Migrants at School: Educational Inequality and Social Interaction in UK and Germany

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Summary: We test potential social costs of educational inequality by analysing the influence of spatial and social segregation on educational achievements. In particular, based on recent PISA data sets from the UK and Germany, we investigate whether good neighbourhoods with a relatively high stock of social capital lead to larger 'social multipliers' than neighbourhoods with low social capital. Estimated 'social multipliers' are higher for German early tracking schooling system than for comprehensive schools in the UK. Aggregating data and employing the Oaxaca-Blinder decomposition, it turns out that the educational gap between natives and migrants is mainly due to the 'endowment effect' provided by the socioeconomic background of parents and cultural capital at home. Some adverse 'integration effects' do exist for female migrants in Germany who lose ground on other groups.

Key words: identification, social interaction, reflection problem, empirical analysis, education, peer effects, migrants

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1. Introduction

Both in the Anglo-Saxon countries and in France and Germany, inequality between educational groups has increased recently: In the United States and in Britain, wage inequality between and within educational groups has risen dramatically since about the 1970s. In France and Germany, there has been hardly any change in wage inequality between educational groups until the end of the last century (see Fitzenberger 1999; Kahn, 2000 Acemoglu 2003), but wage gaps between educated and low skilled groups do widen in Germany during the most recent years (see Dustmann et al., 2007). Moreover, the distribution of employment and unemployment incidence across educational groups became more unequal to the detriment of the lower educated (see Entorf, 1996; Fitzenberger, 1999; Puhani, 2004, for Germany; Machin, 1997, and Machin and Van Reenen, 1998, for the UK).

Because the low education groups seem to suffer most from economic shocks such as the current global financial crisis, questions of education increasingly grab the attention of educational scientists, labour economists as well as politicians. The debate immediately relates to the access and amount of education for disadvantaged groups, and prompts research aiming at an analysis of the nature and causes of the persisting lack of social mobility, and an examination of the avenues of improving the social mobility of less privileged children (through schooling and higher education). One special group of interest among the student population at risk to be affected by educational inequality are those students having an immigration background.

Most of the existing contributions focus on the relatively poor socio-economic background of migrants (see, among others, Gang & Zimmermann, 2000; Frick & Wagner, 2001; Bauer & Riphahn, 2007). The debate has been given renewed impetus by the results of the Programme for International Student Assessment (PISA; see OECD, 2001, for first results). In fact, these data reveal that the performance of children with a parental migration background differs strongly across countries (Ammermüller 2005; Entorf & Minoiu, 2005). By using educational achievement data from other sources (TIMMS and PIRLS), Hanushek and Wössmann (2006) as well as Schnepf (2007) confirm that besides highly variant socioeconomic backgrounds also language problems can be considered a main source of internationally differing performances of migrant students. After analysing immigrants' disadvantage of ten high immigration countries she concludes that natives are on average as much as one grade ahead in their maths skills compared to immigrants in Germany and Switzerland. The situation is different in traditional countries of immigration (New Zealand, Canada, Australia) where the more privileged parental backgrounds of (selected) migrants lead to less significant or even positive (Canada) differences between educational achievements scores of migrants and natives (see Entorf and Minoiu 2005). In the UK, where the majority of migrants come from Western countries such as Ireland, USA and India, evidence in Entorf and Minoiu (2005) and

Schnepf (2007) reveal that there is a gap only for those migrant students who have a non-English language background.

However, all studies reveal that there remains a considerable educational disadvantage of immigrants not explained by observed individual heterogeneity. This indicates that immigrants face further barriers that might be related to unobserved heterogeneity (note that most studies quoted above are based on cross-sectional data) and unfavourable factors arising from their lacking integration into (Western) societies. For instance, given that immigrants are concentrated in large cities and the suburban areas, equality of educational opportunities is limited by spatial and social segregation and the resulting emergence of 'good' or 'bad neighbourhoods', i.e. by 'peer effects'. Peer effects in the context of schooling have been studied by Hoxby (2000), Hanushek et al. (2003), among others.

However, a comparatively neglected factor which still seems highly relevant for the composition of peers is the impact of schooling systems. Some authors discuss whether, in addition, the early tracking into different-ability schools at age 10 as in Austria and Germany might have negative consequences on school performance for children who come to school with language and social deficits, a high proportion of whom come from families with a migration background (see Dustmann, 2004, for a critical assessment of the selective German school systems). Under such circumstances the question of peer effects cannot be disentangled from the influence of prevailing national schooling systems.

Entorf and Lauk (2008) have recently investigated the role that peer effects and social integration of migrants play for their schooling achievements in selected nations. Their approach is based on the idea that education might have additional positive external effects (non-market benefits) due to nonmarket interactions (via 'social multipliers'; see Glaeser & Scheinkman, 2000; Glaeser *et al.* 2003). The novelty of the Entorf and Lauk paper is that by taking migrant-to-migrant, native-to-migrant and native-to-native peer relations into account, they are able to test and confirm the hypothesis that early tracking reinforces and even amplifies existing socioeconomic pre-school disadvantages of children with a migration background, because (high) social interaction mainly takes place within the group of migrants and within the group of natives (with detrimental educational effects to migrants), but less so between both groups. In this paper we estimate the model using data on PISA math scores and analyse differences between social interaction parameters obtained for German and UK students.

A serious limitation for the aforementioned technique is the lack of PISA panel data such that evidence on the role of institutional structures can be gained only by international comparison. Overcoming the limitations of the PISA data in the Entorf-Lauk model can be achieved with a strategy inspired by the first of the two identification strategies, as these are described in the Hoxby paper (2000), where the notion of first differences in cohorts is used. The basic advantage of this approach is twofold. First, deviating from most previous empirical investigations which analyse potential reasons for the educational gap between migrants and natives in separate equations, we focus on aggregate observational units at school level such that for each school we can directly estimate endogenous differences in educational achievements dependent on explanatory differences of explanatory student factors and school characteristics. This leads to some Oaxaca-Blinder decomposition of the native-migrant PISA gap. The second point is that taking differences between migrants and natives at the school level mitigates the problem of unobserved heterogeneity, as unobserved school factors δ_s common to all students i(s) at school s are differenced out, and heterogeneity due to unobserved true individual abilities (such as intelligence) is expected to be similar for migrants and natives when group averages are considered.

Our results show that the socioeconomic background of parents and cultural capital at home are the most important factors for educational success in both countries. Using the equivalent Oaxaca-Blinder decomposition, it also turns out that the educational gap between natives and migrants is mainly due to the 'endowment effect' provided by these factors. 'Discriminatory effects' cannot be detected. Some adverse 'integration effects' do exist for female migrants in Germany who lose ground on other groups. Estimated 'social multipliers' are higher for the German early tracking schooling system than for comprehensive schools in the UK. This result is detrimental for most migrant students at least in Germany, because multiplier effects magnify the prevailing educational inequality between students who enter schools with a low parental socio-economic background and children from more privileged families.

This paper is organized as follows. In the second section we discuss methodological issues; we focus on the identification of endogenous social effects, the so - called reflection problem and we connect this to the propagation of the spillover effects, embodied in what is known as the social multiplier in the relevant literature. We extend this section first by discussing the baseline model as an identification strategy that will allow the detection of the presence (if any) and the quantification of peer effects in a setting appropriate to inquire educational inequality, and, second, by estimating a model allowing presence of unobserved heterogeneity components, eliminated by taking differences between the group of natives and migrants. The last section concludes and summarizes the results.

2. Social Multipliers as Potential Source of Educational Inequality

2.1. Identification of endogenous social effects - The reflection problem

An example of the difficulty to identify parameters of interest in the presence of endogenous variables is that of the reflection problem in the social sciences (Manski

1993, 1995, 2000). Social interaction has already been studied both theoretically and empirically to the extent that a well-defined framework is established in the field of economics; it has already been treated in a theoretical framework (as in Becker, 1974) to comprehend the channel through which the behaviour of a person is affected by the characteristics of his/ her family members. It can be deemed as a form of externality (c.f. Glaeser & Scheinkman, 2000), bearing the sense of interactions occurring between individuals in the absence of prices. Empirical analysis of social interaction and behaviour is hindered by the fact that it resembles the situation at which a person sits in front of a mirror and can see his reflection but, nevertheless, it cannot be distinguished whether at the same time the moves the person makes are caused by his own reflection or are merely reflected. Simultaneously, a second impediment is selection, for individuals tend to choose their peers, neighbourhoods or networks. Thus, unlike identification of parameters in market outcomes[1], behaviour in non-market settings and environments is still under the scope of broad analysis and develops constantly. Key questions to be answered refer to the influence that the group behaviour might exert on individuals' behaviour of the same group and the tendency of the group's individuals to behave in a similar manner, whereas applications refer initially to the fields of econometrics of crime, economics of education or labour economics. The incipient step towards identification would be to obtain prior information that specifies the group and reveals its characteristics. If this information could be extracted, then identification depends upon underlying relationships between variables in the population.

Although Manski (1993) discusses identification of endogenous social effects in a number of models (linear models, non-linear/ non - parametric models as well as dynamic models), special attention is drawn here to linear parametric models, a choice justified by the employment of a linear (in means) parametric model in order to illustrate the estimation of social interaction parameters in education, where the outcome is the achievement of students.

Following Manski (1993) in our attempt to delve identification strategy issues, we usually assume - at first - that a random sample (y, x, z) is available from the population. y would represent the scalar outcome or behaviour, x all variables which capture same institutional environments and/ or group characteristics and, finally, (z, u) summarize direct socio - economic composition and ability. The scalar outcome y is specified in the following way:

(1) $$y = \alpha + \beta E(y \mid x) + E(z \mid x)'\gamma + z'\eta + u$$

meaning that, econometrically, the outcome is modelled so that it varies with the mean of the outcome conditional on all variables that represent similar institutional

[1] Renown examples cited when market outcomes are concerned is the two-equation demand-supply system and the Mincerian to estimate returns to schooling.

environments. Note, though, that the conditional on both x and z the mean of the error term is different from zero: $E(u \mid x, z) = x'\delta$ (absence of zero conditional mean assumption).

Taking the conditional expectation with respect to both x and z by using the law of iterated expectations, we obtain the mean regression of y on (x, z):

(2) $$E(y \mid x, z) = \alpha + \beta E(y \mid x) + E(z \mid x)'\gamma + z'\eta + x'\delta .$$

Each of the parameters β, γ and δ represents an *endogenous*, an *exogenous* and a *correlated* effect respectively. The presence of the expected value of y conditional on x at right - hand side reveals the explanatory role of endogenous social effects on individual outcomes provided $\beta \neq 0$. This follows from the presumption that the outcome varies with the mean of the outcomes of the peers and is exactly the source of the reflection problem. Parameter $\gamma \neq 0$ depicts the exogenous effect, for variable z includes the exogenous variables. Likewise, parameter $\delta \neq 0$ expresses the correlated effect, capturing similarity in behaviour among peers (presence of group effects). Furthermore, by assuming that the mean regressions of y on (x, z), of y on x and of z on x can be consistently estimated, one can use the last equation and integrate it with respect to z, assume $\beta \neq 1$ and solve for $E(y \mid x)$ in order to obtain the 'social equilibrium':

(3) $$E(y \mid x) = \frac{\alpha}{1-\beta} + E(z \mid x)'\frac{\gamma + \eta}{1-\beta} + x'\delta\frac{1}{1-\beta}$$

As seen above, it is possible to identify functions of the parameters of interest if $\beta \neq 1$, but not the parameters themselves and, of course, cannot distinguish among endogenous, exogenous and correlated effects. Substituting $E(y \mid x)$ from (3) into (2), yields the reduced form equation:

(4) $$E(y \mid x, z) = \frac{\alpha}{1-\beta} + E(z \mid x)'\frac{\gamma + \beta\eta}{1-\beta} + z'\eta + x'\delta\frac{1}{1-\beta} .$$

Although we are not able to discern between endogenous and exogenous social effects, we are allowed to detect the presence - if any - of a social effect provided $[1, E(z \mid x), x, z]$ are linearly independent in the population. Presence of a social effect means that $\gamma + \beta\eta \neq 0$ for the numerator. Thus, either $\gamma \neq 0$ or $\beta\eta \neq 0$ must be true. Unfortunately, we are also not able to disentangle the effect of social interactions from effects due to unobserved group characteristics.

There are two cases in which identification is achieved using some exclusion criteria. First, by assuming exclusive presence of endogenous effects, which amounts to imposing $\gamma = \delta = 0$ on the parameter vector. This pure endogenous model can be estimated in a two–stage procedure; by using sample data one can retrieve a nonparametric estimate of the mean outcome given x, and use this estimate later on to identify the social interactions parameter β with least squares. The second case is described by Graham and Hahn (2005), where one assumes absence of exogenous social effects, i.e. $\gamma = 0$. Using a quasi-panel approach, estimating the between groups model identifies η, and upon the availability of an instrumental variable, 2SLS provide an estimate for the composite parameter $\eta/(1-\beta)$; thus, the magnitude of the (endogenous) social effect can be inferred in a completely parametric procedure.

2.2. The Social Multiplier

Social interaction will have a multiplicative effect as in the sense of the Keynesian multiplier in the macro economy, due to the presence of endogenous social effects (and not of exogenous or correlated effects). Hence, one would also be interested in identifying those resulting *social multipliers* i.e. quantify spillover effects[2] caused by peers. The social multiplier embraces both direct and indirect effects on the individual’s behaviour, the direct emanating from the change in the individual’s behaviour, whereas the indirect stemming from the change in the behaviour of the peer group. Thus, the presence of a social multiplier should render at least problematic the employment of aggregate - level data when aiming at inferring individual - level elasticities.

Glaeser *et al* (2000, 2003) have set up theoretical models of non-market interactions and connect the presence of a strong social multiplier with the presence of multiple equilibria. In practice, the empirical method extensively used to measure social interaction parameters and, subsequently, calculate social multipliers, is modelling in an econometric equation the individual outcome as the dependent variable and the average outcome of the relevant peer group as part of the explanatory variables. Of course, the average outcome does not include the individual itself[3]. Examples of the existence of the social multiplier in applied work include the impact of education on wages (Acemoglu & Angrist, 1999), the impact of demographics on crime (Levitt, 1999), group membership among college roommates (Sacerdote, 2001) and peer effects of within and between migrants and natives in schooling (Entorf & Lauk, 2008).

Intuitively, the social multiplier would not constitute anything else but the ratio of a coefficient coming from a regression using aggregate data - for instance country level data - and one from a regression using individual level data (given that coefficients are identified). In the simplest case, if a regression yields a coefficient γ on the social

[2] They are also characterised as *positive spillovers* or *strategic complementarities* in Glaeser *et al* (2000, 2003).
[3] This will become obvious from the baseline model in section 2.3.

interaction variable, then the magnitude of the social multiplier would equal $1/(1-\gamma)$. Glaeser, Sacerdote and Scheinkman (2003) have provided the framework for the simple case, but also developed it further in order to accommodate (i) sorting across neighbourhoods, (ii) individuals' characteristics and actions affecting the individual outcome, and, eventually, (iii) different degree of peer influence according to distance of the peer.

2.3 The Baseline Model as Identification Strategy

Emphasis is placed herein upon the choice of the strategy that will allow identification of the social interaction parameters and illustration of the strategy's applicability when the researcher is provided with appropriate data. One empirical strategy used extensively in practice to identify peer effects is that of the baseline model. As in Hoxby (2000), the baseline model is usually formulated by the following equation:

$$y_{ij} = \alpha + b\overline{y}_j^{-i} + X_{ij}c \tag{5}$$

where y_{ij} is the scalar outcome for individual i belonging to group j, α is some constant, $\overline{y}_j^{-i}$ is the average of the outcome for all individuals in group j excluding individual i, and X_{ij} is a vector of all other characteristics and factors that one might expect they affect individual i's outcome. In the schooling environment chosen in this paper, y_{ij} would represent student i's achievement score in mathematics, $\overline{y}_j^{-i}$ would stand for the mean student score in mathematics achieved by student i's peer group[4], and X_{ij} encompasses all other student-specific explanatory variables.

Entorf and Lauk (2008) provide a comprehensive empirical analysis and interpretation of the educational inequality between migrants and natives. Using their notation, one can identify peer effects in education between and within *migrants* and *natives* by modelling a two-equation system as follows:

$$\begin{aligned} P^m_{i_s sf} &= \beta^m{}' X_{i_s s} + \delta^m{}' R_s + \gamma^m_m \overline{P^m_{sf}} + \gamma^m_n \overline{P^n_{sf}} + \varepsilon^m_{i_s sf} \\ P^n_{i_s sf} &= \beta^n{}' X_{i_s s} + \delta^n{}' R_s + \gamma^n_m \overline{P^m_{sf}} + \gamma^n_n \overline{P^n_{sf}} + \varepsilon^n_{i_s sf} \end{aligned} \tag{6}$$

where $P^m_{i_s sf}$ is the PISA score for migrant student i in school s for field $f \in \{mathematics, reading, science\}$, $P^n_{i_s sf}$ as before but for native student i in school s in field f, $\overline{P^m_{sf}}$ and $\overline{P^n_{sf}}$ are the respective averages of PISA mathematics (reading or science) scores of migrant and native peer groups at the school - level, R_s includes all school-specific resources at school s, and $X_{i_s s}$ all student specific-variables.

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[4] What exactly is defined as peer group and who exactly is included is very important for the analysis, both in terms of econometric estimation and interpretation of the resulting coefficients.

This is merely an extension of the baseline model which facilitates to address questions regarding, on the one hand, cross-sectional comparisons of the different schooling systems among the countries included in the PISA dataset, and, on the other hand, potential educational inequalities arising between students with and without a migration background. As made obvious from the system of equations (6), peer effects will be estimated at the school level. The authors select four groups of countries, namely: a) traditional countries of immigration: Australia, Canada, New Zealand, b) countries of "labour migration" and non-comprehensive school systems: Austria, Germany, c) countries of "labour migration" and comprehensive school systems: Denmark, Sweden, Norway, and d) countries of Central and Eastern Europe: Czech Republic, Hungary, and Russia. The groups are chosen as such in order to capture specific educational/ institutional and immigration conditions that prevail in each of the groups of countries. This is of great importance once one wishes to explore differences in educational performance, which in turn helps to test the hypothesis that early tracking reinforces segregation effects. Estimation of system (6) quantifies the effect of the migrants' social integration and the role of non-comprehensive schooling systems on their achievement, both closely related to the presence and extent of educational inequality. The merit of this approach is being evinced by the results, which make reference to all possible combinations and directions of peer effects, i.e. migrant - to - migrant, migrant - to - native, native - to - native and native - to - migrant. The implications on each country's followed immigration policy can be immense.

Still interest lies on the impact of the schooling systems and tracking at the age of 10 on the social integration of children with a poor socioeconomic or immigration background.

The question that arises immediately after the presentation of the estimable baseline equations is the connection to Manski's effects, as those were described in section 2. Most importantly, the equation in system (6) models the *endogenous* effects, which yield the parameters of social interaction, namely γ_m^m, γ_n^m, γ_m^n and γ_n^n. As in Manski's equation (1), the average achievement score of the peers has to be included as an explanatory variable. Were we to exclude it, we would be confronted with an omitted variable bias in our estimations. At the same time, including this average will induce a simultaneity bias problem, for student $i's$ relevant mathematics achievement score will be present both at right - hand (dependent variable) and left - hand (independent variable) sides of any of the two equations of system (6), but, moreover, for student i constitutes him/ herself a peer for the rest of the members of the peer group, hence it may be the case he/ she partially determines the achievement score of the peer group under discussion. Thereby, the link to the reflection problem has become clearer. The problem is alleviated by disregarding the contribution of student i, when calculating these averages.

In a similar way, system (6) comprehends the *exogenous* individual effects, meaning all explanatory variables that are student-specific, for instance the student's gender, type of family structure, parents' education level etc. The third of Manski's effects, i.e. the *correlated* effect is present through the correlated *environmental* effects, meaning school-specific explanatory variables that are commonly faced by the students, i.e. living in the same small village or town, sharing the same quality of a school's educational resources etc.

Another common source of possible perturbation linked to the econometric modelling of peer effects is that of *selection*[5], that will eventually result in the presence of some *sorting bias*. In this context, self-selection arises from the fact that individuals tend to choose the group and the members of the groups in which they belong to, i.e. students may choose their peers. Furthermore, selection emerges because some parents tend to choose/ control the school their child will attend or because some schools' decisions on accepting a certain student is based on the student's previous performance, residence or parents' characteristics and status. This bias diminishes by the inclusion of an appropriate school-specific set of variables, while the verification of the reduction of the bias is controlled with performing a set of robustness checks regressions.

The last point that seeks attention is the issue of identifying the social multipliers. An exogenous change that influences the mathematics achievement of one student, will in turn affect the achievement of another adjacent student; this can initiate a chain of interactions among the students, which as a spillover effect will tend to multiply and magnify the original dimension of the impact. Entorf and Lauk (2008) tackle this by aggregating individual results within groups and within schools, which after solving a two-equation system for the average achievement scores for both migrant and native students yields the following:

$$(7) \qquad M^m = \frac{1}{1-\gamma_m^m - \frac{\gamma_n^m \gamma_m^n}{1-\gamma_n^n}} \qquad \text{and} \qquad M^n = \frac{1}{1-\gamma_n^n - \frac{\gamma_m^n \gamma_n^m}{1-\gamma_m^m}}$$

where M^m is the resulting multiplier for migrants and M^n the multiplier for natives. A point to notice is the connection with the social multiplier studied by Glaeser *et al* (2000, 2003), as mentioned in section 2.2., where the simple case emerges from the estimable version of (5), i.e. $y_{i_s s} = \alpha + b\overline{y}_s^{-i} + X_{i_s s}c + \varepsilon_{i_s s}$ when we disregard existence of any impact from one group to another. Consecutively, calculation of social multipliers can reveal the impact of social interaction in an environment as simple as described by equation (5) or even in a more intricate framework as the one presented

[5] Depending on the question of interest, the problem of selection can be addressed by the employment of sample selection models.

by system (6), which allows disentangling peer effects between and within students with and without a migration background.

3. Data, Descriptive Evidence and Estimation of Social Multipliers

The data used to empirically estimate the baseline model of peer effects and the model of unobserved heterogeneity are taken from the Programme for International Student Assessment (PISA), conducted every three years by the Organisation for Economic Co-Operation and Development (OECD 2000, 2003, 2006) to assess the performance of 15-year olds in reading, mathematics, science and problem solving. In this study we utilise all three waves, i.e. the PISA 2000, 2003 and 2006 reports and use students' scores on mathematical ability to see the evolving of statistics of interest. For estimation purposes, we use the 2006 Report and scores in mathematics. According to the PISA study, assessment on mathematics aims at evaluating *"The capacity to identify and understand the role that mathematics plays in the world, to make well-founded judgements and to use and engage with mathematics in ways that meet the needs of that individual's life as a constructive, concerned and reflective citizen. Related to wider, functional use of mathematics, engagement requires the ability to recognise and formulate mathematical problems in various situations*[6]". The sampling design used for the construction of the PISA dataset is a two-way stratified sampling[7]; the first stage treats schools within each country as the sampling unit, i.e. schools having 15-year old students are sampled with probabilities proportional to a measure of size. The minimum number of schools was 150 or all if there were fewer of 150. In the second stage the sampling unit is 15-year old students within the first stage sampled schools. At most 35 students (target cluster size) were selected with equal probability; the minimum required number was 20 so as to ensure accuracy.

Obviously, the sample design is that of a clustered sample; hence, we might find it difficult to accept that students belonging to the same school are truly independent, since some characteristics may be common but, nevertheless, not captured by the variables already included in the PISA dataset; it seems reasonable to be prepared to accept correlation among students within the same school, especially of those that may belong in the same classroom (the PISA dataset does not include a class identifier - only a school identifier - thus, we are provided with no information on this matter), but not any among the schools of each country, i.e. presence of within school correlation, but not of between school correlation. Adjustment to calculate robust standards errors is explicitly rendered necessary before proceeding into making any valid statistical inference.

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[6] Programme for International Student Assessment, "Learning for Tomorrow's World, First Results from PISA 2003", OECD 2004.
[7] In some countries a three-stage sampling design was used, where the first stage now entails sampling geographical areas with probability, again, proportional to size sampling.

Another issue emerging with the use of stratified and clustered data, as already mentioned, is the probability proportional to size sampling for schools within a country, the assignment of schools in strata and the sampling of students within schools (some students had to be excluded). This means that sampling weights, provided already in the dataset, must be employed in order to obtain representative coefficients or results. General treatment of stratified and clustered data has already been studied by DuMouchel & Duncan (1983), who point out the necessity of carrying out Weighted Least Squares regressions to ensure that representative students and schools are used in the analysis; Moulton (1986) underlines the inappropriateness of Ordinary Least Squares when errors are potentially correlated within groups (or clusters). Deaton (1997) provides the framework for regressions in the case of clustered samples. In practice, Woessmann (2003) applies some of the aforementioned techniques in the estimation of within-country cross-sectional education production functions using the TIMSS (Third International Mathematics and Science Study) dataset. Lastly, Wooldridge (2006) extensively analyses the econometric methods that should be applied when the researcher is faced with cluster-samples.

Table 1 provides descriptive statistics on selected variables for Germany and the UK. The share of migrants (defined as students both of whose parents were born abroad) ranges between 14% to 16% in Germany, and between 8% to 9% in UK. The share of female participants is about 50% for both countries. OECD PISA scores are standardized such that the OECD mean is 500. Table 1 reveals that migrants clearly fall behind in Germany, where the educational gap amounts to 73 to 83 PISA points. As already stated above for the PISA 2000 (reading) score (Entorf & Minoiu, 2005; Schnepf, 2007), the math score of migrants is also below that of natives in UK, but to a lesser extent (between 15 and 40 points). Given the high intergenerational correlation of education found for both countries (see Entorf & Minoiu, 2005), it is perhaps not surprising that differences between migrant and native students are more pronounced for Germany than for the UK: Whereas the parental socio-economic parental background of migrants and natives measured by ISEI (i.e. the International Socio-Economic Index of Occupational Status) strongly differs in Germany, there is practically the same background for both student groups in the UK (in both countries average ISEI is about 45 for native parents).

Table 1: Descriptive statistics on selected variables, PISA Mathematics Scores (2000, 2003, 2006)

Year		Country	
		Germany	UK
Share of migrants	2000	0.156	0.090
	2003	0.156	0.079
	2006	0.143	0.088
Share of females	2000	0.508	0.502
	2003	0.497	0.532
	2006	0.484	0.505
Differences in PISA Scores	2000	-83.350	-40.751
	2003	-82.896	-15.278
	2006	-73.156	-25.512
Differences in ISEI	2000	-8.979	0.277
	2003	-11.069	-0.490
	2006	-11.010	-1.935
Ratio of all migrants (=100%) in top 10% schools	2000	0.049	0.099
	2003	0.040	0.121
	2006	0.055	0.144
Ratio of all migrants (=100%) in bottom 10% schools	2000	0.184	0.292
	2003	0.142	0.097
	2006	0.213	0.158
Ratio of between school variance	2000	0.611	0.363
	2003	0.639	0.338
	2006	0.668	0.313

*Observations are weighted by student weights. Authors' own calculations.

Segregation and high clustering of migrants in neighbourhoods might have a negative impact on immigrants' educational achievement since there is less social interaction with natives than in mixed environments. Pupils are likely to be influenced by their peers' school ambitions and these are likely to be different in highly segregated schools. An indicator of (positive or negative) segregation is the allocation of migrant students to top or bottom ranked schools, as measured by average PISA scores. Table 1 reveals that there seems to be some symmetry for presence of migrants in top and bottom ranked schools in the UK (note, however, that figures in the UK fluctuate due to a rather small number of migrant students, see in particular the high outlying share of migrants in bottom ranked schools in 2000), while some stark contrasts do exist for Germany. Contrary to the situation in Germany, more than 10% of migrants reach top levels (implying overrepresentation of migrants in top schools; equal performance and opportunities of migrants and natives would imply that 10% of each group would reach the 10% top levels). In Germany, only about 5% are likewise successful, while about 15% are allocated to the bottom 10% schools. This discrepancy is presumably based on the disadvantaged socioeconomic status of migrant families and reinforced by the German schooling system based on early tracking by skill level which selects the majority of migrants into the lowest ranked secondary school, i.e. the *Hauptschule*.

The last column of Table 1 shows the decomposition of the PISA score variance into its between-school and within-school shares. Results reveal differences which most likely are caused by characteristics of comprehensive versus ability-tracking schooling systems. The high ratio of between school variance in Germany is mainly driven by the heterogeneity of abilities across different types of schools (*Gymnasium*, *Realschule*, *Gymnasium*), whereas students in the UK are allocated to different tracks within a comprehensive school system (with only few exceptions).

Summing up, Germany and the UK mainly differ with respect to the socioeconomic status of migrants' (typically Western immigrants in the UK, Turks and Eastern Europeans in Germany) which has also led to strong segregation of migrants in bottom ranked schools in Germany. This contrast between the two countries seems to be reinforced by the early separation into different schools compared to the general attendance of comprehensive schools in the UK.

Below (Table 2) we provide estimation results for equation (6) for Germany and the UK, and calculation of the social multipliers (Table 3).

Table 2: Estimation of Baseline Model for Pisa Math Scores 2006, Germany and the UK

Dependent Variable: Mathematics score	**Germany**		**United Kingdom (UK)**	
	Natives	**Migrants**	**Natives**	**Migrants**
Female	-32.278 (2.321) [0.000]	-29.529 (5.288) [0.000]	-14.776 (2.302) [0.000]	-13.063 (8.606) [0.133]
Grade 8, Germany	-73.917 (4.683) [0.000]	-76.082 (8.420) [0.000]	_	_
Grade 9, Germany	-36.403 (2.475) [0.000]	-39.755 (7.664) [0.000]	_	_
Grade 11, UK	_	_	10.644 (8.042) [0.187]	2.228 (32.047) [0.945]

Foreign Born	-1.024 (14.415) [0.943]	15.537 (5.152) [0.003]	10.103 (7.787) [0.196]	5.453 (9.181) [0.554]
National Language at Home	24.839 (7.008) [0.001]	18.251 (5.927) [0.003]	-16.205 (11.276) [0.153]	4.144 (8.818) [0.640]
More than 100 Books at Home	24.839 (2.677) [0.000]	6.636 (5.818) [0.257]	29.364 (2.998) [0.000]	30.807 (8.473) [0.000]
Home Educational Resources	3.063 (1.415) [0.032]	-1.108 (2.937) [0.707]	11.472 (1.714) [0.000]	15.006 (6.565) [0.025]
Economic, Social and Cultural Status	1.773 (1.634) [0.280]	9.406 (3.285) [0.005]	13.557 (1.945) [0.000]	16.551 (4.499) [0.000]
Student Teaching Staff Ratio	0.301 (0.213) [0.160]	0.630 (0.704) [0.373]	-0.005 (0.401) [0.989]	2.716 (2.013) [0.181]
Quality of School's Educational Resources	-0.389 (0.898) [0.666]	4.694 (2.992) [0.120]	0.439 (0.835) [0.599]	3.172 (3.657) [0.388]
Village / Small Town	-0.647 (2.246) [0.774]	0.533 (6.130) [0.931]	-0.852 (1.941) [0.661]	-3.919 (10.439) [0.708]
Selection by Residence	-3.627 (2.515) [0.151]	-3.233 (6.493) [0.620]	-0.244 (1.855) [0.895]	0.512 (10.278) [0.960]
Selection by Performance	-1.195 (2.240) [0.594]	-4.244 (5.994) [0.480]	18.318 (4.143) [0.000]	12.619 (16.324) [0.442]
Responsibility for curriculum and assessment	-1.568 (1.352) [0.248]	6.981 (4.296) [0.107]	1.454 (1.252) [0.247]	-4.925 (7.616) [0.519]
Responsibility for Resource Allocation	1.772 (2.560) [0.490]	7.059 (6.676) [0.293]	-1.072 (0.952) [0.262]	5.198 (5.932) [0.383]
Public School	0.645 (6.364) [0.919]	20.268 (18.400) [0.273]	5.974 (4.125) [0.149]	-30.982 (20.220) [0.129]
Mean of math score, natives	**0.670**	**0.715**	**0.577**	**0.328**

	(0.051) **[0.000]**	(0.074) **[0.000]**	(0.039) **[0.000]**	(0.139) **[0.021]**
Mean of math score, migrants	**0.103** (0.031) **[0.001]**	**0.030** (0.079) **[0.700]**	**0.057** (0.013) **[0.000]**	**0.197** (0.103) **[0.059]**
R- Squared	0.633	0.653	0.376	0.449
Observations	2332	410	3850	379

*Estimation Method: OLS. All regressions include a constant. Robust standard errors are reported in parentheses and p - values in brackets.

Table 3: Calculation of Social Multipliers

	Social multiplier effects	
	M^m **(migrants)**	M^n **(natives)**
Germany	1.339 (0.132)	3.936 (0.790)
United Kingdom (UK)	1.318 (0.174)	2.501 (0.245)

* Standard errors in parentheses

The detailed description of explanatory variables can be found in the Appendix. Note that we define ‘migrants’ as students both of whose parents were born abroad. The specification resembles the one by Entorf and Lauk (2008) on PISA reading scores and is based on standard individual and school factors already employed by Wößmann (2003), Jürges und Schneider (2004), Ammermüller (2005) and others. The novelty of our approach lies in its separate modelling of migrant and native achievements and in considering peer effects arising from the influence of both migrant and native mean achievements. Looking at the equation for natives from both countries first, estimated coefficients are largely as expected from previous research on student PISA achievements. As has been found in the literature, school specific factors turn out to be insignificant when individual factors are controlled for (except ‘selection by performance’ for schools in the UK). Among the most significant factors, our results confirm the important role of the parental cultural and socio-economic background. In both countries, ‘more than 100 books at home’ and ‘home educational resources’ contribute to the variance of PISA in a highly significant way. The ‘economic, social and cultural status’ (which replaced ISEI from previous studies) seems to be covered by ‘books at home’ in Germany, while it is significant for the UK. In both countries male students have higher scores than their female compatriots. This result reverses the outcome based on the ‘reading’ PISA scores which showed superior performance of females (see, e.g., Entorf & Lauk, 2008).

Estimation results for migrants in Germany deviate from those of migrants in the UK in several respects. The reason might be seen in the fact that the ‘median migrant’ originates from Turkey in Germany, while he is from a Western industrialized country in the UK.[8] Leaving aside strong effects arising from the fact that the test was performed by pupils attending lower than 10^{th} grade, it is perhaps not surprising that the language of the host country spoken at home (i.e. migrant parents speak German to migrant children) turns out being one of the most important factors of educational success for migrants in Germany, while this variable has no significant impact in the UK. As the English language poses no serious problem for the large majority of immigrants to the UK (contrary to the German language for migrants in Germany), it is confirmed not being an obstacle for solving mathematical problems.[9]

The high and significant effect for 'foreign born' (indicates whether migrant is born in the country or not) reflects further problems of integration conditional on the long list of already included factors. It is high and significant in Germany (but not in the UK) which confirms the different nature of immigration in both countries. As regards the background of parents, 'more than 100 books at home' is nicely suited for discriminating between advantaged students endowed with cultural capital from well educated homes and less advantaged students from labour migrant families in the UK, as having 'more than 100 books at home' or not has the effect of more than 30 PISA points. This variable is less relevant in Germany. Here, but also in the UK, the parental background is significantly covered by the 'economic, social and cultural status'.

The somewhat surprising insignificance of 'books at home' and 'home educational resources' in the migrant equation for Germany might be the result of dominant and highly significant peer effects, as part of the exogenous influence is now covered through the channel of endogenous effects. Irrespective of whether we consider the equations for migrants or natives, the influence of the native peer group achievement is always higher than the influence of the migrant peer group, and the impact of native peers is higher in Germany than in the UK. The reverse impact, i.e. from migrants to migrants or from migrants to natives is much smaller in both countries, and remains insignificant for the German migrant equation. The migrant-to-migrant propagation is more pronounced in the UK (estimated coefficient = 0.20), but only weakly significant (p-value = 0.059) which is also affected by the rather small number of observations (379).

How do estimates from Table 2 translate into social multipliers? In Table 3, we provide numerical values of social multipliers presented in (7). Standard errors are

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[8] According to SOPEMI 2002 (OECD 2003), 2.59 million (which equals 4.3 percent of the British population) non-nationals were living in Great Britain of which the biggest group (436 thousand) is Irish, followed by migrants from the US (148 thousand), India (132 thousand), Italy (102 thousand), France and Pakistan (both 82 thousand).

[9] Note that 'language spoken at home' is also a significant factor for natives from Germany. According to the definition of migrants, 'natives' also include children from at least one or two second-generation immigrants born in the country. Thus, the positive sign reveals persistent integration problems of second-generation (or even third-generation) immigrants in Germany.

calculated using the delta method. In both countries the size of the multiplier effect on natives is higher than the impact on migrants, with the multiplier of the German schooling system (3.9) clearly exceeding the UK one (2.5). Both coefficients are significantly above unity, i.e. the benchmark case without any social interaction. This also holds for migrants in Germany (1.34) but not for migrants in UK (1.32), where standard errors are somewhat higher.

These estimates are in line with results presented in Entorf and Lauk (2008). Multiplier effects magnify the prevailing educational inequality between students with a low parental socio-economic migration background and children from more privileged families. This conclusion holds for all equations, i.e. for both native and migrant students. It is also confirmed that such multipliers seem to be higher in ability differentiated school systems (like Germany) than in comprehensive schools (like the UK). However, when compared to Scandinavian countries, multipliers in the UK are still high: multipliers based on 'reading' have only been 1.7 for natives and 1.1 for migrants for a group 'Denmark, Norway and Sweden' (see Entorf and Lauk, 2008.)[10]

4. Explaining Inequality, Consideration of Unobserved Heterogeneity

A serious limitation of employed PISA data sets is their cross-sectional structure. As well known in applied econometric work, unobserved heterogeneity might affect consistency of parameter estimates and cause some omitted variable bias. Hoxby (2000) suggests using first differences from cohorts in order to get rid of cohort-specific and cohort-invariant unobserved factors. This procedure is not feasible due to the nature of PISA data which collects data from 15-year old teenagers with only few observations based on different years of birth. We proceed in an alternative way which should eliminate a large fraction of student and school specific unobserved heterogeneity (unfortunately, class specific effects cannot be observed due to lacking class identifiers). At the same time, by taking the distance between natives and migrants educational achievements, we are going to analyse and evaluate inequality increasing and dampening factors.

We start by considering student *i* at schools *s* whose student achievement is being affected by individual and school specific factors introduced in the previous section. According to our notion of inequality, we distinguish between migrant and native students. In addition, we account for unobserved heterogeneity at student and school level, leading to the following equations:

(8) $$P^m_{i(s)} = X^m_{i(s)}\beta^m + \gamma^m_{i(s)} + \delta^m_s + \varepsilon^m_{i(s)}$$

(9) $$P^n_{i(s)} = X^n_{i(s)}\beta^n + \gamma^n_{i(s)} + \delta^n_s + \varepsilon^n_{i(s)}$$

[10] Likewise in the 'reading' context, the respective multipliers have been 4.0 and 1.45 (i.e. very close to results presented in this study) for students from the aggregate group 'Austria and Germany'.

where

$P_{i(s)}^{j}$: PISA score in mathematics of student i in school s, $j = m, n$

$X_{i(s)}^{j}$: vector of student specific characteristics, both student and school varying

$\gamma_{i(s)}^{j}$: unobserved student characteristics

δ_{s}^{j}: unobserved school characteristics.

Taking the average over all students in school s gives

(10) $$P_s^j = X_s^j \beta^j + \gamma_s^j + \delta_s^j + \varepsilon_s^j, \; j = m, n.$$

There is no reason to believe that intelligence (or true mean achievement or ability) is on average different between the group of native and the group of migrant students. Moreover, migrants and natives allocated to the same school have identical school neighbourhoods and share common resources such that it is sensible assuming that $\delta_s^m = \delta_s^n$.[11]

Taking the difference between natives and migrants equations yields:

(11) $$(P_s^n - P_s^m) = X_s^n \beta^n - X_s^m \beta^m + (\varepsilon_s^n - \varepsilon_s^m).$$

Equation (11) identifies the list of factors having a significant impact on the native-migrants gap, but it does not properly account for underlying reasons of inequality. Adapting the idea of the Oaxaca-Blinder (1973) decomposition of the gender wage gap to the educational gap[12], background factors can be seen in different endowments of natives and migrants (X_s^n, X_s^m, i.e. different socioeconomic backgrounds etc.), but also in different parameters β^n and β^m. This ‘coefficient effect’, which is interpreted as ‘discrimination’ in the gender wage differential (unequal pay despite identical qualification), and the ‘endowment effect’ can be identified from the following transformation of equation (11):

(12) $$(P_s^n - P_s^m) = (X_s^n - X_s^m)\beta^n + X_s^m(\beta^n - \beta^m) + (\varepsilon_s^n - \varepsilon_s^m)$$

In the context of PISA gaps, some adverse ‘coefficient effects’ (if existent) would consist in less sensitive responses to exogenous migrant factors than to native factors. This could be due to insufficient integration hindering success in school despite ‘normal’ individual and institutional background factors, interaction problems

[11] Of course, this assumption excludes racial discrimination such as unequal treatment of natives and migrants by teachers in common.

[12] Ammermüller (2007) applied a similar approach by analysing the difference between students in Germany and Finland.

between teachers and pupils, different attitudes or efforts between migrants and natives, but also due to mere discrimination.

Equations (11) and (12) are estimated using ordinary least squares; results are presented in Tables 4 to 7. The histogram of the left hand side variable is depicted for both countries in Figures 1 and 2. As expected from reported individual differences between natives and migrants in Table 2, the mean (28) is positive, but it is well below 73 (the distance detected in Table 2) in Germany, because students are segregated by skill level such that this difference of 28 reflects inequality within schools, not between-schools. This does not hold for the comprehensive school system in the UK. Here the mean is 8, i.e. not that far from the figure in Table 2 (i.e. 25). The higher homogeneity of German schools can also be seen by the higher standard deviation of distances within school in the UK (68) compared to (46) in Germany.

Figure 1: Differences in schools' PISA scores, Germany

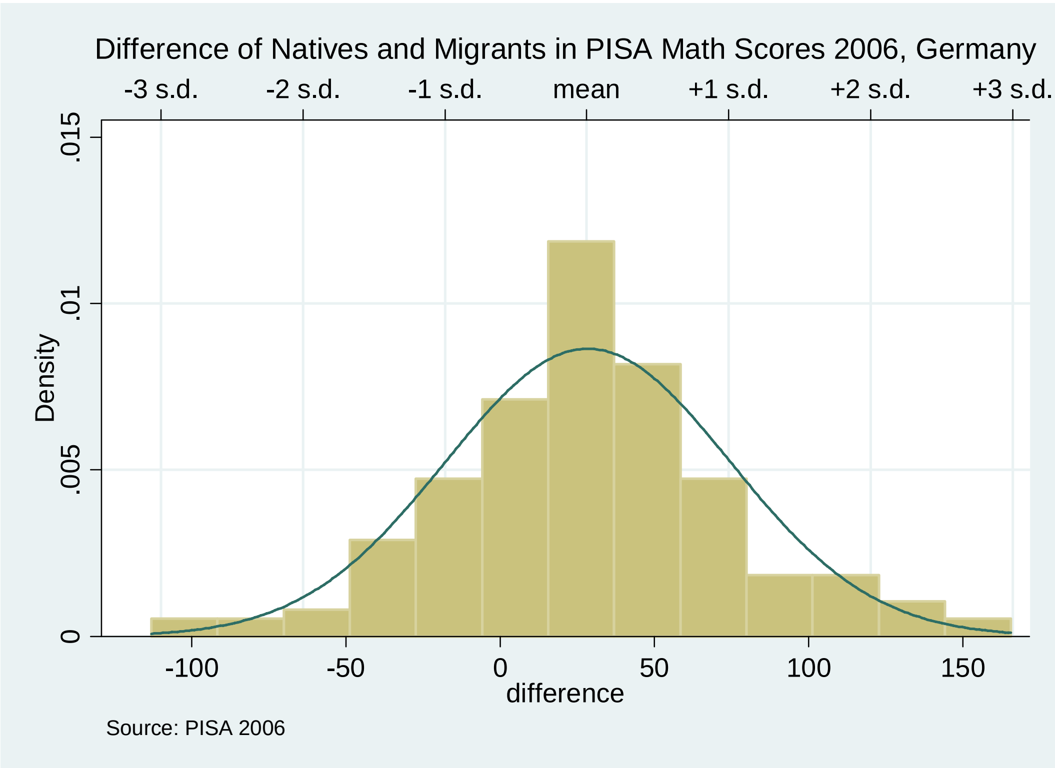
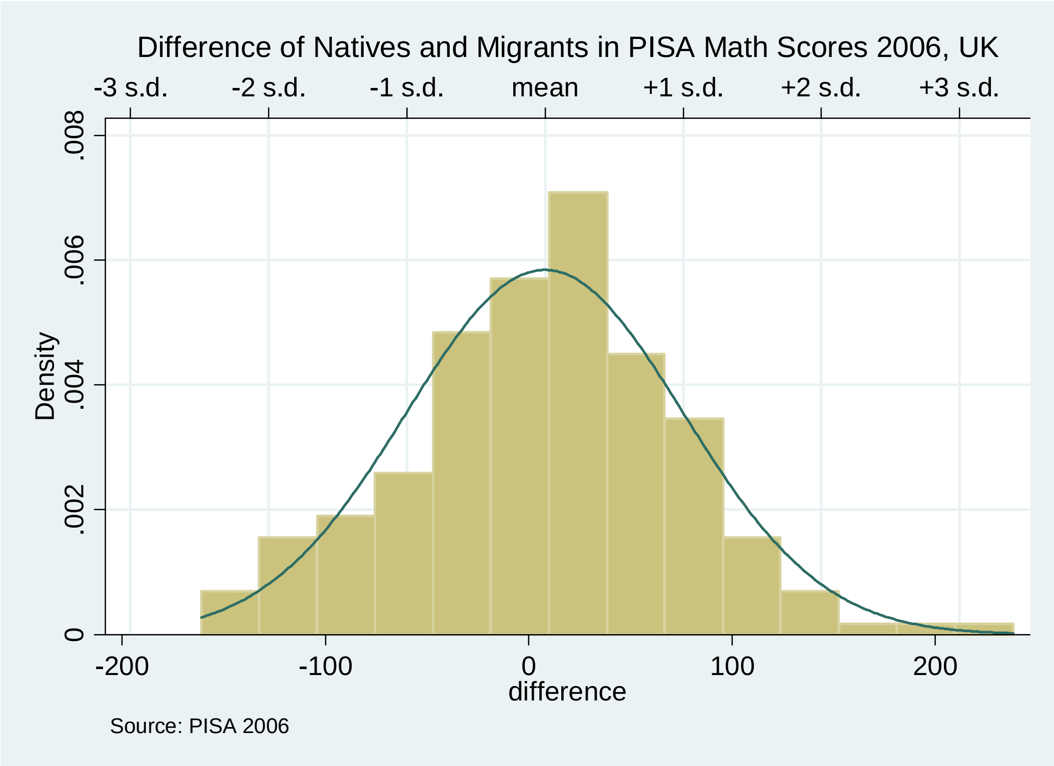


Figure 2: Differences in schools' PISA scores, UK



For the UK, the availability of home educational resources plays a crucial role. This, too, is related to parental background and confirms that absence of resources such as a quiet place to study, a desk for study, a dictionary and calculators at home further might increase educational inequality. It is remarkable that statistical significance is mainly limited to migrant factors. Thus, it is mainly the improvement of the migrants' situation rather than the deterioration of the natives' situation that would diminish the gap between natives and migrants in the UK.

Table 4: Estimation results for equation (11), Germany

Dependent Variable: Difference in Math Scores Between Natives and Migrants (model specification: $(P_s^n - P_s^m) = X_s^n \beta^n - X_s^m \beta^m + \varepsilon_s$)				
Explanatory Variables	Germany			
	(1)		(2)	
	β^n	β^m	β^n	β^m
Share of females	4.493 (19.584) [0.819]	-44.113 (10.209) [0.000]	0.956 (20.463) [0.963]	-44.710 (9.555) [0.000]
Home Educational Resources	-12.418 (13.588) [0.362]	2.443 (6.483) [0.707]	-	-
Economic, Social and Cultural Status	10.831 (13.348) [0.418]	7.921 (6.470) [0.223]	17.071 (7.052) [0.017]	9.435 (5.401) [0.082]
Share of More	42.217	12.367	-	-

than 100 Books at Home	(27.452) [0.126]	(12.459) [0.322]		
Share of Foreign Born	-81.996 (75.197) [0.277]	0.436 (9.635) [0.964]	-	-
Share of Language Spoken at Home	1.257 (31.001) [0.968]	1.968 (9.657) [0.839]	-	-
Constant	-11.675 (29.507) [0.693]		2.821735 (12.795) [0.826]	
R - Squared	0.195		0.159	
Observations	177		177	

*Estimation Method: OLS. All regressions include a constant. Robust standard errors are reported in parentheses and p - values in brackets.

Table 5: Estimation results for equation (11), UK

Dependent Variable: Difference in Math Scores Between Natives and Migrants (model specification: $(P_s^n - P_s^m) = X_s^n\beta^n - X_s^m\beta^m + \varepsilon_s$)				
Explanatory Variables	**United Kingdom (UK)**			
	(1)		(2)	
	β^n	β^m	β^n	β^m
Share of females	-36.995 (23.804) [0.122]	-27.348 (15.018) [0.070]	-39.287 (23.535) [0.097]	-29.150 (14.844) [0.051]
Home Educational Resources	0.667 (23.053) [0.977]	23.208 (9.079) [0.011]	-0.782 (21.008) [0.970]	23.008 (8.748) [0.009]
Economic, Social and Cultural Status	26.773 (18.462) [0.149]	15.359 (8.000) [0.056]	28.765 (14.136) [0.043]	18.490 (6.687) [0.006]
Share of More than 100 Books at Home	2.632 (31.517) [0.934]	14.521 (13.041) [0.267]	-	-
Share of Foreign Born	143.130 (118.470) [0.228]	3.689 (13.348) [0.783]	-	-
Share of Language Spoken at Home	20.225 (43.215) [0.640]	-6.563 (13.779) [0.634]	-	-
Constant	-15.471 (43.224) [0.721]		5.242 (12.021) [0.663]	
R - Squared	0.152		0.140	
Observations	202		202	

*Estimation Method: OLS. All regressions include a constant. Robust standard errors are reported in parentheses and p - values in brackets.

Tables 6 and 7 decompose the PISA gap between natives and migrants into two parts, endowment and ‘integration/discrimination’ (‘coefficient effect’). In the two countries under investigation, this viewpoint confirms that differences in student achievements mainly arise due to less advantaged endowments for migrants. In particular, the socioeconomic status of parents (UK) and the cultural capital endowment at home (‘books at home’, Germany) play crucial roles.

Table 6: Estimation results for Oaxaca specification (12), Germany

Dependent Variable: Difference in Math Scores Between Natives and Migrants (model specification: $(P_s^n - P_s^m) = (X_s^n - X_s^m)\beta^n + X_s^m(\beta^n - \beta^m) + \varepsilon_s$)				
Explanatory Variables	**Germany**			
	(1)		(2)	
	β^n	$(\beta^n - \beta^m)$	β^n	$(\beta^n - \beta^m)$
Share of females	4.493 (19.584) [0.819]	48.606 (23.579) [0.041]	-0.733 (19.536) [0.970]	45.660 (22.443) [0.043]
Home Educational Resources	-12.418 (13.588) [0.362]	14.862 (13.565) [0.275]	-	-
Economic, Social and Cultural Status	10.831 (13.348) [0.418]	2.910 (15.372) [0.850]	-	-
Share of More than 100 Books at Home	42.217 (27.452) [0.126]	29.850 (29.868) [0.319]	43.300 (15.430) [0.006]	23.485 (14.811) [0.115]
Share of Foreign Born	-81.996 (75.197) [0.277]	-82.433 (76.185) [0.281]	-	-
Share of Language Spoken at Home	1.257 (31.001) [0.968]	-.711 (31.345) [0.982]	-	-
Constant	-11.675 (29.507) [0.693]		-9.795 (12.290) [0.427]	
R - Squared	0.195		0.175	
Observations	177		177	

*Estimation Method: OLS. All regressions include a constant. Robust standard errors are reported in parentheses and p - values in brackets.

Table 7: Estimation results for Oaxaca specification (12), UK

Dependent Variable: Difference in Math Scores Between Natives and Migrants (model specification: $(P_s^n - P_s^m) = (X_s^n - X_s^m)\beta^n + X_s^m(\beta^n - \beta^m) + \varepsilon_s$)				
Explanatory Variables	**United Kingdom (UK)**			
	(1)		(2)	
	β^n	$(\beta^n - \beta^m)$	β^n	$(\beta^n - \beta^m)$
Share of females	-36.995 (23.804) [0.122]	-9.647 (18.549) [0.604]	-31.650 (23.032) [0.171]	-9.858 (17.427) [0.572]
Home Educational Resources	0.667 (23.053) [0.977]	-22.540 (24.976) [0.368]	-	-
Economic, Social and Cultural Status	26.773 (18.462) [0.149]	11.446 (18.191) [0.531]	25.143 (11.971) [0.037]	-1.407 (10.171) [0.890]
Share of More	2.632	-11.889	-	-

than 100 Books at Home	(31.517) [0.934]	(32.013) [0.711]		
Share of Foreign Born	143.130 (118.470) [0.228]	139.441 (117.463) [0.237]	-	-
Share of Language Spoken at Home	20.225 (43.215) [0.640]	26.789 (40.475) [0.509]	-	-
Constant	-15.471 (43.224) [0.721]		10.557 (10.356) [0.309]	
R - Squared	0.152		0.097	
Observations	202		202	

*Estimation Method: OLS. All regressions include a constant. Robust standard errors are reported in parentheses and p - values in brackets.

Some 'integration effect' can only be observed for Germany. Here β^n on females significantly exceeds β^m by 45.6 when evaluated at X_s^m . As can be seen from previous results, females perform worse in math than their male schoolmates. Table 6 reveals that at the within-school level, the generally poor math performance of females seems to be particularly low for migrants. At first glance, these results seem to be at odds with coefficients based on individual data, but it should be recalled that the coefficient is related to the mean of X_s^m , and that educational achievement gaps estimated from individual data mainly stem from between school differences in Germany. As migrants in Germany mainly origins from Turkey, of which many have strongly religious roots with traditional roles in family issues, female students from these insufficiently integrated families not only lose ground on male schoolmates but also on their female native peers. Here some effort by German educational and immigration policy is required to encourage girls and parents from Arab countries to break with traditional roles of home countries and to rouse their interests in mathematics (and other scientific and technical fields).

5. Summary and Conclusions

The paper analyses the educational achievement of native and migrant students in Germany and UK. Comparing these two countries is interesting for several reasons: First, although the UK is a European country, the 'median migrant' is different for the typical 'labour migrant' in countries like Germany or France. She or he is better educated and the majority origins from Western countries, contrary to the typical 'guestworker' in Germany who has Turkish roots or stems from Eastern countries. Second, schooling systems differ: Germany allocates students according to their skill level to separate schools at the early age of 10, whereas the UK mainly follows the concept of comprehensive schools. Third, in both countries intergenerational correlation of education is among the highest in Europe (Entorf and Minoiu, 2005).

Given this institutional framework, the paper studies social interaction across and between the groups of natives and migrants using individual data on educational achievement (PISA, 2000, 2003, 2006). Results confirm that the question of peer effects cannot be disentangled from the influence of prevailing national schooling systems. Indeed, estimation results for migrants in Germany deviate from those of migrants in the UK in several respects, but there are some similarities, too:

a) As the English language poses no serious problem for the large majority of immigrants to the UK (contrary to the German language for migrants in Germany), it is perhaps not surprising that the language of the host country spoken at home (i.e. migrant parents speak German to migrant children) turns out being one of the most important factors of educational success for migrants in Germany, while this variable has no significant impact in the UK.

b) As regards the background of parents, for the UK 'more than 100 books at home' seems to be nicely suited for discriminating between advantaged students endowed with cultural capital from well educated homes and less advantaged students from labour migrant families. Having 'more than 100 books at home' or not has the effect of more than 30 PISA points. This variable is less relevant in Germany. Here, but also in the UK, the parental background is significantly covered by the factor 'economic, social and cultural status'.

c) When inspecting the impact of 'social interaction' on educational achievement, the influence of the native peer group achievement is always higher than the influence of the migrant peer group, and the impact of native peers is higher in Germany than in the UK. The migrant-to-migrant propagation is more pronounced in the UK. In both countries the resulting size of the multiplier effect on natives is higher than the impact on migrants, with the multiplier of the German early tracking schooling system clearly exceeding the UK one. Evidently, multiplier effects magnify the prevailing educational inequality between students entering schools with a low parental socio-economic migration background and children from more privileged families, in particular in ability differentiated school systems (like Germany).

The PISA initiative provides a rich set of explanatory variables, but consideration of unobserved heterogeneity is limited by the cross-sectional character of data. In order to mitigate the problem of unobserved factors, we consider differences between PISA scores of natives and migrants at the aggregate school level. At the same time, by taking the distance between natives' and migrants' educational achievements, we are going to analyse and evaluate factors that might increase or dampen educational inequality. It turns out that the share of females (results are based on math performance (PISA 2006); here girls perform worse than their male schoolmates) and parental background (measured by 'economic, social and cultural status' and/or 'more than 100 books at home') are confirmed as being significant.

Employing the equivalent Oaxaca-Blinder specification, it turns out that the educational gap between natives and migrants is mainly due to the 'endowment effect' (i.e. the more advantaged socioeconomic background and the higher cultural capital of natives). Some 'integration effect' can only be observed for Germany, where female migrants seem to fall behind. We conclude that German educational and immigration policy should encourage girls with a migration background (typically from traditional Islamic countries) to break with traditional roles of home countries and to rouse their interests in mathematics (and other scientific and technical fields).

References

Acemoglu, D. and J.D. Angrist (2001), 'How Large Are Human Capital Externalities? Evidence from Compulsory Schooling Laws', in: B. S. Bernanke and K. Rogoff (eds.), *NBER Macroeconomics Annual 2000*, MIT Press.

Acemoglu, D. (2002), 'Technical Change, Inequality, and the Labor Market', *Journal of Economic Literature*, 4, 7-72.

Acemoglu, D. (2003), 'Cross-Country Inequality Trends', *Economic Journal*, 113, F121-F149.

Ammermüller, A. (2005), 'Poor Background or Low Returns? Why Immigrant Students in Germany Perform so Poorly in PISA' *ZEW Discussion Paper* No. 05-18, ZEW, Mannheim.

Bauer, P., R. Riphahn (2007), 'Heterogeneity in the Intergenerational Transmission of Educational Attainment: Evidence from Switzerland on Natives and Second Generation Immigrants' *Journal of Population Economics* 20 (1), 121-148.

Becker, G. S. (1974), 'A Theory of Social Interactions', *Journal of Political Economy,* 82(6), 1063-1093.

Blinder, A. (1973), 'Wage Discrimination: Reduced Form and Structural Estimates', *Journal of Human Resources* 8, 436-455.

Deaton A. (1996), 'The Analysis of Household Surveys', *The Johns Hopkins University Press*, Baltimore.

DuMouchel W.H., Duncan G.J. (1983), 'Using Sample Survey Weights in Multiple Regression Analyses of Stratified Samples', *Journal of the American Statistical Association*, 78, 535-543.

Dustmann, Ch. (2004), 'Parental Background, Secondary School Track Choice and Wages', *Oxford Economic Papers*, 56, 209-230.

Dustmann, Ch., J. Ludsteck and U. Schönberg (2007), Revisiting the German Wage Structure, IZA DP. 2658.

Entorf, H. (1996), ‚Strukturelle Arbeitslosigkeit in Deutschland: Mismatch, Mobilität und technologischer Wandel', in: B. Gahlen, H. Hesse and H.J. Ramser (Editors), *Arbeitslosigkeit und Möglichkeiten ihrer Überwindung*, Tübingen: J.C.B. Mohr, 139-170, 1996.

Entorf, H., N. Minoiu (2005), 'What a Difference Immigration Policy Makes: A Comparison of PISA Results in Europe and Traditional Countries of Immigration', *German Economic Review*, 6 (3), 355-376.

Entorf, H., Lauk M. (2008), 'Peer Effects, Social Multipliers and Migrants at School: An International Comparison', *Journal of Ethnic and Migration Studies.*

Fitzenberger, B. (1999), ‘Wages and Employment Across Skill Groups, An Analysis for West Germany’, *Heidelberg: Physica/Springer*.

Frick, J.R., G. Wagner (2001), ‘Economic and Social Perspectives of Immigrant Children in Germany’, *IZA Discussion Paper* No 301, IZA, Bonn.

Gang, I.N. and K.F. Zimmermann (2000), ‘Is Child Like Parent?: Educational Attainment and Ethnic Origin’, *Journal of Human Resources*, **35**, 550-569.

Glaeser, E.L. and J.A. Scheinkman (2000), ‘Non-Market Interactions’, *NBER Discussion Paper* No. 8053, Cambridge, MA.

Glaeser, E.L., Scheinkman J.A. (2003), “The Social Multiplier”, *Journal of the European Economic Association*, 1 (2-3), 345-353.

Graham B. and Hahn J. (2005), ‘Identification and Estimation of the Linear-in-Means Model of Social Interactions’, *Economics Letters*, 88(1), 1-6.

Hanushek, E.A., J. Kain, J. Markman, S.G. Rivkin (2003), ‘Does Peer Ability Affect Student Achievement?’ *Journal of Applied Econometrics,* 18 (5), 527-544.

Hanushek, E.A., L. Wössmann (2006), ‘Does Educational Tracking Affect Performance and Inequality? Differences-in-Differences Evidence Across Countries’ *Economic Journal,* 116 (510), C63-C76.

Hoxby, C. (2000), ‘Peer Effects in the Classroom: Learning From Gender and Race Variation’, *NBER Working Paper* No. 7867, Cambridge, MA.

Jürges, H., K. Schneider (2004), ‘International Differences in Student Achievement: An Economic Perspective’ *German Economic Review*, 5(3), 357-380.

Kahn, L.M. (2000), ‘Wage Inequality, Collective Bargaining, and Relative Employment from 1985 to 1994: Evidence from Fifteen OECD Countries’, *Review of Economics and Statistics*, 82, 564-579.

Levitt S. (1999), ‘The Limited Role of Changing Age Structure in Explaining Aggregate Crime Rates’, *Criminology,* 37(3), 581-597.

Machin, S. (1997), ‘The decline of labour market institutions and the rise in wage inequality in Britain’, *European Economic Review*, 41(3-5), 647-657.

Machin, S. and J. Van Reenen (1998), 1998. ‘Technology and Changes in Skill Structure: Evidence From Seven OECD Countries’, *The Quarterly Journal of Economics*, 113(4), 1215-1244.

Manski, C.F. (1993), ‘Identification of Endogenous Social Interactions: The Reflection Problem’, *Review of Economic Studies,* 60(3), 531-542.

Manski, C.F. (1995), ‘Identification Problems in the Social Sciences’, *Cambridge: Harvard University Press*.

Manski, C.F. (2000), ‘Economic Analysis of Social Interactions’, *Journal of Economic Perspectives*, 14(3), 115-136.

Moulton, B. R. (1986), ‘Random Group Effects and the Precision of Regression Estimates’, *Journal of Econometrics*, 32(3), 385-397.

Oaxaca, R. (1973), ‘Male-Female Wage Differentials in Urban Labor Markets, *International Economic Review*, 14, 673-709.

OECD (2001), ‘The OECD Programme for International Student Assessment (PISA)’, http://www.pisa.oecd.org/ (October 5, 2004).

OECD (2003), ‘Trends in International Migration’, SOPEMI 2002, Paris.

Programme for International Student Assessment, “Learning for Tomorrow’s World, First Results from PISA 2003”, OECD 2004.

Puhani, P. (2004), ‘What Happened to Wage and Non-Employment Structures During the ‘Dutch Employment Miracle’?’, University of St. Gallen Department of Economics *Working Paper Series*, Department of Economics, University of St. Gallen.

Sacerdote, B. (2001), ‘Peer Effects with Random Assignment: Results for Dartmouth Roommates’, *The Quarterly Journal of Economics*, 116, 681-704.

Schnepf, S. (2007), ‘Immigrants’ Educational Disadvantage: An Examination Across Ten Countries and Three Surveys’, *Journal of Population Economics*, 20(3), 527-545.

Wooldridge, J. (2006), 'Cluster-Sample Methods in Applied Econometrics: An Extended Analysis', Department of Economics, Michigan State University, https://www.msu.edu/~ec/faculty/wooldridge/ current%20research/clus1aea.pdf

Wößmann, L. (2003), 'Schooling Resources, Educational Institutions and Student Performance: the International Evidence', *Oxford Bulletin of Economics and Statistics*, 65, 117-170.

A P P E N D I X

Description of explanatory variables in equation (6) - baseline model:

a) Individual characteristics and backgrounds of students

- ***Mathematics Score:*** Students' performance score in mathematics

- ***Female***: Binary Dummy variable, which takes the value 1 if the pupil is female

- ***Grade***

    For Germany:

    - ***Grade 8***: Binary Dummy variable, which takes the value 1 if the pupil attends 8th grade or lower

    - ***Grade 9***: Binary Dummy variable, which takes the value 1 if the pupil attends 9th grade

    - ***Grade 10***: Binary Dummy variable, which takes the value 1 if the pupil attends 10th grade or 11th

    For the UK:

    - ***Grade 11***: Binary Dummy variable, which takes the value 1 if the pupil attends grade 11th

-***Foreignborn***: Binary Dummy variable, which takes the value 1 if the pupil was not born in the country of test

-***National Language at Home***: Binary Dummy variable, which takes the value 1 if the pupil deploys mostly (the) national language(s) or other national dialects at home

-***More than 100 Books at Home***: Binary Dummy variable, which takes the value 1 if the pupil reported having more than 100 books in his/ her home

-***Home Educational Resources:*** PISA 2006 Index of Home Educational Resources

-***Economic, Social and Cultural Status***: PISA 2006 Index of Economic, Social and Cultural Status

b) School-specific factors

- ***Student-Teaching Staff Ratio***: Total number of pupils divided by the total number of teachers (whereby part-time teachers are counted as one half of a full-time teacher)

- ***Quality of School's Educational Resources***: Index of the quality of the school's educational resources, derived from school principals' reports on lack of instructional materials, laboratory equipment etc. concerning the learning by 15-year-olds

- ***Village/ Small Town***: Binary Dummy variable, which takes the value 1 if the school is located in a village or a small town (up to 15,000 people)

- ***Selection by Rresidence***: Binary Dummy variable, which takes the value 1 if the school very often or regularly considers residence in a particular area when students are admitted to the school

- ***Selection by Performance***: Binary Dummy variable, which takes the value 1 if the school very often or regularly considers the student's record of academic performance when students are admitted to the school

- ***Responsibility for Curriculum and Assessment***: PISA 2006 Index for school's Responsibility for Curriculum and Assessment as a measure of the school's Autonomy

- ***Responsibility for Resource Allocation***: PISA 2006 Index for school's Responsibility for Resource Allocation as a measure of the school's Autonomy

- ***Public School***: Binary Dummy variable, which takes the value 1 if the school is managed directly or indirectly by a government organisation

- ***Mean of Mathematics Score***: Mean of fellow - students' performance scores in mathematics. The variable is calculated both as the mean of the reading score of natives and as the mean of the reading score of migrants.

Description of explanatory variables in equation () – unobserved heterogeneity:

-***Share of Migrants***: proportion of migrant student in the school