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TEACHER CONTEXT EFFECT ON PUPILS' STANDARDIZED FRENCH TEST IN A SWISS SCHOOL: A MULTILEVEL ANALYSIS

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Abstract— **This article reports a study addressing how teachers influence pupils' standardized mark for French classes in a primary and secondary school in Switzerland. The sample consists of grades 7 and 8 with pupils from 10 to 12 years old. Seven classrooms with a total of 132 pupils have been randomly selected. Each classroom has its own teacher. A multilevel analysis shows that 17% of the response variance is explained by teacher effect. In other words, about 17 points out of 100 are due to teacher effect in these French classes.**

Keywords: **Multilevel analysis, Swiss school, teacher effects, marks on a standardized French test.**

I. INTRODUCTION

Since the end of the 1950s, many research studies have shown that significant inequalities in academic success are linked to the social and cultural background of pupils. In addition, the role of contextual factors in these inequalities is also the subject of a relative consensus within the scientific community. More specifically, the school in which a pupil is educated would be a relevant unit of analysis to explain certain variations in skills acquisition.

The school mix flow, which emerged from the 1980s, focused primarily on exploring the effect of school specific characteristics in terms of their composition and how it influences behavior and student achievement (Petrucci et al., 2018). The most important area in exploring the effects of the school context is whether, as such, the school attended affects pupils' progress or attitudes. The research trend of school effectiveness, which has been very much developed since the 1980s and is largely Anglo-Saxon, has produced an extensive body of work on the basis of large surveys (Duru-Bellat, 2003; Duru-Bellat et al., 2004).

The school effect has been studied extensively for a long time (Caldas and Bankston, 1997; Duru-Bellat, 2003; Crahay and Monseur, 2006). Now our idea is to focus on the class effect and the teacher effect. Research on these effects began in the United States and was especially developed during the years 1960-1970 within the framework of the process-product paradigm, a trend which attempted to relate teachers' pedagogical techniques to student achievement. Underpinning the work on class effects and teacher effects is the idea that student learning is linked, at least in part, to what happens in the classroom, and in particular to the teacher's tutelage. Although the experimental evidence of a class effect only appeared at the beginning of the 1970s (Hanushek, 1971; Veldman and Brophy, 1974), as early as the 1960s a number of studies had pointed out that some classroom practices, especially verbal interaction patterns, were associated with the level of student learning (Bianco and Bressoux, 2009).

The two main research questions in the present study are these: (a) Do teachers influence the outcome in the study of French? If yes, what is the magnitude of this teacher effect? (b) Do teachers vary significantly in their capabilities to improve a pupil's marks in French? If so, it would be very interesting to know if these differences could be explained by a teacher's characteristics (gender, academic qualifications, years of classroom experience and teaching style). But since there are only seven teachers in our sample, we must leave that question for another study that includes more teachers.

II. THEORETICAL FRAMEWORK

In this paper we continue to develop a theoretical and practical rationale for multilevel modeling of teacher effects. We argue that it is not enough to look only at individual pupil characteristics to explain marks on a standardized test of French. It is also very important to understand the contexts in which pupils evolve and learning occurs (McDonald et al., 2006). Unfortunately, we cannot take the class effect into account since the class effect and the teacher effect are confounded: each classroom has its own teacher. Bianco and Bressoux (2009) have taken into account both the teacher and the class effects in their researches.

Teacher contextual effects can clearly influence learning because each pupil is affected by multiple factors, widely understood to account for variation in learning. There is empirical evidence from sociological and psychological studies of teacher influences in classroom conditions to impede or promote learning (Ames and Ames, 1984; McDonald et al., 2005). In most prior studies data were analyzed using single level regression models (Carbonaro, 2005). Other studies employing multilevel analysis included the school level (McCoach, O'Connell and Levitt, 2006; Van Houtte, 2004) but ignored the class level and teacher level analyses. Studies have indicated that teachers have a significant influence on pupils' learning (Darling-Hammond and Youngs, 2002; Odden, Borman and Fermanich, 2004). Nye, Konstantopoulos and Hedges (2004) summarised results of 15 teacher effect estimates which were reported in five studies (Armour, 1976; Goldhaber and Brewer, 1997; Hanushek, 1971; 1992; Murnane and Phillips, 1981). Authors reported that from 7% to 21% of the variance in student academic achievement is explained by differences in teacher effectiveness. Taking prior student achievement, family socioeconomic status and the school's social composition into account, Rowan, Correnti and Miller (2002) reported that teacher effectiveness explains between 8% and 18% in mathematics and between 4% and 16% in reading. In the STAR project (Student-Teacher Achievement Ratio) Nye, Konstantopoulos and Hedges (2004) reported the inter-class variance in the random intercept full model was 13% (maths) and 7% (reading).

Accordingly, there is no doubt that teachers, who differ in effectiveness (teaching quality), influence pupils' scores. It is not clear however which specific teacher characteristics and teaching styles explain difference in teacher effectiveness as measured by pupils' achievement. Nye, Konstantopoulos and Hedges (2004, p. 237) note "It is widely accepted that teachers differ in their effectiveness, yet the empirical evidence regarding teacher effectiveness is weak". Moreover Hanushek (1986; 1989; 1996; 1997) and Hedges and Laine and Greenwald (1994a; 1994b; 1996) debate about the validity of explanations of differences in teacher effectiveness by characteristics like education, experience and salary (Koniewski, 2014).

Based on a literature review, Odden et al. (2004) identified some teacher factors that were found to be associated with pupils' achievement. These factors include years of teaching (Goldhaber and Brewer, 1997), major of undergraduate study, particularly for mathematics and science teachers (Monk, 1994), degree obtained (Rowan, Chiang and Miller, 1997) and earning of license (Darling-Hammond and Youngs, 2002).

In this paper we use the following teacher variables: years of teaching, degree obtained and teaching style. The intent is to better control for teacher effects to provide more precise estimates of curriculum effects and to continue to explore context effects of teacher**s** in a multilevel analysis. However, since we only have seven teachers, it is unfortunately not possible to investigate in more detail the effect of these variables in this study.

III. MATERIAL AND METHODS

3.1 Linear mixed model (LMM) in the social sciences

In the social sciences, data often have a nested, or hierarchical, structure. For example, data from pupils is often nested because the pupils have the same teacher or are from the same school. Analyzing nested data with fixed-effect models (e.g., ordinary least-squares regression) is problematic since these models have an assumption of independence, which is violated in these nested structures. Linear mixed-effects model, on the other hand, can account for the dependence that arises in nested structures.

3.2 Sample and variables (fixed and random effects)

The study sample includes pupils in grades 7 and 8 (n=132 pupils, n=7 classrooms and n=7 teachers). The pupils, aged 10-12 years old, are all randomly sampled from a single school in a Swiss city. All sampled pupils were born in Switzerland and speak French at home, sometimes in addition to one or more other languages.

To model the variation in the response variable **--**that is *the marks on a standardized French test*-- a mixed-effect model is fitted to account for the correlation among pupils' scores within classrooms. In the model the following pupil-level effects are treated as fixed:

- *gender* (boy or girl),
- *french average on grade 6* (from 3.5 to 6),
- *time to read french books in a week* (less than 30 minutes, between 30 minutes and 1 hour, between 1hour and 2hours, between 2hours and 3hours, more than 3hours),
- *like or not French lessons at school* (yes a lot, yes, not at all).

The variable *teachers* is also included as a random effect. We present a description of all the variables in Table 1.

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Table 1: Descriptive statistics for pupils

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	classrooms [factor]	1. C71 2. C72 3. C73 4. C75 5. C82 6. C83 7. C84	19 (14.4%) 16 (12.1%) 19 (14.4%) 19 (14.4%) 19 (14.4%) 19 (14.4%) 21 (15.9%)		132 (100%)	0 (0%)
2	gender [factor]	1. fille 2. garcon	70 (53.0%) 62 (47.0%)		132 (100%)	0 (0%)
3	frenchTest [numeric]	Mean (sd) : 5 (0.6) min < med < max: 3 < 5 < 6 IQR (CV) : 1 (0.1)	3.00: 1 (0.8%) 4.00: 13 (9.8%) 4.50: 30 (22.7%) 5.00: 36 (27.3%) 5.50: 44 (33.3%) 6.00: 8 (6.1%)		132 (100%)	0 (0%)
4	average6grade [numeric]	Mean (sd) : 5.2 (0.6) min < med < max: 3 < 5.5 < 6 IQR (CV) : 0.5 (0.1)	3.00: 1 (0.8%) 4.00: 5 (3.8%) 4.50: 17 (12.9%) 5.00: 36 (27.3%) 5.50: 50 (37.9%) 6.00: 23 (17.4%)		132 (100%)	0 (0%)
5	teachers [factor]	1. bovey 2. descartes 3. ismaili 4. kaeller 5. mamie 6. mueller 7. pinnard	19 (14.4%) 16 (12.1%) 19 (14.4%) 21 (15.9%) 19 (14.4%) 19 (14.4%) 19 (14.4%)		132 (100%)	0 (0%)
6	time.of.reading [factor]	1. 1ha2h 2. 2ha3h 3. 30mina1h 4. moinsde30min 5. plusde3h	25 (18.9%) 14 (10.6%) 31 (23.5%) 27 (20.4%) 35 (26.5%)		132 (100%)	0 (0%)
7	like.french [factor]	1. non 2. ouibcp 3. ouimoyen	9 (6.8%) 41 (31.1%) 82 (62.1%)		132 (100%)	0 (0%)

3.3 R software and packages

We download and use these packages in the R software (R Core Team, 2021): "lme4", "MASS", "car", "ggplot2", "pbkrtest", "RLRsim", "pbnm", "boot", "sjstats", "gvlma", "r2glmm", "influence.ME", "logspline", "sjPlot" and "bbmle".

3.4 Data analyses – Linear mixed model

We first fit the following nested random-intercept model. More precisely it is a hierarchical linear model:

$$FrenchTest_{ij} = \beta_1 + \beta_2 gender_i + \beta_3 average6grade_i + \beta_4 timeofreading_i + \beta_5 likefrench_i + b_{i1} + b_{i2} teacher_{ij} + \varepsilon_{ij}$$

where $\beta' s$ are the fixed-effects coefficients and b's are the random-effects coefficients for group i, assumed to be multivariately normally distributed. ε_{ij} is the error for observation j in group i. The errors for group i are assumed to be multivariate normally distributed.

We initially fitted some additional models to determine the random-effects structure. These models included random-slopes and interaction terms between *gender* and *like french* and between *average6grade*, *gender* and *like french*. Since the random-intercept model has the smallest AICc, it is the one we adopted (Burnham et al., 2011).

3.5 Model diagnostics

There is no influential point and no collinearity (variance inflation factors < 1.5). Assumptions of normality (Figure 1), linearity and homoscedasticity of the residuals (Figure 2) are met. The qq-plot for random effects (Figure 3) plots random against standard quantiles.

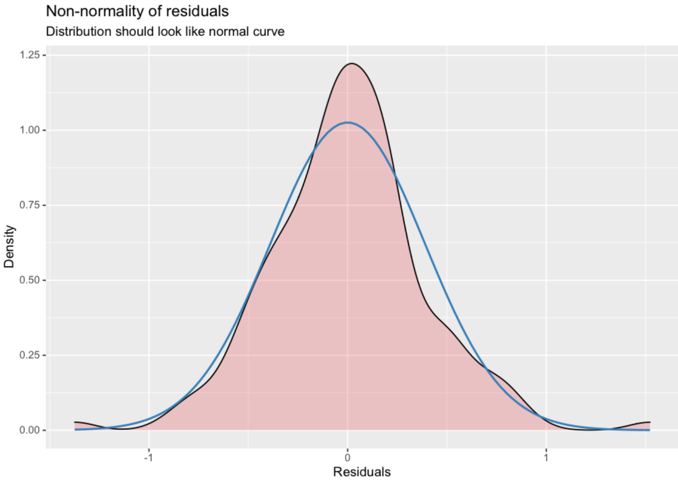

Figure 1: Normality of residuals

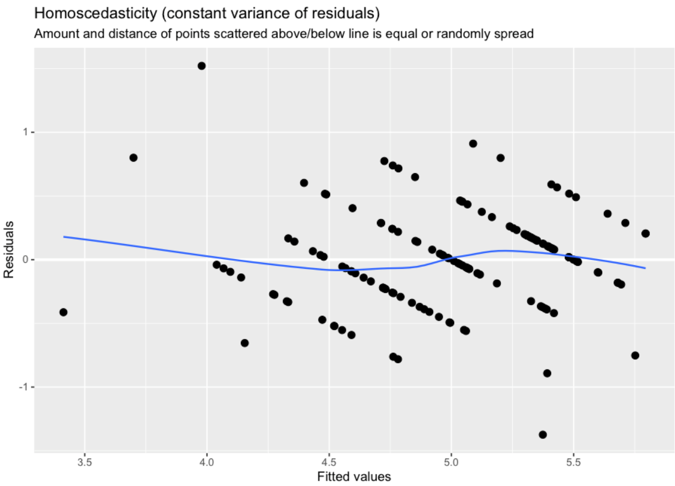

Figure 2: Homoscedasticity of residuals and linearity of the regression function

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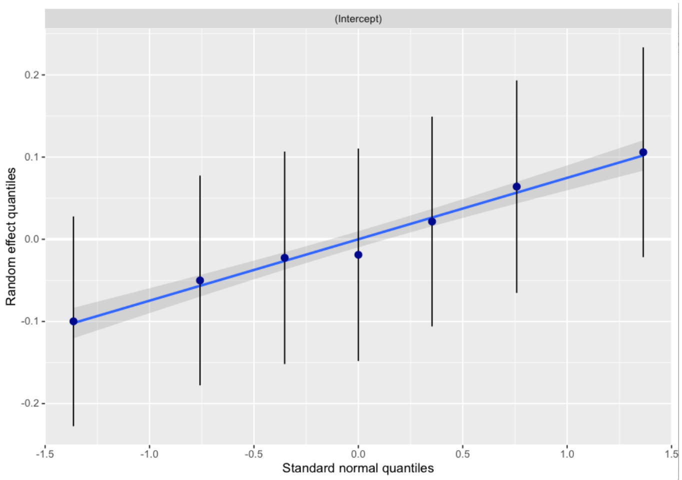

Figure 3: Random effects quantiles with 95% confidence bands

3.6 Testing the prediction of the model using crossvalidation

The model we fit is well specified. But is the model a good model for prediction and inference? Does the model overfit? We use cross validation to verify the validity of the model. The mean squared error (MSE) of the model is 0.0964. After 1,000 iterations of cross validation to assess the out-of-bag accuracy of the MSE value, we have MSE = 0.0968. These two results are so nearly equal that our mixed model is clearly a good one for prediction and for inference (Varin, 2020).

IV. RESULTS AND DISCUSSIONS

Despite the small sample, the model seems well specified – it converges and has no singularity problem so the estimates are well-defined. We can use 95% bootstrap confidence intervals for calculating the uncertainty of the model estimates. These intervals reveal that many of the effects are not statistically different from zero, and this is confirmed by the precise *p*-values using the Kenward-Roger approximation to the degrees of freedom. However four fixed effects are significantly different from zero at level 5%: (i) the grade6 average, (ii) reading time more than 3 hours a week, (iii) like French lessons "yes a lot" and (iv) like French lessons "yes moderately". In our sample the other variables don't impact the response sufficiently to generalize or infer about the "true / population" values. However there is reason to think that they may have an impact on the response; they are retained in the model since their inclusion doesn't bias the results.

The conditional pseudo R-squared – based on Nakagawa et al. (2017) – is interpreted as the variance explained by the entire model, including both fixed and random effects. Since R-squared = 0.734, the fixed and random effects together explain 73.4% (95% CI, [69.7% – 79.2%]) of the variance of the mark in the standardized French test.

Concerning the random effect, we refer to ICC (Intraclass-Correlation Coefficient) "the proportion of the variance explained by the grouping structure in the population" (Hox 2002, p. 15). The teacher-level predictor could be used to explain up to 17% (95% CI, [3% – 25%]) of the variation in the response variable. Roughly speaking we could say that 17 points out of 100 on the standardized test of French are due to differences in teachers.

It is of interest to attribute explained variation to individual predictors. Semi-partial coefficients of determination decompose R-squared into components uniquely explained by individual predictors (Jaeger et al., 2017). The semi-partial correlation of determination of the average6grade fixed effect is 0.41 (95% CI, [0.34 – 0.50]), of time of reading = 0.06 (95% CI, [0.01 – 0.18]) and of like-French is 0.02 (95% CI, [0 – 0.15]). So 41% of the variance of the entire model is explained by the average6grade fixed effect, 6% of the variance by time of reading and 2% by like-French fixed effects. The three fixed predictors explain together nearly half (49%) of the variability of the mark in the standardized French test.

Table 2: Fixed and random effects results

	frenchTest		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.97	0.42 – 1.53	**0.001**
gender [garcon]	-0.11	-0.23 – 0.00	0.054
average6grade	0.71	0.61 – 0.81	**<0.001**
time.of.reading [2ha3h]	0.15	-0.06 – 0.35	0.159
time.of.reading [30mina1h]	-0.07	-0.23 – 0.10	0.415
time.of.reading [moinsde30min]	-0.15	-0.32 – 0.02	0.086
time.of.reading [plusde3h]	0.23	0.06 – 0.39	**0.007**
like.french [ouibcp]	0.33	0.09 – 0.58	**0.008**
like.french [ouimoyen]	0.35	0.13 – 0.57	**0.002**
Random Effects			
σ^2	0.09		
τ_{00} teachers	0.02		
ICC	0.17		
N teachers	7		
Observations	132		

The presentation of the results shows the different stages of the multilevel analytical approach. Is there a significant teacher effect on student learning, that is to say, on the result obtained on the French standardized test? To what extent do the individual characteristics of students (level 1) influence these results? Interpreting the fourth significant fixed effects estimates at 5% level, we can say that the average grade at 6 school degree is really important in determining the actual mark in French standardized test in 7 and/or 8 school degree. A pupil having a high French mark in 6 school degree would get a high French mark in 7 and/or 8 school grade. As we could have imagined, the time of reading more than 3 hours a week is important and also the fact that pupils like or do not like to study French.

As for the random effects estimates, the two of them (teacher and residuals) are statistically different from zero. The first step establishes that there is indeed a teacher effect on student marks in the French standardized test. In other words, a given pupil might get a different result in the French standardized test depending on the teacher he or she has. However the size of this effect is not very large: based on the 95% confidence intervals, from 3% to 25% of the variance of pupils' results is attributable to it. As we have seen in the literature review, many authors reported that from 7% to 21% of the variation in student academic achievement is explained by variation in teacher effectiveness. These results are confirmed by our study.

In short, the difference in the pupils' achievement is mainly the result of differences at the level of the individual pupil and is not attributable to the teacher. This conclusion is not surprising. Indeed we knew that the teacher effect exists, and we discover in this study that this effect is not very large (17%). (With a larger sample size we could of course include more pupil fixed effects in the model.)

The third stage of the analysis would concern the nature of the teacher effect and would allow us to explore how teachers differ in their pedagogy. Our small sample did not permit any conclusions relating the characteristics of teachers (gender, academic credentials, years of classroom experience, teaching style) to differences in student performance. These effects have yet to be determined; they await a larger sample of teachers. Moreover, it would be interesting if we could distinguish class effect from teacher effect. In our study, the two factors are confounded.

V. CONCLUSION

This study should be extended and broadened in an effort to address the unanswered questions. It is very important for scientists who study these questions not to neglect the teacher effect, the elucidation of which could suggest policies on the training of teachers and school administrators. This study could be extended to several schools in a region, or even to an entire country so as to identify regional specificities which would make it possible to advance all students in their schooling and in acquisition of new skills, not only in French. We could consider opening this study to fields like mathematics, science or other disciplines. We really need to continue our quest because the end is not yet in sight and the policy makers may need such results to try to improve the governance of the school as a whole.

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Conflict of interest
The author declares no conflict of interest

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