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Evidence From the PISA 2000 Study

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Educational Production, Endogenous Peer Group Formation and Class Composition – Evidence From the *PISA 2000* Study

by

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Abstract. The majority of empirical papers in the literature on school quality finds no or only small effects of class size and other school quality measures on students' outcomes. This paper analyses the effect of achievement *heterogeneity* and therefore the effect of the composition rather than the pure size of the class on student achievement. In this endeavor, individual-level data from an internationally conducted standardized test, the *PISA 2000* study is utilized. For the case of US schools the influence of a student's peer group is estimated in a pure endogenous effects model and a model also allowing for contextual effects. The potential endogeneity of peer group formation is addressed in an instrumental variable approach. It turns out that heterogenous peer groups have a strong detrimental impact on individual achievement. Moreover, it becomes transparent that contextual variables are important for the extent of peer group effects and the endogeneity of peer group formation.

JEL-Classification: I21.

Keywords: Peer Group Effects, Learning Environment, School Quality.

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1 Introduction

One of the most contentious issues in the literature on school quality is the effect of quality measures like class size or the student-teacher ratio on the individual outcome of a student. A wide range of contributions addresses these questions for different countries and different outcome measures, leading to disconcerting mixed results. It seems safe to argue, though, that the majority of empirical papers in this literature finds a rather small or negligible impact of these school quality measures, whereas only some studies report a substantial effect on student outcomes[1]. This paper analyses the effect of achievement *heterogeneity* and therefore the effect of the composition rather than that of the pure size of the class on individual student achievement using individual-level data from an internationally conducted standardized test, the *PISA 2000* study.

A recent theoretical contribution by Lazear (2001) promises to justify the countervailing findings of the received literature on school quality. The author develops a model of educational production in which the optimal class size is larger for better-behaved students. In this model classroom education is viewed as a public good. That is, the production of educational output for each student decisively depends on the behavior of all other students in the class. In particular, students regularly disrupting lessons produce a negative externality. Therefore, regarding the technology this contribution develops a "disruption" model of educational production. This disruption is modeled by the probability that a given student is not impeding his own or other's learning at any moment in time. Variations in this disruption probability change the optimal class size which would be determined by a profit maximizing (private) school. Because these ideas are central to the empirical analysis conducted in this paper, some of the salient results of the model are summarized below.

Firstly, it is optimal to reduce class size when students are less well-behaved. Secondly, after optimal class size adjustment, educational output per student is higher in the larger classes with better-behaved students than in the smaller classes with less well-behaved students. And perhaps most importantly, total educational output is maximized by *segregating* students by their type of disruption behavior. One of the most important ingredients in this disruption technology is students' ability. The disruption of learning might be particularly prevalent in classes where some less able students regularly ask questions for which most of the other, more able students already know the answer. This definition of disruption builds the starting point for the empirical model estimated in this paper.

Intuitively, the principal idea is that it is not so much the size of a student's class which determines his or her performance but rather its composition, the students' learning environment. That is, putting together a more homogenous group of students in one class makes it easier for teachers to keep them all "on track" and to focus on the specific needs of the complete group. By contrast, in a *less homogenous* group of students it is difficult for the teacher to find the right "mix". This mix would avoid excessive demand for the less able students, while providing enough promotion of the highly able students

[1]See among others Card and Krueger (1992), Card and Krueger (1996a), Card and Krueger (1996b), Coleman et al. (1966), Eide and Showalter (1998), Fertig and Schmidt (2002), Hanushek (1986), Hoxby (2000a), Woessmann and West (2002), Wright (2002).

at the same time. Furthermore, I would argue that a higher dispersion of achievement within the group has a more detrimental impact on individual success the lower is the overall achievement of the group. This implies that a heterogeneous group with a rather low average ability will even be more detrimental for individual achievement than the same degree of heterogeneity would be in an on average higher-ability group.

Other mechanisms than disruption might lead to the same influence of homogeneity on achievement. For instance, it is also conceivable that a more homogenous group fosters the motivation of all students to increase effort and as a result individual achievement, because they do not feel to lag hopelessly behind the majority of their peers. Furthermore, the variation in achievement within a certain reference group might work as a social norm with a more homogenous behavior displaying a stricter norm and vice versa. In all these cases, one might argue that there is a peer group effect in learning. Thus, it does not seem surprising that peer group effects are the focus of a variety of empirical studies on student outcomes[2].

The analysis of individual school achievement as a reaction to peer group effects, as measured by the heterogeneity of achievement, poses three major conceptual challenges. Firstly, it is difficult to measure the degree of homogeneity or heterogeneity within a group. In this paper it is suggested to utilize the *coefficient of variation*, i.e. the ratio of the standard deviation of individual outcomes relative to its mean, within a specific reference group as the measure for heterogeneity. This measure takes into account the average achievement of the group and implies that for a given dispersion around the mean, observed heterogeneity is the higher the lower is the mean, i.e. it is expected that a higher coefficient of variation – which means a higher degree of heterogeneity – displays a negative impact on individual outcomes and vice versa.

Secondly, the impact of belonging to a specific reference or peer group might work through different channels (see Manski (1993) and (2000)), i.e. *endogenous* and *contextual* interactions. It is important to discriminate between these channels since they imply completely different effects of policy interventions. Significant endogenous effects can create a "social multiplier" effect of policy interventions. That is, policy interventions can have a positive spill-over effect to *non-treated* individuals (and back to treated individuals) if they affect the behavior of these non-treated individuals via endogenous interactions with treated individuals (see Durlauf (2000) and Manski (2000)). Contextual interactions, however, do not display such spill-over or feedback effects.

Finally, individuals often have some scope for choice of peer groups through the selection of neighborhood of residence, school, or friends (see e.g. Evans et al. (1992), Gaviria and Raphael (2001) and Rivkin (2001)). In consequence, the conclusions reached by different empirical studies addressing the existence and extent of such peer effects often depend upon the estimation method used to account for the potential endogeneity of reference group choice. This paper uses an instrumental variable approach to

[2]See e.g. Arcidiano and Nicholson (2002), Argys et al. (1996), Ashwort and Evans (2001), Betts and Morell (1999), Case and Katz (1991), Epple et al. (2002), Feinstein and Symons (1999), Garcia-Diez (2000), Gaviria and Raphael (2001), Henderson et al. (1978), Hoxby (2000b), McVicar (2001), Rivkin (2001), Robertson and Symons (1996), Zimmer and Toma (2000).

account for the potential endogeneity of US-students peer group composition in a social interactions framework. It becomes transparent that students peer group composition is a rather strong predictor of individual achievement in a standardized reading literacy test. Estimation results clearly indicate that the higher the heterogeneity of achievement in a student's school, the lower is the individual performance. Furthermore, it turns out that contextual effects play an important role for the extent and endogeneity of peer group effects.

The structure of the paper is as follows. The next section explains the empirical strategy of the chosen approach in more details. Section 3 provides a brief overview on the dataset *PISA 2000* and section 4 presents the empirical results. Finally, section 5 offers some conclusions.

2 Class Composition, Student Achievement and Peer Group Choice

The principal aim of this paper is the investigation of individual student achievement in response to variation in the heterogeneity of achievement in the students' peer group. To provide an analysis that can be interpreted in causal terms, the potential endogeneity of the peer group is explicitly taken into account. Consequently, the counterfactual question asked in this paper is: What would have happened to students' individual achievement if the degree of heterogeneity in their peer group had been different? This situation is clearly unobservable. In an ideal data situation where one observes the same group of students under two different regimes, one with a high and one with a low degree of heterogeneity, it would be possible to compare the outcomes of both regimes to isolate the causal effect of composition on achievement. This data situation, however, is exceptional (see e.g. Boozer and Cacciola (2001), Duflo and Saez (2002), Katz et al. (2001), Sacerdote (2001) and Zimmerman (1999) for contributions exploring the effects of such social experiments).

In this paper we have instead to rely on a cross-sectional data set in an observational study design. Thus, we nee to construct an observable counterpart for this unobservable situation by invoking suitable identification assumptions. Given the influence of students and their parents on school choice particular attention has to be paid to the potential endogeneity of the peer group. In this analysis, the chosen identification strategy is an instrumental variable approach. The estimates compare individual achievement in a specific school with a specific degree of heterogeneity with all other schools in the United States, with different degrees of heterogeneity. This process involves controlling for individual and family background characteristics as well as other school characteristics, to filter out the impact of other covariates on individual school achievement. Furthermore, two different models are estimated: (i) a *pure endogenous effects model* and (ii) a model which allows for endogenous effects as well as exogenous or contextual effects (referred to as the *full model*).

Pure Endogenous Effects Model vs. Full Model
The reason for this distinction is the following. The literature on social interactions (see

especially MANSKI (1993) and MANSKI (2000)) suggests three explanations for the observation that members of the same reference group display similar outcomes: Firstly, there might be *endogenous* effects, i.e. individual achievement varies with the achievement of the reference group. Secondly, this observation might explained by *exogenous* or *contextual* effects, i.e. individual achievement varies with the exogenous characteristics or composition of the reference group. And finally, there might be *correlated* effects, i.e. individual achievement is mainly determined by individual characteristics which are similar for all members of a specific reference group.

Disentangling these three effects in real world data is rather difficult. MANSKI (1993) shows that inference on these different social interaction effects is not possible as long as the researcher has no prior information on the composition of the reference group of an individual. In most empirical studies the reference group is typically assumed as given without providing further evidence for this choice (one noticeable exception is WOITTIEZ AND KAPTEYN (1998)). Furthermore, even if one knows the correct reference group, these different effects will not be identified in a linear regression model of individual achievement on the achievement of the reference group. Intuitively, identification in such a linear model is hampered by the fact that the mean outcome of the reference group is itself determined by the individual outcome of the group members. Thus, it is *a priori* not clear whether the mean outcome of the group affects individual outcomes or if the outcome of the reference group is simply the aggregation of individual outcomes (see MANSKI (2000) and for a formal exposition MANSKI (1993)).

Often such models are identified by assuming that contextual effects do not exist (see e.g. GAVIRIA AND RAPHAEL (2001) or GINTHER ET AL. (2000)) and, consequently, a *pure endogenous effects* model is estimated. This straightforward technical solution of the problem does not seem appropriate, however. Moreover, separating the impact of contextual effects on individual outcomes from that of endogenous interactions is very important, since they yield completely different conclusions for the impact of public policy interventions. The existence of sizeable endogenous interactions leads to a social multiplier effect, i.e. certain interventions are not only able to help the treated individuals, but can also have spill-over effects on non-treated people. This is, however, not the case for contextual effects. Therefore, this paper aims at clarifying the sensitivity of the results to the choice of controlling for the possible existence of contextual effects, as compared to pure endogenous interactions models.

In the case at hand, it is assumed the the reference group is the school of a student. The presumed non-linear relationship between individual achievement and the achievement of the reference group secures identification of both channels of social interaction (see BROCK AND DURLAUF (2001)). Clearly, it is conceivable that there are other groups which might serve as the reference group of a given student, e.g. his or her family or friends. However, since time regularly spend at school comprises a large fraction of a students time every day, it is hoped that the assumption of his or her school as the valid reference group is not completely misleading.

Formally, assume that each student i ($i = 1, .., N$) in school s ($s = 1, ..., S$) is characterized by his or her individual achievement y_{is}, a vector of individual characteristics z_i, the heterogeneity of achievement C_{-is} in the reference group (excluding the contribution

of i), characteristics of his or her school ($school_i$), and an unobserved error term ϵ_{is}. Thus, we have the following reduced-form model

$$y_{is} = \alpha + \beta^{'} z_i + \gamma C_{-is} + \delta^{'} \overline{z}_{-is} + \lambda^{'} school_i + \epsilon_{is}, \tag{1}$$

with

$$C_{-is} = \frac{\widehat{Var}(y_{-is})^{1/2}}{\overline{y}_{-is}}$$

denoting the heterogeneity measure (coefficient of variation) for i's peers in school s and $\overline{z}_{-is}$ being the exogenous socio-economic composition of the reference group, again excluding the contribution of i.

A statistically significant estimate for δ indicates the existence of a contextual effect, whereas γ reflects endogenous interactions. That is, a statistically significant estimate of γ suggests that individual outcomes vary with the standardized dispersion of outcomes in the reference group, whereas a significantly estimated δ indicates that individual achievement varies with the composition of the reference group. Of course, both types of effects can be present simultaneously. In equation (1) both effects are identified due to the non-linear relationship between individual achievement and the mean achievement of the reference group.

In estimating this equation, two serious problems need to be addressed. Firstly, since the coefficient of variation is an estimated regressor, it is contaminated by approximation error. Consequently its own standard error diffuses into the standard error and the value of the estimated parameter in the regression model. This means that the coefficient estimate as well as the "usual" standard error of estimates are likely to be biased downward (see Fuller (1987)). And secondly, the reference group might be a choice variable, if parents decide to send their children to schools where their peers display a comparable ability (see Evans et al. (1992) and Rivkin (2001)). Since student ability and the criteria of parental school choice are unobservable, our peer group measure, the coefficient of variation, is susceptible for being endogenous. This endogeneity of reference group achievement introduces a further downward bias into OLS parameter estimates if there is a positive sorting of students by ability.

Instrumental Variable Approach

To address both of these problems, this paper utilizes an instrumental variable approach. The estimated coefficient of variation is instrumented by two sets of variables which are jointly applied. The first set contains two variables indicating whether a school selects students upon entry by standardized tests and whether the school is private. The second set comprises variables which reflect the *caring behavior* of parents. Parental caring behavior is approximated by variables indicating whether parents regularly talk with their children about their progress in school, or whether parents regularly eat the main meal with their children (for more details see next section). For the estimate of the coefficient of variation only data of all other members of the same school, i.e. without the own contribution of an individual is utilized. Furthermore, in the IV approach the second set of instruments for the estimated coefficient of variation is also constructed *without* the individuals' own contribution. That is, the instruments are indicators for the caring behavior of *all other parents* of students in the same school, neglecting the behavior

of the own parents. The choice of this group of instruments is motivated by the idea that a higher share of parents taking care of their children will result in a more homogenous group of peers which in turn provides a better learning environment for the students.

In such an instrumental variable approach the coefficient of variation is the dependent variable of the first stage regression and, therefore, its standard error will be transferred into the residuals of the first-stage regression. In this application, the standard errors of the second-stage coefficient estimates take those of the first-stage coefficient estimates into account. However, such an approach is only valid if the instruments meet two criteria. Firstly, they have to be related to the regressor of interest, i.e. they have to be correlated with the coefficient of variation. And secondly, they must not exert any direct impact on observed outcomes, i.e. they must not be correlated with students' unobserved ability.

While it is very likely that the instruments meet the first criterion, it is *a priori* not clear whether they also fulfill the second one. Since any instrumental variable approach is always susceptible to validity arguments against the chosen instruments – especially regarding the second criterion – the next paragraphs will discuss this issue in more detail.

Validity of the Instruments
Naturally, it is not possible to test whether the employed instruments are uncorrelated with students' unobserved ability. In consequence, this choice is an identification assumption which has to be judged upon economic reasoning alone. For both groups of instruments it is possible to raise serious reservations against the validity of this identification assumption. Regarding the first group of instruments – the indicators for private and selective schools – especially the private school variable might be susceptible for impinging upon individual achievement by other channels than peer group composition. The existing literature on the effect of private schools on individual educational outcome in the USA provides comprehensive analyses of the large and quite homogeneous group of Catholic schools.

Many studies in this literature demonstrate that Catholic school students perform, on average, better than comparable students in public schools. This finding is robust to the measurement of performance, i.e. whether achievement test data, postsecondary educational achievement or students' earnings is used as outcome measures. However, the explanation of this finding is highly controversial. Coleman et al. (1982) and others, argue that Catholic schools are more effective than public schools due to lower bureaucracy, fewer non-academic objectives or better working relationships between teachers. Murnane et al. (1985) and others, however, argue that this finding is primarily the result of inappropriate controls for selection bias. Furthermore, Murnane et al. (1985) provide empirical evidence that – with appropriate selection controls – certain minority groups benefit from Catholic schooling, whereas the effect of Catholic schooling on educational achievement of white students is, if anything, rather negligible.

The latter result is supported by other studies in the received literature. Bryk et al. (1993), for instance, conduct extensive case studies examining a broad range of Catholic high schools. The authors also find that Catholic schools reduce achievement disparities between disadvantaged and privileged students. Finally, Neal (1997) utilizing additional data sources, provides ample evidence that the effect of Catholic schooling is the

largest for urban minorities and that this result is primarily driven by the fact that the local public school alternatives available for these urban minorities are rather poor.

In consequence, these findings provide arguments for the hypothesis that private schools impinge upon individual student achievement by a positive sorting effect. Apparently, catholic schools as the most prominent example of private schools, attract a relatively homogenous group of students, namely students from minority groups for which comparable public school alternatives do not exist. Since we employ a rather large set of school characteristics which control for the material and immaterial endowment of the schools, this sorting effect strongly suggests that this set of instruments does not display a direct effect on individual test achievement and, therefore, meets the validity criteria outlined above.

Regarding the second group of instruments – measures of the care and interest of the other parents in student i's school for their own children – the most serious threat to the validity of these instruments stems from parental extra-curricular activities. This means that the caring behavior of the parents is not a valid instrument, if there are spill-over effects from a high share of caring parents in the peer group on individual i's ability. Such a spill-over might occur, if caring parents set up special out-of-school courses, like homework cooperation or tutoring of low-performing students which might be motivated by school budget cuts. Such extra-curricular initiatives could then have a direct impact on i's achievement and the chosen instruments are not valid any longer.

However, these arguments require a rather close spatial proximity and a rather high degree of parental altruism, which I would argue is not realistic. In consequence, I proceed with the maintained assumption that the instruments are valid. More details on the variables and their construction are provided in the next section. Finally, to address the problems occurring in models with grouped errors, especially the downward bias in estimated standard errors (see MOULTON (1986) and SHORE-SHEPPARD (1996)), a Huber-White robust estimator is employed, with the error covariance matrix clustered by schools.

3 The Data – *PISA 2000*

The *PISA 2000* study was conducted among the 28 OECD countries plus Brazil, Latvia, Liechtenstein and the Russian Federation in the first half of 2000. The target population are 15 to 16 year old students enrolled in an educational institution at the time of the survey. The primary sample unit, however, were schools. In a second step, in every school a random sample of students from the target population was drawn resulting in a stratified cluster sample. The examination conducted among the students in the sample consisted of a reading, math and science literacy test (for more details and sample questions see OECD (2002)). Furthermore, a wide variety of background information on the students was collected by individual student questionnaires. Among this individual information is the family background of the student, his or her attitudes towards visiting school, his or her learning strategy, a self-assessment of reading pleasure etc. Furthermore, the study also conducted interviews among the principals of the respective schools in order to collect information on the school resources, the number of teachers in the school, the principles

of selecting students etc.

The particular test score of an individual student is not the direct share of correct answers. Rather, it is computed based on a procedure originating in *Item Response Theory* (see e.g. Hambleton and Swaminathan (1989)). Calculated scores are weighted averages of the correct responses to all questions of a specific category (e.g. reading literacy) with the difficulty of the question serving as the weight (see e.g. Warm (1989)). These individual test scores are standardized in a subsequent step so that the unconditional sample mean of the *PISA 2000* scores over all countries equals 500 and their unconditional sample standard error equals 100. The dependent variable in the analysis of this paper is the *reading score* for US-american students, since the reading literature examination requires the most *know-how* and the least *know-that* compared to the math and science part (see OECD (2002)).

The sample for this paper consists of 136 US-schools with more than ten students in the original study to get a rather reliable estimate of the coefficient of variation. The number of students per school in the sample varies between 11 and 34 children with 26.44 being the average number of students per school and 5.45 its standard deviation. Mean achievement in these 136 schools varies between 330.45 and 603.68 points. The explanatory variables[3] comprise individual and family background characteristics, like the students' gender and the education levels of their parents as well as school characteristics, like the schools' student-teacher-ratios and an indicator for schools with poor building conditions. All individual and family characteristics stem from the student questionnaire, whereas school information is provided by the questionnaire of the schools' principals.

The impact of students' peer group is measured by the coefficient of variation in achievement of student i's peers within the same school after excluding i from the calculations. Since this variable is a measure of achievement heterogeneity within the peer group, for reasons laid out above, it is expected that a higher coefficient of variation displays a negative impact on individual reading test scores.

The instruments used in the IV estimations comprise two school characteristics which are assumed to impinge upon individual achievement only via the heterogeneity of achievement in school. These variables are an indicator for schools selecting their students upon entry by placement tests or by their record of academic performance and a variable indicating whether a school is a public or a private school. Furthermore, a set of parent characteristics are used which are supposed to indicate if and how much parents care for their children in general and especially for their school performance. These variables are the share of parents in the reference group (without the parents of individual i) which regularly discuss political and social issues, which listen to classical music together with their child(ren), which regularly discuss school performance, which eat the main meal with their child around a table several times a week and which regularly spent time just talking to their child.

Finally, only the share of females and the share of working parents in the peer group

[3] **Table A1** in the appendix provides the definition of the variables in the dataset and **Table A2** displays some summary statistics.

are considered to model the impact of contextual interactions in order to avoid endogeneity of the contextual variables itself. We do not utilize the parental education levels and no foreigner related information since these variables might be indicators parents base their school choice upon and therefore might be susceptible for being endogenous. Again, both contextual variables are constructed without the contribution of individual i's parents.

4 Empirical Results

The results of the OLS and IV regressions of the preferred specification of a *pure endogenous effects model* are reported in **Table 1**. The preferred specification is the results of a series of Wald tests on the equality of some of the parameters in the model, especially the coefficients of the parental education variables. Furthermore, the estimated standard errors of the coefficient estimates are corrected for the dependence within schools by Huber-White robust standard errors allowing for clustering by schools.

A Hausman test[4] clearly indicates that there is sufficient variation between OLS and IV estimation results to warrant estimation by instrumental variables. The first step of the IV estimation yields satisfactory results regarding the explanatory power of the instruments. The F-test statistic of 35.44 allows to reject the null hypothesis that the set of instruments are jointly zero and the t-tests for the instruments indicate that they are all individually significant except the coefficient of the indicator variable for selective schools. Full results of the first step of the IV estimation are reported in **Table A.3** in the Appendix.

In general, the estimated impact of the explanatory variables in the *pure endogenous effects model* are quite similar for the OLS and the IV approaches. Most of the regressors slightly lose explanatory power and statistical significance. The majority of school characteristics, most notably the student-teacher ratio, do not play a significant role in explaining individual reading test scores in the *PISA 2000* study. Similar, and perhaps more surprisingly, the effect of low parental education compared to that of highly educated parents exhibits no statistically significant impact on students' individual outcomes as well. Furthermore, after controlling for the composition of the reference group, subjectively perceived problems with discipline in school do not display a statistically significant impact either.

[4]The value of the test statistic is 35.11. The 5% critical level of the $\chi^2(20)$-distribution is 31.41.

Table 1: OLS and IV estimation results of *pure endogenous effects model*

VARIABLE	**OLS** Coefficient (t-value)	**IV** Coefficient (t-value)
Female	23.35	22.52
	(7.29)	(6.79)
Both Parents Work	15.14	14.55
	(5.03)	(4.70)
Intact Family	32.34	30.53
	(9.34)	(8.46)
Native Student	-0.38	3.91
	(-0.02)	(0.15)
Both Parents Foreign Born	-12.83	-0.91
	(-0.52)	(-0.03)
Second Generation	17.40	10.40
	(0.71)	(0.38)
Other Language at Home	-34.62	-31.54
	(-5.62)	(-4.73)
Parents with Low Education	-12.56	-6.55
	(-1.61)	(-0.76)
Parents with Medium Education	-12.11	-9.02
	(-2.55)	(-1.78)
Mother with Tertiary Education	10.10	7.67
	(2.73)	(1.93)
Father with Tertiary Education	28.20	25.53
	(7.69)	(6.61)
Student-teacher Ratio	-0.16	-0.16
	(-1.30)	(-1.17)
Homework Feedback	11.70	11.89
	(3.07)	(2.96)
Poor Basic School Conditions	4.24	9.73
	(0.73)	(0.92)
Regular Tests	-9.56	-7.48
	(-0.96)	(-0.69)
Teacher Shortage	-14.75	-23.14
	(-1.51)	(-2.04)
Perceived Problems with Discipline	-8.56	-8.58
	(-1.81)	(-1.71)
Interaction Discipline and Student-teacher Ratio	0.10	0.11
	(1.20)	(1.21)
Heterogeneity Measure	-373.44	-967.80
	(-5.63)	(-5.09)
Constant	535.34	636.13
	(20.72)	(15.44)
F-Test	28.79	34.16
Adjusted R^2	0.17	0.12
Hausman Test	35.11	

Number of observations: 3,407. See Appendix **Table A1** and **Table A2** for a description and summary statistics of the variables. The base category for the parental education variables is *Parents with high education*.

IV results differ quite substantially from those of the OLS estimation for only four variables. Firstly, we observe a very large increase in the estimated impact of the *Heterogeneity measure*, which is more than two and a half times as large in the IV than in the OLS estimations. Secondly, the indicator variable for teacher shortages increases substantially as well and becomes statistically significant. Thirdly, the estimated impact of the medium education level of parents drops and becomes insignificantly. And finally, the estimated value of the coefficient measuring the influence of mothers with tertiary education on individual reading scores decreases and becomes shy of being significant.

The substantial increase (in the absolute value) of the estimated coefficient of the heterogeneity measure, however, indicates that in the *pure endogenous effects model* peer group choice is indeed endogenous and that this measure of peer group influence exhibits rather strong effects. The heterogeneity measure varies between 0.06 and 0.28 in the sample of US-students with 0.17 being the sample mean. Therefore, the IV estimation results suggest that for the typical US-student in the sample, a rather modest increase of 10% in the heterogeneity measure (all other things equal) results in a decline of the reading score of around 17 points. Furthermore, this typical US-student looses approximately 86 points in the reading examination if the heterogeneity measure increases by 50% (c.p.) and around 272 points once he or she is transferred in the school with the highest degree of heterogeneity in sample. Consequently, the effect of the composition of a student's peer group regarding achievement plays a strong role in explaining individual achievement.

These results, however, change quite dramatically if one controls for *contextual effects*. **Table 2** reports the OLS and IV estimation results for the *full model*. The first step of the IV estimation of the *full model* again yields satisfactory results regarding the explanatory power of the instruments. The F-test statistic is 39.55 allowing to reject the null hypothesis that the instruments are jointly zero and the t-tests for the instruments indicate that they are all individually significant except the coefficients for a *Selective school* and for the variable indicating whether parents regularly listen to classical music with their children[5]. However, for the *full model* the Hausman test statistic of 27.38 does not allow to reject the null hypothesis that the difference in coefficient estimates between OLS and IV are not systematic[6].

A closer inspection of the estimation results shows that the difference in the coefficient estimates between OLS and IV is still substantial. However, controlling for the exogenous characteristics of the reference group inflates the estimated standard errors of the coefficient estimates leading to the substantial reduction in the value of the Hausman test statistic. At first glance, this rather surprising result suggests that there might be a problem of collinearity in the model. However, the inspection of the correlation structure of the explanatory variables does not reveal any unusually high correlation coefficients. Although this does not secure the absence of collinearity since there might be a linear relationship between more than two regressors, the probability that this result is the effect of collinearity is rather small.

[5]Full results of the first step of the IV estimation are reported in **Table A.4** in the Appendix.
[6]The 5% critical value of the $\chi^2(22)$-distribution is 33.93.

Table 2: OLS and IV estimation results of *full model*

VARIABLE	**OLS** Coefficient (t-value)	**IV** Coefficient (t-value)
Constant	450.29	600.38
	(13.13)	(12.38)
Female	23.56	22.66
	(7.56)	(7.13)
Both Parents Work	12.84	13.00
	(4.39)	(4.43)
Intact Family	29.60	28.80
	(8.59)	(7.95)
Native Student	7.85	8.93
	(0.34)	(0.36)
Both Parents Foreign Born	-1.57	4.69
	(-0.06)	(0.17)
Second Generation	11.62	7.48
	(0.48)	(0.28)
Other Language at Home	-27.99	-27.05
	(-4.33)	(-4.13)
Parents With Low Education	-11.25	-5.76
	(-1.45)	(-0.67)
Parents With Medium Education	-10.79	-7.96
	(-2.24)	(-1.59)
Mother With Tertiary Education	10.32	7.90
	(2.75)	(1.96)
Father With Tertiary Education	25.55	23.55
	(6.67)	(5.93)
Student-Teacher Ratio	-0.09	-0.10
	(-0.85)	(-0.78)
Homework Feedback	10.34	10.89
	(2.80)	(2.80)
Poor Basic School Conditions	4.16	9.59
	(0.45)	(0.75)
Regular Tests	-5.64	-4.45
	(-0.65)	(-0.43)
Teacher Shortage	-13.75	-20.88
	(-1.64)	(-2.10)
Perceived Problems with Discipline	-9.22	-8.88
	(-2.01)	(-1.84)
Interaction Discipline and Student-Teacher Ratio	0.10	0.10
	(1.14)	(1.14)
Heterogeneity Measure	-278.66	-900.77
	(-3.94)	(-5.27)

Table 2 cont'd: OLS and IV estimation results of *full model*

VARIABLE	**OLS** Coefficient (t-value)	**IV** Coefficient (t-value)
Share of Females in Peer Group	-22.07	-53.80
	(-0.82)	(-2.05)
Share of Working Parents in Peer Group	120.67	78.37
	(5.62)	(2.86)
F-Test	38.45	36.71
Adjusted R^2	0.19	0.14
Hausman Test	27.38	

Number of observations: 3,407. See Appendix **Table A1** and **Table A2** for a description and summary statistics of the variables. The base category for the parental education variables is *Parents with high education*.

Therefore, the reduction in the Hausman test statistic compared to the pure endogenous effects model suggests two different interpretations. Firstly, the exogenous socioeconomic composition of the reference group does indeed account for a large fraction of the effect of unobserved heterogeneity present in the pure endogenous effects model. And secondly, it might be the case that the contextual variables utilized in the full model could be endogenous itself. Sensitivity checks indeed indicate the potential endogeneity of the contextual variables. Dropping the share of working parents in the reference group results in an increase in the Hausman test statistic[7] which is then large enough to allow the rejection of the null hypothesis that there is no systematic difference between OLS and IV results. On the other hand, adding the share of intact families in the reference group – a variable which is highly susceptible for being an indicator parents base their school choice upon – leads to a further drop in the Hausman test statistic to a value of 9.38. Consequently, these results together with the change in the estimated coefficients demonstrate that taking the contextual effects channel into consideration is very important for the existence, extent and endogeneity of peer group influences. Adequately modelling this channel is, however, anything but trivial and has to be conducted carefully.

In general, the OLS and IV estimation results for the *full model* resemble much of the results of the *pure endogenous effects model*. We could observe a decline in the values of the estimated parameters as well as in their statistical significance. The changes for the parental education variables as well as for the *Teacher Shortage* indicator are very similar. Furthermore, there is also a sharp increase in the estimated impact of the heterogeneity measure. Finally, there is a substantial change in the estimation results for the contextual variables. The impact of the share of females in the peer group becomes statistically significant and increases in (absolute) value, whereas the coefficient measuring the influence of the share of working parents in the peer group declines substantially in absolute value. This considerable change can be interpreted as a further indicator for the potential endogeneity of both contextual variables.

Regarding the quantitative impact of the heterogeneity measure, the OLS estimation results suggest that for the typical US-student in the sample, an increase of 10% in the

[7]The value of the test statistic is now 41.56.

heterogeneity measure (all other things equal) results in a decline of the reading score of around 5 (IV: 17) points. Furthermore, this typical US-student looses approximately 25 (IV: 80) points in the reading examination if the heterogeneity measure increases by 50% (c.p.) and around 79 (IV: 253) points once he or she is transferred in the school with the highest degree of heterogeneity in sample. In consequence, the explanatory power of the heterogeneity measure declines substantially if one controls for contextual effects.

5 Conclusions

This paper aimed at identifying the impact of the peer group composition on individual outcomes in a standardized reading examination for a sample of 15-16 year old US-students. To this end, two social interactions models were estimated by an instrumental variable approach to account for the potential endogeneity of US-students peer group composition. It became transparent that for US-students the peer group composition is a rather strong predictor of individual achievement. Furthermore, it turned out that the existence of a contextual effects channel in social interactions is very important for the extent and endogeneity of peer group effects.

IV as well as OLS estimation results clearly indicated that the higher the heterogeneity of achievement in a student's school, the lower is the individual performance. This finding is in line with the theoretical predictions of a model developed by Lazear (2001) and suggests that educational output is maximized in schools with a more homogenous composition of students regarding their achievement.

However, from the perspective of economic and social policy integrated classes might be more attractive than segregated for two reasons (see Lazear (2001)). Firstly, if it is possible to transform low ability into high ability students by letting those with the lower ability being around those with higher ability then it would be efficient to build integrated classes. The existence of endogenous interactions among students of a certain reference group might introduce a social multiplier effect of a program helping the weaker students to catch up. And secondly, segregated classes might exacerbate the effect of educational and, therefore, income inequality because highly able students benefit from segregation whereas low ability students lose. Therefore, programs aiming at the integration of lower performing students into classes where the majority displays high achievement might have a positive effect on individual student performance.

However, it is far from being guaranteed that such a program, as any other attempt in reforming schools, is successful. A careful evaluation of the effects of such programs on individual student outcomes is indispensable. Such programs, however, would provide an additional benefit. If they are conducted as a social experiment they will provide reliable data to further investigate whether and to which extent the composition or any other measure of performance of a reference group affects individual school achievement.

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Appendix

Table A1: Description of Variables

Variable	Description
Reading Score	Difficulty-adjusted test score in the reading literacy test
	Demographic and Family Background
Female	1 if student is female; 0 otherwise
Both Parents Work	1 if student's mother and father are working full-time or part-time; 0 otherwise
Intact Family	1 if student lives together with both parents; 0 otherwise
Native Student	1 if student is a citizen of the country of residence; 0 otherwise
Both Parents Foreign Born	1 if student's parents are both non-citizens of the country of residence; 0 otherwise
Second generation	1 if student's father or mother is foreign born; 0 otherwise
Other Language at Home	1 if the regular language at student's home is different from the respective test language; 0 otherwise
	Parents Education
Parents with Low Education	1 if student's mother or father did not attend school or if student's father or mother completed primary education; 0 otherwise
Parents with Medium Education	1 if student's mother or father completed (lower) secondary education; 0 otherwise
Parents with High Education	1 if student's mother or father completed upper secondary education; 0 otherwise
Mother with Tertiary Education	1 if student's mother completed tertiary education; 0 otherwise
Father with Tertiary Education	1 if student's father completed tertiary education; 0 otherwise
	School-Related Information
Student-teacher Ratio	Student-teacher ratio of respective school
Homework Feedback	1 if students homework is regularly graded or if homework is part of his/her marks; 0 otherwise
Poor Basic Conditions	1 if school is suffering from poor conditions of building structure, poor heating/cooling/lighting systems, lack of instruction space or instruction material; 0 otherwise
Regular Tests	1 if students are assessed four or more times a year using standardized or teacher-developed tests; 0 otherwise

Table A1 cont'd: Description of Variables

Variable	Description
Teacher Shortage	1 if school suffers from a teacher shortage or test language teacher shortage; 0 otherwise
Perceived Problems with Discipline	1 if a student responds that his or her classmates do not listen to what the teacher says, or that there is noise and disorder in the class, or that the teacher has to wait a long time for students to quieten down, or that at the start of class more than five minutes are spent doing nothing in most or every lesson
Interaction Discipline and Student-teacher Ratio	Interaction term between *Perceived Problems with discipline* and *Student-teacher ratio*.
Heterogeneity Measure	Coefficient of variation in school without own contribution
	Instrumental Variables
Private School	1 if the school is a private school; 0 otherwise
Selective School	1 if admission to school is based on student's record of academic performance including placement tests; 0 otherwise
Discuss Political and Social Issues	Share of parents in reference group which discuss social and political issues with their child several times a week
Listen Classical Music	Share of parents in reference group which listen to classical music together with their child several times a week
Discuss School Performance	Share of parents in reference group which discuss with their child how well he/she is doing at school several times a week
Eat Main Meal	Share of parents in reference group which eat the main meal with their child around a table several times a week
Regularly Talking	Share of parents in reference group which spent time just talking to their child several times a week

Table A2: Summary Statistics

Variable	Mean	Standard Error
Reading Score	499.124	100.988
Explanatory Variables		
Heterogeneity Measure	0.178	0.038
Female	0.527	0.499
Both Parents Work	0.551	0.497
Intact Family	0.528	0.499
Native Student	0.870	0.336
Both Parents Foreign Born	0.261	0.439
Second Generation	0.135	0.342
Other Language at Home	0.170	0.375
Parents with Low Education	0.056	0.231
Parents with Medium Education	0.178	0.383
Mother with Tertiary Education	0.292	0.455
Father with Tertiary Education	0.296	0.457
Student-teacher Ratio	38.066	37.596
Homework Feedback	0.622	0.485
Poor Basic School Conditions	0.029	0.169
Regular Tests	0.784	0.412
Teacher Shortage	0.095	0.293
Perceived Problems with Discipline	0.576	0.494
Interaction Discipline and Student-teacher Ratio	22.155	34.323
Instrumental Variables		
Selective School	0.163	0.370
Private School	0.041	0.199
Discuss Political and Social Issues	0.210	0.102
Listen Classical Music	0.063	0.053
Discuss School Performance	0.647	0.116
Eat Main Meal	0.635	0.121
Regularly Talking	0.659	0.119
Contextual Variables		
Share of Females in Peer Group	0.527	0.101
Share of Working Parents in Peer Group	0.551	0.168

Number of observations: 3407. See **Table A1** and text for a description of the variables.

Table A.3: First step IV estimation results of *pure endogenous effects model*

Variable	Coefficient	t-value
Dependent variable: Coefficient of variation		
Female	-0.00021	-0.18
Both Parents Work	-0.00081	-0.67
Intact Family	-0.00063	-0.52
Native Student	0.00646	0.79
Both Parents Foreign Born	0.01697	1.99
Second Generation	-0.01073	-1.25
Other Language at Home	0.00460	1.97
Parents With Low Education	0.00836	3.16
Parents With Medium Education	0.00314	2.04
Mother With Tertiary Education	-0.00260	-1.85
Father With Tertiary Education	-0.00217	-1.52
Student-Teacher Ratio	-0.00010	-3.18
Homework Feedback	-0.00149	-1.21
Poor Basic School Conditions	0.00805	2.26
Regular Tests	-0.00095	-0.39
Teacher Shortage	-0.01297	-6.28
Problems with Discipline	-0.00032	-0.19
Interaction Discipline and Student-Teacher Ratio	0.00002	0.56
Selective School	-0.00204	-1.20
Private School	-0.04113	-13.09
Discuss Political and Social Issues	-0.05040	-7.54
Listen Classical Music	0.05562	4.76
Discuss School Performance	0.04800	7.30
Eat Main Meal	-0.05123	-9.09
Regularly Talking	-0.05581	-8.74
Constant	0.22389	23.03
F-Test	35.44	
Adjusted R^2	0.20	

Number of observations: 3,407. See Appendix **Table A1** and **Table A2** for a description and summary statistics of the variables. The base category for the parental education variables is *Parents with high education.*

Table A.4: First step IV estimation results of *full model*

Variable	Coefficient	t-value
Dependent variable: Coefficient of variation		
Female	-0.00035	-0.31
Both Parents Work	-0.00003	-0.03
Intact Family	0.00030	0.25
Native Student	0.00300	0.37
Both Parents Foreign Born	0.01082	1.29
Second Generation	-0.00743	-0.88
Other Language at Home	0.00203	0.88
Parents With Low Education	0.00758	2.92
Parents With Medium Education	0.00277	1.83
Mother With Tertiary Education	-0.00267	-1.94
Father With Tertiary Education	-0.00141	-1.01
Student-Teacher Ratio	-0.00010	-3.29
Homework Feedback	-0.00045	-0.37
Poor Basic School Conditions	0.00688	1.97
Regular Tests	-0.00122	-0.51
Teacher Shortage	-0.01201	-5.89
Problems with Discipline	0.00003	0.02
Interaction Discipline and Student-Teacher Ratio	0.00002	0.67
Share of Females in Peer Group	-0.02346	-3.98
Share of Working Parents in Peer Group	-0.05308	-11.49
Selective School	-0.00226	-1.35
Private School	-0.04050	-13.08
Discuss Political and Social Issues	-0.04171	-6.33
Listen Classical Music	0.02142	1.81
Discuss School Performance	0.04115	6.36
Eat Main Meal	-0.04247	-7.58
Regularly Talking	-0.04332	-6.74
Constant	0.26015	25.73
F-Test	39.55	
Adjusted R^2	0.23	

Number of observations: 3,407. See Appendix **Table A1** and **Table A2** for a description and summary statistics of the variables. The base category for the parental education variables is *Parents with high education.*