller class size can improve students' performance, or who find that it is a very costly policy, argue that other policies besides class size reduction, such as improving teacher quality, are more important.

Understanding the relationship between teachers' characteristics and students' achievement is obviously of prime importance in the analysis of the education system. Research on this topic has often focused on specific characteristics such as teachers' diplomas, experience and salaries. Few studies have specified the impact of teacher in-service training in developed countries. Angrist and Lavy (2001) present an evaluation of the effect of in-service teacher training in Jerusalem schools. They find that the causal effect of the program on pupils' test scores is significantly positive. The cost-effectiveness analysis suggests that teacher training may provide a less costly means of improving pupil achievement scores than reducing class size or adding school hours.

In France, most studies on teachers have looked at teaching practices, and little empirical work has examined the consequences of teachers' training on students' outcomes. Bressoux (1996) partly fills this gap. In order to study the effect of teachers' training and experience on third-grade pupil achievement, he uses a specific survey on third grade students and teachers in 1991, with a quasi-experimental design. This data source includes three types of teachers: untrained novice teachers, trained novice teachers, experienced teachers. Bressoux finds that training improves students' scores in mathematics. Experience seems also to have a positive impact on pupil achievement.

Importantly though, the experiment used in the above study is not randomized. The ideal situation would involve the random assignment of pupils to the different types of teachers. In fact, Bressoux (1996) shows that classes differ according to the status,

experienced, trained novice or untrained novice, of the teacher. Hence, in the absence of random assignment, Bressoux estimates the impact of training using regressions controlling for numerous variables. The estimated effect is the causal one if no unobserved student or class characteristic is correlated with the teacher's type and with the student's test scores. Otherwise, estimates are potentially biased.

This paper uses the same data, but relies on a methodology that takes care of the non-randomized design. The idea comes from the specificity of experienced teachers. The fact that the allocation of classes is not random is virtually only due to experienced teachers, who can choose their schools, and who often choose advantaged zones. But, in principle and in the data, trained and untrained novice teachers are assigned to almost similar classes. So our paper uses the fact that, when excluding experienced teachers, we are faced with a quasi-randomized design. We check the robustness of this feature using different estimation methods, both conditional and unconditional on other observed variables.

The data used here are very rich. The unit of observation is the student, a very important element for this kind of analysis (see Summers and Wolfe, 1977). Multiple students' characteristics are collected. Furthermore, all students within a third-grade class are included in the sample. This gives us an opportunity to control for class effects. In addition, teachers also provide a lot of information on their personal characteristics, their teaching practices, as well as characteristics of their classes and their schools. Moreover, students' achievement is extremely precisely measured by detailed test scores at the beginning and at the end of the year.

A first aim of this paper is to check that Bressoux's findings on training – better trained teachers induce higher students' outcomes – are robust. To perform this task, we use more recent statistical methods, controlling for the endogenous allocation of classes. The estimation is made excluding experienced teachers, in order to estimate the causal effect of training of novice teachers on pupils. Particular attention is given to heterogeneous effects. A second goal is to see if some particular characteristics of the teachers, such as

their university background (which was not used in Bressoux (1996)), have any impact on their students' outcomes. This paper also examines other class characteristics, more particularly class size. Indeed, when excluding experienced teachers, it appears that class size is not correlated with pupils' initial test scores. There is no sign of a relation between class sizes and class mean initial achievement or class socio-economic background. Thus, it seems that no selection bias in class size allocation is present when the sample is restricted to novice teachers. Consequently, we use similar methods to assess the effect of class size as were used to estimate the effect of training effect.

The findings on the training effect are very close to those found by Bressoux (1996): the training of novice teachers promotes students' learning in mathematics. The method allows also the estimation of heterogeneous effects. We find that in reading, the training effect is significant only in classes with a low proportion of low-achieving students.

We also find that teachers' education background has a significant impact since untrained teachers who majored in sciences at university have the same effect as trained teachers. It seems that their past studies help them to compensate for the lack of training.

The estimated impact of class size implies that reducing class size has a positive and substantial effect on third-graders. These results are close to the findings of Piketty (2004) on the effect of the size of French second-grade classes. Yet, in our paper, the effect appears to be similar for students within the classes. However, it is much larger in classes with a high proportion of initially low-achieving pupils.

The paper is organized as follows. Following a description of the data in Section I, Section II describes the statistical model and the empirical tests. Section III reports the main estimation results and Section IV concludes.

I. Data and descriptive statistics

The data come from a survey conducted by the French Ministry of Education. They cover a sample of classes of third-graders (8 years old) and their teachers. The quasi-experimental design is due to a feature of the system of teachers' training in France. This characteristic implies that some novice teachers start their job before any training.

In France, except for a subset of private schools, teachers are civil-servants recruited and paid by the State. After having passed a competitive examination, primary school teachers are trained in specific schools. At the beginning of the 1990's, these schools were called 'écoles normales'. France was, and still is, geographically divided into administrative 'départements' and there was an 'école normale' in each 'département'.¹

Novice teachers are recruited among students who have passed a competitive examination for entering an 'école normale'. The number of slots is limited and determined each year at the central level, using forecasts for teachers' positions. All applicants are ranked according to their grades in this examination. The students ranked first enter the 'école normale' and are trained during two years. Students who are ranked just after the last admitted candidate on this primary list are assigned and ranked within a waiting list. In September, students who have finished their training at the 'école normale' are assigned to classes not chosen by experienced teachers. But, most often, many job slots remain vacant, because of a greater number of pupils or a greater number of absent teachers than expected two years before. Thus, in October, some students in the waiting list are assigned to these vacant slots. Hence, these persons have to teach a class for an entire school year without receiving any training. They enter the 'école normale' the year after.

The survey was conducted in the school year 1991-1992. The sample included explicitly three categories of teachers: untrained novice teachers, trained novice teachers and

¹ The training schools are now called university teacher training institutes 'Instituts Universitaires de Formation des Maitres (IUFM)' and belong to a region (a region includes several departments).

experienced teachers. The sample covered third-grade students and their teachers in 12 'départements'. The teachers were teaching in third grade classes or in multi-grade classes including third graders. In the 12 'départements' selected, all novice teachers were surveyed while experienced teachers were chosen randomly. Finally, the survey covered 3,842 students and 198 teachers. The numbers of teachers within each category were not perfectly balanced: there were 96 experienced teachers, 66 trained novice teachers and 36 untrained novice teachers (see table 1).²

The information about the students is comprehensive: parents' occupations, sex, month of birth, nationality (French or not), number of years spent in a pre-elementary school, repeated classes (see the statistics in table 2). In addition, two sets of scores are available in the data. In France, there is national testing of all pupils just at the beginning of the third grade, both in reading and mathematics. The reading tests comprise grammar, vocabulary, spelling and reading comprehension *per se*. The mathematics tests comprise arithmetic, geometry and problem-solving. For this specific survey, covered pupils have also been tested at the end of the school year in both subjects, using a design similar to that prevailing in the entry tests. For each of the two subjects, initial and final scores are standardized (mean=100, standard error=15).

In addition, teachers had to answer a questionnaire on their personal characteristics, on their teaching practices and on the characteristics of their classes and their schools. The main variables used in the following are the field of specialization of the teacher during his/her studies at the university (sciences, unknown, other), the class size, the fact that the class is or not a combination class mixing students across grades, the category of the area of the school (rural, semi-rural, urban), and the priority status (see the statistics in table 3). The mean of the class sizes is 23.8 students per class, with a standard deviation of 4.0. By comparison with data on all elementary schools, Piketty (2004) finds that the average class size in the primary schools (first grade to fifth grade) is close to 23.3 in the school year 1991-1992.

² These statistics are slightly different from the ones in Bressoux (1996) because the matching of student data and teacher data has been made a bit differently.

Unfortunately, the scores are not available for all the students. This attrition comes from two reasons. First, some students were not in class when the tests were conducted. Second, for some classes, all the scores are missing. The scores of reading tests are not known for 808 students, including 9 entire classes, and the scores of math tests are not known for 615 students, including 4 entire classes. The class size also is not known for all classes: for 10 classes, the class size is unknown and can not be approximated by the number of students of the sample, because these classes mix students of different grades.

Nevertheless, this attrition should not induce any bias: tables 4 and 5, compared to tables 2 and 3, show that the characteristics of the students whose scores and class size are known do not significantly differ from those of all the students. It seems that the absence of information on the scores or the class sizes have random origins.

The data do not come from an experimental design. In fact, the assignment of the different types of teachers to the classes is not randomized. Indeed, the system of job assignment depends on the teachers' choices. When the choices of different teachers are the same, the final assignments depend on the years of experience and on a mark given by the administration, this mark being well correlated with the years of teaching experience. Hence, as they accumulate experience, teachers are able to choose the schools they want, and mostly go from disadvantaged schools to advantaged ones. On the contrary, novice teachers go to schools that have not been chosen by experienced teachers, or where there are free job slots because some experienced teachers retired or are absent for the year.

The data show that the aggregate characteristics of pupils vary with teachers' types (see tables 6 and 7). Indeed, experienced teachers have on average better classes. In these classes, compared to those with novice teachers, initial scores are higher, the share of non-French pupils is lower, children have fewer siblings, fathers and mothers have more often a high occupation and students less often repeated the first grade. In addition, the

class sizes are on average larger, and the schools are less often in a priority educational area.

The classes with trained novice teachers and those with untrained novice teachers are more alike. Nevertheless, the trained novice teachers are more often in urban areas and in priority zones than the untrained novice teachers.

There is a potential source of bias due to the fact that the trained novice teachers may have had better rankings at the entrance examination at the 'école normale' than the untrained novice teachers. If the examination measures the initial teaching abilities (a fact that should be proved), this bias could imply that the trained novice teachers are better able to teach than the untrained novice teachers. Fortunately (for us), the survey has been conducted during the school year 1991-1992, which is an atypical year, as can be seen in figure 1. Indeed, in 1991, the number of students selected for entry into the teacher training centers was very small. So the surveyed untrained novice teachers, who had taken the entrance examination in 1991, had very good rankings and would have been selected for entry had they competed for the examination during another year, and especially during the year 1989, when the surveyed trained novice teachers had passed their entrance examination. So the selection bias is likely to be weak.

II. Statistical method

The non-randomized assignment of the three types of teachers can also be observed through a regression of initial test scores on student and teacher characteristics. If the coefficients of the dummy variables for the types of the teacher are significant, it means that the assignment is non-randomized since the students have not been exposed to these teachers' teaching yet.

The regression is estimated on all the students. It includes random class effects, in order to take account of the correlation between students within classes. Indeed, class variables

may be not sufficient to control for these correlations. So, it is important to incorporate class effects: without them, the standard deviations could be underestimated. It would be the case with OLS estimation (see Moulton (1986)). However, Moulton stresses the problem of the precision of coefficient estimates, but he also shows that the coefficients may be different when the estimation incorporates random class effects without imposing the absence of correlation between these effects and the other covariates. Indeed, this kind of estimation results in substantial gain in efficiency. Throughout this paper, class effects are estimated through mixed models (see Robinson (1991)). These models allow a general specification of class effects, fixed effects being only a specific case of this specification. Identification of class effects uses more information than for “classic” fixed effects: it uses the variance of the class effects instead of only the mean, thanks to a more general prior distribution (see appendix A).

The results of the regression of initial test scores on teacher type are detailed in table 8 (without any other covariates) and table 9 (including student and class characteristics). They confirm that experienced teachers teach in better classes. Table 8 reports that the correlation between student initial scores and the dummy variable for the teacher experience is significant, in reading and in mathematics as well. These two correlations remain significant, even when controlling for student characteristics. On the contrary, it seems that classes with untrained novice teachers and classes with trained novice teachers are not different in terms of initial achievement, since the correlations between initial scores and the dummy of the teacher training are not significant, with or without other controls. Thus it seems that there is no selection of trained teachers, so that the classes of such teachers appear similar to those of untrained teachers according to pupils’ initial achievement.

This idea is checked with the same regression of initial scores, but with the sub-sample of the pupils having novice teachers. The results are given in table 10 (without any other control) and in table 11 (including student and class characteristics). The coefficient of the training dummy is never significant.

Bressoux (1996) assumes that the selection bias of experienced teachers can be controlled with the observed variables, including initial test scores. The causal interpretation of the coefficients related to the type of teacher relies on the assumption that no selection bias comes from unobserved variables.

This paper takes care of the non-randomized design in order to assess the robustness of the teachers' training effect found in Bressoux (1996). The idea is that trained and untrained novice teachers are randomly assigned to classes, at least according to our observed variables. Hence we have chosen to estimate the training effect on the subsample of novice teachers. In the spirit of matching classes to classes, either taught by trained or untrained novice teachers, we focus on pupils with novice teachers and discard those with experienced teachers. It means that we manage to have a sample of similar students, some have trained novice teachers and constitute the treatment group, and some have untrained novice teachers and constitute the control group. Thus we can expect that no bias perturbs the coefficients in the estimation and that the coefficient of the treatment estimates the causal effect. The idea is close to the one in Angrist and Lavy (2001). In this paper, they observe that the pupils have initially lower score in the treatment group than in the control group. As they would like pupils in the control group to be comparable to pupils in the treatment group, they match individual pupils on the basis of their initial test scores, by dividing test scores into quartiles and comparing treatment and control scores in each quartile. Here, we restrict the sample in order to have similar pupils in the treatment and control group. But, on the contrary to Angrist and Lavy, we keep a regression strategy, in order to control for the other covariates, and more specifically to control for class effects. We will see that these controls are important.

Thus, we will be able to estimate the effect of training on achievement using this specific sample. Nevertheless, we will have to keep in mind this restriction while interpreting the results: what we estimate is the effect of a trained novice teacher on pupils' achievement, compared to the effect of an untrained novice teacher, and not compared to all other kinds of teachers.

In the meantime, we will keep this strategy to estimate the class size effect. Indeed, table 12 reports that the correlation between initial scores in reading and class size is positive and significant when all pupils are included in the regression. When adding other covariates (in table 9), this correlation remains significant and positive, even if it is less significant. On the contrary, tables 11 and 13 report that even without any other control, class size is no more correlated with initial scores when the sample is reduced to the students with novice teachers.

Figures 2 and 3 present these results. These figures show the link between class sizes and class means of initial test scores in reading. The classes with experienced teachers are presented in figure 2 while figure 3 presents the classes with novice teachers. It is clear that all experience teachers teach high achieving classes whereas the scores of the classes with novice teachers are much more dispersed. Also, experienced teachers more often have larger classes. At last, the positive correlation between class size and scores can be seen in figure 2 with experienced teachers, even if it is not obvious, and it appears in figure 3 that there is no more correlation for the classes with novice teachers.

The idea that class size can be positively correlated with the student achievement is well known: the education system is often organized in order to support less advantaged pupils by gathering them in small classes whereas more advantaged students are assigned to larger classes. Hence the differences in class sizes are often in relation to students' socioeconomic background and scores. The selection bias in the relationship between test scores and class size can be generated within schools as well as between schools. This selection bias is one reason why causal effects of class size can be difficult to measure.

There are several reasons explaining why, in France, the selection could be weak for third grade classes. First, the system of attribution of teachers is centralized, and is not supposed to make any difference between schools in terms of resources. The only official exception is the policy of priority area zones (ZEP, 'zones d'éducation prioritaires'). The ZEP policy is a program implemented in 1982, which gives more resources to disadvantaged schools (for a description and an assessment of this program on sixth and

seventh graders, see Benabou, Kramarz, Prost (2003)). According to our data, the classes in the ZEP have on average 23.2 students per class, whereas the mean class size in the non priority zones is 24.1³.

The other case where it is known that some schools have smaller classes than the other schools is the one of rural schools: because of small enrollments, these schools have often small classes, even if they often organize combination classes by mixing students of different grades in a class. Yet the conclusion in terms of selection is not clear since, as we will comment on this later, pupils in rural schools have better achievement at the beginning of the third grade (but improve less during the year).

Nevertheless, there may be selection within schools. This selection is possible in large schools, when there are several third grade classes. Yet we will see that when the enrollment exceeds 30 students, it does not always entail a new third grade class, but sometimes some third graders are assigned to a class with students of other grades. To facilitate this assignment, the school may choose good pupils to go to this combination class, so that students who stay in the larger class are not necessarily the better ones.

The organization of a selection needs large schools. Since experienced teachers are much more often in urban areas, where schools are bigger, this may explain why the selection on initial scores can be observed for classes with experienced teachers and not for novice teachers. On the contrary, it seems that pupils with novice teachers are not assigned to classes with different sizes according to their abilities.

Finally, we will estimate the class effect on the sample excluding experienced teachers. As the correlation between class size and observed initial scores is significant on the whole sample, we suspect that there may also be a selection on unobserved variables, which could disturb the estimation of the causal effect of class size. On the contrary, the

³ The priority zones are more often in urban areas, where classes are larger than in rural areas. So the effective reduction in class size in ZEP schools could be larger than the one given by the raw difference of the two means. A regression of the class size on the dummy variable for ZEP schools, controlling for the rural areas and the combination classes, give a class size smaller of 1.5 students in priority zones.

correlation between class size and initial scores is not significant with the sub-sample of pupils with novice teachers. Hence we assume that the “traditional” bias selection is expurgated. Finally, to check the robustness of our findings, we will also estimate the class size effect on all the students, using instrumental variables.

III. Results

A. Global effects

The results of the estimation of the effects of teacher and class characteristics on pupil achievement are detailed in table 14. It is a regression of final scores on initial scores and student, teacher and class characteristics. The estimation includes class effects and is estimated on the sub-sample of students with novice teachers.

The data include a lot of information about the teachers and their teaching practices. They include in particular the diploma, the subject studied at university, the number of hours per week used for teaching reading or mathematics, the number of hours asked for homework per week, the practice of organizing the class in groups, and how these groups are chosen.

All these variables have been tested in the regression of final test scores on initial scores, student and class characteristics. When the variables on the number of hours per week used for teaching reading or mathematics, the number of hours asked for homework per week, the practice of organizing the class in groups, and how these groups are chosen are added, the coefficients on these variables are not significant. The small number of classes in the sample may prevent from identifying these effects that may be non linear. Therefore, these variables are not included in the final estimation.

The only teacher characteristic that is used is the subject studied at university. More precisely, dummy variables are included for teachers having majored in sciences at

university (12% of novice teachers) and for teachers having majored in a discipline not reported in the survey (roughly 14% of novice teachers). The reference group therefore comprises those teachers who majored in humanities (often French or another language, sociology, psychology, history). Novice teachers are all endowed with similar diplomas since it is compulsory to have a diploma equivalent to two years university to enter an 'école normale'. This was not the case in the past, and among experienced teachers, only a few went to university.

The regressions of final test scores include class characteristics. Some class characteristics can be calculated using the means of individual characteristics. We built class variables such as the share in the class of students with advantaged parents as measured by occupations, the share of girls, the share of non-French students and the share of students who repeated at least one grade. These variables are calculated for each student, excluding his/her own characteristics in the calculation of the means. None of these variables give significant coefficients. They are not included in the regressions presented in this paper. This confirms the difficulty in estimating peer effects without a clean experimental design.

On the contrary, means and standard deviations of initial test scores per class have significant correlations with final scores. For the regression of final scores in reading, the included variables are the class means and standard deviation of initial scores in reading. Likewise, the means and standard deviation included in the regression of scores in mathematics are calculated on initial scores in mathematics. These means are also calculated for each student, excluding his/her own characteristics. Table 14 reports the effects of class characteristics on final test scores, and coefficients of means and standard deviations of initial test scores have negative impacts on pupil improvement, meaning that students have better results in a homogenous class and when the average achievement is not too high.

The estimated impact of training is not significant on reading achievement but it is significant and large on mathematics achievement: students gain more than 3 points on

their final scores when their teacher has been trained. This effect is substantial; it is one fifth of the standard deviation of the final scores. These results are close to the findings in Bressoux (1996).⁴ They are also close to the raw differences of the means: as can be seen in table 6, students with untrained novice teachers have similar initial scores than students with trained novice teachers; yet, they improve much less during the year. The raw differences-in-differences estimator gives an effect of 2.7 in reading, and 2.4 in mathematics. Incorporating student and class characteristics show that the effect is larger in mathematics, since it is close to 3.4. On the contrary, the effect is much weaker in reading, since it is close to 1.3 and is not significant. The estimation of the regression without class effects would have drawn to a significant effect equal to 2.6. Hence incorporating random class effects shows that the coefficient is weaker and non significant.

The teachers' educational background has also a substantial impact. The finding is that teachers who majored in sciences improve their pupils' mathematics achievements more than other teachers do. These teachers are either trained or untrained. The effect is not significantly different for these two kinds of teachers, and not significantly different from the training effect. Hence, even though the training effect is substantial in mathematics achievements, teachers who have not been trained, but who have studied mathematics or sciences when they were at university, compensate for this lack of training. Nevertheless, the sample is small and this result is weak.

The teachers whose fields of specialization are unknown seem to improve their students' achievements, the effect being very significant in reading and slightly less significant in mathematics. This group of teachers comprises some individuals who did not report this information, potentially because of multiple fields of specialization, as well as some teachers who did not go to university. Indeed, very few people were entitled to take the examination for entering an 'école normale' without having studied at university; this was particularly the case of mothers of three or more children.

⁴ In Bressoux (1996), the effect of teacher training is estimated at 0.72, non significant, on reading scores, and 3.37, significant, on mathematics scores.

Nevertheless, it is worth noting that the repartition of teacher among classes according to their field of specialization is not random. The correlations between initial test scores and teacher dummy variables for fields of specialization are significant for the initial mathematic achievement (table 11). Hence, even if the regression of final score control for initial scores, estimates may be affected by selection bias since these teachers appear to be assigned to better classes.

Class size has also a significant impact on students' outcomes. The impact is quite similar in reading and in mathematics. For test scores in reading, the estimated effect is -0.33 while it is evaluated at -0.36 for mathematics achievement. This impact is substantial: reducing the class size by 10 students increases the final test scores of 3 to 4 percentage points. This is nearly the same impact as the one obtained for teachers' training.

This impact seems to be robust to the problem of combination classes. Indeed, the regression is estimated with a sample including multiple-grade classes. In the case of a combination class, the class size is then the size of the entire class, and not the number of third-graders. Yet the dummy for multiple-grade classes is not significant⁵. Likewise, results are similar when excluding these combination classes.

The coefficients of the other class characteristics are also of interest. Students in rural schools increase their achievements much less than the other students. However, as can be seen in table 11, their initial scores are higher. These results are consistent with Brizard (1995) and Thauvel-Richard (1995): pupils in rural schools have better scores at the beginning of their third-grade, but then they tend to improve less.

Students in ZEP schools improve less during the year than other students do. Nevertheless, they have lower scores even at the beginning of the school year. So it is difficult to conclude that it is a causal effect.

⁵ This result is consistent with Oeuvarard (1995).

B. Heterogeneous effects

We then estimate heterogeneous training and class size effects. To estimate the effects on heterogeneous students, the methodology chosen is to split training and class size variables into different kinds of students, in the same regression. Indeed, it is important to keep controlling for class effects. The results appear different when students are divided in sub-groups according to their initial achievements, and the estimations are made separately on each sub-group. This methodology allows us to estimate the effect on some kinds of students within the classes. In addition, we estimate the effects on heterogeneous classes. Thus we will be able to interpret more precisely some results on heterogeneous effects. Indeed, some papers find that the class size effect is larger for low achieving students. We will see that this can be explain by the fact that these low achieving students are more often in disadvantaged classes; but class size affects similarly all students within a class.

Tables 15 and 16 present the results for the regression of final test scores including heterogeneous effects. These effects are measured by breaking down the dummy variable for trained teachers or the class size variable according to the quartiles.

To estimate the heterogeneous effects on pupils, the quartiles are defined by students' initial scores and are measured within the classes. No significant training effects appear for scores in reading. For scores in mathematics, the training effect is maximum for the students of the second quartile: it is close to 4.2 points. For the other students, the effect is equal to 2.7, it may be larger for the more achieving students, but the difference is not significant.

No heterogeneity of the class size effect appears, for scores in reading and for scores in mathematics. So it seems that within the classes, class size affect similarly all students.

The two other ways of defining the quartiles have been chosen to identify different kinds of classes. The first quartiles are the one estimated on the class means of initial scores in reading. The second quartiles are calculated on the share in the classes of less achieving pupils, these less achieving pupils being identified by the first quartile of students according to their initial score in French.

The decomposition reveals significant effects of training on scores in reading for some kinds of classes. These classes are those whose score means are the highest or whose share of less achieving students is the lowest. More precisely, the effect of training is not significant for the less advantaged classes, but it is often significant for the other classes. So the training seems to help teachers to be better able to teach reading, except when they face a class where the mean achievement is low.

For the pupils' achievement in mathematics, the results are less clear. It seems that the results are close to the ones in reading, when we consider the quartiles defined by the share in the classes of less achieving pupils. Once again, the training is no help for less advantaged classes. The training effect is very substantial and significant for the second quartile and is substantial, but not significant, for the fourth quartile.

On the contrary, the class size effect appears much more substantial for less advantaged classes and decreases when the "quality" of the class increases. Indeed, all the coefficients for the class size are strongly negative, between 0.4 and 0.6, but the coefficients for the second, third and fourth quartiles are positive, meaning that the effect is much more substantial for the first quartile. Yet these positive coefficients are not all significant. The clearer results are for the scores in mathematics, with the quartiles defined by the share of less achieving pupils. We can see that for the first quartile, the coefficient is equal to -0.5, it is between -0.3 and -0.4 for the second and third quartile, and it is equal to -0.2 for the fourth quartile.

This heterogeneity is confirmed by table 17, which reports the results of the estimation of class size effect for all schools and for ZEP schools alone, estimated in the same

regression. The coefficients are significant only for ZEP schools and are very substantial: -0.6 in reading and -1.1 in mathematics. This finding confirms recent results obtained by Piketty (2004) who also finds substantial impacts of class size in ZEP school, albeit marginally significant because of the small number of students in ZEP schools in his sample.

These results show that the students in ZEP schools and in disadvantaged classes in general are more sensitive to class size as a group than the other groups of students. It may come from problems of behavior in class, the probability of a troublemaker among students of a class being larger in these schools.

Some papers find heterogeneous effects of the class size among students: in general, the results are that less achieving pupils are more affected by the class size. As less achieving pupils are often in less achieving classes, these results are in fact heterogeneous effects among classes, and not among heterogeneous effects on students within the classes.

C. Instrumental variables for the class size effect

The effect of third-grade class size, as estimated in this paper, stands between -0.3 and -0.4 percentage point of final test scores. Piketty (2004), on second-grade class size, finds an impact of -0.4 to -0.5 percentage point. He applies a methodology developed in Angrist and Lavy (1999). His method is based on the following specificity of French class openings: when second-grade enrollment goes beyond 30, another class is opened in most cases. Hence, the two new classes have an average size of 15 pupils. Piketty uses this discontinuity as an instrumental variable. He finds that a reduction in class size would induce a significant and substantial increase in mathematics and reading scores, and that the effect is larger for low achieving students.

In our data, we find similar specificities as those observed by Piketty (2004) (see figure 4).⁶ There are often two classes when the number of third-graders in the school is greater than 30. Yet there are some classes gathering 34 pupils. And the link between class size and enrollment is complicated by the existence of combination classes. When the enrollment goes just beyond 30 students, the schools do not open another third-grade class, but instead, assign some third-graders to classes with students of other grades.

When we exclude combination classes, there is less diversity in class sizes. Figure 5 shows the link between the enrollment of third graders and the class sizes. Yet when there are two classes, these classes have often different sizes; it could then be a source of bias if the sizes are determined according to the socio-economic background or the achievement of the students.

To check the robustness of our class size effects estimated on the novice teachers, we use instrumental variables on the whole sample. The instrument is based upon the enrollment of third-graders in the school when we exclude combination classes. In order to work with all classes, the instrument is also based upon the numbers of third-graders and students who are in a class with third-graders (see figure 6). In all cases, the instrumental variable is the mean of the class sizes in the school: the sizes of the third-grade classes in the first case and those of all classes with third-graders in the second case. This instrument takes care of the selection bias which exists when schools organize classes so that small classes gather low achieving students and high achieving students are assigned to larger classes.

As can be seen on figures 5 and 6, the instrumental variable is very close to the actual class size. Indeed, in our data, we identify few schools with more than one third-grade class. And when there are two classes, the sizes of these two classes are not very different. Hence the findings are easy to foresee: the results estimated with the instrumental variable are very close to the OLS results.

⁶ On the contrary to Piketty (2004), Figure 4 shows all classes, including combination classes. In addition, the classes are third-grade classes and not second-grade classes. At last, our data are less reliable than those used by Piketty because we do not always observe all third-grade classes in schools.

The idea in Angrist and Lavy (1999) is to use the discontinuity of the class size resulting from the creation of several classes when the enrollment goes beyond some level, assuming that this discontinuity is exogenous. One way of using this discontinuity is to estimate the class effect only when the enrollment is close to the “breaking point”. We use this method by estimating our instrumented regression for school where the enrollment is close to 34 students, the “breaking point” according to our data. We have chosen to restrict the sample to enrollments between 29 and 40 or between 24 and 45. The coefficients are then much more substantial, even if they are not always significant (see table 18).

All these results confirm the size of the effect: class size effect is between -0.3 and -0.5 percentage point of the final test scores.

IV. Conclusions

Thanks to the use of other statistical methods, this paper confirms the finding of teachers’ training effect found in Bressoux (1996). The data used have a quasi-experimental design; the French system is such that some novice teachers teach before being trained. The effect of teachers’ training is substantial: final test scores in mathematics of students with a trained teacher are greater by 3 percentage points than the scores they would have had if their teachers had not been trained. The estimation of heterogeneous effects shows that the training effect on reading achievement is significant in the classes with a low share of less achieving students.

The importance of teachers’ training is confirmed by the effect of teachers’ educational background. Teachers who majored in sciences at university improve their students’ outcomes in mathematics. This impact is the same for trained and untrained teachers. It

means that for the untrained, past scientific studies compensate for the lack of training in mathematics.

The effect of class size is shown to be significant and negative: a smaller class size improves student achievement. The impact is evaluated between -0.3 and -0.5 percentage points. Hence, training teachers is equivalent to reducing class size by 10 students, in terms of final test scores in mathematics. It is worth noting that this equivalence is true on average. But the effects vary according to the characteristics of the classes. The effect of class size is even more beneficial in classes with a high share of low achieving students; these students would benefit most from a decrease in class size. The effect is particularly large for classes in priority education areas. On the contrary, it seems that this type of classes do not benefit from the training of their teachers.

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Appendix A: Class effects estimated with mixed models

The mixed model is written:

$$Y = X\beta + Z\gamma + \varepsilon$$

where γ and ε are Gaussian:

$$E \begin{bmatrix} \gamma \\ \varepsilon \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \text{ and } \text{Var} \begin{bmatrix} \gamma \\ \varepsilon \end{bmatrix} = \begin{bmatrix} G & 0 \\ 0 & R \end{bmatrix}$$

The endogenous variable Y is explained with covariates X multiplied by fixed-effects parameters β and with covariates Z multiplied by random-effects parameters γ .

For estimating class effects, the matrix Z is composed of class dummies. The vector γ is then a vector of random class effects. We assume that variance matrices G and R are diagonal: $G = \sigma_1^2 I$ and $R = \sigma^2 I$. G diagonal means that the random effects are uncorrelated.

G and R can be estimated by the method of restricted/residual maximum likelihood (REML). Coefficients are then determined with Henderson's mixed model equations:

$$\begin{bmatrix} X' \hat{R}^{-1} X & X' \hat{R}^{-1} Z \\ Z' \hat{R}^{-1} X & Z' \hat{R}^{-1} Z + \hat{G}^{-1} \end{bmatrix} \begin{bmatrix} \hat{\beta} \\ \hat{\gamma} \end{bmatrix} = \begin{bmatrix} X' \hat{R}^{-1} Y \\ Z' \hat{R}^{-1} Y \end{bmatrix}$$

Thus, if the eigenvalues of $\hat{G} \rightarrow \infty$, then $\hat{G}^{-1} \rightarrow 0$, and the system is identical to the one of the estimation of fixed effects.

Appendix B: Tables and figures

Table 1: Number of students and classes according to the type of the teacher

	Number of teachers	Number of pupils
Experienced teachers	96	2045
Trained novice teachers	66	1180
Untrained novice teachers	36	617
Total	198	3842

Table 2: Statistics on the student variables

Variable	N	Mean
Month of birth	3842	6.52
At least one year younger	3842	0.02
Girl	3842	0.48
Nationality: foreigner	3842	0.17
1 sibling	3842	0.35
2 siblings	3842	0.27
3 or more siblings	3842	0.28
Father's occupation: high	3842	0.33
Mother's occupation: high	3842	0.17
Pre-elementary school: less than 3 years	3842	0.21
Pre-elementary school: more than 3 years	3842	0.18
One repeated grade in pre-elementary school	3842	0.02
First grade repeated	3842	0.12
Second grade repeated	3842	0.07
Third grade repeated	3842	0.07
Initial test score in reading	3568	100.00 (15.00)
Initial test score in math	3629	100.00 (15.00)
Final test score in reading	3258	100.00 (15.00)
Final test score in math	3390	100.00 (15.00)

Note: Standard deviations are reported in parentheses for non-dummy variables. High occupation corresponds to self-employed worker, executive, teacher, professor, technician, and foreman.

Table 3: Statistics on the teacher and class variables

Variable	N	Mean
Experienced teacher	198	0.48
Trained novice teacher	198	0.33
Untrained novice teacher	198	0.18
Field of specialization: sciences	198	0.12
Field of specialization: unknown	198	0.39
Class size	188	23.85 (3.98)
Combination class	198	0.33
Rural	198	0.15
Semi-rural	198	0.18
Priority educational area (ZEP)	198	0.24

Note: Standard deviations are reported in parentheses for non-dummy variables. The field of specialization is unknown when the teacher did not answer the question or when the teacher did not go to the university.

Table 4: Statistics on the student variables, for students whose characteristics are all known

Variable	N	Mean
Month of birth	2754	6.56
At least one year younger	2754	0.02
Girl	2754	0.48
Nationality: foreigner	2754	0.16
1 sibling	2754	0.36
2 siblings	2754	0.28
3 or more siblings	2754	0.27
Father's occupation: high	2754	0.33
Mother's occupation: high	2754	0.17
Pre-elementary school: less than 3 years	2754	0.20
Pre-elementary school: more than 3 years	2754	0.16
One repeated grade in pre-elementary school	2754	0.01
First grade repeated	2754	0.11
Second grade repeated	2754	0.06
Third grade repeated	2754	0.06
Initial test score in reading	2754	100.23 (14.83)
Initial test score in math	2754	100.50 (14.94)
Final test score in reading	2754	100.17 (14.91)
Final test score in math	2754	100.28 (15.01)

Note: Standard deviations are reported in parentheses for non-dummy variables.

Table 5: Statistics on the teacher and class variables, for students whose characteristics are all known

Variable	N	Mean
Experienced teacher	176	0.48
Trained novice teacher	176	0.35
Untrained novice teacher	176	0.17
Field of specialization: sciences	176	0.11
Field of specialization: unknown	176	0.41
Class size	176	23.85 (3.99)
Combination class	176	0.29
Rural	176	0.15
Semi-rural	176	0.18
Priority educational area (ZEP)	176	0.26

Note: Standard deviations are reported in parentheses for non-dummy variables

Table 6: Statistics on the student variables by type of teacher

Variable	Experienced teachers		Trained novice teachers		Untrained novice teachers	
	N	Mean	N	Mean	N	Mean
Month of birth	2045	6.52	1180	6.48	617	6.58
At least one year younger	2045	0.02	1180	0.01	617	0.02
Girl	2045	0.48	1180	0.49	617	0.48
Nationality: foreigner	2045	0.14	1180	0.21	617	0.18
1 sibling	2045	0.39	1180	0.29	617	0.34
2 siblings	2045	0.26	1180	0.28	617	0.29
3 or more siblings	2045	0.25	1180	0.35	617	0.26
Father's occupation: high	2045	0.36	1180	0.30	617	0.30
Mother's occupation: high	2045	0.19	1180	0.15	617	0.14
Pre-elementary school: less than 3 years	2045	0.20	1180	0.20	617	0.24
Pre-elementary school: more than 3 years	2045	0.19	1180	0.17	617	0.18
One repeated grade in pre-elementary school	2045	0.02	1180	0.02	617	0.01
First grade repeated	2045	0.10	1180	0.15	617	0.14
Second grade repeated	2045	0.07	1180	0.07	617	0.06
Third grade repeated	2045	0.07	1180	0.07	617	0.07
Initial test score in reading	1923	102.30 (14.46)	1089	97.02 (15.26)	556	97.87 (15.00)
Initial test score in math	1963	101.51 (15.48)	1079	98.41 (14.09)	587	97.88 (14.43)
Final test score in reading	1768	102.75 (14.26)	1026	97.31 (15.22)	464	95.46 (15.13)
Final test score in math	1835	102.25 (14.39)	1029	98.34 (15.06)	526	95.42 (15.51)

Note: Standard deviations are reported in parentheses for non-dummy variables.

Table 7: Statistics on the teacher and class variables by type of teacher

Variable	Experienced teachers		Trained novice teachers		Untrained novice teachers	
	N	Mean	N	Mean	N	Mean
Field of specialization: sciences	96	0.09	66	0.15	36	0.11
Field of specialization: unknown	96	0.67	66	0.12	36	0.17
Class size	86	24.79 (3.48)	66	22.79 (3.96)	36	23.53 (4.65)
Combination class	96	0.26	66	0.36	36	0.47
Rural	96	0.13	66	0.11	36	0.31
Semi-rural	96	0.15	66	0.18	36	0.28
Priority educational area (ZEP)	96	0.19	66	0.32	36	0.25

Note: Standard deviations are reported in parentheses for non-dummy variables.

Table 8: Regression estimates of the correlation between initial test scores and teacher type

	reading		math	
	Coefficient	Standard error	Coefficient	Standard error
Constant	98.41 **	(1.63)	98.65 **	(1.66)
Experienced teacher	4.07 **	(1.90)	3.22 *	(1.96)
Trained novice teacher	-1.27	(1.98)	-0.54	(2.06)
Number of students	2937		3123	
Number of classes	180		184	
Class level residual variance	68.02		83.87	
Individual level residual variance	156.88		142.62	

Note: Regression of the **initial** test scores of **all the students whose characteristics are known**; the covariates are only the dummy variable for the type of the teacher. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 9: Regression estimates of the correlation between teacher and class characteristics and initial test scores

	reading		math	
	Coefficient	Standard error	Coefficient	Standard error
Constant	95.94 **	(3.99)	96.47 **	(4.86)
<i>Pupil characteristics:</i>				
Month of birth	-0.36 **	(0.07)	-0.39 **	(0.06)
At least one year younger	4.91 **	(1.65)	2.22	(1.58)
Girl	3.16 **	(0.43)	-0.61	(0.41)
Nationality: foreigner	-4.14 **	(0.69)	-2.56 **	(0.66)
1 sibling	-0.96	(0.77)	-0.96	(0.75)
2 siblings	-1.57 *	(0.80)	-1.41 *	(0.78)
3 or more siblings	-4.36 **	(0.86)	-3.29 **	(0.83)
Father's occupation: high	3.18 **	(0.52)	3.83 **	(0.50)
Mother's occupation: high	3.21 **	(0.63)	3.56 **	(0.61)
Pre-elementary school: less than 3 years	-1.50 **	(0.64)	-1.00	(0.62)
Pre-elementary school: more than 3 years	-0.15	(0.72)	1.01	(0.69)
One repeated grade in pre-elementary school	-3.98 **	(1.96)	-6.07 **	(1.83)
First grade repeated	-7.04 **	(0.70)	-4.67 **	(0.67)
Second grade repeated	-3.64 **	(0.89)	-1.10	(0.86)
Third grade repeated	-6.78 **	(0.90)	-5.13 **	(0.86)
<i>Class characteristics:</i>				
Experienced teacher	3.71 **	(1.52)	3.05 *	(1.82)
Trained novice teacher	0.42	(1.57)	1.06	(1.88)
Class size	0.25 *	(0.14)	0.22	(0.17)
Combination class	1.68	(1.33)	0.79	(1.61)
Rural	0.91	(1.72)	4.17 *	(2.14)
Semi-rural	1.07	(1.43)	1.52	(1.76)
Priority educational area (ZEP)	-4.67 **	(1.30)	-2.40	(1.59)
Number of students	2937		3123	
Number of classes	180		184	
Class level residual variance	36.78		64.42	
Individual level residual variance	127.18		124.22	

Note: Regression of the **initial** test scores of **all the students**; the covariates include student and class characteristics. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 10: Regression estimates of the correlation between initial test scores and teacher type, on pupils with novice teachers

	reading		math	
	Coefficient	<i>Standard error</i>	Coefficient	<i>Standard error</i>
Constant	98.42 **	(1.75)	98.61 **	(1.46)
Trained novice teacher	-1.29	(2.12)	-0.45	(1.81)
Number of students	1361		1468	
Number of classes	96		98	
Class level residual variance	79.30		61.12	
Individual level residual variance	166.78		147.64	

Note: Regression of the **initial** test scores of **the students with novice teachers and whose characteristics are known**; the covariates are only the dummy variable for the type of the teacher. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 11: Regression estimates of the correlation between teacher and class characteristics on initial test scores, on pupils with novice teachers

	reading		math	
	Coefficient	Standard error	Coefficient	Standard error
Constant	95.92 **	(5.92)	97.10 **	(5.18)
<i>Pupil characteristics:</i>				
Month of birth	-0.34 **	(0.10)	-0.46 **	(0.09)
At least one year younger	3.14	(2.69)	2.48	(2.59)
Girl	3.34 **	(0.67)	-0.81	(0.62)
Nationality: foreigner	-2.96 **	(1.02)	-1.62 *	(0.94)
1 sibling	-0.71	(1.24)	-1.22	(1.17)
2 siblings	-1.54	(1.27)	-1.53	(1.20)
3 or more siblings	-4.77 **	(1.34)	-3.85 **	(1.26)
Father's occupation: high	2.67 **	(0.82)	3.75 **	(0.78)
Mother's occupation: high	3.88 **	(1.03)	4.12 **	(0.99)
Pre-elementary school: less than 3 years	-0.44	(0.98)	-0.03	(0.91)
Pre-elementary school: more than 3 years	0.07	(1.23)	1.46	(1.10)
One repeated grade in pre-elementary school	-2.25	(3.07)	-2.48	(2.66)
First grade repeated	-5.60 **	(1.00)	-2.89 **	(0.93)
Second grade repeated	-3.21 **	(1.43)	-0.60	(1.29)
Third grade repeated	-6.52 **	(1.53)	-3.38 **	(1.34)
<i>Class characteristics:</i>				
Trained novice teacher	0.36	(1.84)	1.59	(1.53)
Field of specialization: sciences	3.63	(2.44)	3.58 *	(2.14)
Field of specialization: unknown	1.77	(2.41)	3.55 *	(2.08)
Class size	0.20	(0.21)	0.15	(0.18)
Combination class	-0.22	(2.13)	-0.79	(1.79)
Rural	2.25	(3.06)	5.04 *	(2.63)
Semi-rural	1.07	(2.30)	2.95	(1.89)
Priority educational area (ZEP)	-4.57 **	(2.02)	-2.73	(1.70)
Number of students	1361		1468	
Number of classes	96		98	
Class level residual variance	48.65		35.16	
Individual level residual variance	142.80		133.94	

Note: Regression of the **initial** test scores of **the students with novice teachers**; the covariates include student and class characteristics. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 12: Regression estimates of the correlation between initial test scores and class size, on all pupils

	reading		math	
	Coefficient	<i>Standard error</i>	Coefficient	<i>Standard error</i>
Constant	91.21 **	(4.29)	93.77 **	(4.51)
Class size	0.36 **	(0.18)	0.26	(0.19)
Number of students	2937		3123	
Number of classes	180		184	
Class level residual variance	72.13		85.56	
Individual level residual variance	156.85		142.63	

Note: Regression of the **initial** test scores of **all the students whose characteristics are known**; the covariates are only the class size variable. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 13: Regression estimates of the correlation between initial test scores and class size, on pupils with novice teachers

	reading		math	
	Coefficient	<i>Standard error</i>	Coefficient	<i>Standard error</i>
Constant	93.61 **	(5.64)	96.67 **	(5.03)
Class size	0.17	(0.24)	0.07	(0.21)
Number of students	1361		1468	
Number of classes	96		98	
Class level residual variance	79.09		61.12	
Individual level residual variance	166.79		147.63	

Note: Regression of the **initial** test scores of **the students with novice teachers and whose characteristics are known**; the covariates are only the class size variable. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 14: Estimated effects of teacher and class characteristics on final test scores

	reading		math	
	Coefficient	Standard error	Coefficient	Standard error
Constant	52.85 **	(7.24)	58.75 **	(9.91)
<i>Pupil characteristics:</i>				
Month of birth	0.09	(0.06)	0.06	(0.07)
At least one year younger	4.27 **	(1.70)	3.73 **	(1.89)
Girl	2.27 **	(0.43)	-0.79 *	(0.45)
Nationality: foreigner	0.39	(0.65)	1.20 *	(0.69)
1 sibling	-0.64	(0.78)	-0.59	(0.85)
2 siblings	0.17	(0.80)	-0.19	(0.87)
3 or more siblings	-0.05	(0.85)	0.35	(0.92)
Father's occupation: high	1.51 **	(0.52)	0.13	(0.57)
Mother's occupation: high	0.81	(0.65)	1.21 *	(0.72)
Pre-elementary school: less than 3 years	-0.34	(0.62)	-0.64	(0.67)
Pre-elementary school: more than 3 years	1.26	(0.78)	0.03	(0.81)
One repeated grade in pre-elementary school	-6.41 **	(1.94)	-3.89 **	(1.94)
First grade repeated	-5.43 **	(0.64)	-3.84 **	(0.68)
Second grade repeated	-3.86 **	(0.90)	-2.37 **	(0.94)
Third grade repeated	-2.14 **	(0.97)	-3.01 **	(0.98)
Initial test score	0.76 **	(0.02)	0.79 **	(0.02)
<i>Teacher characteristics:</i>				
Trained novice teacher	1.33	(1.14)	3.44 **	(1.35)
Field of specialization: sciences	-0.04	(1.53)	3.37 *	(1.84)
Field of specialization: unknown	4.68 **	(1.49)	3.09 *	(1.79)
<i>Class and school characteristics:</i>				
Class size	-0.33 **	(0.13)	-0.36 **	(0.15)
Combination class	0.86	(1.33)	0.98	(1.56)
Mean of initial scores in the class	-0.21 **	(0.06)	-0.24 **	(0.08)
Standard deviation of initial scores in the class	-0.29 *	(0.17)	-0.62 **	(0.23)
Rural	-2.51	(1.89)	-5.00 **	(2.26)
Semi-rural	-1.41	(1.44)	0.35	(1.68)
Priority educational area (ZEP)	-2.07	(1.33)	-3.58 **	(1.49)
Number of students	1361		1468	
Number of classes	96		98	
Class level residual variance	18.00		27.07	
Individual level residual variance	56.93		70.50	

Note: Regression of the **final** test scores of **the students with novice teachers**; the covariates include student and class characteristics (including initial test scores), together with teacher characteristics. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 15: Heterogeneous effects of training

quartile defined by:		training dummy	training dummy and second quartile	training dummy and third quartile	training dummy and fourth quartile
students' initial scores (quartiles within the classes)	reading	1.39 (1.27)	-0.21 (0.75)	-0.35 (0.86)	0.35 (1.08)
	math	2.71* (1.47)	1.45* (0.83)	0.76 (0.94)	0.90 (1.15)
class means of initial scores in reading	reading	-2.86 (2.21)	5.58* (3.22)	6.80** (3.10)	5.07 (3.09)
	math	2.32 (2.07)	2.77 (2.14)	1.28 (2.45)	1.43 (2.77)
shares in the classes of less achieving pupils (inverse order of quartiles)	reading	-1.07 (1.77)	3.54* (1.86)	1.15 (2.05)	4.57* (2.39)
	math	0.99 (1.95)	5.69** (2.10)	0.82 (2.31)	3.91 (2.54)

Note: Regression of the **final** test scores of **the students with novice teachers**; the covariates include student, class characteristics and dummy variable of trained teachers, broken down according to the quartiles. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 16: Heterogeneous effects of class size

quartile defined by:		class size	class size and second quartile	class size and third quartile	class size and fourth quartile
students' initial scores (quartiles within the classes)	reading	-0.28** (0.13)	-0.04 (0.03)	-0.06 (0.04)	-0.07 (0.05)
	math	-0.37** (0.16)	0.03 (0.03)	0.01 (0.04)	0.00 (0.05)
class means of initial scores in reading	reading	-0.57** (0.27)	0.41 (0.37)	-0.09 (0.40)	0.42 (0.35)
	math	-0.47** (0.17)	0.09 (0.08)	0.10 (0.10)	0.21* (0.12)
shares in the classes of less achieving pupils (inverse order of quartiles)	reading	-0.39** (0.15)	0.06 (0.08)	0.02 (0.10)	0.17 (0.13)
	math	-0.53** (0.16)	0.19** (0.08)	0.12 (0.09)	0.34** (0.11)

Note: Regression of the **final** test scores of **the students with novice teachers**; the covariates include student, class characteristics and class size variable, broken down according to the quartiles. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 17: Effect of class size in the ZEP schools and in the other schools

	class size	class size and ZEP school
reading	-0.21 (0.14)	-0.58* (0.32)
math	-0.14 (0.16)	-1.06** (0.36)

Note: Regression of the **final** test scores of **the students with novice teachers**; the covariates include student, class characteristics and class size variable, broken down according to ZEP schools and other schools. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Table 18: Effect of class size estimated with or without instrumental variable

	All classes			
	OLS	IV	IV (29-40)	IV (24-45)
reading	-0.36** (0.10)	-0.39** (0.10)	-0.18 (0.49)	-0.44** (0.22)
math	-0.43** (0.12)	-0.44** (0.12)	-0.84* (0.45)	-0.67** (0.23)

	Without combination classes			
	OLS	IV	IV (29-40)	IV (24-45)
reading	-0.35** (0.12)	-0.36** (0.12)	-0.24 (0.33)	-0.32 0.20
math	-0.49** (0.14)	-0.50** (0.14)	-0.80* (0.43)	-0.54** (0.21)

Note: Regression of the **final** test scores of **all the students**; the covariates include student, class characteristics and instrumented variable of class size. The two last columns correspond to the estimation on the sub-samples restricted to some sizes of the enrollment. The coefficients are estimated through a mixed model, with class effects. Standard errors are reported in parentheses. **p<0.05 *p<0.10

Figure 1: Evolution of the number of individuals directly selected for entry into the teacher training college and of the number of individuals recruited on the waiting list, between the years 1986 to 1992

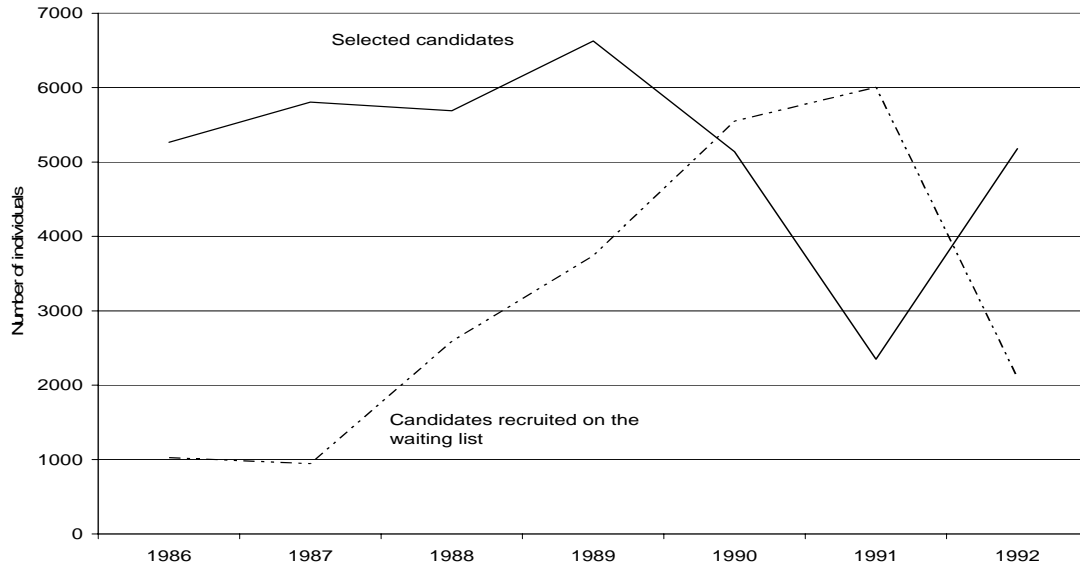


Figure 2: Class sizes and mean scores in reading for classes with experienced teachers

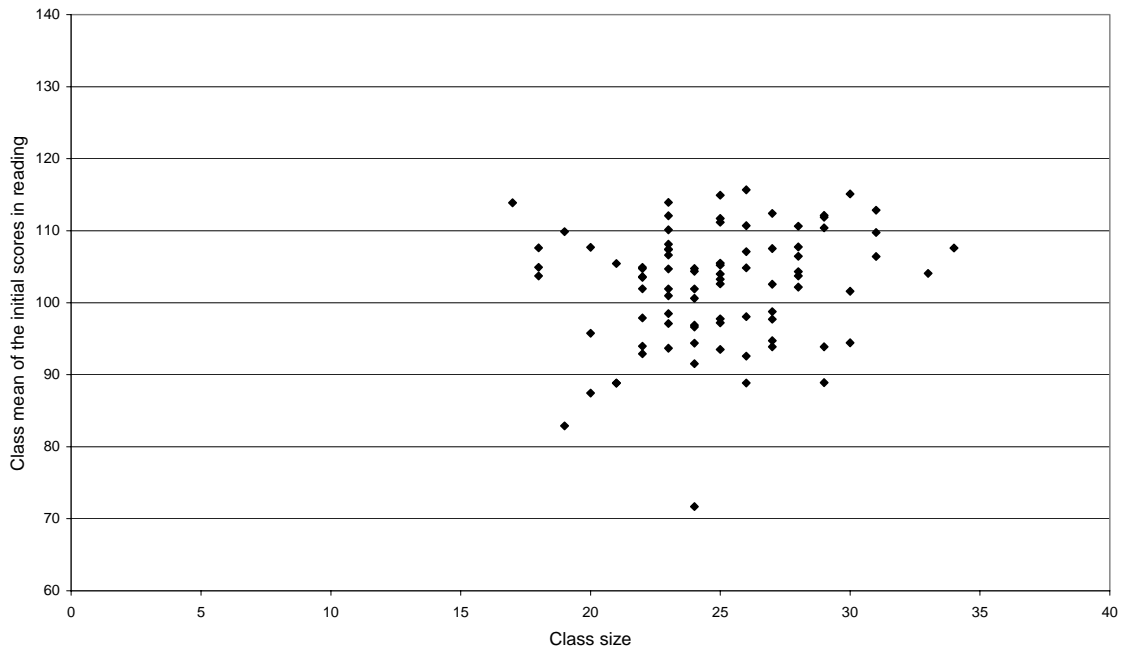


Figure 3: Class sizes and mean scores in reading for classes with novice teachers

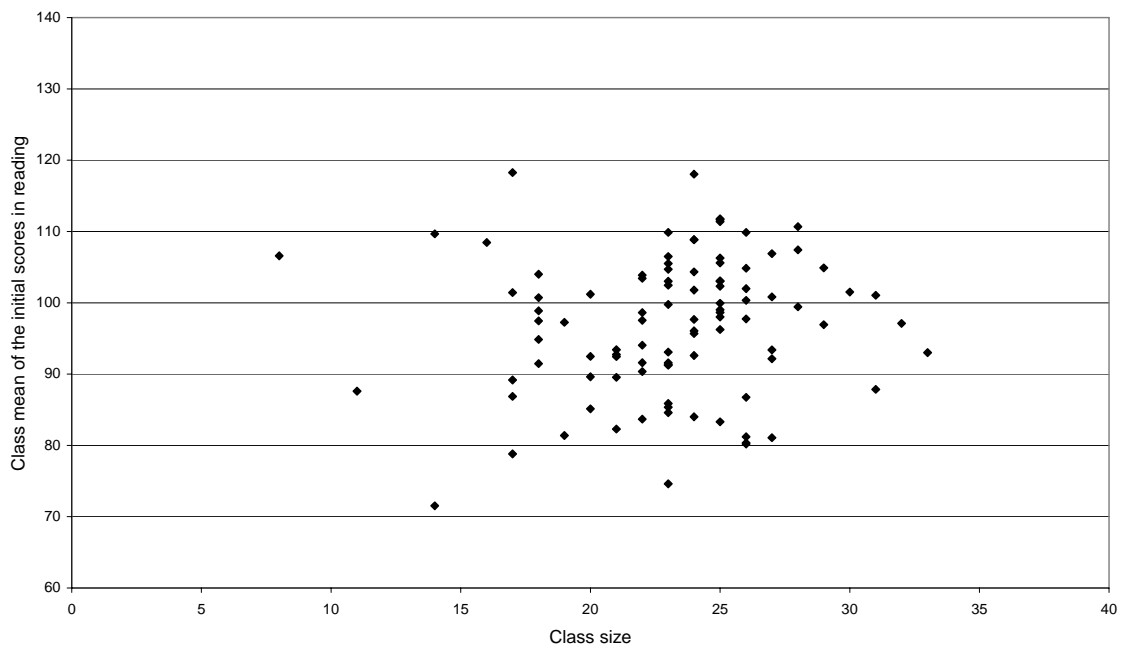


Figure 4: Enrollment and number of third-graders per class

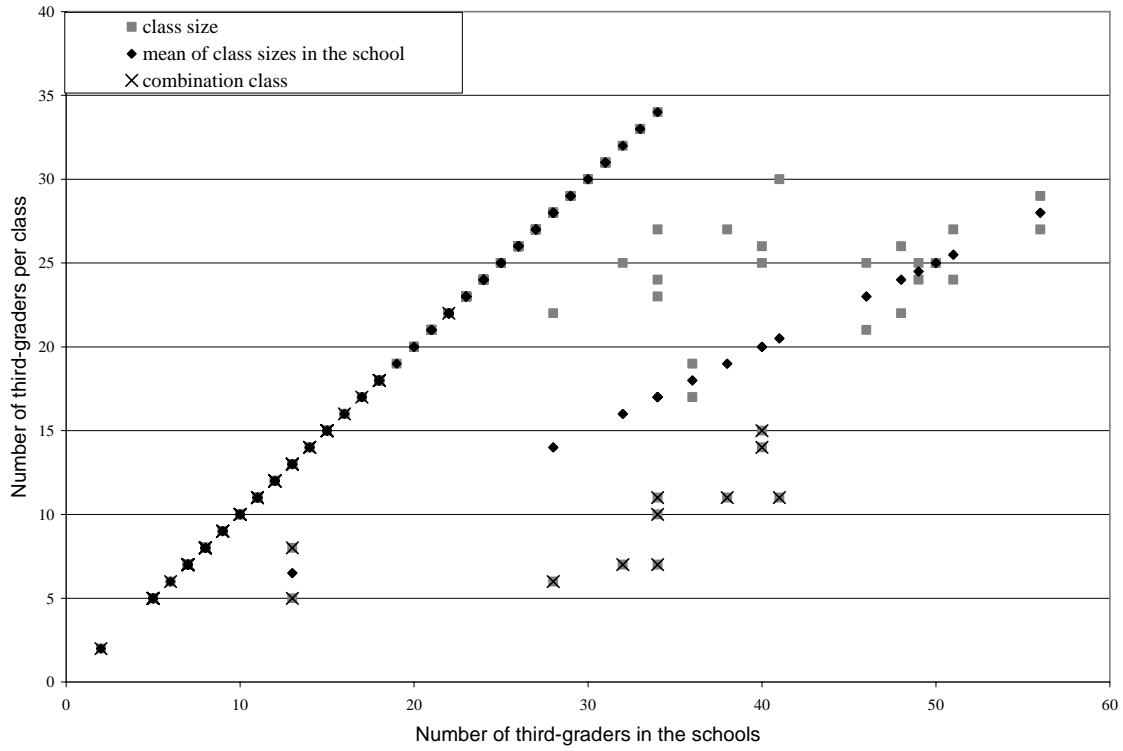


Figure 5: Enrollment and class size for third-graders, excluding combination classes

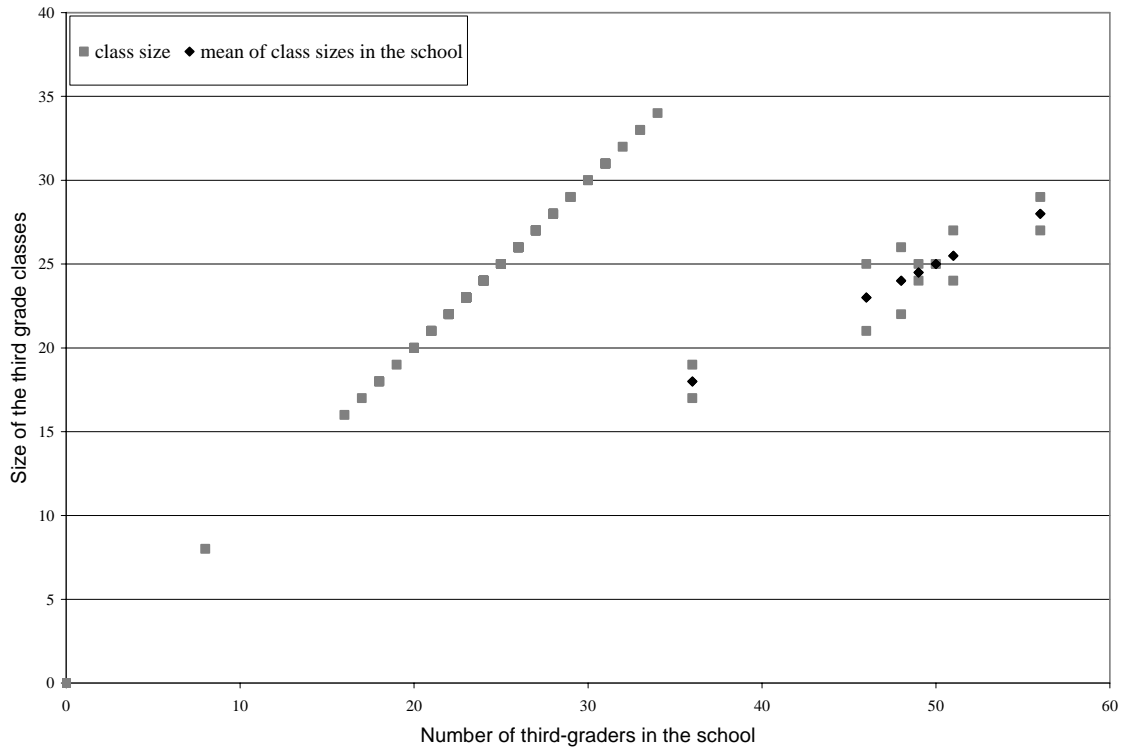


Figure 6: Enrollment of third-graders and students who are combined in a class with third-graders and class size

