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CLASSROOM COMPETITION, STUDENT EFFORT, AND PEER EFFECTS

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ABSTRACT

This paper studies how rewards based on class rank affect student effort and performance using a game-theoretic classroom competition model and data from the resettlement of Southeast Asian refugees in the US. The paper finds that variation in the presence of strong or weak students changes the incentives and test scores of incumbent students depending on their ability group in accord with the competition model, with increases in the number of strong students lowering effort among strong and weak incumbents but raising the test scores of weak incumbents. The results suggest that competition induced by rank-based rewards within homogeneous ability groups lowers overall effort levels, while the presence of strong students directly augments the performance, but not the effort levels, of weak students despite the competition. The paper also rules out a number of alternative explanations for these school composition effects, including disruptions, teacher-initiated changes in curriculum in response to changing class composition, selective incumbent-student school exit, and endogenous responses of refugee location choices to school performance.

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1. Introduction

It is common practice in educational institutions around the world to use a student's rank among her peers to provide rewards. These may include exam and course grades, academic honors, admission to selective schools, and/or financial support. Indeed, class rank from grade school through college, for given individual performance measures, has been shown to have significant long-term effects (Denning *et al*., forthcoming; Murphy and Weinhardt, forthcoming; Elsner, 2021). The classroom is thus a place of competition, a setting in which payoffs depend not only on one's individual performance but that of one's peers.

In this paper we examine theoretically and empirically the consequences of competition in the classroom for student effort and performance. We use game-theoretic tournament models to derive testable implications for how changes in the ability composition of students in the classroom affect a student's exam outcomes and effort. The theoretical part of our work relates to the literature on contests with asymmetric competitors, most closely with Stein (2002) and Cornes and Hartley (2005). Tournament models generally indicate that competition, which arises when rewards depend on one's performance relative to others, reduces individual performance. Stein derived the Nash equilibrium for linear input functions and showed that the equilibrium effort of all the contestants, except possibly the strongest one, weakly decreases when one of the competitors becomes stronger.

We provide for the first time comparative statics results for the general input functions considered in Cornes and Hartley (2005) but we also consider a model with more sophisticated agents who anticipate their peers' responses. In this model students take into account that their alike peers will always match their own effort, reducing even more the marginal return to effort relative to that in Nash-equilibrium games in which agents assume that their peer's effort remains fixed. The key point is that in a context in which rewards are based on relative performance increasing effort has little return if one knows that that peer students will also match that effort increase. In this non-myopic model, changes in class composition have differential effects on students depending on their own capability as found in most of the newer empirical studies of classroom peer effects but unlike in the predictions of the Nash-equilibrium model.

Empirical applications of competitive game-theoretic models are scarce. Brown (2011) used the results of Stein from the Nash model to inform her empirical work, based on golf tournament scores, showing that the presence of a superstar depresses the effort levels of the competitors. Similarly, Banerjee (2021) showed that the presence of more competitors reduces the accuracy of forecasts by stockbrokers.[1] We find exploiting the large resettlements of Southeast Asian refugees across the United States in the late 1970's and 1980's, that, consistent with the non-myopic classroom competition model, when there is an increase in the number of more able students effort levels and test scores of all incumbent students decline; when weaker students are added, however, the effort levels of the more able incumbent students increase and those of the weaker students decrease.

The main data set we use to test the competition models for the classroom, the restricted-use version of the National Education Longitudinal Survey (NELS:88), a nationally representative survey of US 8th-grade students in 1988 followed through high school, suggests that grade competition was salient in US schools in the late 1980's and early 1990's. School administrators were asked to comment on the statement that students in the 8th grade faced grade

[1] Applications of the contest theory to an educational setting are few. Xu and Pak (2021) analyzed the comparative statics of a contest model with symmetric input functions and resource constraints in a highly competitive environment where an interior equilibrium does not exist, and the equilibrium effort is always increasing in the resource. In contrast, the competitive environment in our setting is not as severe and allows the equilibrium to be interior.

competition, and 50.4% responded that this was accurate or very much accurate. This competition, moreover, was not just a consequence of the presence of awards such as admission to "gifted" classes being based on grades (77.8% of students in the 8th grade attended schools using this criterion). Grade competition was also evidently actively encouraged. In the second and third rounds (10th grade, 12th grade) of the panel, teachers were asked whether students were "encouraged to compete for grades." 87.6% (83.8%) of 10th (12th) grade students were in schools in which the sampled teachers said the statement was at least "somewhat accurate."[2]

Beyond high school, many universities use class rank as admission and/or student aid criteria and thus potentially induce competition among high schoolers. We examined the admission criteria from the web sites of the state university systems in all 50 US states for the academic year 2023-24. Nineteen systems explicitly used class rank for either admission or financial aid, covering more than 50% of all US high-school students.[4]

Given the ubiquity of classroom competition at every school level, it is difficult to rigorously test whether and how competition affects student performance by comparing competitive and non-competitive classrooms or schools. Thus, we assess the consequences of classroom competition from competition-model comparative statics that exogenously alter the ability composition of students. Our empirical work testing these models thus fits into the mostly empirical literature on peer effects in schools, which examines how exogenous changes in the

[2]The response scale for the 10th-grade question was from 1 to 5, with 1= "not accurate at all," 3="somewhat accurate," 4="accurate," and 5="very accurate." The 12th-grade scale was in three categories: 1="not accurate," 2= "somewhat accurate," and 3="very accurate."

[4]This statistic may underestimate the use of class rank for admission by the systems. For example, Indiana University, which does not include class rank among its listed admission criteria, reports the fraction of the entering class in the top 10% of their high-school class, suggesting that their admission record contains class rank and is valued by the school.

composition of students affect student outcomes. A key takeaway from this literature (Hoxby, 2000; Sacerdote, 2014) is that peer effects of are multidimensional; the effects on student performance varies both by the ability of the treated and the treatment groups. Our comparative statics from the non-myopic model have this property.

Another common empirical finding of the school peer effects literature (e.g., Hoxby, 2000) is that the presence of strong students is associated with the improved performance of weak incumbents. We thus incorporate into the non-myopic competition model strong students directly assisting weak students (a direct peer effect). We find, consistent with the competition model in which stronger students also help directly weaker students, that adding strong students to the classroom lowers the effort of strong and weak incumbents, lowers the test scores of strong incumbents, but raises the test scores of weak incumbents. We also show that the findings we obtain on test score and effort level effects cannot be explained by initial refugee location assignments being affected by native-born student performance, teacher adjustments in curriculum, selective classroom disruptions, parent shifts in homework assistance, labor-market effects, or by strong-student school exit.

In the large literature on classroom peer effects, which uses a variety of empirical methods to establish the casual effects of variation in student composition on student outcomes, there are two important lacunae. First, the competitive aspects of classrooms or grades resulting from ranking or other aspects of classroom rewards are ignored in interpreting results or deriving hypotheses.[2] Relatedly, one of the principal identification strategies of empirical studies of peer

[2] An exception is Hoxby and Weingarth (2005). They examine, among a large number of other models, what they call the “invidious comparison model,” in which the presence of strong and weak students affects the performance of their peers by affecting their rank, with strong students depressing peers’ performance and weak students increasing performance. Their empirical findings and our game-theoretic models and our empirical findings do not conform to these predictions.

effects, random or quasi-random assignment of students, which have high internal validity, provide results that have reduced external validity and in particular cannot be compared to ours. For example, in Booij *et al*. (2017) in which the ability composition of students was experimentally varied within tutorial groups for one year, the estimates may not capture competition effects that occur at the school or class level unless the students are competing or are made to compete against one another within the groups. Studies that use temporary changes in classroom compositions, such as evacuees from hurricane disasters (Imberman *et al*., 2014) or from temporary surges in asylees (Figlio and Özek, (2019), when many of the treatment groups quickly return to their origin school or country or move to other locations, may also not capture competition effects if incumbent students do not view the temporary classmates as competitors compared with their incumbent peers. In our empirical work we use a nationally-representative sample of incumbent native-born students as the treated group and the assignments of Southeast Asian refugees to locations throughout the United States by resettlement agencies as our treatment. These refugees are likely to permanently settle because they receive location-specific support, although they are free to move domestically after their initial resettlement assignment.[3]

Results based on one or two school systems may also not be representative of all school systems with respect to grade competitiveness, and thus may not be revealing of competition effects generally. Indeed, Imberman *et al*. (2014) use data from Louisiana and Houston schools, which according to the NELS:88 data for eight-graders are substantially less competitive than the average across all 8th grades in the United States. Less than 14.6% of 8th-graders are in public schools in which school heads in Harris county, the main county of Houston, find the statement

[3] Our identification strategy is closest to that of Hoxby and Weingarth (2005), who exploit the permanent reassignment of students across schools in Wake county, North Carolina to identify how changes in classroom composition affect the performance of incumbent students.

that students face grade competition accurate; the corresponding figure for Louisiana public schools is 40%. That figure is 35.6% for the public Florida schools that were studied by Figlio and Özek (2019). These are all below the national average of 48.3%.[4] We find that our results supporting the competition model are significantly stronger in schools where grade competitiveness is indicated to be more salient.

A second shortcoming of the peer effect classroom literature is that the mechanisms and behavior by which changes in the composition of students affect performance outcomes are generally absent.[5] The main dependent variables in the studies are test score outcomes rather than behavior, in particular, student effort. Clearly, student test scores reflect individual effort by students, perhaps accompanied by direct assistance from peers and parents, and a key question is how a student's effort is affected by her peers. Our comparative statics are in terms of student effort and in our empirical tests we examine both standardized test score outcomes – performance - and measures of student effort – homework time and class attendance. Indeed, we show the contrast between effort and test score effects helps identify one aspect of direct peer influence in a competitive classroom setting. And we provide evidence on the direct effects of both measures of effort on test scores, which are substantial.

Almost all the literature on classroom peer effects is atheoretical. A notable exception is Duflo *et al*. (2011) who construct a formal model of teacher effort and curriculum choice with a direct peer effect. However, student effort is ignored. Our approach is similar in spirit to Bursztyn *et al*. (2019). They model and derive tests from the model for how classroom culture,

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[4]The principal of only one of the three public schools that are represented in the NELS:88 in Wake county, North Carolina, from where Hoxby and Weingarth (2005) estimated classroom peer effects, reports on grade competitiveness so we do not have a good measure of the competitive environment in that study.

[5] Important exceptions are Lavy *et al*. (2012), who examine the role of classroom disruptions in affecting student performance, and Imberman *et al*. (2012), who look at absenteeism and disciplinary infractions. We also look at disruption and infractions to assess if they can explain our empirical findings on peer effects.

differing by whether being smart or being social are valued by classroom peers, affects student choices, leading in some cases to purposeful lower achievement when actions are visible. In our case, the classroom culture consists of students vying for rewards based on relative performance. And although, as noted, student competition is pervasive, we find suggestive evidence that our results are stronger in schools characterized by school heads as being highly grade-competitive.

Our empirical tests are based on three data sets. The restricted-use NELS:88, newly-released annual data from the Office of Refugee Resettlement (ORR) (Dreher *et al*., 2020) covering the period 1975 to 2008 on the initial assigned county locations of all refugees resettled in the United States, and Census data. Key advantages of the restricted-use NELS:88 data, besides the provision of extensive information on student and school characteristics, are that there is information on both student test scores and student effort, as well as the behavior of parents and teachers. There is also extensive information on the characteristics and behavior of the parents of the students. The availability of information on parent characteristics enables us to stratify students by family background (parent schooling and income) rather than on student performance. This avoids the reflection problem (Manski, 1993).[6]

The competition models provide predictions as to how changes in the number of strong and weak students affects the effort and academic outcomes of the two groups. Our empirical strategy is to obtain the empirical counterparts to the 2x2 matrix of comparative-static results for each outcome measure by estimating how variation in the numbers of Southeast Asian refugee students, stratified into strong and weak groups based on parental schooling, affects the test

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[6] In many prior studies (e.g., Booij et al., 2017; Imberman et al., 2014; Huang and Zu, 2020) student "ability" is measured by pre-treatment test scores or grades, which also avoids the reflection problem. However, as the basic point of the student peer literature is that a student's performance depends on classmate composition, individual past performance outcomes do not identify a student's own ability and potential – test scores and grades are in part social outcomes. Thus, stratifications of students based on these measures may mischaracterize the individual ability distribution of students in treatment and treated groups.

scores and effort levels of incumbent native-born students, also divided into two groups based on parental schooling.[7] We focus on Southeast Asian (SEA) refugees - those from Cambodia, Laos and Vietnam - because of the large size of this relatively culturally homogenous group who escaped from their home countries for similar reasons. SEA refugees made up 79% of all US refugees from 1975, the initial year of re-settlement, through1988, the first round of the NELS:88, totaling 875,095 persons.

There are three main threats to establishing causation that we directly address. First, the contemporaneous locations of immigrants or refugees are choices, and may be influenced by school student performance. We use the ORR data on the initial county assignment of refugees. Refugees, unlike immigrants or asylees, do not choose their initial locations.[8] Of course, those location assignments, made by a set of local agencies working with the US State Department, are not randomized. We use a variety of tests and estimation procedures to deal with this problem, including testing directly whether the initial refugee location assignments are responsive to the native-born test scores of schools and by using panel-data techniques across counties within labor markets. We show that the resettlement agencies' initial refugee location assignments are, net of observable school and housing market characteristics that the agencies do take into account, *and within labor markets* are, unlike the contemporaneous locations of the refugees (who are free to move once resettled), orthogonal to native-born test scores. We then use the cumulative predicted location of refugee students based on initial location assignments as instruments for the number and type of SEA refugee students in the schools and counties for

[7] We use semi-nonparametric econometric methods to provide support for the four-way classification and to show our results are robust to treating ability groups as varying continuously by parent background.
[8] Figlio and U. Özek (2019) and Figlio *et al*. (2021) estimate the effects of Haitian asylees and all immigrants, respectively, on native-born academic performance. These groups choose their initial and subsequent locations.

cross-sectional identification, and initial assignment locations and shift-share instruments based on first year (1975) assignments and national changes in refugees for the panel-data estimates.[9]

The second threat to identification is that the influx of refugees into local labor markets may affect the local returns to schooling and thus influence incentives for schooling, as shown by McHenry (2015) and Hunt (2016). We eliminate this possibility by including commuting zone fixed effects in all specifications, so that we are gaining identification from variation in the number and type of refugee students within labor markets across counties and from changes in the number of predicted refugee students by county net of all changes in labor markets.

A third threat to identification is that the impact of variation in the numbers of refugee students reflects student flight, particularly of strong native-born students (Betts and Fairlie, 2003; Li, 2009; Figlio *et al*., 2021). We show that between tenth and 12th grade less than 3.4% of strong native-born students change schools. Our IV estimates, based on the NELS:88 second and third-round student panel of how changes in the composition of refugee students affect native-born test scores, are thus immune to selective exit as well as any permanent difference in school characteristics. The results from the panel estimates are similar to those from the cross-sectional estimates and are in conformity with the non-myopic competitive model in which students take into account the behavior of their peers. All cross-section and panel estimates pass the standard under-, weak- and over-identification tests.

Identification is not just the establishment of causality but of the identification of the theory-based relationships or mechanisms that give rise to the causal effects. We show that the set of three sets of 2x2 estimates we get for both test scores and the two effort measures (12 coefficient signs) conform to the comparative statics results from the non-myopic model of

[9] The serial correlation in the initial locations of refugees, based on the algorithms of the resettlement agencies, is less strong than that of immigrants (Bartel, 1979), who choose their initial locations.

competition with peer effects. And we also show that the results contradict a model of teacher behavior in which teachers facing a mixed composition of students choose a curriculum to maximize average test scores and show empirically that variation in the number and type of refugee students does not affect teacher behavior and does not differentially affect personal disruptions to strong and weak native-born students.

We also find, however, direct evidence on peer student assistance consistent with the peer effect incorporated in our competition model and the rise in the test scores of weak native-born students in response to an increase in strong refugee students, despite no increase in own effort. Supporting this result, we find that increases in the number of strong refugee students increases homework assistance from fellow students for weak native-born students but decreases help for native-born strong students.[10]

Finally, to assess the importance of effort in scholastic achievement and its role in explaining classroom of school peer effects, we estimate a test score production function inclusive of both peer, disruption and effort effects. We find that student homework time and class skipping, our two main measures of effort, net of disruption and peer effects, have strong effects on test scores for both strong and weak students. We also find, however, that for the strong incumbent students, net of homework time and class skipping, the additions of strong and weak refugee students have no remaining effects on test scores – all of the significant peer effects we find on test scores for this group are due to peer effects on effort. There is thus no remaining black box for peer effects on strong students. But we also find that net of own effort, there remains a direct positive effect of strong student peers on weak students, consistent with

[10] We also find that parents of weak native-born students reduce the amount of time they assist with homework when there is an increase in the number of strong SEA refugee students. The increase in test scores by the weak native-born thus appears to be solely a direct peer effect.

our evidence on peer effects on weak-student student test scores and effort arising from the increased presence of strong students as well as direct evidence on peer homework assistance.

2. Classroom Competition models

Here, we present the theoretical model that frames our empirical work. We will test for the existences and consequences of classroom competition by deriving comparative statics from models that assume students are competing. The model set-up is based on Tullock (1980)'s model of imperfectly discriminating competition, in which a population of N heterogenous agents, $i = 1, \ldots, N$, compete with each other for a prize by exerting effort, $e_i \geq 0$. An individual's (expected) utility is

$$u_i(e_1, \ldots, e_N) = v_i P_i(e_1, \ldots, e_N) - c_i(e_i),$$

where $v_i > 0$ is the prize, $P_i(e_1, \ldots, e_N)$ is the probability of obtaining the prize, and the twice-differentiable function $c_i(e_i)$, with $c_i(0) = 0$ and $c_i' > 0$, is the cost of effort. In the contest literature, $P_i(e_1, \ldots, e_N)$ is often called the contest success function and takes the following general form:

$$P_i(e_1, \ldots, e_N) = \frac{f_i(e_i)}{f_1(e_1) + \cdots + f_N(e_N)}, \quad \text{if } \sum_k f_k\,(e_k) > 0 \text{ and } \frac{1}{N} \text{ otherwise,}$$

where f_i, with $f(0) = 0$ and $f_i' > 0$, is a twice-differentiable function that transforms effort into the input to the competition and can be interpreted as individual achievement.[11] Any prize that is

[11] In the traditional interpretation of Tullock's model, contestants compete for a single prize (that is, there is only one winner), but this need not be. Our interpretation of the model is that of students striving to achieve an educational success in a competitive environment. Such an interpretation only requires that the probability of achieving success is increasing in the student's own effort and decreasing in others' and does not require that there is exactly one successful student in the competition.

based on an individual's rank in a group, for example, creates a tournament among individuals, and thus effort will be affected by the efforts of other members of the group.

To keep the model simple and directly related to the empirical work we carry out to test the model, we assume that the classroom population is divided into two groups, with N_1 high-achieving students in group 1 and N_2 low-achieving students in group 2. We say that a student is stronger than another student if she values success more, has a higher productivity of effort, or has a lower marginal cost of effort. More precisely, we have the following definition.

Definition 1. Student i is said to be *stronger* than student j if $v_i \geq v_j$, $f_i' \geq f_j'$, and $c_i' \leq c_j'$, with at least one of the inequalities holding strictly.

Let $i, j \in \{1,2\}$, where $i \neq j$, index the two groups. All members of the same group have identical input and cost functions. We say that group i is stronger than group j if students in group i are stronger than students in group j. Theorem A.2 in Appendix A shows that in equilibrium a stronger student exerts a greater effort than a weaker student as expected. That is, the stronger group consists of higher individual achievers who have a greater chance of winning the prize. We also assume that the members of the same group exert the same effort level in "equilibrium."

There are multiple senses in which an equilibrium can be defined, and we consider two. The first one arises if we assume that individuals take their competitors' efforts as fixed when they are setting their effort level. That is, the individuals do not think that their competitors will react to their effort level. The equilibrium that arises from this assumption is the classic Nash equilibrium. The second one arises when individuals have enough foresight to think that their effort level will have an influence on their competitors. In particular, we assume that individuals think that their effort levels will be matched by the individuals in their own group (but not by the members of the other group). The equilibrium that arises from such an assumption is similar to the "collusive" equilibrium in the IO literature. Since we are not proposing that the competitors are consciously colluding, we assume that students know how much effort their ability peer group is exerting and match based on this foresight. We call this equilibrium the "non-myopic equilibrium."

While the Nash-equilibrium competition model has been used in an empirical application (Brown, 2011), we believe it is a less-realistic depiction of competition. Moreover, as we show in Appendix A, it delivers the prediction that everyone's equilibrium effort decreases no matter which group's size increases.[12] That is, the different strengths of the two treatment or treated groups are irrelevant to the sign of the response functions. It does not matter if the classroom adds weak students or strong students, the effects on the effort levels of the weak and strong incumbents is always negative. This contradicts most of the literature on peer effects, which shows that the effects of changing the composition of the classroom are heterogeneous.

We now develop the model in which students, rather than act on the belief that their competitors' effort will stay fixed in response to a change in classroom composition as in the Nash model, take into account that their effort levels will be matched by competitors in their own group. We first set out the model with no other peer effects other than those which arise from the competition. We then add a direct peer effect whereby strong students directly augment the test scores of weak students, given own effort.

[12] The comparative statics in this paper are obtained in marginal terms, whereas group sizes change by a whole number. The comparative static for a whole number change can be found by integrating the marginal effect, which would not change the sign of the effect because the marginal effect has a constant sign.

a. *Non-myopic equilibrium*. We begin with the non-Nash assumption that individuals foresee that their effort choice will be matched by their competitors within their group. That is, if an individual adjusts her effort from e_i to e', every other e_k, where k and i are in the same group, will change to e' as well. This means that the marginal returns from increasing effort will be even lower than in the Nash-equilibrium model.

In this non-myopic model the contest success function is

$$P_i(e_i, e_j, N_i, N_j) = \frac{f_i(e_i)}{N_i f_i(e_i) + N_j f_j(e_j)},$$

where e_i and e_j, $i \neq j$, are the effort levels of the representative members of the two groups. The first and the second order conditions for the optimal effort problems are:

$$\text{FOC:} \quad \frac{\partial u_i(e_i, e_j, N_i, N_j)}{\partial e_i} = v_i \frac{\partial P_i(e_i, e_j, N_i, N_j)}{\partial e_i} - c_i'(e_i) \text{ is } \begin{cases} \leq 0 & \\ = 0 & \text{if } e_i > 0. \end{cases}$$

$$\text{SOC:} \quad \frac{\partial^2 u_i(e_i, e_j, N_i, N_j)}{\partial e_i^2} = v_i \frac{\partial^2 P_i(e_i, e_j, N_i, N_j)}{\partial e_i^2} - c_i''(e_i) \text{ is } \begin{cases} \leq 0 & \text{(necessary)} \\ < 0 & \text{(sufficient).} \end{cases}$$

The above expressions are similar to those in the Nash equilibrium setting. The crucial difference is in the derivatives of the contest success function:

$$\frac{\partial P_i(e_i, e_j, N_i, N_j)}{\partial e_i} = \frac{f_i'(e_i)\left(N_i f_i(e_i) + N_j f_j(e_j)\right) - f_i(e_i) N_i f_i'(e_i)}{\left(N_i f_i(e_i) + N_j f_j(e_j)\right)^2} = \frac{f_i'(e_i) N_j f_j(e_j)}{\left(N_i f_i(e_i) + N_j f_j(e_j)\right)^2}. \tag{1}$$

$$\frac{\partial^2 P_i(e_i, e_j, N_i, N_j)}{\partial e_i^2} = \frac{f_i''(e_i) N_j f_j(e_j)}{\left(N_i f_i(e_i) + N_j f_j(e_j)\right)^2} - \frac{f_i'(e_i) N_j f_j(e_j) 2 N_i f_i'(e_i)}{\left(N_i f_i(e_i) + N_j f_j(e_j)\right)^3}. \tag{2}$$

Letting e_i^* and e_j^* be the equilibrium effort levels, let

$$\tilde{P}_i\left(e_i^*, e_j^*, N_i, N_j\right) = v_i \frac{\partial P_i\left(e_i, e_j, N_i, N_j\right)}{\partial e_i}\Big|_{\left(e_i^*, e_j^*\right)} = \frac{v_i f_i'(e_i^*) N_j f_j\left(e_j^*\right)}{\left(N_i f_i(e_i^*) + N_j f_j\left(e_j^*\right)\right)^2}, \tag{3}$$

denote the marginal benefit of effort at the equilibrium. They key difference from the Nash-equilibrium model is that the marginal benefit of effort, given by (3) is lower than in the Nash equilibrium model because individuals now anticipate that increases in their effort will be matched by their competitors. Lemma B.1 in Appendix B shows that the second-order condition is satisfied when $\frac{f_i''}{f_i'} \leq \frac{c_i''}{c_i'}$, which we assume. Thus, the equilibrium condition at an interior equilibrium (e_1^*, e_2^*) is:

$$F(e_1^*, e_2^*, N_1, N_2) = \begin{bmatrix} \tilde{P}_1(e_1^*, e_2^*, N_1, N_2) - c_1'(e_1^*) \\ \tilde{P}_2(e_1^*, e_2^*, N_1, N_2) - c_2'(e_2^*) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \tag{4}$$

We derive comparative statics results by implicitly differentiating the equilibrium condition (4). The results differ from those obtained in the Nash equilibrium model, where increasing the size of any group reduces the equilibrium effort of all groups. The cross effect in the non-myopic equilibrium is not always negative and depends on the relative strength of the two groups. In particular, we have the following result.

Theorem 2. *Suppose group 1 is stronger than group 2. Then we have*

$$\frac{\partial e_1^*}{\partial N_1} < 0, \quad \frac{\partial e_2^*}{\partial N_1} < 0, \quad \frac{\partial e_1^*}{\partial N_2} > 0, \quad \text{and} \quad \frac{\partial e_2^*}{\partial N_2} < 0.$$

The key difference from the Nash-equilibrium model is that entry by a stronger competitor discourages everyone, but the entrance of a weaker competitor induces the stronger incumbents to increase their effort while discouraging weaker ones (see Appendix B for details). In the Nash equilibrium model, the marginal benefit of effort always falls when a new student enters the competition. Therefore, students in that model will reduce their effort to re-equalize the marginal benefit and the marginal cost whenever a new student enters. However, in the non-myopic model, the marginal benefit may rise or fall when there is a new entry, and, as a result, student efforts may increase or decrease.

To understand the difference in results across the two models, recall that in the Nash model, students assume that no one will match their effort when they are calculating their marginal benefit of effort, $\tilde{P}_i^{\mathrm{NE}}$. In the simple case where all the students are identical and exert the same effort in the equilibrium, the marginal benefit of effort is roughly inversely proportional to the number of competitors.[13] Thus, the marginal benefit falls whenever a new student joins the

[13] As seen in Appendixes A and B, the marginal benefits in the Nash equilibrium model and the non-myopic equilibrium model are, respectively,

$$\tilde{P}_i^{\mathrm{NE}} = \frac{v_i f'_i(e_i)\left((N_i-1)f_i(e_i)+N_j f_j(e_j)\right)}{\left(N_i f_i(e_i)+N_j f_j(e_j)\right)^2} \quad \text{and} \quad \tilde{P}_i^{\mathrm{NM}} = \frac{v_i f'_i(e_i) N_j f_j(e_j)}{\left(N_i f_i(e_i)+N_j f_j(e_j)\right)^2}.$$

To see the difference between the two marginal benefits more clearly, remove the common term $v_i f'_i(e_i)$ from the two marginal benefits and approximate $N_i - 1$ by N_i. Then we have

$$\begin{aligned}
\tilde{P}_i^{\mathrm{NE}} &\approx \frac{N_i f_i(e_i)+N_j f_j(e_j)}{\left(N_i f_i(e_i)+N_j f_j(e_j)\right)^2} = \frac{1}{N_i f_i(e_i)+N_j f_j(e_j)} \\
\tilde{P}_i^{\mathrm{NM}} &\approx \frac{N_j f_j(e_j)}{\left(N_i f_i(e_i)+N_j f_j(e_j)\right)^2} = \left(1-\frac{N_i f_i(e_i)}{N_i f_i(e_i)+N_j f_j(e_j)}\right)\left(\frac{1}{N_i f_i(e_i)+N_j f_j(e_j)}\right) \approx \left(1-\frac{N_i f_i(e_i)}{N_i f_i(e_i)+N_j f_j(e_j)}\right)\times \tilde{P}_i^{\mathrm{NE}}.
\end{aligned}$$

In the special case where everyone is identical, we have $f_i(e_i) = f_j(e_j)$. Thus,

$$\tilde{P}_i^{\mathrm{NM}} \approx \left(1-\frac{N_i}{N_i+N_j}\right)\times \tilde{P}_i^{\mathrm{NE}}.$$

competition. In contrast, when a student in the non-myopic model is calculating her marginal benefit of effort, she knows that some of her effort will be wasted because it will be matched by some of her competitors. Thus, she discounts the marginal benefit, and hence withholds her effort, relative to the Nash model. For example, if no one will match her effort, then no effort is wasted, and the marginal benefit is the same as the Nash model marginal benefit. If everyone will match her effort, then all the effort is wasted, and the marginal benefit is zero. More generally, if x fraction of students will match her effort, then x fraction is wasted, and the marginal benefit is $\tilde{P}_i^{\mathrm{NM}} = (1-x)\tilde{P}_i^{\mathrm{NE}}$ (see footnote 13). Thus, when a new student who will not match her effort enters the competition, her marginal benefit may rise or fall because there are two opposing effects: $\tilde{P}_i^{\mathrm{NE}}$ falls but $1-x$ rises.

To summarize in terms of effort, compared to the Nash model, a student in the non-myopic model withholds some of her effort, and the withholding rate depends on the fraction of effort that will be wasted by matching. When a non-matching student enters the competition, the base amount of effort she wants to exert decreases, but the withholding rate also decreases. Thus, she may end up decreasing or increasing her effort depending on which of the two effects dominate. Because our model features two heterogeneous groups, it is really the proportion of the group effort, not simply the proportion of students, that matters. However, the basic intuition remains the same.

Finally, to clarify that the competition effect from an increase in the number of strong or weak students is not mechanically due to a class size effect on the probability of obtaining a prize we consider how the equilibrium effort in the non-myopic model changes when the members of the weaker group are swapped for those of the stronger group. That is, the stronger group's size (N_1) is increased, and the weaker group's size (N_2) is decreased while the population size is kept constant at N. To reduce confusion, we use $\hat{e}_i$ to denote the equilibrium effort when swapping is being considered: $\hat{e}_i(N_1) = e_i^*(N_1, N - N_1)$. Thus,

$$\frac{d\hat{e}_i}{dN_1} = \frac{\partial e_i^*}{\partial N_1} + \frac{\partial e_i^*}{\partial N_2}\left(\frac{dN_2}{dN_1}\right) = \frac{\partial e_i^*}{\partial N_1} - \frac{\partial e_i^*}{\partial N_2}.$$

In the non-myopic model strong students work harder when faced with increased competition from the weak students ($\frac{\partial e_1^*}{\partial N_2} > 0$) but are discouraged by the increased competition from the fellow strong students ($\frac{\partial e_1^*}{\partial N_1} < 0$). Thus, when the swap occurs, both effects work in the same direction and unambiguously reduce the strong students' effort:

$$\frac{d\hat{e}_1}{dN_1} = \frac{\partial e_1^*}{\partial N_1} - \frac{\partial e_1^*}{\partial N_2} = (-)\ -\ (+) < 0.$$

In contrast, weak students are discouraged by an increased competition from anyone, making the effect of a swap ambiguous:

$$\text{sign}\left(\frac{d\hat{e}_2}{dN_1}\right) = \frac{\partial e_2^*}{\partial N_1} - \frac{\partial e_2^*}{\partial N_2} = (-)\ -\ (-) = \text{ambiguous}.$$

That is, an increased competition from having more strong students makes the weak students lower their effort while reduced competition from having fewer fellow weak students encourages them to raise their effort. The direction of the combined effect depends on which of the two effects dominate. We derive a theorem, reported in Appendix B, that provides sufficient conditions for weak-student effort to decline.

b. *Non-myopic equilibrium with a direct peer effect*. So far, we have assumed that an individual's achievement depends only on her own effort level. It is only because of the contest that her choice of effort depends on the composition of her peers. Identification of the existence of a contest comes from the four predictions of the model for effort levels and individual achievement levels by strong and weak competitors in response to the changing composition of peers. We now ascertain whether and how the predictions of the model are altered when we allow individual achievement to be a function of both own effort and peer composition and whether, therefore, we can, in the context of the competition model, identify a direct peer effect in a competitive setting. In particular, we allow the presence of stronger students to directly increase the individual achievement of the weaker students, given their own effort, while maintaining that the individual achievements of the stronger group depend only on their own effort.[14] We call this the direct peer effect.

Formally, f_2 is now a function of both e_2 and N_1, with $\frac{\partial f_2(e_2,N_1)}{\partial N_1} > 0$. Thus, the contest success functions are now:

$$P_1(e_1,e_2,N_1,N_2) = \frac{f_1(e_1)}{N_1 f_1(e_1) + N_2 f_2(e_2,N_1)} \quad \text{and} \quad P_2(e_1,e_2,N_1,N_2) = \frac{f_2(e_2,N_1)}{N_1 f_1(e_1) + N_2 f_2(e_2,N_1)}.$$

These changes do not affect the first-order and the second-order conditions for effort optimization or the equilibrium condition, apart from the inclusion of N_1 as an argument in f_2. Thus, letting $'$ (prime) and $''$ (double prime) continue to denote differentiation with respect to effort, the marginal benefits at the equilibrium remain the same:

[14] A direct positive peer effect is built into the model of Duflo *et al*. (2011) and many empirical studies find that an increase in the number of strong students increase the performance of incumbents. In our empirical application, the new entrants in the competition are refugee students from non-English speaking countries, who presumably have some language difficulties, and the peer effect we have in mind is peer homework assistance. Thus, it seems reasonable to assume that strong refugee students may not be able to help the strong native students but nevertheless be able to help the weaker natives. This result for strong student direct peer effects on strong students may thus have less external validity.

$$\tilde{P}_1(e_1^*, e_2^*, N_1, N_2) = v_1 \frac{\partial P_1(e_1, e_2, N_1, N_2)}{\partial e_1}|_{(e_1^*, e_2^*)} = \frac{v_1 f_1'(e_1^*) N_2 f_2(e_2^*, N_1)}{\left(N_1 f_1(e_1^*) + N_2 f_2(e_2^*, N_1)\right)^2}$$

and $$\tilde{P}_2(e_1^*, e_2^*, N_1, N_2) = v_2 \frac{\partial P_2(e_1, e_2, N_1, N_2)}{\partial e_2}|_{(e_i^*, e_j^*)} = \frac{v_2 f_2'(e_2^*, N_1) N_1 f_1(e_1^*)}{\left(N_1 f_1(e_1^*) + N_2 f_2(e_2^*, N_1)\right)^2}.$$

Since the second-order condition is satisfied under our assumption, the equilibrium condition at an interior equilibrium (e_1^*, e_2^*), where $e_i^* > 0$, is:

$$F(e_1^*, e_2^*, N_1, N_2) = \begin{bmatrix} \tilde{P}_1(e_1^*, e_2^*, N_1, N_2) - c_1'(e_1^*) \\ \tilde{P}_2(e_1^*, e_2^*, N_1, N_2) - c_2'(e_2^*) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \tag{5}$$

As before, comparative statics are analyzed by implicitly differentiating the equilibrium condition (5). However, the derivations are more complex because N_1 now affects the equilibrium by directly affecting the individual achievement of the weaker group as well. We obtain

Theorem 3. *Suppose* $\frac{f_i''(e_i^*)}{f_i'(e_i^*)} < \frac{c_i''(e_i^*)}{c_i'(e_i^*)}$ *for all i. Suppose further that* $\frac{\partial f_2(e_2^*, N_1)}{\partial N_1} > 0$, $\frac{\partial f_2'(e_2^*, N_1)}{\partial N_1} < 0$, *and* $N_1 f_1(e_1^*) \in \left(N_2 f_2(e_2^*, N_1),\ N_2 f_2(e_2^*, N_1) + \frac{2 f_1(e_1^*) f_2(e_2^*, N_1)}{\frac{\partial f_2(e_2^*, N_1)}{\partial N_1}}\right)$. *Then*

$$\frac{\partial e_1^*}{\partial N_1} < 0, \quad \frac{\partial e_1^*}{\partial N_2} > 0, \quad \frac{\partial e_2^*}{\partial N_1} < 0, \quad \text{and} \quad \frac{\partial e_2^*}{\partial N_2} < 0.$$

In addition, the sign of $\frac{d f_2(e_2^*, N_1)}{d N_1}$ *is ambiguous.*

Theorem 3 lays out the conditions that are needed so that the equilibrium effort levels respond in the same way to changes in the composition of peers as in the non-myopic contest model yet leave the individual achievement of the weaker group free to increase when stronger competitors enter. The first new condition is that the cross partial derivative of f_2 is negative, meaning that the peer effect is stronger the lower the individual effort of the weaker group. The second is that $\frac{\partial f_2(e_2^*, N_1)}{\partial N_1}$, the peer effect, is sufficiently small.[15] Provided that these two conditions are satisfied, whether weaker-group individual achievement increases or decreases depends on the additional details of $f_2(e_2, N_1)$.

Thus, the direct peer effect between weak and strong students is identified in the context of peer competition when an increase in the number of strong students (i) lowers the effort of the weaker group but their individual achievement levels weakly increase and (ii) stronger-group effort levels and achievement both decline due to competition.

3. Optimal Curriculum Model

In the previous models we ignored teacher behavior. Can teacher behavior yield similar results to those obtained from the peer competition models? In Appendix C, we develop a simple model of teacher behavior in which teachers seek to maximize the average test score of a class consisting of strong and weak students. They do this by selecting the fraction of the curriculum that is best-suited to the strong students, thereby making the strong students more productive and the weak students less productive. We show that the comparative statics of this model of teacher behavior confronting a heterogeneous class are the opposite from those delivered by the competitive equilibrium models. In this model strong students benefit from adding more strong students, without any direct peer effects, while adding more weak students benefits weak students and hurts strong students. We derive similar comparative statistics for student effort arising from student composition effects on teacher curriculum choice, showing that these

[15] The requirement is that $N_1 f_1(e_1^*)$ is less than the upper bound stated in the theorem, and the upper bound is large if the peer effect is small.

too do not conform to the competition model predictions even when there are direct peer effects of strong students on weak students as incorporated in the competition models.

4. Data sets

a. *Office of Refugee Resettlement data*. To test the competition models we estimate the impact of variation across counties and over time in the number of Southeast Asian (SEA) refugee students (Cambodian, Laotian, Vietnamese), divided into two groups by parental schooling, on native-born student performance and effort, also divided into two groups based on family background characteristics. Our main data source for the SEA refugees is the newly-released micro data set describing all refugees who re-settled in the United States from 1975 through 2008 from the US Office of Refugee Resettlement (Dreher, *et al.* 2020). The data provide information on country of origin, year of resettlement, the county of initial location, age, gender and schooling attainment for the refugees.

We focus on SEA refugees as our main treatment group for three reasons. First, the magnitudes of SEA refugee flows into the United States since 1975 up through the periods covered by our main data set describing students are very large: 875,095 SEA refugees re-settled in the United States from 1975, the initial year of re-settlement, through 1988, the first round of the National Education Longitudinal Survey:88 (NELS:88) that we use to examine native-born student performance. SEA refugees during this 14-year period made up 79% of all refugees. Figure 1 plots the cumulative sum of all refugees, SEA refugees, and the combined sum of SEA and former-USSR refugees, the second largest group of refugees over the period, who re-settled in the United States from 1975 through 2008 based on the ORR data. Figure 2, which plots refugee re-settlements by year, indicates that there were substantial fluctuations in refugee inflows over the period. The figure also shows a defect in the data base - there is a gap in the plots in 1990 because only the first three months of re-settlements are recorded in that year. This gap will partly constrain our empirical strategy, as described below.

The second reason we focus on SEA refugees for our treatment variables is that the *initial* locations of refugees are not the choices of the refugees themselves. Unlike the locations of all non-refugee immigrants at a point in time, which reflect both initial location choices and subsequent internal migration, refugee initial locations are assigned by the US Department of State in co-operation with a set of non-profit resettlement agencies working with approximately 200 affiliates located across the United States. At any point in time, the locations of incumbent refugee populations, of course, reflect internal migration choices, which are unconstrained for refugees and all other immigrants. Thus, we use the projected sums of the initial county locations of the refugees from the ORR data as instruments for the current county-level refugee populations at the county level, stratified by age, gender, and schooling. Importantly, there is considerable spatial variation in refugee initial locations, in part due to the spatial spread of agency affiliates. Figure 3 displays the map issued by the US State Department Bureau of Population, Refugees, and Migration (USBPRM) showing the locations of the program affiliates in 2011, and Figure 4 maps the initial locations of the SEA refugees in the period 1987-1990, which we will focus on in our empirical tests.

The resettlement agencies do not, of course, randomize initial locations. The stated criteria on the web site of the USBPRM for selecting refugee locations are: “availability of affordable and safe housing, school capacity, medical care, and employment opportunities.” We take into account these non-random determinants of initial refugee resettlements in three ways. First, all estimates are based on spatial and time-series variation of refugee initial locations *within* labor markets (county variation within commuting zones). Our estimates are thus net of all variations in labor-market characteristics, including variations in the number of refugee workers in local labor markets that can influence local perceptions of schooling returns (McHenry, 2015) and may have influenced initial refugee re-settlement. Second, we use information on school and housing characteristics reflecting agency criteria. Third, we test extensively for the specific endogeneity that is a threat to our identification strategy - that agency-based initial refugee locations are based on local native-student school performance and behavior. In addition to carrying out a battery of standard instrumental-variables diagnostic tests, we use the ORR annual county-level data to assess directly whether, within labor markets, initial SEA refugee placements, in contrast to total refugee populations, are significantly associated with prior native-student test outcomes. Finally, we use the NELS:88 panel data, which require much weaker identification assumptions, to estimate the effects of refugee students on native-born test scores, with both student and school characteristics absorbed in fixed effects.

There is an additional reason for using projections based only on initial refugee placements as instruments for current refugee populations besides the exogeneity of initial refugee placements to the outcome variables of interest: the counts of refugees by location at any point in time are measured with error if they come from samples or even if they come from Census counts. The ORR data set is based on administrative records and thus does not have sampling error or reflect census miscounts. Of course, the county-level counts of current population refugees based on initial-location projections are measured with error because the actual current refugee populations in counties also reflect their internal migration, so they cannot themselves be used as treatment variables.[16]

[16]The validity of this instrument also relies on the assumption that prior refugee students who subsequently left the location, net of the effects of current refugee students, have an insignificant effect on current native-born student behavior and performance. In our panel analysis we test directly for lagged cumulated effects.

b. *Restricted-use National Education Longitudinal Study of 1988 (NELS:88) data*. The NELS:88 is a nationally-representative panel survey of students starting with a sample of over 25,000 8^{th}-graders in 1988 who were additionally surveyed in 1990 and 1992. In addition to information on students, teachers, parents, schools, and neighborhoods, the restricted-use version of these data identifies the locations of the schools and residences of the students at the county level. This permits matching with the ORR initial refugee settlement data at the county level and the identification of commuting-zone based labor markets. Of the 850 counties represented in the NELS:88 baseline, 79.3% of them had at least one initially-assigned Southeast Asian refugee of 8^{th}-grade age in 1988. Given the spatial and inter-temporal variation in SEA refugees, the NELS:88 data set contains substantial cross-sectional variation in the treatment variables at the student, school, and county level as well as over time for the same student.

A key feature of the NELS:88 is that, unlike data based solely on school records, both test scores (achievement) and measures of effort (homework time, classes skipped) are provided. In addition, there is information elicited from parents on their inputs to student achievement and their characteristics. The availability of the latter permits us to stratify the students based on pre-school human capital using parental schooling attainment and income rather than on endogenous equilibrium student performance measures. As long as there are peer effects, pre-treatment academic outcomes such as test scores, grade repetitions or subject grades will reflect prior classroom influences and endogenous effort and thus may lead to the misclassification of which students are strong and weak, which are purely individual characteristics.

The data also identify the nativity of the students and parents, and specifically identify SEA-born students. We created four groups of students in accord with the model. The treated strong students were those who were native-born and for whom both parents had schooling attainment above high school and whose household income was in the top half of all incomes.[17] The same parental criteria were applied to identify the strong SEA foreign-born students, the strong treatment group. For the weak students in both the treated and treatment groups, we selected those students for whom neither parent had schooling above high school and household income was less than the top quartile. Our results are not sensitive to the classification criteria. We will show below that our results are similar when we use a continuous measure of parental schooling to differentiate students.

Although we classified students based only on family background variables, these sharply differentiate the academic performance of the strong and weak treated and treatment students. Figure 5 displays the 8th grade combined math and reading achievement test z-scores for the four groups. As can be seen, the strong group average z-score was around half a standard deviation above the mean, while those for the weak students were below average, particularly among the native-born. The differences between the strong and weak student scores within each nativity groups is statistically significant at at least the 0.01 level.

Despite the lower performance of the weak groups, a large percentage of them - 89% for native-born and 70% for foreign-born SEA students - report in the 8th grade that they expect to go to college. This is lower than the percentages for the strong students (92-94%), as shown in Figure 6. College admission criteria, which typically include class rank as criteria for admission or financial aid, thus potentially induce competitive peer-group behavior for both strong and weak groups, although more significantly for the strong than the weak among the native-born.

[17] [3]In the labor literature, skilled workers are generally classified as those with schooling above high school (Card, 1985).

We will first exploit using our ORR instrumental variables the cross-sectional variation in the number of weak and strong SEA refugee students at the school level from the first round of the NELS:88, which is the only round that contains information both on test score outcomes and student effort. There are three weaknesses of the baseline cross-sectional data. First, we do not have information prior to 8th grade on a student's prior exposure to the refugee groups.[18] Second, the effects we identify may reflect selective school flight particularly by strong native-born students (Betts and Fairlie, 2003; Cascio and Lewis, 2012; Fairlie and Resch, 2002; Li, 2009; Figlio *et al*., 2021). Third, although we have a large number of school characteristics, it is possible that refugee effects may reflect omitted school characteristics. We will use the NELS:88 panel data on the students to assess the robustness of our results to these concerns, assessing the impact of time-series variation in SEA refugee students at the county level for the same student attending the same school net of the student's prior test score outcome.

An important constraint on the use of the panel data is censoring due to dropouts. While drop-out rates in the 8th-grade are negligible for both the weak and strong students, by the third round, 16.2% of the weak native-born students had dropped out of school, compared to only a negligible 2.5% of the strong students. Lacking any credible strategy for correcting for the selectivity associated with school-leaving, we will only use the student panel data to estimate test score impacts from variation in the number of strong and weak refugee students, net of student and school fixed effects, on the strong native-born students, as detailed below.

c. *5% public-use samples from the decennial Censuses 1970-2010.* We use the decennial Census sample data to create the county-level SEA refugee treatment groups for the NELS:88

[18] Figlio et al. (2021), who have complete histories of the exposure of native-born student incumbents to foreign-born classmates, find that their results for the effects of the number of foreign-born classmates on native-born student test scores and disruptive behaviors are not sensitive to variation in the degree to which it is assumed past exposure matters.

panel data. The Census samples provide information on the country of birth for everyone included in the samples, along with the arrival dates of the foreign born. The personal and household level identifiers in the data also permit stratification of student-age persons by the schooling of their parents thus permitting stratifying students by parental human capital.

There are two limitations of the Census data for our analyses. First, the public-use samples only provide county location information for counties with a population size of 250,000 or more. Although the Census-identified counties make up only 34.6% of the counties represented in the NELS:88 baseline, because the vast majority of refugees appear to be assigned initially to large counties 80% of all of the 8th-grade school-age Southeast Asian refugees in 1988 that were assigned initial locations from 1975 to 1988 are represented in the Census counties that match with the NELS:88 counties. And, all of the matched Census-identified counties have at least one 8th-grade SEA refugee student in 1988 based on the initial assignments of the refugees.

The second limitation of the Census Public-Use data is that only current county locations are provided, and not the counties at entry. This means that for appropriately matching the SEA refugee students from the Census to the NELS:88 1988 and 1992 rounds for the panel analysis we have to use information on retrospective arrival dates (e.g., counting only the foreign-born SEA arriving before 1989 for matching with the 1988 NELS:88 round) and have to assume the current location is where the SEA foreign-born resided at entry. This assumption is less of a problem for identifying the locations of SEA refugee arrivals for the first (1988) and second (1990) rounds NELS:88 rounds, obtained from the 1990 Census, and is worst for the NELS:88 1992 panel round, which requires us to use the 2000 Census county locations and arrivals before 1992. Of course, we will use our SEA refugee instruments based on the initial counties and arrival dates from the ORR data, which will correct for these measurement errors in the Census variables as well as for the endogenous location choices of the foreign-born.[19]

5. Empirical Method: NELS:88 Cross-Section

We first test the competition models using the initial round of the NELS:88 data, which is the only round to provide both test scores and measures of effort, specifically weekly homework hours and number of classes skipped during the week. We estimate the following equation for native-born 8th-grade students *i* in school *j* in group *g* (strong and weak) located in county *k* and commuting zone *n* at time *t*:

$$E_{ijgknt} = \beta_{1g} R^{T}_{jknt} + \beta_{2g} R^{H}_{jknt} + \mathbb{Z}_{ijgknt}\gamma_{1g} + \mathbb{Q}\gamma_{2g} + c_{kn} + \mu_{ijgkn} + e_{ijgknt}\,, \tag{6}$$

where E = standardized combined reading and math test score, homework hours, or classes skipped; R^T and R^H = the total number of SEA *foreign-born* students in the school and the number whose mother had at least a high-school education, respectively; $\mathbb{Z}, \mathbb{Q}$ = vectors of student and school characteristics, respectively; μ_{ijgk} = student fixed effect; and c_{kn} = commuting zone fixed effects.

In this equation β_{1g} = the effect on group-*g* native-born student effort and achievement from an increase in the total number of weak SEA students, β_{2g} = the effect on group-*g* student effort and achievement from exchanging one weak SEA student for a strong SEA student. This is the effect of homogenizing a class. And $\beta_{1g} + \beta_{2g}$ = the effect on native-born group-*g* student

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[195]It appears that the reported retrospective arrival dates reported by the SEA foreign-born in the Censuses area reasonably accurate, at least at the national level. That is, they match up well at the national level with the ORR SEA refugee data and with administrative visa data issued to SEA immigrants based on US State Department data, as shown in Figure A1 in the Appendix, which tracks year-to-year changes in ORR SEA refugee arrivals, SEA visas issued, and arrival flows calculated from the Census retrospective reports for the years 1996-2007.

effort and achievement from an increase in the total number of strong SEA students. Table 1 provides the sign predictions for the β coefficients for each of the dependent variables that correspond to the comparative statics of the non-myopic competition and the optimal curriculum models that also incorporate the possibility that strong students assist weak students.[20]

The student control variables in (6) include age, gender, race=Black, and parental income. School control variables include grade size, the number of teachers, whether the school is public or private, and whether admission to the school is selective. To control for labor-market characteristics, which the resettlement agencies explicitly take into account in refugee location assignments, we include a full set of commuting-zone fixed effects. Thus, only variation within commuting zones across counties contributes to identification of the β's. By including commuting-zone fixed effects we also eliminate the possibility that variations in the populations of refugee students affect the performance of native-born students by altering the local returns to schooling via labor-market general-equilibrium effects. We also control for the fraction of the county population that is urban and median housing value.

The principal threat to identification is that the presence of SEA foreign-born is related to the unobservable characteristics of the students that affect their school performance and behavior μ_{ijgk} – that immigrants migrate to or away from schools based on student achievements and effort. We thus estimate equation (6) using IV, where the first-stage equation is:

$$R^{l}_{jknt} = \delta^{l}_{1g} r^{T}_{kn} + \delta^{l}_{2g} r^{H}_{kn} + \delta^{l}_{3g} r^{10}_{kn} + \mathbb{Z}_{ijgknt}\delta_{4g} + \mathbb{Q}_{jknt}\delta_{5g} + c_{kn} + \mu_{ijgkn} + \zeta_{ijgknt}, \qquad (7)$$

[20] This specification assumes that there are no effects on current test scores or effort from the history of exposure to strong and weak SEA foreign-born students. This assumption is consistent with the findings in Figlio and Özek (2019). We also test below for lagged effects using the panel data from the NELS:88 and find that the contemporaneous results are robust to the existence of lagged effects as fully embodied in the lagged test score.

where l =T or H; $r_{kn}^{T}, r_{kn}^{H}, r_{kn}^{10}$ = the *projected* total number of student-age (8th-grade) SEA *refugees* in the county, the number of SEA refugee maternal-age women with at least a high-school degree, and the number of SEA refugees who arrived at least 10 years ago, respectively, based only on the initial assigned locations identified in the ORR data. Because the instruments vary at the county level, we cluster standard errors at that level.

Across counties in the 1988 round, the correlation between the projected number of 8th-grade SEA refugees based on initial locations from the ORR data and the number of 8th-grade SEA foreign-born in the NELS:88 data is 0.85. Figure 7 provides a scatterplot of the two variables. The instruments thus appear to have power. By using only the initial assigned locations of refugee students and mothers as the basis for our instruments we eliminate biases from the endogenous internal migration of the foreign-born. Our key identification assumption is thus that within labor markets the initial county locations of refugees assigned by the resettlement agencies is not a function of native-born academic performance. In addition to diagnostic tests of weak, under- and over-identification, we test directly this assumption below. We also assess below whether our results are due to the selective "flight' of native-born students or are biased by the omission of school characteristics using the panel data on student test scores.

6. Estimates from NELS:88 8th-Graders

*a. Test scores***.** The first column of Table 2 reports OLS estimates of the determinants of the standardized tests scores of all of the 8th-grade native born students and including only the total number of SEA foreign-born students in the specification from the NELS:88 baseline data. As expected, native-born students from higher-income families and in private schools perform better on the exams. However, there is no statistically significant relationship between native-born student test scores and the total number of SEA foreign-born students. In the second column we report the IV estimates, using the same unstratified specification. The results are similar – there is no statistically significant relationship between the total number of SEA foreign-born students and the test score performance of native-born students, with the diagnostic statistics indicating that result is not the consequence of weak instruments.

In Table 3 we report estimates that stratify both the native-born and the foreign-born SEA students, in accord with the model. The estimates that do not control for commuting-zone fixed effects, in columns one and three, appear to have a weak instrument problem, but the estimates with the commuting-zone fixed effects included, in columns two and four, deliver diagnostic tests that reject under identification, weak instruments, and the exogeneity of the numbers of foreign-born SEA students.

The estimates of the β coefficients in columns two and four are consistent with the non-myopic competition model of student behavior but are inconsistent with the optimal curriculum model based on teacher behavior. The estimates indicate that an increase in the number of strong SEA students or swapping a strong for a weak SEA student reduces the test scores of the strong native-born students while an increase in the number of weak SEA students (total SEA students, controlling for the number of strong SEA students) increases the test scores of the strong native-born and lowers the test scores of the weak native-born students. These results are the opposite of what the model of optimal curriculum adjustment predicts and are consistent with the absence of teacher responses reported in the NELS:88.[21]

[21] Although there is no information on curriculum types within subject matter, the first round of the NELS:88 contains reports by teachers on how many hours per day they teach to separate groups within the classroom, which would facilitate customizing curriculum by student strength. We estimated the effects of changes in the number of weak and strong refugee students on the number of hours the teacher spent teaching separate groups using the same estimation procedure and specification as in Table 2. The results, reported in Appendix Table A1, indicate that

All of the β estimates when commuting zone fixed effects are included in the specification are statistically significant at conventional levels of significance. The point estimates from the second column, fifth row indicate that a one standard-deviation increase in the number of high-background SEA foreign-born students decreases the test scores of the strong native-born students by 0.14 standard deviations. Increasing the number of strong SEA refugee students while decreasing the number of weak SEA students by the same amount (swapping), from the second column second row β, decreases native-born test scores by 0.33 standard deviations. An increase in the number of weak SEA refugee students, from the coefficient in the first row of the second column, however, increases the strong native-born student test scores by 0.81 standard deviations and reduces the test scores of the weak native-born students by 0.27 standard deviations.

The estimates also indicate that increasing the number of strong SEA students by one standard deviation increases the test scores of the weak native-born students by an insignificant 0.05 standard deviations. However, consistent with the extended non-myopic competition model that incorporates a direct positive spillover effect from the strong on the weak, swapping strong SEA students for weak SEA refugee students by the same amounts increases the test score of the weak native-born students by 0.10 standard deviations. We will show below that this increase incumbent weak-student test score performance is not due to the increased effort by the native-born and thus appears to be a direct peer effect.

To assess whether the differences in signs across the native-born student groups are sensitive to the cutoffs we used for our grouping criteria based on parental schooling, we re-

changes in the composition of the refugee students do not lead to any teacher adjustments in classroom stratification. Booij *et al*. (2017) also find that teachers do not adjust their teaching in response to variation in the ability composition of students in mixed classrooms.

estimated equation (6) allowing all of the coefficients to vary continuously with an index of the human capital of the student's parents, namely the sum of the two parents' schooling attainments using the locally-weighted functional coefficient model (LWFCM) of Chaglin and Ning (2001).[22] The plots of the test score β coefficients and their 95-percent confidence intervals for the strong and weak SEA foreign-born students from the estimates of this more general specification are plotted in Figures 8 and 9, respectively. Each of the coefficient plots are single-crossing and thus correspond both to the four-way grouping and the signs of the estimates reported in Table 3. In particular, the native-born student test score coefficients for the strong SEA students are positive when the students parental schooling levels are low and turn negative at parental schooling totals over 20. Similarly, the effects of an increase in weak SEA students on native-born student test scores are negative for all lower-schooled parents and are positive for all higher schooled parents.

b. *Is it competition*? We will examine the behavioral mechanisms for the test score results derived from the competition models, and alternative explanations for these results, below. We can, however, also assess if the set of native-born student test score relationships we found, which are consistent with the non-myopic competition model, are more pronounced where there is direct evidence that grade competition is a salient feature of the students' environment. To do this we make use of both the school administrators' characterizations of grade competition in the student's school and the information on state university admission criteria.

We first define a school as having a competitive environment if the school administrator answers "accurate" or "very much accurate" to the statement that "students face competition for

[22] If a parent or guardian was absent (single mothers, single fathers), we set the schooling of that parent to zero.

grades." By this criterion 58.4% (45.6%) of strong (weak) native-born students are in such schools.[23] We then define a competitive environment using a broader definition in which we consider the student's environment to be competitive if either the student's school is characterized as competitive, as defined above, or if the state university system in the state in which the student resides uses class rank as an admission criterion. By this definition, 80.1% of strong and 73.2% of weak native-born students are in an academic competition. Thus, we modify equation (6) to add interactions between the refugee variables and an indicator variable for the local presence of grade competition alternatively for the two definitions of student competition.[24]

The first two columns of Table 4 report the estimates of the effects of the two groups of SEA refugee students on the test scores of the strong native-born students in competitive and non-competitive environments for the two definitions. For both definitions, the effects of the two groups of SEA refugee students on the native-born student test scores match the signs in Table 3 and are stronger in absolute value in competitive environments. In column one the effects are stronger in absolute value and only statistically significant (at at least the 10% level, one-tailed test) in competitive schools. In that column the positive point estimate for the weak SEA refugee student effect on strong native-born students test scores is over 14 times higher in competitive compared with non-competitive schools, and the negative effect of swapping a strong SEA refugee student for a weak SEA refugee student on strong native-born born test scores is 23.5 times higher in absolute value in competitive schools. These differences are statistically significant at the .07 and .08 levels of significance, respectively. When the broader definition of

[23] We also allowed the coefficients to vary across the five response categories. We tested whether the top two category coefficients, both of which were statistically significant, were the same and could not reject that hypothesis at conventional levels of significance. We could also reject that the coefficients in the top two categories were the same as those in the bottom three at at least the 5% level of significance.
[24] Results are similar when we allow all coefficients to differ by the competition indicator.

competition is used, as reported in the second column of the table, the results are similar, with the coefficients replicating the signs in Table 3 and only attaining statistical significance (at at least the 2.5% significance level, one-tailed test) where there is competition.[25]

For the weak native-born students, the results are less clear. In part this may be due to the existence of the peer effect – indeed, the third column indicates that the positive effect of the number of strong SEA refugee students on the test scores of the weak native-born is only seen in non-competitive schools; competition may reduce the willingness of strong students to help weak students. However, none of the estimates attain statistical significance, which may be due to weak student behavior being less affected by grade or college competition, the existence of the peer effect, or the inability of the instruments to identify cleanly the different effects by competition for this group. Our findings on student effort, discussed below, shed more light on these mechanisms.

c. *Determinants of initial refugee location assignments*. The biggest threat to our IV strategy to identify the effect of variation in the number of SEA foreign-born students on the test scores of native-born students using cross-section variation is that the initial location assignments of the SEA refugees, the basis for our instruments, are influenced by native-born student test scores – the resettlement agencies select initial locations, within commuting zones, based on school performance. Because we have a time-series of refugees by county, we can directly test this assumption. In Appendix D we report our tests of the exogeneity of both the initial assigned

[25] A shortcoming of these tests is that school grade competition may be correlated with other school characteristics that mediate the effects of SEA student presence on native-born student test scores. We regressed the school grade competition variable on the set of school characteristics that we include in the specification (6). Only the income of the parents of the native-born students was statistically significant. Including interactions of the SEA student variables with the parent income variable in addition to the competition interactions did not change the signs or magnitudes of the competition interaction coefficients. Standard errors increased, but this is due to the fact that neither of the income interaction coefficients was statistically significant; thus, their inclusion merely added noise to the equation.

locations of the SEA refugees and their actual subsequent to native-born 8th-grade student test scores at the county level using ORR and Census data. The findings are consistent with our assumption that initial refugee resettlement locations at the school and county levels are orthogonal to native-born test scores within labor markets and with the test statistics in Table 3 rejecting the exogeneity of the variation in the actual numbers of 8th-grade SEA foreign-born students to shocks to 8th-grade native-born test scores.

d. *Effort*. We now examine the behavioral mechanisms behind the test score results, starting with those that are highlighted by the competition models – student effort. We assess if the test score effects reflect changes in effort levels in response to the variations in the number of strong and weak foreign-born students, as indicated by the model. We replace test scores by the two measures of effort available in the baseline of the NELS:88 – hours of homework time and number of classes skipped during the week – and estimate equation (6) with the same four-way stratification, including commuting-zone fixed effects in the specification. Table 5 reports the IV estimates, for which the diagnostic test statistics again indicate rejection of weak or under identification and also pass the over-dentification test.

The set of β coefficients corresponding to the effects of the number of strong and weak SEA students on the effort levels of the strong native-born students in Table 5 are consistent with the non-myopic model, indicating that the test score results for the strong native-born students are due at least in part to changes in effort – an increase in the number of strong SEA students, or swapping a strong for a weak SEA student, reduces homework time and increases the number of skipped classes by the strong native-born students, while an increase in the number of weak SEA students does not decrease either effort measure. The point estimates indicate that a one standard deviation increase in the number of strong SEA students reduces the homework hours of the strong native-born students by about 0.8 hours per week, or 11%. The homework hours of the weak native-born students are also reduced, by 0.74 hours, or 13%. That the weak native-born reduce their homework time in response to an increase in the number of strong SEA refugee students but display no decrease in test scores, as seen in Table 3, suggests that the strong SEA students have positive spillover effects on the weak native-born, as incorporated in the augmented non-myopic competition model with direct strong-weak achievement spillovers.

The results for class skipping by the strong native-born students mirror those for homework time, as expected. A one standard deviation increase in the number of strong SEA students increases the probability of class skipping by the strong naïve-born students by a statistically significant 7.6 percentage points, more than a doubling. Similarly, while the addition of weak SEA refugee students marginally reduces class skipping by the strong native-born students, it increases class skipping by the weak native-born students. Increases in the number of strong SEA refugee students, however, reduce class skipping by the weak native-born students – a one standard deviation increase in strong SEA students reduces the probability of class skipping by the weak native-born by a statistically significant 3.7 percentage points, which is a 38% reduction. Thus, the weak native-born students appear to be more exposed to the presence of strong students in the classroom when there are more strong students.

e. *Direct evidence on the positive spillovers from increased numbers of strong SEA students*. We can gain more insight as to why native-born weak students test scores appear not to fall when there are more strong SEA students in the same grade (Table 3) without any increase in effort by the weak native-born students (Table 5) using the third-round NELS:88 data on homework assistance from classroom peers. In (only) the third round (12^{th} grade), the students were asked “Did a classmate/friend help you with your homework?”. 85.4% (79.2%) of the strong (weak) students responded affirmatively. The question we address here is whether there are shifts in which students are assisted by peers when there are changes in the composition of strong and weak students.

Using the third-round data, we estimated, employing the same IV strategy and control variables as we used for estimating the determinants of test scores and effort, the effects of variation in the numbers of strong and weak SEA foreign-born students on whether a native-born student received peer homework assistance.[26] The key hypothesis we tested is that weak native-born students are more likely to receive homework help when there are more strong SEA foreign-born students in the school, in accord with the model incorporating direct positive peer effects of strong students on weak students.[27] The analysis is reported in Appendix E, where we find that an increase in the number of strong SEA students increases the probability of a weak native-born student being helped by other students, consistent with the evidence that test scores of the weak rise without an increase in their total homework time and with there being a direct peer effect. We also find that parents provide less homework assistance in response to the increase in strong SEA refuge students, so the improvement in weak-student test scores that we found is not due to parent help.

f. *Disruption effects*. Lavy *et al*. (2011) found that in Israeli schools one of the mechanisms by which weak students affected the academic performance of other students was

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[26] A caveat associated with the third-round data is that 16.2% of the weak native-born students present in the first round had dropped out by the third round, while only 2.5% of the strong native-born 8th-grade students were not present in the third round. If native-born weak-student drop-out rates are lower when there are more strong SEA foreign born students, a result consistent with the positive externalities seen in the test score data, some of the homework assistance effect of the strong SEA foreign-born students may reflect negative selection – the presence of weaker students among the weak.

[27] A weakness of the data is that the identity of the peer providing homework assistance is not provided. Thus, we cannot know whether the increase in peer homework assistance for weak native-born students is specifically coming from strong SEA refugee peers.

via disruption in the classroom, including violence. To assess whether our findings on the differing effects on native-born student test scores from changes in the composition of SEA students are due to disruption, and not just from changes in effort levels due to competition effects, we tested the hypotheses that students' experiences of disruption were not affected differentially by weak and strong SEA foreign-born students for either strong or weak native-born students. That is, the null we are testing is that disruption effects are homogeneous by treatment and treated group, in contrast to competition effects with learning spillovers.

Students were asked in the first round of the NELS:88 whether *in school* they a) had something stolen, b) were physically threatened, c) were offered to purchase drugs. We define a student as having a disruptive experience if they had answered affirmatively to any of the three questions on personal classroom disruption. 56.6% of the strong students and 61.8% of the weak students by this definition experienced a classroom disruption. Using the same specification and estimation procedure we used for the test scores and effort measures, we estimated the effects of the number of strong and weak SEA foreign-born students on the probabilities of strong and weak native-born students experiencing disruption.

Table 6 reports the estimates of SEA foreign-student disruption effects. The results suggest that there are no statistically significant effects of either refugee group on weak and strong native-born personal disruptions, and we could also not reject that the effects of weak and strong SEA refugees on strong and weak native-born are the same. Disruption effects thus do not appear to explain the patterns that we find for the differing effects of strong and weak SEA foreign-born students on weak and strong native-born test performance as measured by test score outcomes, which are, however, consistent with the findings on effort and on peer assistance predicted by the non-myopic competition model with learning externalities.

7. NELS:88 Panel Data Estimation

In this section we discuss our use of the panel data in the NELS:88 to address both internal validity concerns and alternative explanations for our results. There are three main concerns we address. First, the spatial variation in the instruments, despite the direct evidence on initial refugee assignment orthogonality to test scores, might have limited power, although even with fewer counties, the tests detect the endogeneity of current refugee locations. Second, the effects of SEA foreign-born students on observed native-born student performance may reflect selective exit by the native-born. For example, in response to an increase in the number of strong SEA foreign-born students, parents of strong native-born students may switch schools to reduce competition, leaving behind the less strong within the group, as has been found in previous studies of the effects of foreign-born on student outcomes. The negative coefficient obtained identifying the effect of the number of strong SEA foreign-born students on the test scores of the strong native-born may just reflect negative selection due to positive selective exit. Third, there may be omitted school characteristics that may be correlated with the presence of SEA foreign-born students and affect test scores.

We difference equation (6) and estimate the differenced equation across the rounds of the NELS:88 for the same native-born student:

$$\Delta E_{ijgknt} = \beta_{1g}\Delta R^{T}_{jknt} + \beta_{2g}\Delta R^{H}_{jknt} + \Delta \mathbb{Z}_{ijgknt}\gamma_{1g} + \Delta \mathbb{Q}\gamma_{2g} + \Delta c_{kn} + \Delta e_{ijgknt}\,, \tag{8}$$

where Δ is the time-series difference operator.[28] By following the same native-born student over time identification of the effects of the SEA foreign-born on native-born student performance

[28] Note that the commuting-zone fixed effects coefficients are permitted to shift over time, capturing any changes in local labor markets between the periods.

comes from variation in their numbers over time for the same student. The estimates thus are not biased by native-born student flight.[29] Differencing, by eliminating the student fixed effect, means that the validity of instruments based on *prior* refugee assignment locations to predict the changes then only requires that the time-varying shocks do not influence those assignments, for example if the shocks are iid. We will relax this assumption as well below.

A limitation of the panel data is that only test scores are provided in each round; there is no information on effort as there is in the first round. A second limitation is that, because test scores are only available for students in school, the panel is subject to selectivity bias due to selective dropping out. This is only consequential for the weak students – by the third round 16.2% of the weak students had dropped out, while only 2.5% of the strong students were absent in the 12th gradeut. We thus restrict our use of the panel data to the strong students.[30]

A second limitation of the panel data is that subsequent to the first round we do not have representative information on classmates in the school in order to quantify the number of SEA foreign-born students at the school level, as we could do using first round data. Thus, we use the number of SEA foreign-born strong and weak students in the counties in which the schools are located that we take from the 1990 and 2000 Census data. This, again, restricts the analysis to the larger counties, but as we have discussed, these counties capture most of the SEA refugee initial location assignments. The panel estimates identify the effects on native-student test scores from

[29] The method of identifying the effects of foreign-born students using variation across siblings in the same school (Figlio and Ozek, 2015; Figlio et al., 2021) effectively eliminates the negative bias due to selective flight. However, because the cross-sibling estimates are obtained from households that chose not to exit the public school system, the estimates may underestimate the negative effects of foreign-born students on the performance of strong native-born students (the ones most likely to flee) if the school migration negatively affects the migrating students (e.g., directly or from going to schools that are inferior matches). Our method does not rely on a sample that has choice-based bias.

[30] We examine the determinants of dropping out for both strong and weak students in a separate project using Census data. Consistent with our findings on direct peer effects, increases in the number of strong refugee students decreases the drop-out rates of native-born high-school students.

changes in the number of strong and weak SEA refugee students in the county in which the native-born students reside (or attend school).[31]

We will separately estimate equation (8) using the first and third rounds and the second and third rounds because of other features of our data. We use the first (1988) and third (1992) rounds, skipping the second (1990) round, for two reasons: a) parental income is not available in the second round and b), because of the absence of full-year ORR data on initial refugee resettlement location assignments in 1990, our instruments are weaker for predicting the changes in the number of SEA foreign-born students between 1990 and 1992.

We use three different instrumental-variables strategies to predict the ΔR_{kt} between 1988 and 1992. First, we use the change between 1988 and 1992, $\Delta r_{kn}^{T}, \Delta r_{kn}^{H}, \Delta r_{kn}^{10}$, in the projected number of student-age (8th-grade) SEA refugees in the county in 1988, the number of SEA refugee maternal-age women with at least a high-school degree in 1988, and the total number of SEA refugees who arrived at least 10 years ago, respectively, based on the initial assigned locations identified in the ORR data. Second, we use lagged instruments – the values of $r_{kn}^{T}, r_{kn}^{H}, r_{kn}^{10}$ in the first round 1988. The validity of these instruments only requires that the initial resettlement location assignments in 1988 are orthogonal to shocks to the changes in native-born student test scores after 1988.

As our third instrument strategy, we use a shift-share prediction of the change in the refugee populations, where the shift share is defined by:

[31] When we estimate equation (6) for the strong native-born students from the cross-section using county-level aggregates of the SEA refugee students, the results are similar to those we obtained using school-level SEA students. The county-level based estimates, for both test scores and the two effort levels, are reported in Appendix Table A2.

$$\Delta r_{kt} = \frac{r_{k0}}{r_0} \Delta r_t \ ,$$

where Δr_t = the national change in all SEA student-age refugees and female maternal-age refugees between 1988 and 1992 allocated among the counties according to the assigned distribution of SEA refugees across counties in 1975 (first year of entry), r_{k0}/r_0. The validity of these instruments only requires that the initial location assignments in 1975 are orthogonal to the shocks to changes in native-born student test scores between 1988 and 1992.

We also use the panel rounds two and three, despite the limitations – absence of parental income and weaker and more limited instruments[32] - associated with the second round. Estimating (8) from the differences in test scores between the second and third rounds has two key advantages. First, it enables us to control perfectly for (fixed) school characteristics. This is because less than 3.9% of the strong native-born students changed schools between 10th and 12th grades. By restricting this sample to these non-movers, school characteristics are absorbed in the student fixed effect. The estimates will thus not be biased by selection or by omitted (permanent) student or school characteristics unless there are significant changes in a school's characteristics over time. The second advantage from estimating (8) from the second and third rounds is that we can include the lagged test score, which will absorb, net of the student fixed effect, all past influences on the native-born student's current human capital, including those due to the influence of prior SEA foreign-born students in the classes of the native-born. This obviates the need to assume that the time-varying errors are not serially correlated.

8. Panel Data Estimates

[32] We cannot use the shift-share instrument because the change in the total number of refugees between 1990 and 1992 based on the ORR data is inaccurate due to the missing refugee assignment data for part of 1990.

a. Rounds one and three panel. Table 7 reports the student fixed-effects IV round-one and three estimates of the effects of changes in the county-level number of weak and strong SEA foreign-born students on changes in the test scores of the strong native-born students by instrument type. The estimates are based on specifications that omit commuting-zone fixed effects. The identification test statistics indicate that all three instruments pass the weak-instruments, under-identification and over-identification tests, with the lagged instrument-based results showing the strongest test results. All three also indicate rejection of the null that the changes in county-level SEA foreign-born students are exogenous to the changes in shocks to native-born student test scores.

The β estimates in the three columns of Table 7 are similar in magnitude and statistically significant. And the sets of coefficients conform in sign to those obtained from the cross-section, as reported in Table 3, with an increase in the number of strong (weak) SEA students lowering (increasing) the test scores of the strong native-born students, as predicted by the non-myopic competition model. It thus does not appear that the estimates from the cross-section are wholly due to selective school exit by strong native-born students.

The first three columns of Table 8 present the estimates of the effects of the SEA refugee students on native-born test scores in specifications including commuting-zone fixed effects for the three instrument sets. Including the commuting-zone fixed effects absorb all *changes* in the relevant labor markets over the period, so that identification now comes from changes in the SEA foreign-born on native-born student test scores net of any changes in labor markets. The SEA student effects are therefore net of any effects on labor market schooling returns.

For all three instrumental-variables the signs of the β coefficients are the same as the results from the panel estimates obtained with commuting-zone fixed effects excluded. The magnitudes and significance levels for the negative effects of variation in the number of strong SEA students on native-born student test scores are similar to those in Table 7. However, the point estimates for the effects of the weak SEA foreign-born are substantially reduced and are not different from zero, although all positive. The key difference in the results is that we now cannot reject the exogeneity of the change in the SEA foreign-born students within labor markets.[33] As a consequence we report the first-differenced results without using instruments in the fourth column of Table 7, which are similar to the estimates obtained using IV.

b. Rounds two and three panel. The first column of Table 9 reports the student, school and commuting-zone IV fixed effects (FE) estimates of the β coefficients from the sample of strong native-born students present in rounds two and three and attending the same school in both rounds. As noted, we use as instruments only the projected number of the SEA refugees by type for 1990, corresponding to the second-round of the panel survey and the initial round of the rounds two and three panel, because the changes in these variables from 1990 to 1992 will be error-ridden due to the truncation of the 1990 refugee assignment data in 1990. The β coefficients, which are immune to bias from omitted student fixed characteristics, omitted effects from any changes in labor markets, and any omitted school characteristics, are statistically significant (at at least .05 level of significance, one-tailed test), and again conform in sign to the predictions of the non-myopic competition model.[34] In the second column we report the fixed-effects estimates obtained without using instruments because, although the instruments are strong, we cannot reject the hypothesis that the changes in the numbers of SEA students are

[33]This non-rejection is not due to weak instruments, as indicated in the first-column results based on the instrument set using projected changes in refugee locations between 1988 and 1992.

[34] The estimates from the first- and third-round panel indicate that changes in family income are not statistically significant. We therefore do not expect that the omission of this variable due to data constraints is biasing the results from the second- and third-round panel.

exogenous, net of the student and commuting zone fixed effects. Indeed, the column-two FE-IV β estimates are very similar to the column one FE estimates in magnitude and precision.

In the third column of Table 9 we report FE estimates that include the student's lagged test score in the specification. In this specification the FE coefficient on the lagged dependent variable will be biased negatively, and we see that the lagged test score coefficient is negative and statistically significant. Despite its inclusion, and its potentially imparting bias to all of the estimated coefficients, the β coefficients are virtually unchanged from those seen in the first two columns of the table. To correct the bias we use instruments to predict the lagged test score, namely adding to the instrument set the projected number of SEA refugee students and the projected number of SEA refugee highly-schooled mothers up through 1988, the year of the first lagged test score, to the instruments projected to 1990, the first contemporaneous test score used to obtain the column-two FE-IV estimates.

The FE-IV estimates for the lagged test score specification are reported in the last column of the table. The use of instruments cuts the point estimate of the lagged test score by 46%, and its effect now becomes statistically insignificant. Although the estimates in the last column suffer from a weak instrument problem; nevertheless, there is again little change in the β coefficients. Taken together the results in Tables 7 and 9 indicate that the estimates of the effects of strong and weak SEA foreign-born students on the school performance of strong native-born students, which conform to the predictions of the non-myopic competition model, are robust to selective flight by native-born students, omitted school characteristics, omission of lagged cumulative refugee-student effects, and bias due to the endogenous initial resettlement patterns of refugees.

9. Are There Peer Effects Net of Student Effort? Suggestive Evidence

We used the panel data to verify that our cross-sectional results, which examined the determinants of both academic achievement and effort measures, are robust to identification strategies and levels of aggregation of the treatment variables. We have emphasized, as embodied in the competition models, that a key mechanism by which changes in the composition of student peers affect the achievement of student incumbents is by altering their choice of how much effort to supply. We now explore, returning to the cross-sectional data, whether the effort variables we examined have important effects on test scores and whether the peer effects we found on test scores can be fully explained by their effects on effort. That is, we estimate the effort production function of the model inclusive of direct peer effects.

In particular, we estimate the effects of the two refugee student variables on the standardized test scores of the strong and weak native-born students net of the effects of own homework time and class skipping, and net of personal classroom disruptions and school characteristics. The school characteristics we include in the second-stage test score effort function include variables indicating whether the school is public and whether the school has selective admissions, 8^{th}-grade enrollment size, and the teacher-student ratio. We also add additional endogenous inputs, including an exam tutor, and parent input behaviors. These estimates of the effort production function with direct peer effects will also provide quantitative evidence on whether and by how much homework time and class skipping, our two main measures of own academic effort, affect student achievement.

We treat the two refugee student and the input variables as endogenous, and use a subset of the exogenous right-hand-side variables in the specification used for obtaining the estimates in Table 3 as instruments. In particular, we assume that net of (i) the refugee student numbers, (ii) the measures of native-born student effort, and (iii) any personal classroom disruption events, the following variables affect a student's effort but do not directly affect the student's test score: parental income, urbanization, county population size, county median housing value, the fraction of the county population that is urban, and the commuting zone (labor-market) variables We are thus assuming, for example, that local labor market factors fully captured by the commuting-zone fixed effects, such as the skill composition of workers, affect the returns to schooling and thus incentives for schooling effort, as in McHenry (2015) and Hunt (2016).

The first and fourth columns of Table 10 report the estimated IV coefficients for the SEA refugee student variables measured at the school level and the effort variables for the strong and weak native-born students, respectively. For both groups of native-born students, the own effort and disruption variables have the expected signs, and homework time is statistically significant and positive for both student groups. Importantly, the coefficients associated with the two groups of SEA refugee students, which capture peer effects, now are jointly statistically insignificant for both native-born student groups.[35] There is, however, a weak instrument issue for the weak native-born student group - while the robust, cluster-adjusted F-statistics for the identifying set of instrumental variables associated with the two effort variables and the personal disruption variable are strong - over 100 for each - that for the number of school-level SEA refugee high-background students is less than 10 for the weak native-born students.

Given the weak instrument problem for the weak native-born students, we re-estimated the equations for both groups of native-born students replacing the school-level SEA refugee students variables by their county-level aggregates, from Census data, as we did for the panel data estimates. We use the same set of instruments as we did for estimating the coefficients

[35] Of the school-specific variables, only the teacher-student ratio is statistically significant, and positive.

reported in columns one and four using the school-level SEA refugee student variables. The estimates using these county-level SEA refugee student variables and including the same set of input and school variables as in the first specification are reported in columns two and five of the table for the two native-born student groups.

When we use the county-level SEA refugee student variables, all of the first-stage F-statistics for the endogenous right-hand-side variables are now over 70 for both native-born student groups.[36] For the strong native-born students we continue to find that there are no statistically significant student peer effects net of the effort variables, while the two effort variables retain their statistical significance and have the expected signs. For the strong students there thus appears to be no remaining black box for peer effects - the changing composition of peers influences student performance, shaped by classroom competition, solely by affecting how much they choose to work, here as measured by homework time and class attendance.

In contrast, for the weak native-born students, the SEA refugee student peer effects are now jointly significantly different from zero even net of incumbent native-born student effort. Importantly, we find that, net of own effort, a greater number of strong SEA refugee students increases the test scores of the weak native-born students, consistent with the direct positive peer effect we incorporated in our competition model effort production function and with our findings that the presence of strong SEA refugee students did not increase weak native-born student homework time but did increase peer assistance with homework. This is additional evidence that strong SEA refugee students appear to aid the performance of weak native-born students directly, not by affecting how much they exert effort.

[36] The robust, cluster-adjusted F-statistics associated with the school- and county-level SEA refugee students are reported in Appendix Table A3.

In the third and sixth columns we report estimates from a specification that adds the endogenous exam tutor and two endogenous parent input variables – whether the parents often limit the students TV time and whether the parents check the student's homework. These additional variables are statistically significant for the strong native-born student group, with the use of the tutor notable increasing the test score by one full standard deviation. The three additional parent and tutor variable coefficients, however, are jointly insignificant for the weak student group. The key results are that the SEA refugee student coefficients remain jointly statistically insignificant for the strong native-born students but remain jointly significant for the weak native-born students and retain their signs when these input variables are added.

The statistically-preferred set of estimates for the weak native-born students is in the fifth column of the table, which omits the insignificant parent and tutor inputs. The point estimates from column five indicate that the effect on weak native-born student test scores from a one standard deviation increase in the number of strong SEA refugee students in the student's county of residence, for given own homework time and class attendance, increases the test score for weak native-born students by 0.069 standard deviations. The homework time point estimate, which is statistically significant, indicates this direct peer effect on the test score performance of the weak native-born students is equivalent to increasing their homework time per week by 0.8 hours. Homework time itself has a substantial effect on test score performance - a one standard deviation in homework time per week increases the test score by 0.89 standard deviations, for both weak students and strong students. Thus, the peer effects we find on homework time for the strong native-born students, a direct measure of student effort, appear to be identify an important mechanism by which student peers affect academic performance, effects which are in turn consistent with models of classroom competition.

10. Conclusion

In this paper we have examined the consequences for student effort and performance when students are rewarded based on their relative class standing using game-theoretic competition models to guide our analysis. Based on a model in which students within similar-ability peer groups recognize that their efforts will be matched, and in which stronger students assist weaker students, we show using a variety of identification strategies, that the student composition of classes matter, in particular ways, for student outcomes and effort across ability groups. In particular, we find, based on variations in school student composition due to the resettlement of large numbers of Southeast Asian refugees in the late 1970's and 1980's in the United States, that consistent with the competition cum peer-effect model, increases in strong (refugee) students reduce the effort levels of strong and weak incumbent (native-born) students, decrease the test scores of incumbent strong students, but increase the test scores of weak incumbent students. Conversely, increases in the number of weak students decrease the effort and test scores of weak incumbent students but increase the effort and test scores of strong incumbent students.

Classroom competition, induced by rewards based on the relative position of a student in a class or grade and in the absence of direct peer effects, thus appears to lower the returns to student effort and lowers student learning. We also found evidence that for strong incumbent students, all of the peer effects we found on test scores could be explained by changes in their effort, as measured by homework time and class skipping, both of which have significant and strong direct effects on test scores, net of peer and school characteristics and parent effort. For weak native-born students, however, we found that there remain positive peer effects from strong refugee students on weak native-born students net of their effort, consistent with ancillary evidence on peer homework assistance and our model.

Our findings have implications for school policies. Class and school stratification by ability not only eliminates the positive learning spillover for weaker students that we find but may also lower the effort levels of students, particularly strong students in schools that are more competitive. Our results based on the competition effects on student effort might explain why the learning gains for a (marginally) able student from being in a highly-competitive school that selects in more able students may be small compared to when that same student attends a school that is less competitive and has weaker students (Abdulkadiroglu *et al*., 2014) when one considers both effort and direct spillover effects.

Our findings also have implications for refugee policy. The results suggest that resettling families with high human capital will increase the learning of weaker native-born students while reducing the learning (via competitive effort effects) of high-human capital native-born students, thereby decreasing inequality in the long run. On the other hand, increasing the flow of low human capital refugees increases effort and learning among more able native-born students but decreases effort and learning among the weaker native-born students. Admitting a balanced group of refugees in terms of human capital will thus have little net effect on the performance of native-born students, as these heterogeneous effects are offsetting. Indeed, we do find that the net effect of the large influx of Southeast Asian refugees on incumbent native-born student test scores was negligible, despite the significant differential effects by refugee and native-born student abilities.

Finally, although we think that taking into account the competitive nature of classroom reward systems, student effort and peer effects is important for understanding student learning in schools, in future work models of the classroom performance of students should incorporate teacher and parent behavior as well. While we could find no evidence that teacher and parent behavior alone could explain our results, we did find evidence of parent assistance responding to classroom composition. In addition, while we found evidence that student peer assistance was responsive to classroom peer composition, a better understanding of the incentives for students to help one another in a competitive environment is needed.[37]

[37] Wu *et al.* (2023) find that strong students locationally paired with weak students within a classroom only provide help to their weaker-student counterpart when given monetary incentives.

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Figure 1. Cumulative Number of SE Asian Refugees, SE Asian + USSR Refugees, and Total Refugees, 1975-2008

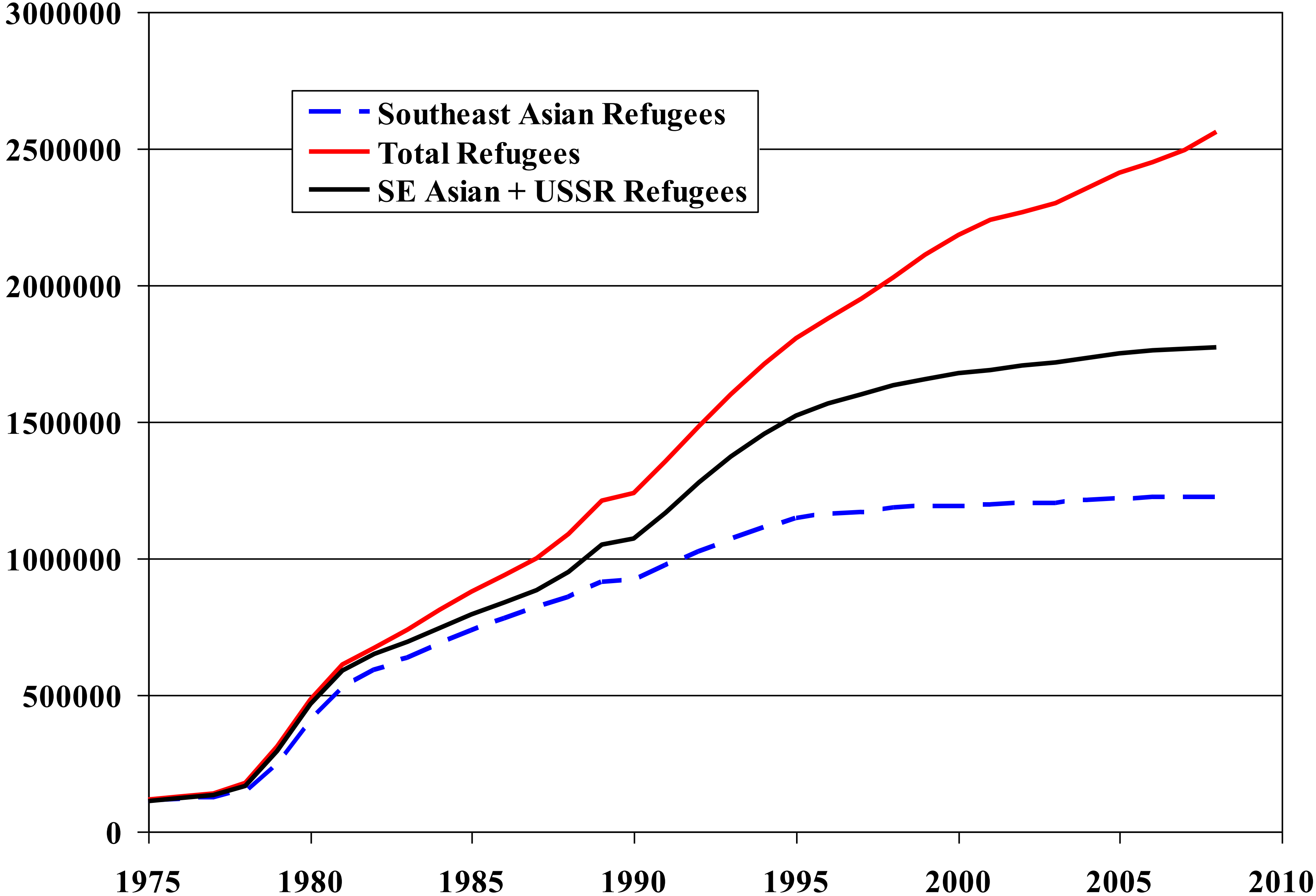


Figure 2. New Refugee Resettlements by Arrival Year, Southeast Asian Refugees, SE Asian + USSR Refugees, and Total Refugees: 1975-2008

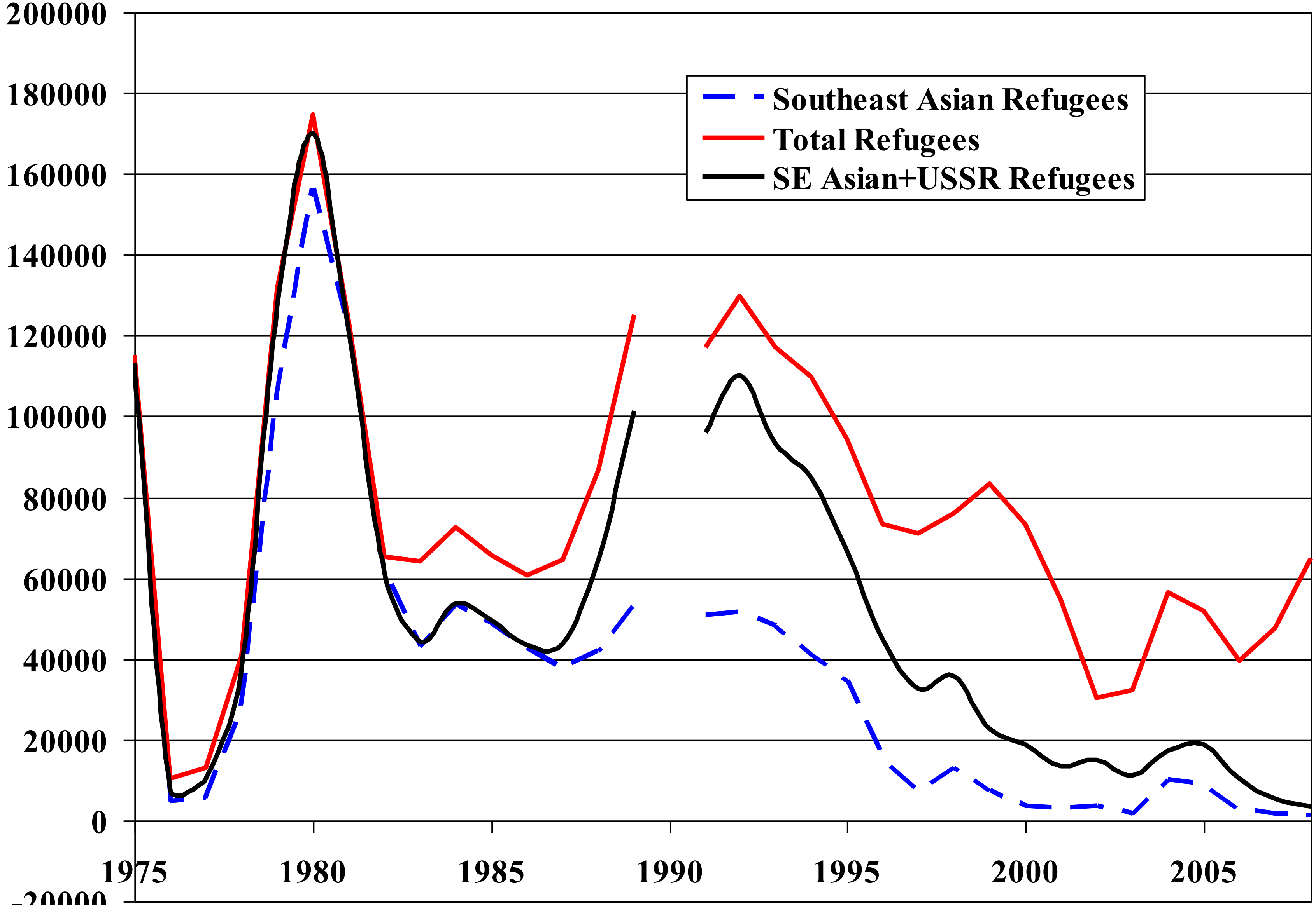
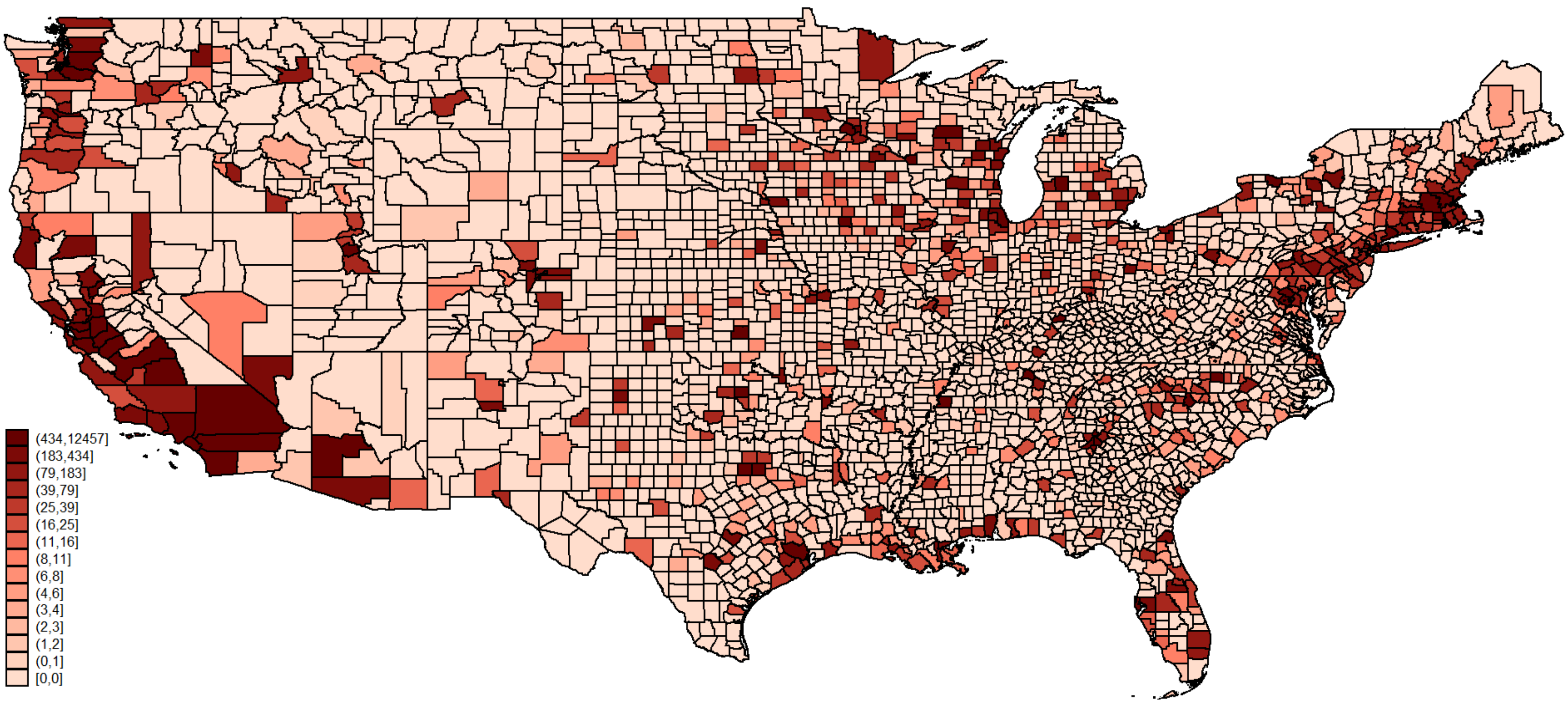


Figure 4. Initial FIPS Locations of Southeast Asian Refugees, 1987-90

Data Source: Office of Refugee Resettlement



February, 2011

Figure 3 FY2011 Reception and Placement Program Affiliate Sites

Source: Bureau of Population, Refugees, and Migration, US Department of State

Figure 5. Combined Math and Reading Achievement Tests Z-Scores for Southeast Asian Foreign-born and Native-born 8th-Grade Students, by Parent Schooling

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, Parent Survey, 1992."

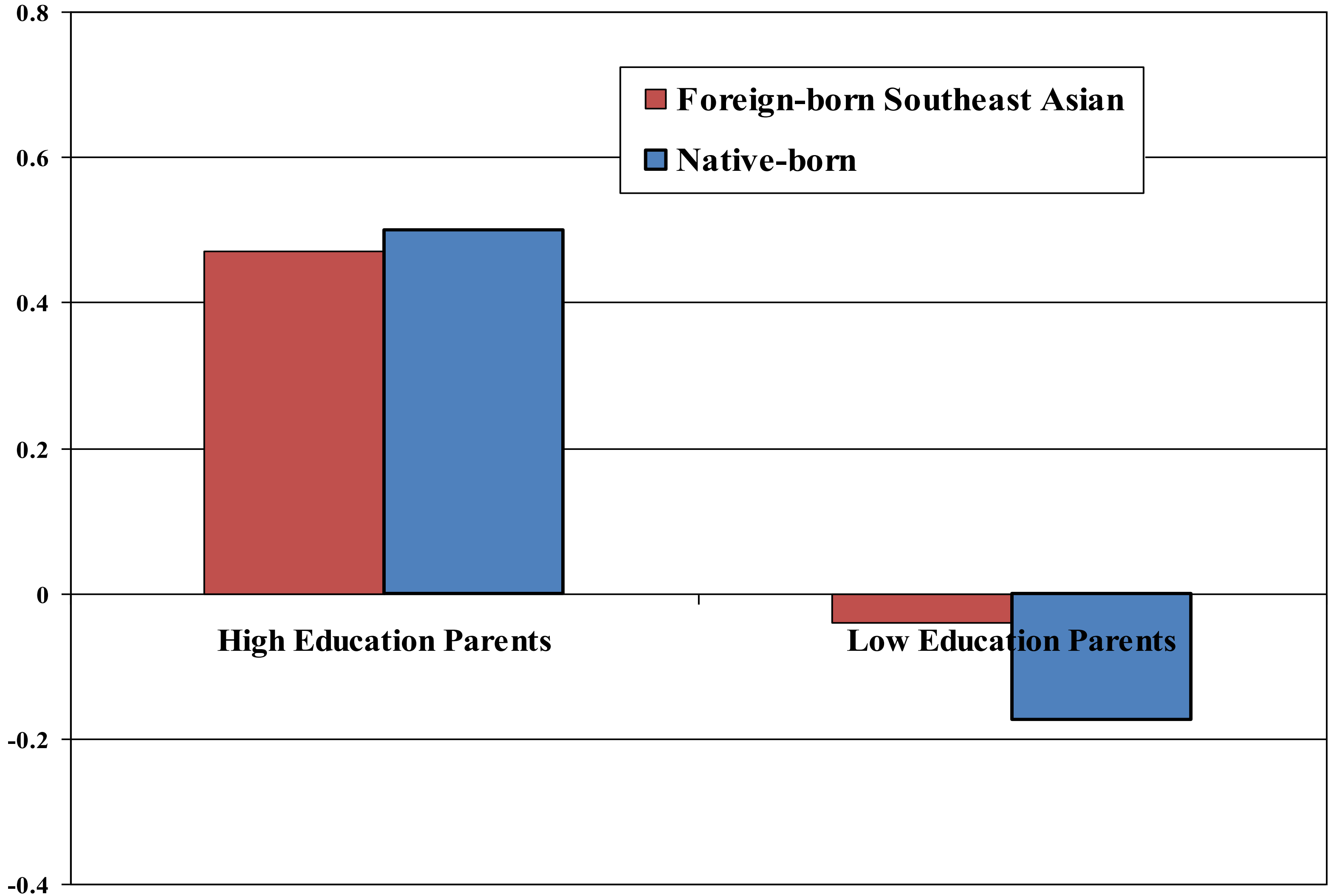


Figure 6. Percentage of Southeast Asian Foreign-born and Native-born 8th-Grade Students Who report They Expect to Go to College, by Parent Schooling

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, Parent Survey, 1992."

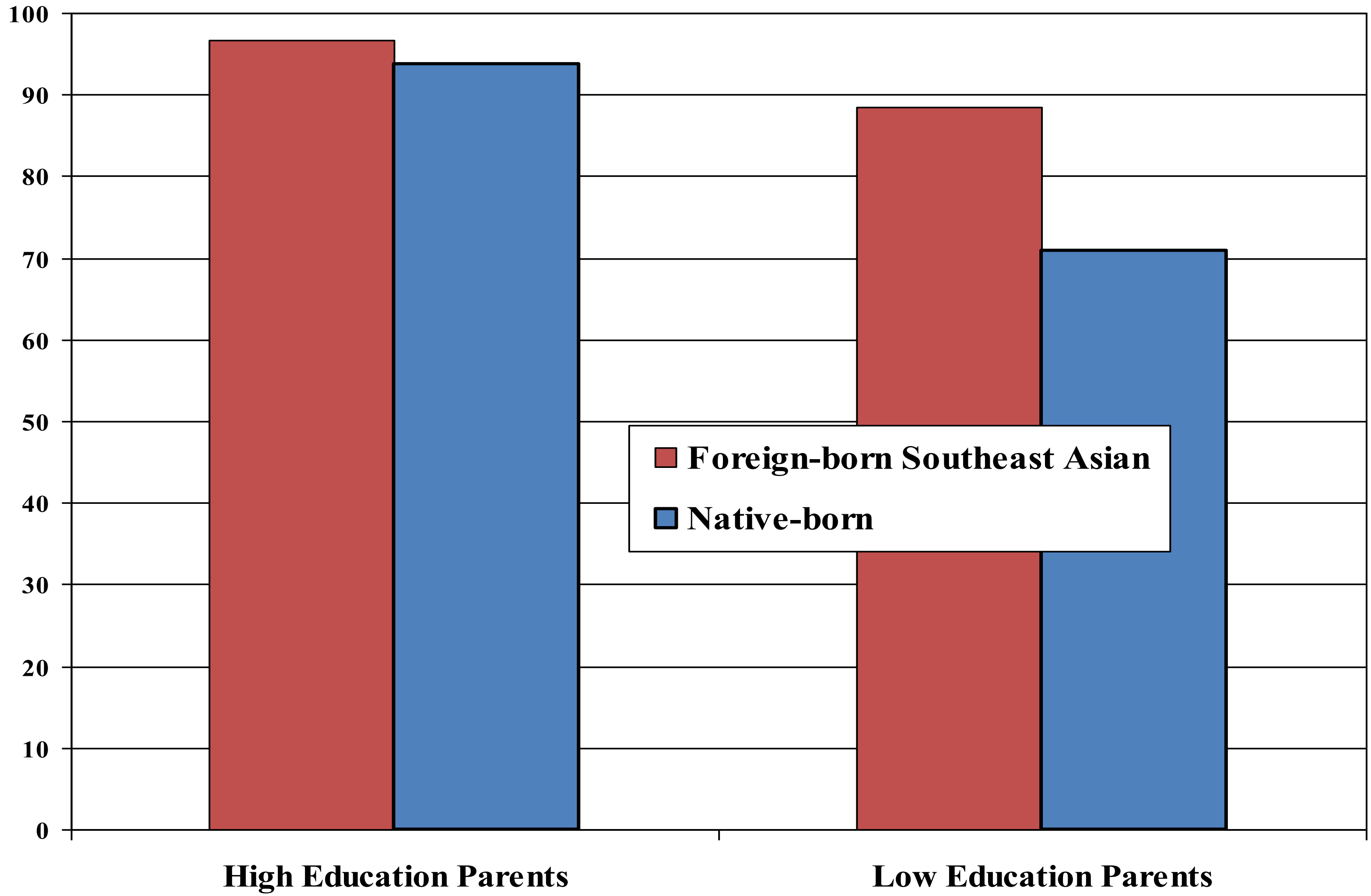


Figure 7. Relationship Between the Number of Predicted Southeast Asian Refugee 8th-graders and the Number of NELS:88 Southeast Asian Foreign-Born 8th-graders Across Counties

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, Parent Survey, 1992."

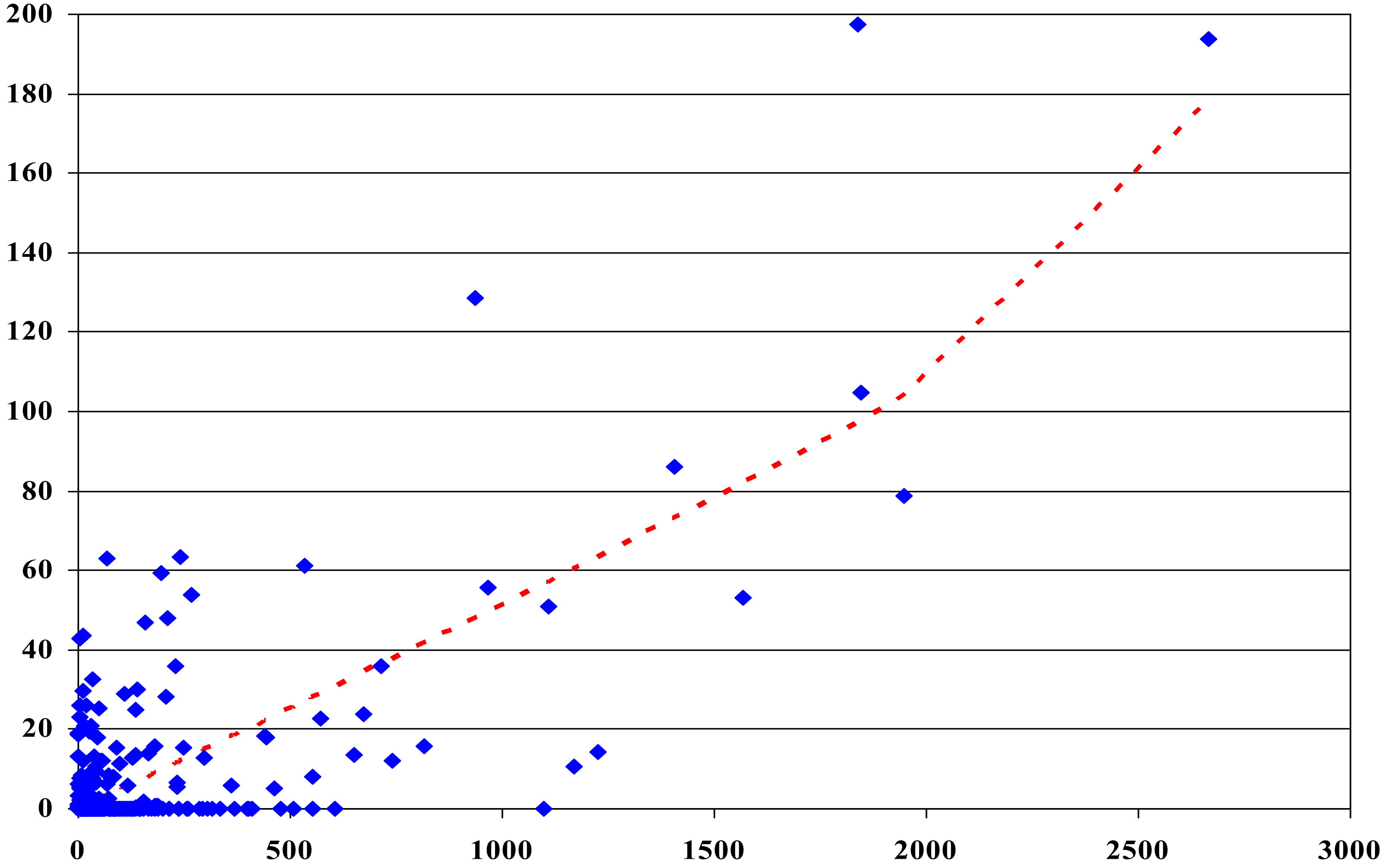


Figure 8. LWFCM Estimates of the Effects of High-background 8th-grade Southeast Asian Refugee Students on Native-Born Test Z-Scores, by the Total Years of Schooling of the Native-Born Student Parents

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, Parent Survey, 1992."

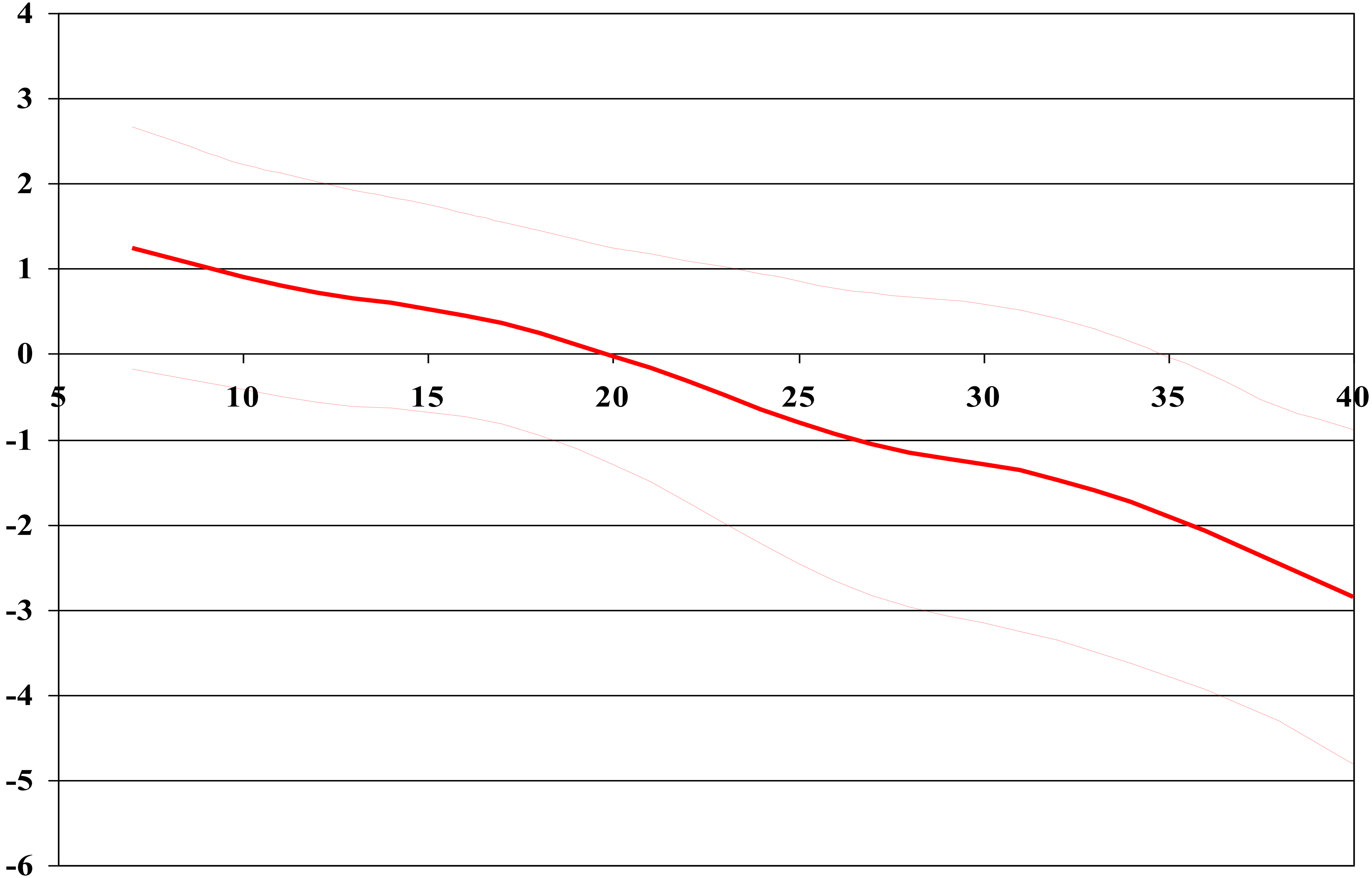
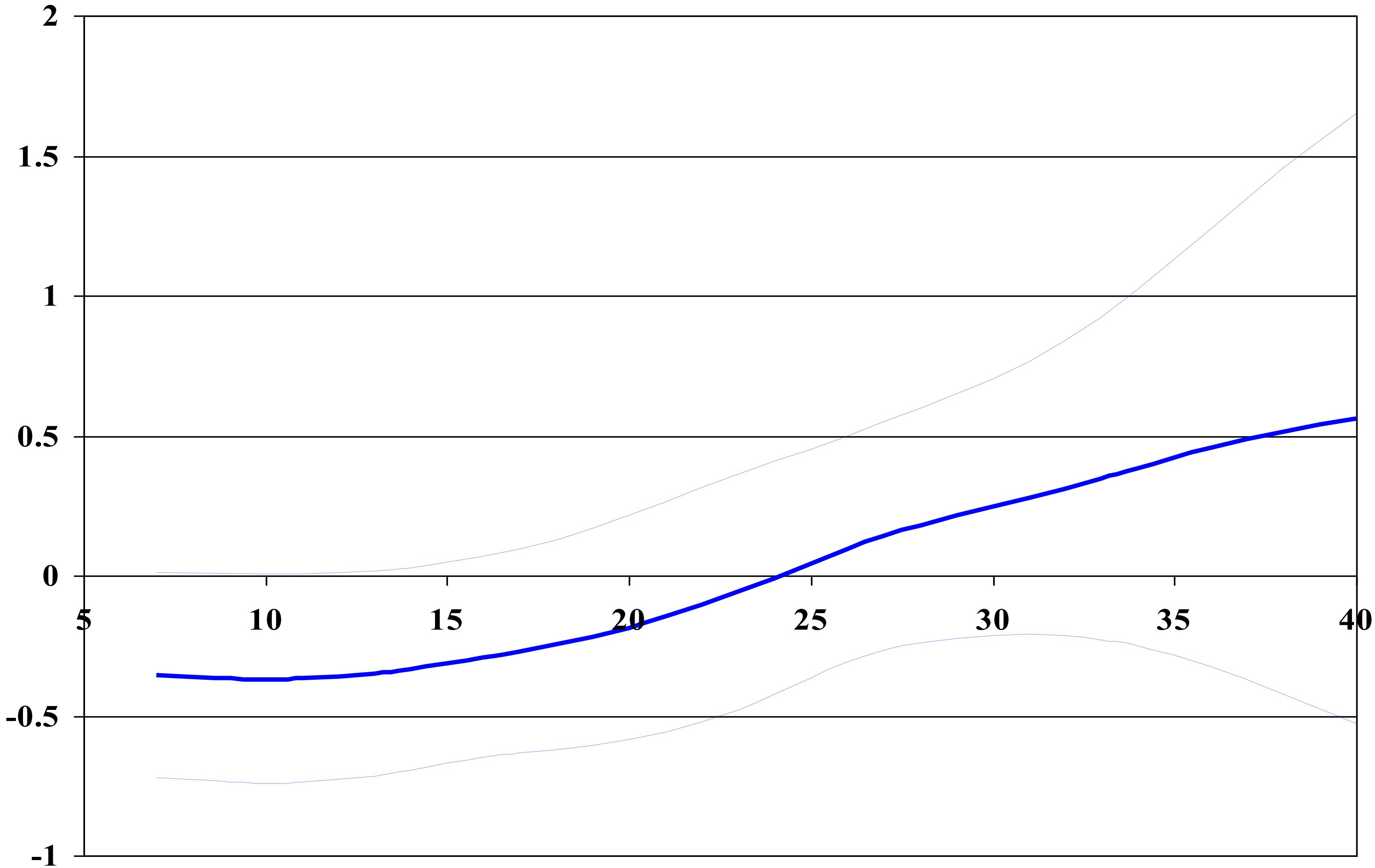


Figure 9. LWFCM Estimates of the Effects of Total 8th-grade Southeast Asian Refugee Students on Native-Born Math and English Z-Scores, by the Total Years of Schooling of the Native-Born Student Parents

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, Parent Survey, 1992."



Appendix Figure A1.Southeast Asian Refugees Admitted, PRA Visas Issued, and Foreign-Born in 2000, by Arrival Year, 1986-1999

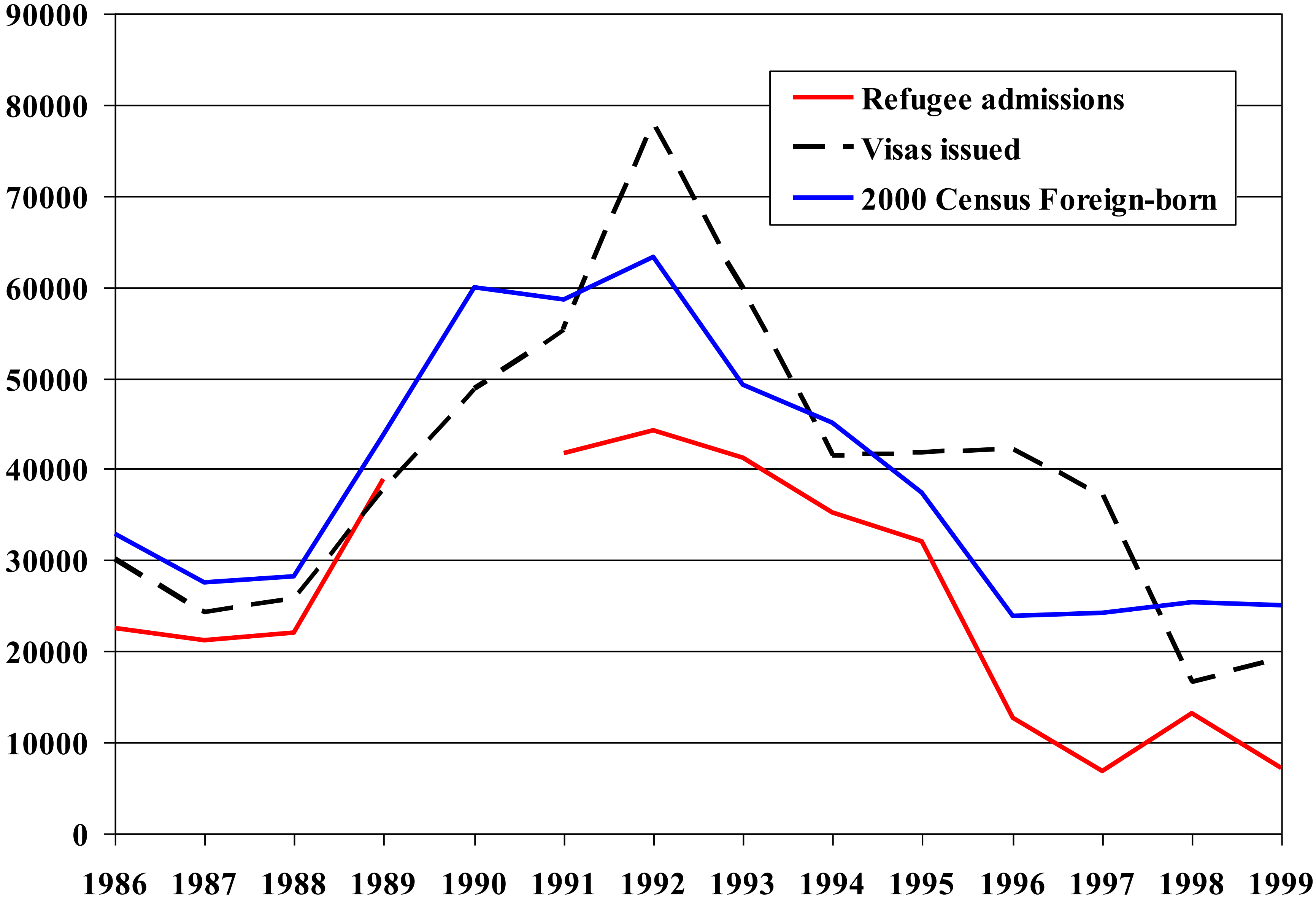


Table 1
Predicted Signs of Coefficients in the Estimating Equation
Based on the Non-myopic Tournament with a Direct Peer Effect and the Optimal Curriculum Models

Outcome variable	Test Scores		Homework Time		Skipping Class	
Coefficient/Student *g*	Strong	Weak	Strong	Weak	Strong	Weak
	Non-Myopic Tournament Model					
β_{1g}	+	-	+	-	-	+
β_{2g}	-	?	-	-	+	+
	Optimal Curriculum Model (with Effort Complementarity)					
β_{1g}	-	+	-	+	+	-
β_{2g}	+	?	+	-	-	+

Table 2
OLS and LIML IV Estimates of the Effects of Southeast Asian Refugee Students on Native-born Student Standardized Math and English Test Scores: 1988 NELS Baseline

Variable/Estimation procedure	OLS	IV
Total number of SEA eighth-grade refugee students[a]	0.0408 (0.0324)	-0.0647 (0.166)
Family income (x10^{-6})	2.61 (0.158)	2.60 (0.153)
Female	0.00607 (0.0154)	0.00619 (0.0154)
Black	-0.558 (0.0273)	-0.562 (0.0288)
Private school	0.396 (0.0625)	0.390 (0.0674)
Urban	0.00105 (0.000395)	0.00116 (0.000427)
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	-	11.1 [0.011]
Kleibergen-Paap Wald F (weak identification) [10% 5.44]	-	20.4
Hansen J $\chi^2(1)$	-	3.62 [0.16]
Endogeneity test $\chi^2(2)$	-	0.845 [0.36]
Number of students	17,620	17,620
Number of clusters	680	680

Standard errors clustered at the FIPS county level in parentheses. Control variables also include: age, race=Black, population size in the school's zip code, whether the school is public or private, whether the school has a restricted admission policy, total eighth grade school enrollment, percent urban in the county in 1990, median housing value in the county in 1990.
[a]Endogenous variable. Instruments include the number of SEA refugees aged 13-15 in 1988 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1988 in the FIPS county, and the number of SEA refugee women aged 36-54 with at least a high-school degree in 1988 in the FIPS county based on the SEA refugees originally assigned to the county since 1975.
SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, and Parent Survey, 1988."

Table 3
LIML IV Estimates of the Effects of Southeast Asian Refugee Students by Background on Native-born Student Standardized Math and English Test Scores, by Native-born Student Background: 1988 NELS Baseline

Variable/Native-born student type	Strong		Weak	
Total number of SEA eighth-grade refugee students (NSEA)[a]	1.20 (0.452)	1.52 (0.759)	-0.326 (0.126)	-0.653 (0.157)
Number of SEA eighth-grade refugee students with high background (NSEAH)[a]	-2.26 (0.832)	-2.67 (0.910)	1.27 (0.946)	1.11 (0.623)
Family income ($x10^{-6}$)	1.18 (0.170)	0.919 (0.176)	3.46 (0.500)	3.01 (0.472)
Female	0.055 (0.028)	0.032 (0.030)	0.025 (0.018)	0.028 (0.184)
NSEA + NSEAH	-1.72 (0.659)	-1.14 (0.588)	0.944 (0.927)	0.455 (0.559)
FE commuting zone	N	Y	N	Y
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	3.33 [0.188]	4.82 [0.089]	2.49 [0.288]	6.31 [0.043]
Kleibergen-Paap Wald F (weak identification) [10% 5.44]	2.92	14.8	2.32	21.0
Hansen J $\chi^2(1)$	0.392 [0.53]	0.827 [0.36]	0.474 [0.491]	0.123 [0.73]
Endogeneity test $\chi^2(2)$	4.60 [0.10]	6.43 [0.040]	2.71 [0.26]	9.34 [0.009]
Number of students	5,340	5,340	10,380	10,380
Number of clusters	570	570	630	630

Standard errors clustered at the FIPS county level in parentheses. Control variables also include: age, race=Black, population size in the school's zip code, whether the school is public or private, whether the school has a restricted admission policy, total eighth grade school enrollment, percent urban in the county in 1990, median housing value in the county in 1990. Native-born students in the strong group have both a father and mother with at least some schooling beyond high school and are in the upper half of the SES categories. Neither parent of weak native-born students has schooling beyond high school and all are below the top SES group. [a]Endogenous variable. Instruments: the number of SEA refugees aged 13-15 in 1988 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1988 in the FIPS county, and the number of SEA refugee women aged 36-54 with at least a high-school degree in 1988 in the FIPS county based on the SEA refugees originally assigned to the county since 1975.
SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student,and Parent Survey, 1988."

Table 4
IV Estimates of the Effects of Southeast Asian Refugee Students by Background on Native-born Student Standardized Math and English Test Scores, by Native-born Student Background and by Competition Environment: 1988 NELS Baseline

Native-born student type	Strong		Weak	
Competition environment	School	School or University	School	School or University
Number of weak SEA refugee students[a]: no competition	0.123 (0.459)	0.911 (2.02)	-1.83 (0.960)	-4.37 (7.49)
Number of weak SEA refugee students[a]: competition	1.79 (0.924)	1.23 (0.522)	-0.222 (0.176)	-0.510 (0.301)
Swapping strong/weak SEA refugee student: no competition	-0.401 (0.661)	-0.496 (2.35)	5.27 (3.77)	7.79 (7.83)
Swapping strong/weak SEA refugee student: competition	-9.44 (4.95)	-2.62 (0.744)	–3.50 (4.80)	0.983 (1.36)
Number of strong SEA refugee students[a]: no competition	-0.279 (0.431)	0.415 (0.601)	3.44 (2.93)	3.42 (7.61)
Number of strong SEA refugee students[a]: competition	-7.65 (4.71)	-1.38 (0.399)	-3.73 (4.84)	0.473 (1.12)
Percent in competitive env.	58.4	80.1	45.6	73.2
Number of students	5,340	5,340	10,380	10,380
Number of clusters	570	570	630	630

Standard errors clustered at the FIPS county level in parentheses. Control variables are the same as in Table 3. Native-born students in the strong group have both a father and mother with at least some schooling beyond high school and are in the upper half of the SES categories. Neither parent of weak native-born students has schooling beyond high school and all are below the top SES group. Competition "school" is defined by whether the school administrator responds to the statement "Students face competition for grades" by answering either as "accurate" or "very accurate" (50.2% of 8th-graders). Competition including university competition is defined as either school competition or the state university system admission criteria includes class rank (75.5% of 8th-graders).

[a]Endogenous variable. Instruments include the number of SEA refugees aged 13-15 in 1988 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1988 in the FIPS county, and the number of SEA refugee women aged 36-54 with at least a high-school degree in 1988 in the FIPS county based on the SEA refugees originally assigned to the county since 1975.

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, School, Student, and Parent Survey, 1988."

Table 5
LIML IV Estimates of the Effects of Southeast Asian Refugee Students by Background on Native-born Student Homework Time and Class Skipping, by Native-born Student Backgound:1988 NELS Baseline (Eighth Grade)

Variable/Native student group	Strong		Weak	
Dependent variable	Homework	Skip classes	Homework	Skip classes
Total number of SEA eighth-grade refugee students (NSEA)[a]	2.09 (1.99)	-0.190 (0.155)	0.660 (0.848)	0.0898 (0.050)
Number SEA refugee students, high background (NSEAH)[a]	-6.49 (2.46)	0.616 (0.181)	-8.20 (2.14)	-0.408 (0.176)
Family income (x10^{-6})	3.29 (0.0846)	0.0217 (0.0466)	3.07 (1.77)	-0.110 (0.115)
Female	0.338 (0.164)	-0.0117 (0.0071)	0.236 (0.085)	-0.0326 (0.0064)
NSEA + NSEAH	-4.40 (1.82)	0.426 (0.130)	-7.54 (1.96)	-0.318 (0.151)
FE commuting zone	Y	Y	Y	Y
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	4.80 [0.091]	4.92 [0.085]	6.43 [0.040]	7.068 [0.029]
Kleibergen-Paap Wald F (weak identification) [10% bias 5.44]	13.6	13.7	20.9	28.0
Hansen J $\chi^2(1)$	0.020 [0.89]	0.203 [0.65]	0.00 [0.995]	0.030 [0.86]
Endogeneity test $\chi^2(2)$	3.83 [0.15]	4.92 [0.085]	3.94 [0.14]	3.86 [0.15]
Number of students	5,230	5,330	9,940	10,170
Number of clusters	570	570	630	630

Standard errors clustered at the FIPS county level in parentheses. Control variables are the same as in Table 2.

[a]Endogenous variable. Instruments include the 1988 county-level number of SEA refugees aged 13-15, the 1988 county-level number of SEA refugees in the United States for at least 10 years, and the 1988 county-level number of SEA refugee women aged 36-54 with at least a high-school degree based on the SEA refugees originally assigned to the county since 1975.

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, and Parent Survey, 1988."

Table 6
IV Estimates of the Effects of Southeast Asian Refugee Students by Background on Whether Native-born Students were Adversely Affected by Classmates (Disruption), by Background: NELS88 Baseline (8^{th} grade)

Variable/Native student group	Strong	Weak
Total number of Southeast Asian eighth-grade refugee students[a]	-0.0535 (0.186)	-0.188 (0.115)
Test of difference across native-born: $\chi^2(1)$ [*p*]	0.60 [0.437]	
Number of Southeast Asian eighth-grade refugee students, high background[a]	0.598 (0.378)	0.368 (0.454)
Test of difference across native-born: $\chi^2(1)$ [*p*]	0.48 [0.490]	
Test of difference within native-born: $\chi^2(1)$ [*p*]	1.44 [0.231]	1.09 [0.296]
FE commuting zone	Y	
Number of students	15,790	
Number of clusters	340	

Standard errors clustered at the FIPS county level in parentheses. Control variables are the same as in Table 1.

[a]Endogenous variable. Instruments include the number of SEA refugees aged 13-15 in 1988 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1988 in the FIPS county, and the number of SEA refugee women aged 36-54 with at least a high-school degree in 1988 in the FIPS county based on the SEA refugees originally assigned to the county since 1975. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, and Parent Survey, 1988."

Table 7
Student Fixed Effect IV Estimates:
The Effects of Student-Age Southeast Asian Refugees by Background in the County on High Family Background Native-Born Student Standardized Math and English Test Scores:
NELS 1988-1992 Panel

Instrumental variable type	Change in Assignments	Lagged Assignments	Shift-Share
Total number of SEA refugee students (NSEA) in the county[a]	0.000254 (0.000083)	0.000236 (0.000067)	0.000156 (0.000071)
Number of SEA refugee students with high background in the county (NSEAH)[a]	-0.000985 (0.000181)	-0.00106 (0.000166)	-0.000662 (0.000300)
Family income ($x10^{-6}$)	-0.130 (0.337)	-0.135 (0.336)	-0.131 (0.336)
NSEA + NSEAH	-0.000731 (0.000123)	-0.000823 (0.000123)	-0.000507 (0.000246)
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	8.57 [0.036]	27.9 [0.000]	5.91 [0.052]
Kleibergen-Paap Wald F (weak identification) [5% bias critical value 11.04]	22.3	95.4	41.8
Hansen J $\chi^2(1)$	2.64 [0.27]	4.34 [0.11]	0.000 [0.99]
Endogeneity test $\chi^2(2)$	6.80 [0.033]	6.20 [0.045]	5.68 [0.058]
Number of students	1,190	1,190	1,190
Number of clusters	170	170	170

Standard errors clustered at the FIPS county level and year in parentheses. Control variables in columns 2 and 3 also include: the student-teacher ratio and the population size in the school's zip code. County fixed effects are in all specifications. Native-born students in the High group have both a father and mother with at least some schooling beyond high school and are in the upper half of the SES categories. [a]Endogenous variable. The assignment change instruments: the projected change between 1988 and 1992 in the total number of student-age SEA refugees, the projected number of female SEA refugees aged 34-50, and the projected number of SEA female refugees aged 34-50 with a high school degree or above based on the initial assigned county locations of the SEA refugees since 1975. The lagged assignment instruments include the panel first-year projected total numbers in the three groups based on the initial assigned county locations of the SEA refugees since 1975. The shift-share instrument multiplies the county shares of the three groups of SEA refugees in 1975 by the change in the total number of SEA refugees between 1988 and 1992. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88/92), "Baseline and Second Follow-up, Student, School, and Parent Survey, 1988 and 1992."

Table 8
Student and Commuting-Zone Fixed Effect OLS and Fixed Effect IV Estimates:
The Effects of Student-Age Southeast Asian Refugees by Background in the County on
High Family Background Native-born Student Standardized Math and English Test Scores:
NELS 1988-1992 Panel

Instrumental variable type	Change in Assigments	Lagged Assignments	Shift-Share	OLS
Total number of SEA refugee students (NSEA) in the county[a]	0.000102 (0.000099)	0.000159 (0.000091)	0.0000646 (0.000104)	0.000579 (0.000794)
Number of SEA refugee students with high background in the county (NSEAH)[a]	-0.000977 (0.000325)	-0.00101 (0.000521)	-0.000888 (0.000496)	-0.000939 (0.000323)
Family income (x10^{-6})	-0.131 (0.350)	-0.131 (0.350)	-0.130 (0.349)	-0.133 (0.368)
NSEA + NSEAH	-0.000875 (0.000305)	-0.000856 (0.000496)	-0.000823 (0.000530)	-0.000881 (0.000306)
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	34.9 [0.000]	14.3 [0.003]	8.83 [0.012]	-
Kleibergen-Paap Wald F (weak identification) [5% relative bias critical value 11.04]	53.9	3.94	8.95	-
Hansen J $\chi^2(1)$	0.962 [0.62]	0.693 [0.71]	1.07 [0.30]	-
Endogeneity test $\chi^2(2)$	1.58 [0.454]	4.46 [0.107]	0.054 [0.974]	-
Number of students	1,190	1,190	1,190	1,190
Number of clusters	170	170	170	170

Standard errors clustered at the FIPS county level and year in parentheses. Control variables in columns 2 and 3 also include: the student-teacher ratio and the population size in the school's zip code. County fixed effects are in all specifications. Native-born students in the High group have both a father and mother with at least some schooling beyond high school and are in the upper half of the SES categories. [a]Endogenous variable. The assignment change instruments include the projected change between 1988 and 1992 in the total number of student-age SEA refugees, the projected number of female SEA refugees aged 34-50, and the projected number of SEA female refugees aged 34-50 with a high school degree or above based on the initial assigned county locations of the SEA refugees since 1975. The lagged assignment instruments include the panel first-year projected total numbers in the three groups based on the initial assigned county locations of the SEA refugees since 1975. The shift-share instrument multiplies the county shares of the three groups of SEA refugees in 1975 by the change in the total number of SEA refugees between 1988 and 1992. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88/92), "Baseline and Second Follow-up, Student, School, and Parent Survey, 1988 and 1992."

Table 9
Student, Commuting Zone and School Fixed-Effect and IV-FE Estimates
of the Effects of Southeast Asian Refugee Students by Background
on Strong Native-born Student Standardized Math and English Test Scores:
NELS:88 Panel 1990-92, Students in the Same School in Both Years

Variable/Estimation procedure	FE-IV	FE	FE	FE-IV
Total number of county SEA refugee students (NSEA) x10^{-3}	0.0174[a] (0.0110)	0.0175 (0.0101)	0.0187 (0.0108)	0.0181 (0.0100)
Number of SEA county refugee students with high background (NSEAH) x10^{-3}	-0.372[a] (0.0982)	-0.406 (0.0894)	-0.396 (0.0972)	-0.401 (0.0900)
Lagged Z-score	-	-	-0.158 (0.0270)	-0.0850[b] (0.126)
NSEA + NSEAH x10^{-3}	-0.354 (0.0924)	-0.388 (0.0869)	-0.378 (0.0941)	-0.382 (0.0873)
FE commuting zone	Y	Y	Y	Y
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	16.6 [0.001]	-	-	12.6 [0.014]
Kleibergen-Paap Wald F (weak identification) [10% 10.3]	193.9	-	-	7.28
Hansen J $\chi^2(1)$	1.81 [0.40]	-	-	1.83 [0.61]
Endogeneity test $\chi^2(2)$	1.75 [0.25]	-	-	0.057 [0.81]
Number of students	1,560	1,560	1,560	1,560
Number of clusters	190	190	190	190

Standard errors clustered at the FIPS county level in parentheses. Native-born students in the Strong group have both a father and mother with at least some schooling beyond high school and are in the upper half of the SES categories. [a]Endogenous variable. Instruments include the number of projected SEA refugees aged 15-17 in 1990 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1990 in the FIPS county, and the number of SEA refugee women aged 38-56 with at least a high-school degree in 1990 in the FIPS county based on the SEA refugees originally assigned to the county since 1975. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88/88/90/92), "Baseline, First and Second Follow-up, Student, School, and Parent Survey, 1988, 1990 and 1992."

Table 10
Peer Effects and the Production of Achievement, by Native-Born Student Type and Refugee Student Aggregation
The Dependent Variable is the Standardized Combined Math and Test Score of 8th-Graders

Native-born student group	Strong			Weak		
Sample/variable	School-level, All NELS Counties	County-level, IPUMS Counties		School-level, All NELS Counties	County-level, IPUMS Counties	
Total number of SEA eighth-grade refugee students[a]	0.0338 (0.0289)	0.0000895 (0.0000609)	0.0000372 (0.0000671)	-0.130 (0.088)	-0.000157 (0.000061)	-0000922 (0.0000534)
Number of SEA refugee students, high background[a]	-0.01865 (0.372)	-0.000248 (0.000257)	-0.000136 (0.000270)	0.111 (0.352)	0.000359 (0.000282)	0.000115 (0.000231)
Test joint significance of refugee variables $\chi^2(2)$	1.37 [0.504]	4.43 [0.109]	0.31 [0.856]	2.57 [0.276]	22.1 [0.000]	16.8 [0.000]
Homework time[a]	0.0617 (0.00933)	0.0690 (0.0135)	0.0612 (0.0125)	0.0546 (0.0128)	0.0893 (0.0152)	0.0850 (0.0147)
Skip classes[a]	-0.639 (0.218)	-1.07 (0.345)	-1.39 (0.356)	-0.156 (0.212)	0.183 (0.319)	0.205 (0.313)
Incurred personal disruption[a]	-0.430 (0.118)	-0.274 (0.175)	-0.246 (0.172)	-0.105 (0.119)	0.0215 (0.156)	0.100 (0.162)
Tutor for exams	-	-	1.03 (0.321)	-	-	0.346 (0.548)
Parent limits TV watching often	-	-	0.544 (0.180)	-	-	-0.827 (0.252)
Parent checks homework often	-	-	-0.178 (0.179)	-	-	0.0945 (0.178)
Endogeneity test F	4.71(5,559) [0.000]	2.98(5,247) [0.012]	6.93(8,247) [0.000]	1.27(5,612) [0.276]	4.26(5,253) (0.001)	3.82(8,253) [0.000]
Number of students	5,040	3,440	3,430	8,790	5,230	5,200
Number of clusters	560	250	250	610	250	250

Standard errors clustered at the FIPS county level in parentheses. Control variables include student race, age, and gender and school variables: 8th-grade enrollment size, public school, selective school, and the school teacher-student ratio.

[a]Endogenous variable. Instruments include parental income, the median housing value in the county, fraction of the county urban, county population size, commuting-zone fixed effects, and the projected county-level number of SEA refugees aged 13-15, the projected 1988 county-level number of SEA refugees in the United States for at least 10 years, and the projected 1988 county-level number of SEA refugee women aged 36-54 with at least a high-school degree based on the SEA refugees originally assigned to each county since 1975. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, and Parent Survey, 1988."

Appendix Table A1
LIML IV Estimates of the Effects of Southeast Asian Refugee Students by Background on the Number of Classroom Hours Teaching Separate Groups: NELS:88 Baseline (8th-grade)

Variable	Separating Classroom Hours
Total number of SEA 12th-grade refugee students (NSEA)[a]	0.311 (0.252)
Number of SEA 12th-grade refugee students with high background (NSEAH)[a]	-0.226 (0.498)
NSEA + NSEAH	0.0850 (0.434)
Commuting zone controls	Y
Test joint significance of NSEA and NSEAH $\chi^2(2)$	1.55 [0.46]
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	5.39 [0.068]
Kleibergen-Paap Wald F (weak identification) [10% bias critical value 5.44]	14.8
Hansen *J* $\chi^2(1)$	0.24 [0.48]
Endogeneity test $\chi^2(2)$	1.20 [0.55]
Number of observations	16,340
Number of clusters	670

Standard errors clustered at the FIPS county level in parentheses. Specification is the same as in Table 1. Instruments include the number of SEA refugees aged 13-15 in 1988 in the FIPS county, the number of SEA refugees in the United States for at least 10 years in 1988 in the FIPS county, and the number of SEA refugee women aged 35-54 with at least a high-school degree in 1988 in the FIPS county based on the SEA refugees originally assigned to the county since 1975.
SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, Teacher, and Parent Survey, 1988."

Appendix Table A2
LIML IV Estimates of the Effects of Southeast Asian Refugee Students in the County by Background on the Standardized Test Scores of and Homework Time and Class Skipping by Strong-background Native-born Students: 1988 NELS Baseline IPUMS Census Counties

Dependent variable	Z-score	Homework	Skip classes
Total number of SEA eighth-grade refugee students in the county (NSEA)[a]	0.00020 (0.0000619)	0.000740 (0.000338)	-0.0000811 (0.0000129)
Number SEA high-background refugee students in the county (NSEAH)[a]	-0.0007683 (0.000369)	-0.00358 (0.00222)	0.000452 (0.000104)
Family income (x10^{-6})	0.984 (0.144)	2.98 (0.981)	0.0153 (0.0564)
Female	0.0672 (0.0323)	0.396 (0.193)	-0.0160 (0.00795)
NSEA + NSEAH	-0.000568 (0.000330)	-0.00284 (0.00204)	0.000371 (0.0000963)
FE commuting zone	Y	Y	Y
Kleibergen-Paap LM $\chi^2(2)$ (underidentification)	15.3 [0.001]	15.3 [0.001]	15.5 [0.000]
Kleibergen-Paap Wald F (weak identification) [10% bias 5.44]	33.0	32.6	33.1
Number of students	3,680	3,540	3,610
Number of clusters	250	250	630

Standard errors clustered at the FIPS county level in parentheses. Control variables are the same as in Table 2.
[a]Endogenous variable. Instruments include the 1988 county-level number of SEA refugees aged 13-15, the 1988 county-level number of SEA refugees in the United States for at least 10 years, and the 1988 county-level number of SEA refugee women aged 36-54 with at least a high-school degree based on the SEA refugees originally assigned to the county since 1975. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, and Parent Survey, 1988."

Appendix Table A3

Robust, Cluster-Adjusted First-stage F-statistics of the Set of Excluded Instruments for the Test Score Production Function, by Endogenous Input Variable, Student Group and SEA Refugee Student Aggregation

	Strong Native-born		Weak Native-born	
Variable/group	School-level SEA students	County-level SEA students	School-level SEA students	County-level SEA students
Total SEA students	19462	1237	15724	1133
High-backgound SEA students	13123	71.0	6.49	2040
Homework time	638.6	207.9	4965	4071
Skip classes	169460	1828	3998	792.3
Personal disruption	164.3	583.1	927.7	304.7

The instruments are the projected county number of 8th-grade SEA refugee students, high-school educated maternal-age SEA refugee women, and SEA refugees residing in the US for at least 10 years based on their initial assigned county locations; the county population size, the percent of the county that is urbanized, county median housing value, parent income, and commuting-zone dummy variables. SOURCE: U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS:88), "Baseline, Student, School, and Parent Survey, 1988."