Social Interactions Through Space and Time: Evidence from College Enrollment and Academic Mobility

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Abstract

In the recent years, the importance of one's group of peers-be that friends, colleagues, neighbors- has been widely emphasized in the literature. In this paper, we ask whether individuals derive utility from conformity in college enrollment and academic mobility. We propose a new methodology in mitigating reflection and endogeneity issues in identifying social interactions. We exploit a special institutional setting, in which schools are very close to each other, allowing for students from different schools to interact. We investigate utility spillovers from the educational choices of students in consecutive cohorts. Spatial variation allows us to identify social interactions in groups of various sizes. Using a new dataset that spans the universe of high school graduates, we estimate general equilibrium effects of social interactions. We find positive and significant externalities in the decision to enrol in college and the decision to migrate to a different city among peers that belong to the same social group.

Keywords: college enrollment, social interactions, mobility, geography, reflection problem
JEL Classification: I26, J24

1 Introduction

In the recent years the literature on the role of social interactions in economic behavior has expanded rapidly. This doesn't come as surprise when one thinks the importance of those effects in every day decision-making. The basis of decision-making though in almost every context is information. Humans are social beings and we naturally collect information through social interactions in order to inform our goals and choices. This is even more pronounced among adolescents. In developmental science, it has been widely argued that adolescents and young adults regularly mimic the choices and behavior of role models in their environment(Bell (1970)).

Brock and Durlauf (2001) define social interactions as the idea that an individual's marginal utility with respect to other individuals' choices in his reference group is positive. The desire to conform induces prevalent patterns of behavior even among agents with heterogeneous tastes over externalities from other individuals' choices (Bernheim (1994)). Social interactions within a reference group have been shown to affect students' achievement. However, there is little evidence on the effect of social interactions on the decisions of college enrollment and academic mobility. Moreover, social interactions can explain variation in choices across groups with similar characteristics. For example, Schelling (1973) provide early evidence of social interactions in binary choice in a profusion of contexts such as driving style and athletic play. Intuitively, conformity causes social interactions to be interconnected with neighborhood effects. Physical proximity amplifies the interplay of utility spillovers from other agents' choices and the combined effect becomes area specific. In an educational context, Garner and Raudenbush (1991) provide evidence of a positive relation between neighborhood quality and educational attainment.

There is evidence that peers' decision affect scholastic performance in elementary, middle and high school but also during college. Hoxby (2000) examines the effect of social interaction in grade school and finds that students who were randomly assigned to classes with students who have high reading scores relative to the school and grade, received higher reading scores.

Hanushek et al. (2003) find that peer achievement has a positive effect on achievement growth. In particular, 0.1 standard deviation increase in peer average achievement leads to a 0.02 increase in student's performance. Zimmerman (2003) examines the effect of social interaction using freshmens' SAT score. He finds strong positive social interaction effects among roommates at almost all parts of the ability distribution. Cipollone and Alfonso (2007) find strong social interactions inter alia the decision to stay longer in school. When men were exempted from the compulsory military services -due to an earthquake- and stayed longer in school, the graduation rates of young women in the affected areas rose by about 2 percentage points. Fletcher (2006) using survey data, finds strong evidence of social interactions college preferences and college enrollment. Giorgi et al. (2007) find that ones' behavior influences the educational decision while in college, indicating the importance of social interaction even at a later stage of someone's academic life. Sacerdote (2011) examines social interaction effects at the room and accommodation level where students are randomly assigned. He does not find any significant influence of peers.

In this paper we examine the effect of social interactions on the decisions of adolescents and young adults regarding college enrollment and academic mobility. We use a new dataset from Greece that contains information on exam scores, college enrollment and educational mobility for every student in six cohorts. We exploit the particular institutional setting in Greece, in which schools are build very close to each other. This setting allows for rich variation of school characteristics within a relatively contained geographical area. We exploit this exogenous variation in group characteristics over time and space to address the endogenous nature of the social interaction groups. The social interaction effects are defined as contextual interactions that induce different mappings from individual characteristics to outcomes (Bryk and Raudenbush (2001)). Reference groups are viewed as ecologies in which the social backgrounds affect individual choices of otherwise similar agents (Raudenbush and Sampson (1999)).

Similar age peers in one's vicinity consist a natural reference group that provide valuable and otherwise costly information, necessary in academic decision making. We widen the reference group and examine social interactions with respect to a series of reference groups: school peers in same cohort, school peers in different cohorts, same age students in the neighborhood and preferacture, different age students in neighborhood and preferacture.

There are particular advantages in having the universe of high school graduates for a country. First, we can identify general equilibrium effects as opposed to partial equilibria with respect to specific groups of students. Second, we are able to observe different reference groups. A student may be affected by the decisions of same age or older peers in his school, neighborhood or preferacture. We contribute to the literature by comparing the size of the social interaction effects across distance in space and age.

Empirical analysis of social interactions on students' decisions has been open to question because of the difficulties in disentangling these effects from other confounding influences.[1]. We use binary choice models and instrumental variable techniques, exploiting spatial and time variation to combat potential endogeneity problems and the well known "reflection-problem" (Manski (1993), Manski (2000)). There are two sources of potential endogeneity: Self selection into social groups and common shocks that affect every member of a social group. Reflection may arise from reverse causality between the outcomes of members in the same groups are their decisions are simultaneous. These challenges are standard in the social interactions literature. The institutional setting behind our study refrains students from endogenously select their peers in school, facilitating the validity of the identification strategy. Moreover, the geographical density of schools allows us to define social groups wider than a student's schoolmates. Motivating from the idea of role modelship, we battle the simultaneity challenge by investigating social interaction between peers in consecutive school cohorts.

We find positive spillover effects between one's decision to enrol in college and that of their peers. More specifically, the results found here indicate that

[1] The existing literature that deals with identification of the social comparison effects use either laboratory experiments (Armin and Andrea (2006)), natural experiments (Zimmerman (2003)), quasi-experimental designs (Hoxby (2000)), or fixed effects (Hanushek et al. (2003))

students who attend a high school with 10 percent more schoolmates who enrol in college are 4.5 percent more likely to attend college. We also find positive spillovers regarding the decision of educational mobility. Students are 16 percent more likely to move to a different city to study if their older peers in school do so, 10 percent more often. We find that these externalities decrease with the size of reference group.

The policy implications of social interactions can be indirect. The skills and resources that characterise a reference group are usually fixed. As a consequence, an improvement in someone's group characteristics means an equivalent deterioration in someone else's group attributes. Some may argue that the redistribution in favor of disadvantaged students can act as a boost in their scholastic outcomes, when the redistribution comes from more advantaged areas where students might depend less on their peers' quality. For example, Arcidiacono and Nicholson (2005) suggest that the existence of social interaction effects supports claims against school vouchers. This is because, the best students leaving public schools can be detrimental to the students left behind.

The paper is organized as follows. Section 2 describes the unique dataset used and the institutional setting related to college admission. The empirical strategy used to identify social interactions is analysed in Section 3. We present and discuss the results in college enrollment and educational mobility in Section 4. Finally, Section 5 concludes.

2 Data and Institutional Setting

2.1 How are students admitted to college

The transition from high school to post-secondary education in Greece is based on an unusually systematic and transparent allocation of student to university departments[2] In particular, every high school student who completes the twelfth grade receives an admission score, which is the only criterion for university admission and weights: (i) her performance in national

[2]Every tertiary education institute in Greece is public as free education is a constitutional right. Degrees awarded by private colleges are not recognized by the state.

twelfth grade exams [3] (ii) her grade twelve within school performance which is a combined score for homework and midterm exams in each subject.

After receiving their admission scores, students are required to submit a list of ranked choices of specific departments in universities that are relevant to their twelve grade track. For example, students outside the Classics track cannot list Law schools. Each university department generally offers one major of bachelor degree and no minor specializations can be declared. Every university department admits a pre-specified number of students. A computerized system at the Ministry of Education ranks students by their admission score and assigns the highest ranked student to her preferred choice. It then moves to the next student and assigns her to the first department in her list in which there is an available place, and so and so forth. In this context, students have incentives to truthfully reveal their preferences.

University departments must enrol the students assigned to them by the Ministry of Education. The Ministry of Education announces the score of the last admitted student in each university department. The last admitted students in more prestigious departments have generally higher scores in comparison to those in less prestigious ones. Once a student admitted they cannot transfer to a different major. College education is completely publicly funded and every student is exempted for college fees. Private donations to colleges are against the law.

[3] The twelfth grade exams are written exams administered nationally only once every year and last from late May to early June. The exams are proctored and marked externally. Exam markers do not observe the name, school, or even the city of the student whose paper they grade. Students usually take six component exams, with a combination of common subjects(Language, Mathematics, Physics, Biology or History) and four compulsory track-specific subjects and one elective exam. There are three tracks: Classics, Natural Sciences and Technical Studies. The overall score is the unweighted average of these scores. Students who fail are allowed to retake the exam the next year. In addition, students are not allowed to take the national exams early.

2.2 Data

For the empirical analysis we construct a unique dataset of all students graduating from high school in Greece from 2003 to 2009. We obtain the information from various sources:

1. Administrative data from the Hellenic Ministry of Education containing course taking information and exam grades in the final year, gender, year of birth, graduation year and college admission information. In addition, the total number of places in tertiary education in each year is provided.

2. School specific information such as name of school, type of school (private, public[4], experimental[5]), geographical coordinates, name of preferacture it belongs to[6], distance to nearest college. There are 1319 high schools in Greece[7].

3. The Ministry of Finance provided us with average net income information at the postcode of the school in 2009 Euro.

4. The Ministry of Internal Affairs provided us with urban density information. Urban areas are those with more than 20,000 inhabitants.

5. Geographical coordinates for every tertiary education institute in Greece. There are fifty five college campuses. Not all campuses offer the same majors.

Our analysis disentangles school peer effects from social interaction effects by exploiting variation of school characteristics within each neighborhood. This is possible because of the geographical density of schools in

[4]Students are assigned to public schools according to a school district system

[5]Admission to experimental schools is based on a lottery

[6]There are fifty two preferactures in Greece. Preferactures are classified by the Hellenic National Statistical Authority

[7]Of which, 112 are private, and 1207 public. Of those 1207 public schools, 23 are experimental. There are no private experimental schools in Greece. 74 evening high schools for employed people of usually older age are excluded from our analysis

Greece. The median distance of a school from each nearest neighbouring school is 0.32 miles.[8] We use cluster analysis to define and construct neighborhoods within a mile from each school. We construct 406 clusters that cover the whole country. Every cluster is a neighborhood that contains all twelve-grade students who attend any other high school within a mile (1.06 miles) radius from one's high school[9]. The other comparison group we use refers to social interactions from peers in the same preferacture. In our analysis, a preferacture contains all twelve-grade students in other neighborhoods within the administrative borders of a preferacture. Figures 1 maps all high schools and tertiary education institutes in our dataset. Distance of each school from the nearest tertiary education institute is used as proxy for college accessibility.

Our analysis uses information regarding characteristics and choices of older school peers. Because of this, we use data on student cohorts from 2004 to 2009[10] Furthermore, our discussion of academic mobility refers to the decisions of students to move to a different preferacture in order to study, given they were admitted to some college. Thus, for this part, we focus only on admitted students.[11]Lastly, we drop 35,808 obs. for which the group of schoolmates overlapped perfectly with the social group of their neighborhood. Similarly, we drop 2,433 obs. for which their neighborhood overlapped perfectly with their preferacture social group. [12] This exclusion allows us to compare spillover effects from social groups of various sizes. We

[8]Mean of distance from nearest neighbour: 1.85 miles. Standard deviation: 18.37 miles. 25th percentile:0.07 miles. 75th percentile: 0.77 miles.

[9]We exploit the fact that many schools were built very close to each other in most urban settings in Greece. This is more prevalent in Attica, the region surrounding the city of Athens, the capital of Greece. To give an example, in the cartier of Grava in Athens, there are six high schools next to each other along with several elementary and middle schools that form a humongous school building complex. According to the 2001 census, Attica holds around 36 percent of the total population.

[10]The first cohort in our sample, 2003 (size: 59,102 obs.), is used as a reference group for the 2004 cohort.

[11]In the academic mobility analysis we exclude 60,356 students who did not enrol in college.

[12]These observations come from 157 clusters. Thus 250 clusters remain.

consolidate our sample by dropping observations with missing values.

Table 1 describes our pulled data across cohorts. Fifty seven percent are females. Ninety percent of the students reside in urban areas. More than 90 % of schools are public. Although, mean postcode income among private schools is significantly higher compared to public schools, mean national exam score doesn't seem to differ much. Experimental schools are in more affluent areas in comparison to other public schools as revealed by their higher mean postcode income. The mean national exam score of students attending experimental schools is much higher than the score achieved by students in private or public schools. Each cluster contains on average 4 schools and 929 student observations. Each preferacture contains on average 25 schools, 9 clusters and 6,943 student observations.

3 Empirical Strategy

We exploit inter-preferacture variation in unobservables that determine social norms to explain differences in college enrollment among students with otherwise similar characteristics. We start off my defining one's reference group as his same age school peers. Then, we widen the comparison group to incorporate social interactions in the neighborhood level and social norms in the preferacture level. We investigate the hypothesis that social or collective behavior patterns drive individual preferences because agents derive utility from conformity. Using this rich dataset, we investigate the effect of social interactions on the decision to enrol in college using the following regression:

$$\mathbb{1}(Enrol=1)_{i,s,t} = \alpha + \gamma \sum_{i \neq j} \frac{\mathbb{1}(Enrol=1)_{j,s,t}}{N_{s,t}-1} + \delta \sum_{i \neq j} \frac{X_{jst}}{N-1} + \beta X_{i,s,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \tag{1}$$

We regress the decision to enrol in college of student i from school s and year t on the mean enrollment of his peers in school s in year t and other controls. Our covariates include gender, admission score, dummies for chosen track in the final year of high school, dummies for private and experimental schools, a dummy for urban area, elective specialty in senior year, distance to nearest college campus, year dummies, logarithm of postcode income, and year dummies. $\sum_{i \neq j} \frac{X_{jst}}{N-1}$ is a vector of all others' characteristics in school s excluding student i.

The main coefficient of interest is γ, which captures how the mean enrollment of someone's school peers affects his decision to enrol in college. Initially, we employ ordinary least squares and maximum likelihood as estimation methods. There are at least two sources of potential bias here: (1) endogeneity and (2) the reflection problem (Manski (1993), Manski (2000)).

Firstly, unobserved heterogeneity that drives selection into social groups may bias our estimates. Nevertheless, self selection of students into schools is restricted in our setting because students are assigned to public schools[13] based on geographical criteria and they cannot choose their school peers endogenously, by construction. Therefore, social group membership is as good as random, since it does not depend on observables.

Secondly, endogeneity may result from unobserved common group effects, such as teacher and school quality, that affect every student in a social group and render the identification of social interactions challenging. We contribute to the literature by mitigating the endogeneity challenge that stems from common group shocks. We take advantage of a special institutional setting with rich spatial and over time variation in school characteristics. We use cluster analysis to construct geographical units wider than the school district; namely neighborhoods and preferactures. Those geographical units are big enough to allow for school diversity but also compact enough to capture common behavioral patterns in the area.

Reflection may arise because we cannot distinguish whether someone's action is the cause or the effect of his peers' outcomes. In other words, one's decision is simultaneous with that of his peers. We battle the simultaneity challenge by using time lagged gender composition in the school, neighborhood and preferacture level, as female prevalence contributes to a less disruptive and less violent environment. (Lavy and Schlosser (2011)) Here, we exploit the panel aspect of our data with respect to group characteristics.

[13] 92 % of students in our sample attend public or public experimental schools

Estimating equation (1) using OLS will lead to biased results. In order to address these concerns we propose the proportion of girls in someone's reference group in the previous period as a source of variation for mean enrollment in college. The intuition is that an individual's academic outcome may be related with their gender, but not the gender composition of their environment. This satisfies the exclusion restriction for the validity of our instrument.

Using the proportion of girls in someone's last year's reference group as an IV relies on the assumption that this proportion has no other effect on someone's decision to enrol in college than through its effect on last year's mean college enrollment and thus this year's someone decision to enrol in college. It is important to note that any factor affecting the proportion of girls in all geographic units in the same way, such as a female fertility decline 17 years before, will be captured by year fixed effects and would thus not invalidate the identification strategy.

The first stage regression is as follows:

$$\sum \frac{\mathbb{1}(Enrol = 1)_{g,t}}{N_{g,t} - 1} = \phi + \kappa \sum \frac{\mathbb{1}(Female = 1)_{g,t}}{N_{g,t} - 1} + \sum_{i \neq j} \frac{X_{jst}}{N - 1} + \beta X_{i,g,t} + \kappa T_t + \mu S_s + e_{g,t} \tag{2}$$

$$g \in \{\{school\}, \{neighborhood\}, \{preferacture\}\}$$

where $\sum \frac{\mathbb{1}(Female=1)_{j,t}}{N-1}$ is the proportion of females in geographical unit g and year t. We also include school and year specific controls. The second stage regressions are as follows:

$$\mathbb{1}(Enrol = 1)_{igt} = \alpha + \sum_{i \neq j} \frac{X_{jst}}{N - 1} + \gamma \sum_{i \neq j} \frac{\mathbb{1}(Enrol = 1)_{j,g,t}}{N_{g,t} - 1} + \beta X_{i,g,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \tag{3}$$

$$\mathbb{1}(Enrol = 1)_{igt} = \alpha + \sum_{i \neq j} \frac{X_{jst}}{N - 1} + \gamma \sum_{i \neq j} \frac{\mathbb{1}(Enrol = 1)_{j,g,t-1}}{N_{g,t-1} - 1} + \beta X_{i,g,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \tag{4}$$

where $\mathbb{1}(Enrol = 1)_{igt}$ is the decision of student i in geographical unit g and year t to enrol in college.

Next, we turn to academic mobility. We believe that there might exist social interaction effects in the decision to migrate. We model a person's decision to move to a different preferacture in order to pursue tertiary education, given that they were admitted to some college. This decision is a function of the average decision in one's environment as specified in our regression model:

$$\begin{aligned} \mathbb{1}(Migrate = 1|Enrol = 1)_{i,g,t} = \alpha + \gamma \sum_{i \neq j} \frac{\mathbb{1}(Migrate = 1|Enrol = 1)_{j,g,t}}{N_{g,t} - 1} + \sum_{i \neq j} \frac{X_{jst}}{N - 1} \\ + \beta X_{i,g,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \end{aligned} \tag{5}$$

We use an instrumental variable approach together with school and year fixed effects in order to estimate the effect of social interaction in the decision of students to move to another city to attend college. Again gender composition seems a likely candidate for an instrumental variable. The proportion of females in a geographical unit g may create an environment more condusive to collective migration as exhibited by average patterns of behavior but it has no direct effect on an individual's decision to migrate.

The first stage regression is as follows:

$$\begin{aligned} \sum \frac{\mathbb{1}(Migrate = 1|Enrol = 1)_{g,t}}{N_{g,t} - 1} = \phi + \kappa \sum \frac{\mathbb{1}(Female = 1)_{g,t}}{N_{g,t} - 1} + \beta X_{i,g,t} + \sum_{i \neq j} \frac{X_{jst}}{N - 1} \\ + \kappa T_t + \mu S_s + e_{g,t} \end{aligned} \tag{6}$$

$$g \in \{\{school\}, \{neighborhood\}, \{preferacture\}\}$$

where $\sum \frac{\mathbb{1}(Female=1)_{j,t}}{N-1}$ is the proportion of females in geographical unit g and year t. The second stage regressions are as follows:

$$\begin{aligned} \mathbb{1}(Migrate = 1|Enrol = 1)_{igt} = \alpha + X\beta + \sum_{i \neq j} \frac{X_{jst}}{N - 1} + \gamma \sum_{i \neq j} \frac{\mathbb{1}(Migrate = 1|Enrol = 1)_{j,g,t}}{N_{g,t} - 1} \\ + \beta X_{i,g,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \end{aligned} \tag{7}$$

$$\mathbb{1}(Migrate=1|Enrol=1)_{igt} = \alpha + X\beta + \sum_{i\neq j}\frac{X_{jst}}{N-1} + \gamma\sum_{i\neq j}\frac{\mathbb{1}(Migrate=1|Enrol=1)_{j,g,t-1}}{N_{g,t-1}-1}$$
$$+\beta X_{i,g,t} + \kappa T_t + \mu S_s + \epsilon_{ist} \tag{8}$$

where $\mathbb{1}(Migrate = 1|Enrol = 1)_{igt}$ is the decision of student i in geographical unit g and year t to migrate to a different preferacture in order to study, given she got admitted to some college.

Our main specifications are equations 4 and 8, estimated at the neighborhood and preferacture level. When estimated at the geographical units of neighborhood or preferacture, these specifications address both the endogeneity and simultaneity issues. At the neighborhood level (preferacture level), coefficient γ picks up the effect of mean behavior of one's older peers in his neighborhood (preferacture), on his decision to enrol in college (specification 4) and migrate to a different city (specification 8).

Potential threats to our analysis may include the following: Actual networks may be very different from ecologies in one's vicinity. In addition, social media may allow for peer effects that are independent of proximity and render our analysis of spatial social interactions irrelevant. This is less of a fear though as internet penetration is relatively low in Greece [14]. Parents, relatives and much older individuals in a student's environment may influence his/her academic decisions more than his/her one year older peers in school, neighborhood or preferacture.

4 Results and Discussion

We take advantage of the rich dataset to explore the decision to enrol in college, controlling for a series of student, school and postcode-specific characteristics. Variable enrollment captures the number of available places in tertiary education in the whole country in each student's graduation year.

[14]This is more understandable when one takes into account that Greece has 227 inhabited islands, most of which are quite far from the mainland and have outdated telecommunications infrastructure (Ellinikos Organismos Tourismou (EOT), "Greek islands", April 2012).

We also include a dummy for students who were born in the first quarter of each year, following Angrist and Krueger (1992), who found significant differences in school outcomes for those students. Distance to nearest college proxies accessibility to tertiary education(Turley (2009)).

Table 2 shows linear probability model estimates for three specifications. Specifications (1), (2), (3) model social interactions in the school, neighborhood and preferacture level respectively. All coefficients of interest are positive and statistically significant, revealing strong positive externalities at all three levels. An increase of a hundred percent in other same-age school peer's college enrollment, increases one's probability of college enrollment by 8.3 percent, ceteris paribus. This effect decreases at the neighborhood and preferacture level, as social interactions and social norms become weaker when social groups widen. Table 4 and 3 report results using the probit and logistic model respectively.

A common concern in estimating social interactions or peer effects is the so-called reflection problem (Manski (1993)). In specifications (3) and (4) we mitigate the reflection problem by considering social interactions among students in consecutive school cohorts. Moreover, endogeneity from unobserved group specific shocks is alleviated by exploiting within-neighborhood and within-preferacture variation in school characteristics. Controlling for school-related covariates, we isolate variation attributable only to social interactions. To address further potential unobserved heterogeneity issues, we employ the novel identification strategy of relying on variation in gender composition to explain differences in mean college enrollment in school, neighborhood, and preferacture level. We use an instrumental variables approach to explore social interactions in space and time. Our instrument, gender composition, is hypothesized to affect mean college enrollment since female-heavy school environments are found to be less disruptive and less violent (Lavy and Schlosser (2011)). Nevertheless, gender composition doesn't affect one's outcome of college enrollment, ceteris paribus. This satisfies the exclusion restriction for the validity of our instrument.

We investigate whether conformity works not only in different levels of physical proximity but also among agents with different age. Therefore, we model one's outcome as a function of the behavior pattern exhibited by agents in the previous cohort. Tables 5 and 6 report first and second stage estimates, respectively. Both tables distinguish between social interactions among same-age peers and those among peers in consecutive cohorts. We also report second stage probit model estimates in Table **??**, for robustness.

Our strong first stage estimates allow us to confidently identify the causal path of social interactions. In our setup, the proportion of girls is a strong predictor of mean enrollment. Moreover, the model is just identified as we have one instrumental variable and one endogenous variable. Stock and Yogo (2002) characterize instruments to be weak not only if they lead to biased IV results but also if hypothesis tests of IV parameters suffer from considerable size distortions. They propose values of the Cragg and Donald (1993) minimum eigenvalue statistic for which a Wald test at the 5 percent level will have an actual rejection rate of less than 10 percent. In our case the critical value is 16.38 which is always below the first stage Cragg-Donald statistic we find for the school, neighborhood and preferacture level regressions regarding college enrollment (32.01, 34.09, 30.2 respectively) and academic mobility (582.42, 2,849, 3,594 for the school, neighborhood and preferacture respectively).

Using the proportion of girls in one's environment as an instrument for mean enrollment and academic mobility, we estimate social interaction effects using 2SLS. Our first stage estimates in specification (6) indicate a strong identification of the endogenous variable. Our second stage estimates suggest positive utility spillovers through space and time, with the size of the effect depending on the size of the reference group. Intuitively, social interactions among students of consecutive cohorts are important, as older peers may function as role models. We find positive and significant spillover effects among peers in consecutive cohorts using different definitions of social groups. For instance, a ten percent increase in the proportion of students attending college a in one's neighborhood a year before, increases his probability of enrolling in college by 0.02 percent. Similarly, a ten percent increase in the proportion of students migrating to another city the year before, increases one's probability of migrating to a different city by

0.4 percent. Students who were born in the first quarter of the calendar year are more likely to enrol in college by 0.7 to 0.11 percentage points, depending on specification, all else equal.

Moreover, we explore social interactions in the decision to study in a different city. Educational mobility is suggested in the literature to be greatly affected by social norms, labor market structure and income (Tremblay (2005)). We focus on those students who enrol in college between 2004 and 2009 (sample size: 320,828). Our models include controls for school, year and area specific characteristics. We begin our analysis by estimating specification (5) using standard OLS, probit and logit regression models. Our estimates reveal positive social interactions among same-cohort peers and smaller positive externalities among students in consecutive cohorts.

Our findings suggest significant positive externalities among same-cohort students but significant smaller negative externalities among students in consecutive cohorts. Females are found to be less likely by 1 percentage point to move to a different city to study, all else equal. Educational mobility is also less common among better students by 2-3 percent.

5 Conclusion

This paper investigates social interactions in college enrollment and academic mobility. When social interactions are not taken into account, educational treatments may result in misallocation of resources and may fall short of policy goals. Our results aim to inform public policies that target ability mismatch. We use a novel dataset from Greece that contains the universe of high school graduates from 2004 to 2009. We employ binary choice models and instrumental variable techniques to estimate utility linkages at different space and time levels.

We find that the choices of a person's peers affect his decision to enrol in college endogeneity of social interaction groups. Our evidence supports the hypothesis that individuals derive utility from conformity, with the size of the externality decreasing in space distance. We exploit within-neighborhood, within-preferacture and over time variation in gender composition to explain differences in mean college enrollment, in order to identify the effect of the latter on a person's decision to enrol in college. Mean college enrollment in school, neighborhood and preferacture level predicts one's probability of college enrollment, when we mitigate endogeneity based on area, school and student characteristics. We battle reflection problem issues by using time lagged school, neighborhood and preferacture student gender compostion as an instrument for unobserved heterogeinity in college enrollment, as female prevalence contributes to a less disruptive and less violent school environment.

Our results show that one is more likely to enrol in college and move to another city to pursue post secondary education when many of his peers make the same choices. A ten percent increase in one's neighborhood and preferacture older peers' college enrollment increases his probability of college enrollment by 0.02 and 0.3 percent, respectively. In addition, a ten percent increase in same age peers' college outcome increases one's outcome by 0.4 both in neighborhood and preferacture level.

Despite the vast literature on the topic, two crucial identification challenges remain: common correlated group effects and simultaneity. Our contribution to the literature is threefold. First, using a new and rich dataset of the universe of high school graduates in Greece, we estimate general equilibrium effects of social interactions in college enrollment and academic mobility. Second, we propose a new approach in alleviating challenges in identifying spillover effects by using time lagged group characteristics. Third, we provide evidence on social interactions using a special institutional setting that allows for spatial variation of group characteristics. So far, the existing literature on social interactions has focused almost exclusively on scholastic performance. The only exemptions to out knowledge are Sacerdote (2011) who identify the effect of social interactions on drinking, drug use, and criminal behavior and Giorgi et al. (2007) who finds significant effects on the choice of college major. While our paper has examined several important determinants of college enrollment and the choice of college major, several avenues of future research remain. Understanding the mechanism that underlies social interactions is the next big question in the literature. Future research could push forward the front of understanding the mechanism that underlies social interactions.

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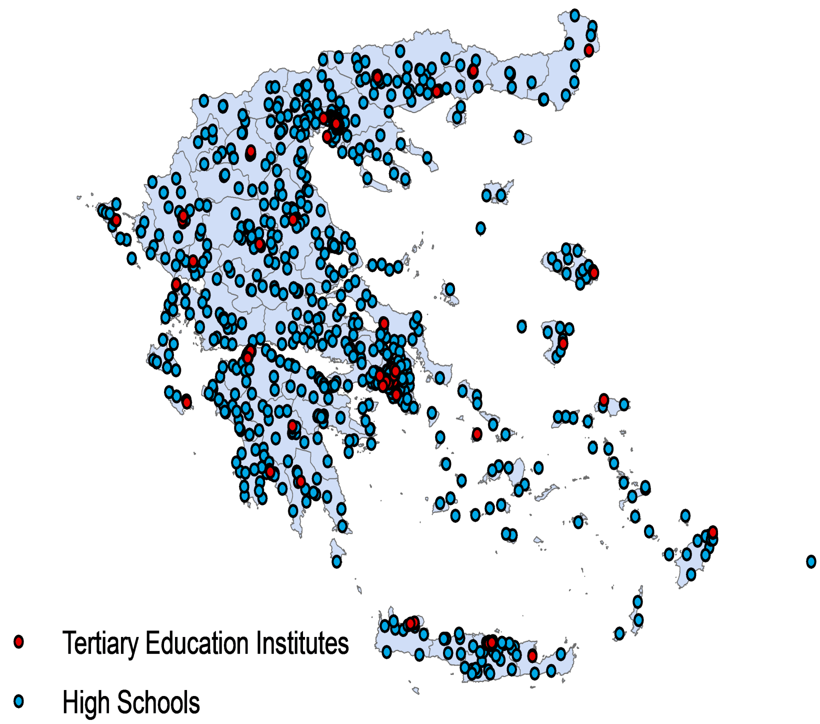

Figure 1: Map of schools

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	N
Panel A: Individual Level					
First quarter of birth	0.16	0.368	0	1	320,828
Female	0.567	0.495	0	1	320,828
National Exams Score	13.16	4.062	0.52	19.95	320,828
If enrolled	0.812	0.391	0	1	320,828
Mobile students	0.748	0.434	0	1	260,472
Specialty in Classics	0.365	0.481	0	1	320,828
Specialty in Natural Science	0.154	0.361	0	1	320,828
Specialty in Technical Studies	0.484	0.5	0	1	320,828
Postcode Income (Euro, 2009)	29,464	8,441	9,573	122,879	320,828
Aggregate Enrollment	60,206	6,372	52,450	68,136	320,828
Panel B: School Level					
Private	0.081	0.266	0	1	1,319
Income if private (Euro, 2009)	30,575	18,378	16,085	122,879	1,319
National score if private	13.69	2.70	4.7	17.34	1,319
Experimental	0.022	0.149	0	1	1,319
Income if experimental (Euro, 2009)	29,754	14,775	17,583	74,798	1,319
National score if experimental	14.40	1.00	12.23	16.17	1,319
Public	0.89	0.31	0	1	1,319
Income if public (Euro, 2009)	19,327	5,565	9,573	74,798	1,319
National score if public	12.26	1.56	2.97	16.36	1,319
Urban	0.898	0.301	0	1	1,319
Distance to nearest college campus(in miles)	10.871	24.083	0.105	1095.452	1,319
No of students in each school	46	34	0.16	179	1,319
Panel C: Neighborhood Level					
No of schools in each neighborhood	4.449	5.014	2	35	250
No of students in each neighborhood	929.291	1,246.298	8	10,559	250
Panel C: Preferacture Level					
No of schools in each preferacture	25.365	47.409	4	332	52
No of neighborhoods	9.058	19.113	1	133	52
No of students in each preferacture	6,943	15,621	502	109,096	52

Note: Data span six cohorts 2004-2009 of 60.119 students on average. Number of schools: 1319. Among those 413 high schools are in Athens or the surrounding suburbs. The national exam score ranges from 0 to 20. Mobile students are those who move to a different city in order to study.

Table 2: Linear Probability Model Estimates

Dependent Variable: College Enrollment						
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Enrolled$_t$	0.083	0.043	0.030			
	(0.011)	(0.013)***	(0.010)***			
% Born in 1st quarter$_t$	0.011	-0.001	0.005			
	(0.009)	(0.021)	(0.041)			
% Enrolled$_{t-1}$				-0.040	-0.018	-0.002
				(0.009)***	(0.010)	(0.010)
% Born in 1st quarter$_{t-1}$				0.017	0.024	0.061
				(0.011)	(0.024)	(0.046)
Born in 1st quarter	0.007	0.007	0.007	0.007	0.007	0.007
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Female	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.001)**	(0.001)***	(0.001)***	(0.001)***	(0.001)**	(0.001)***
Admission Score	0.069	0.069	0.069	0.069	0.069	0.069
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828
R^2	0.50	0.50	0.50	0.50	0.50	0.50

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 3: Logit Model Estimates

	Dependent Variable: College Enrollment					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Enrolled$_t$	0.011	0.043	0.030			
	(0.009)	(0.013)***	(0.010)***			
% Born in 1st quarter$_t$	0.006	-0.001	0.006			
	(0.009)	(0.022)	(0.040)***			
% Enrolled$_{t-1}$				-0.040	-0.002	-0.002
				(0.009)***	(0.010)	(0.010)
% Born in 1st quarter$_{t-1}$				0.017	0.025	-0.631
				(0.011)	(0.024)	(0.460)
Born in 1st quarter	0.007	0.007	0.008	0.008	0.008	0.008
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Female	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.001)**	(0.001)***	(0.001)***	(0.001)***	(0.001)**	(0.001)***
Admission Score	0.069	0.069	0.069	0.069	0.069	0.069
	(0.000)***	(0.001)***	(0.0010)***	(0.001)*	(0.001)*	(0.001)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828
$Pseudo-R^2$	0.50	0.50	.50	0.50	0.50	0.50
$Log-likelihood$	61,117	61,045	60,970	46,782	46,434	67,685

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 4: Probit Model Estimates

	Dependent Variable: College Enrollment					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Enrolled$_t$	1.673	2.097	2.335			
	(0.069)***	(0.176)***	(0.278)***			
% Born in 1st quarter$_t$	2.455	3.620	4.214			
	(0.098)***	(0.196)***	(0.320)***			
% Enrolled$_{t-1}$				0.603	0.691	0.428
				(0.061)***	(0.084)***	(0.080)***
% Born in 1st quarter$_{t-1}$				-0.300	-0.915	-1.050
				(0.129)**	(0.193)***	(0.244)***
Born in 1st quarter	0.081	0.066	0.066	0.1172	0.119	0.118
	(0.012)***	(0.0131)***	(0.013)***	(0.012)***	(0.011)***	(0.012)***
Female	-0.142	-0.146	-0.147	-0.135	-0.138	-0.134
	(0.009)***	(0.010)***	(0.009)***	(0.009)***	(0.010)***	(0.009)***
Admission Score	0.508	0.523	0.5268	0.4965 0.497	0.4978	
	(0.003)***	(0.0043)***	(0.004)***	(0.0032)***	(0.003)***	(0.0032)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828
$Pseudo-R^2$	0.52	0.52	0.52	0.52	0.52	0.52
$Log-likelihood$	78,539	76,587	74,285	67,132	67, 392	69,308

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 5: First stage estimates

Dependent variable:	Mean College Enrollment$_t$					
	school	neighborhood	preferacture	school	neighbourhood	preferacture
Proportion of girls$_t$	0.006	0.024	0.042			
	(0.001)***	(0.003)***	(0.003)***			
% Born in 1st quarter$_t$	0.063	-0.809	-0.894			
	(0.003)**	(0.002)***	(0.001)***			
Proportion of girls$_{t-1}$				0.003	0.005	0.074
				(0.001)***	(0.003)***	(0.005)***
% Born in 1st quarter$_{t-1}$				0.147	-0.592	-0.860
				(0.003)***	(0.003)***	(0.003)***
Female	-0.001	0.001	0.001	-0.001	-0.003	0.001
	(0.0003)***	(0.0002)***	(0.0001)***	(0.0004)***	(0.0003)***	(0.0002)***
Admission Score	0.006	0.006	0.006	0.006	0.006	0.006
	(0.0001)***	(0.00003)***	(0.00002)***	(0.0001)***	(0.00003)***	(0.00003)***
Born in first quarter	0.030	0.010	0.007	0.027	0.008	0.008
	(0.001)***	(0.0001)***	(0.0004)***	(0.001)***	(0.0007)***	(0.001)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828
R^2	0.32	0.33	0.33	0.31	0.32	0.32
F-statistic 1st stage	11,418	23,394	58,848	6,564	24,067	10,349

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 6: IV Second Stage Estimates

	Dependent Variable: College Enrollment					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Enrolled$_t$	2.619	-0.402	-0.100			
	(0.700)***	(0.269)	(0.212)			
% Born in 1st quarter$_t$	0.281	0.077	0.123			
	(0.068)***	(0.030)**	(0.043)***			
% Enrolled$_{t-1}$				8.045	7.256	0.061
				(3.944)***	(2.341)***	(0.016)***
% Born in 1st quarter$_{t-1}$				0.231	0.324	0.061
				(0.034)***	(0.196)***	(0.016)***
Admission Score	0.054	0.069	0.069	0.029	0.056	0.069
	(0.004)***	(0.001)***	(0.001)***	(0.020)	(0.010)***	(0.000)***
Female	-0.001	-0.002	-0.002	-0.001	0.002	-0.002
	(0.001)	(0.001)**	(0.001)*	(0.003)	(0.004)	(0.001)**
Born in first quarter	0.008	0.007	0.007	0.008	0.011	0.007
	(0.002)***	(0.001)***	(0.001)***	(0.004)*	(0.004)**	(0.001)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 7: IV Probit Estimates for the Decision to enrol

	Dependent Variable: College Enrollment					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Enrolled$_t$	-1.204	2.086	2.727			
	(1.598)	(0.009)***	(0.040)***			
% Born in 1st quarter$_t$	1.286	3.582	0.187			
	(0.704)*	(0.059)***	(0.346)			
% Enrolled$_{t-1}$				-3.834	6.389	3.368
				(0.494)***	(0.339)***	(0.315)**
% Born in 1st quarter$_{t-1}$				-1.158	-2.889	0.061
				(0.095)	(0.599)***	(0.016)***
Admission Score	0.050	0.060	0.064	0.067	0.078	0.447
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.002)***
Female	0.049	0.039	0.037	0.070	0.055	-0.119
	(0.004)***	(0.006)***	(0.004)***	(0.005)***	(0.005)***	(0.008)***
Born in 1st quarter	0.101	0.098	0.095	0.007	0.069	0.063
	(0.006)***	(0.006)***	(0.006)***	(0.008)	(0.006)***	(0.001)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	320,828	320,828	320,828	320,828	320,828	320,828
$Log-likelihood$	179,313	227,316	219.714	179,313	234,885	243,427

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 8: LPM Migration Decision

	Dependent Variable: Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Migrated$_t$	-0.026	0.084	0.018			
	(0.025)	(0.025)***	(0.008)**			
% Born in 1st quarter$_t$	-0.000	-0.002	0.047			
	(0.016)	(0.024)	(0.019)**			
% Migrated$_{t-1}$				-0.090	-0.027	0.016
				(0.016)***	(0.022)	(0.004)***
% Born in 1st quarter$_{t-1}$				0.004	0.029	-0.010
				(0.015)	(0.024)	(0.018)
Born in 1st quarter	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Admission Score	-0.023	-0.023	-0.023	-0.023	-0.023	-0.023
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
R^2	0.30	0.30	0.30	0.30	0.30	0.30
N	260,472	260,472	260,472	260,472	260,472	260,472

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. A intercept is also included.

Table 9: Logit Migration Decision

	Dependent Variable: Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Migrated$_t$	5.793	5.380	6.293			
	(0.092)***	(0.161)***	(0.197)***			
% Born in 1st quarter$_t$	-0.003	0.389	1.429			
	(0.109)	(0.376)	(2.110)			
% Migrated$_{t-1}$				5.743	5.703	6.575
				(0.098)***	(0.148)***	(0.129)***
% Born in 1st quarter$_{t-1}$				-0.047	0.300	-1.433
				(0.181)	(0.339)	(0.471)***
Born in 1st quarter	-0.005	-0.005	-0.006	-0.006	-0.008	-0.005
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
Female	-0.111	-0.107	-0.096	-0.105	-0.110	-0.101
	(0.016)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***
Admission Score	-0.173	-0.173	-0.184	-0.175	-0.175	-0.185
	(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.010)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	260,472	260,472	260,472	260,472	260,472	260,472
$Pseudo - R^2$	0.28	0.25	0.28	0.28	0.26	0.29
$Log - likelihood$	-105,407	-109,558 4	-104,803	-105,638	-107,949	-104,187

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 10: Probit Migration Decision

	Dependent Variable: Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Migrated$_t$	3.339	3.093	3.431			
	(0.046)***	(0.087)***	(0.107)***			
% Born in 1st quarter$_t$	0.005	0.214	1.253			
	(0.059)	(0.223)	(1.153)			
% Migrated$_{t-1}$				3.304	3.268	3.607
				(0.049)***	(0.079)***	(0.063)***
% Born in 1st quarter$_{t-1}$				-0.019	0.131	-0.762
				(0.098)	(0.201)	(0.235)***
Born in 1st quarter	-0.003	-0.003	-0.003	-0.003	-0.004	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Female	-0.053	-0.052	-0.044	-0.050	-0.054	-0.047
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
Admission Score	-0.087	-0.089	-0.092	-0.089	-0.089	-0.093
	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	260,472	260,472	260,472	260,472	260,472	260,472
$Pseudo - R^2$	0.28	0.25	0.28	0.27	0.26	0.28
$Log - likelihood$	-105,674	-109,975	-105,768	-105,952	-108,389	-105,095

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 11: First stage estimates for migration decision

	Dependent Variable: Mean Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
Proportion of girls$_t$	0.040	0.289	0.258			
	(0.004)***	(0.005)***	(0.007)***			
% Born in 1st quarter$_t$	-0.043	-0.113	0.931			
	(0.004)***	(0.009)***	(0.013)***			
Proportion of girls$_{t-1}$				0.061	0.337	0.403
				(0.004)***	(0.006)***	(0.009)***
% Born in 1st quarter$_{t-1}$				-0.006	0.054	1.735
				(0.006)	(0.009)***	(0.012)***
Admission Score	0.0002	0.001	0.002	0.0006	0.001	0.002
	(0.0001)*	(0.0001)***	(0.0002)***	(0.0003)***	(0.0001)***	(0.0002)***
Female	0.002	0.003	-0.001	0.001	0.002	-0.001
	(0.0008)**	(0.007)***	(0.001)	(0.0008)	(0.0007)***	(0.001)
Born in 1t quarter	-0.0006	-0.0007	-0.0002	-0.006	-0.0008	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	260,472	260,472	260,472	260,472	260,472	260,472
R^2	0.37	0.39	0.26	0.37	0.39	0.30
$F - statistic 1st stage$	8,893	9,708	5,386	8,963	9,818	6,688

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 12: IV Estimates for Migration Decision

	Dependent Variable: Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Migrated$_t$	1.088	0.905	2.227			
	(0.204)***	(0.039)***	(0.064)***			
% Born in 1st quarter$_t$	0.003	0.027	-1.966			
	(0.016)	(0.021)	(0.068)***			
% Migrated$_{t-1}$				1.196	0.953	1.711
				(0.139)***	(0.037)***	(0.042)***
% Born in 1st quarter$_{t-1}$				-0.004	0.029	-2.891
				(0.013)	(0.019)	(0.077)***
noalign Admission Score	-0.022	-0.023	-0.026	-0.023	-0.023	-0.025
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Female	-0.014	-0.014	-0.009	-0.014	-0.014	-0.010
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Born in 1st quarter	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Speciality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	260,472	260,472	260,472	260,472	260,472	260,472

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.

Table 13: IV Probit Estimates for Migration Decision

	Dependent Variable: Migration Decision					
	(1)	(2)	(3)	(4)	(5)	6)
Sample:	School	Neighborhood	Preferacture	School	Neighborhood	Preferacture
% Migrated$_t$	4.398	3.042	1.679			
	(0.723)***	(0.159)***	(0.245)***			
% Early enrolled$_t$	0.052	0.206	2.788			
	(0.071)	(0.091)**	(0.204)***			
% Migrated$_{t-1}$				4.611	3.235	3.144
				(0.449)***	(0.156)***	(0.216)***
% Early enrolled$_{t-1}$				-0.011	0.133	0.086
				(0.056)	(0.082)	(0.395)
National Exams Score	-0.086	-0.089	-0.083	-0.086	-0.089	-0.092
	(0.003)***	(0.001)***	(0.002)***	(0.002)***	(0.001)***	(0.001)***
Female	-0.055	-0.052	-0.043	-0.051	-0.053	-0.047
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.007)***
Born in first quarter	-0.002	-0.003	-0.003	-0.002	-0.004	-0.003
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Specialty FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
N	260,472	260,472	260,472	260,472	260,472	260,472
$Log - likelihood$	-37,767	-24,313	-93,489	-39,279	-23,352	-98,738

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the school level. An intercept is also included.