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Testing the Convergence Hypothesis in Immigrant Academic Achievement: A Longitudinal Analysis

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Abstract

Based on a model of human capital accumulation, we study convergence in academic achievement of native-born and immigrant students. The model captures the idea that human capital accumulation is a dynamic process depending on cognitive achievement accumulated at previous stages of a student's academic life. This theoretical formalization provides a framework for the empirical analysis of dynamic trajectories of academic performance. We find that foreign-born students start at lower levels of performance in reading and higher levels of performance in math. Foreign-born students catch up in reading and converge to a higher long run level of performance, however. The nativity gap does not fade in time. The theoretical model allows us to predict that foreign-born will converge to higher achievement levels across all ethnicities. This process is slow and convergence takes 14-15 years. Once we add student fixed effects the results are unchanged, the convergence speed reduces however to 1.5-2 years.

1 Introduction

Immigrants are good for U.S. schools, especially in the specific central cities where they settle. For example, while Detroit, Cleveland and Baltimore schools are losing students and closing facilities, New York City's public school population has been growing or stable over the last ten years, due in part to the influx of immigrants and their native-born siblings. (Education Week, 2005; Council of Great City Schools, 2005). In addition, at any point in time, researchers generally find that immigrants outperform native-born students and thus bring up the school district average performance, a valued outcome in the era of educational accountability standards such as those written into the federal No Child Left Behind legislation of 2001. Nevertheless, some ethnographers and prominent scholars warn that this good news may be short-lived. In 2001, Marcelo Suarez-Orozco wrote that "... among immigrants today, length of residence in the United States seems associated with declining health, school achievement and aspirations."(Suarez-Orozco, 2001) While the hypothesis that the superior academic performance of immigrant students 'disappears' with time in the U.S. - that is, immigrant performance converges to match the lower performance of native-born students - has intuitive appeal, relatively little quantitative research has examined this hypothesis. Further, there is a dearth of research that specifically examines the convergence hypothesis using a comparative, longitudinal design. This paper takes a step in that direction, investigating the disparity in performance on standardized tests between immigrant and native-born students - 'the nativity gap'- in New York City over time to find out if, indeed, the immigrant advantage fades.

In addition to the obvious negative outcome for immigrants of declining achievement, the question of immigrant performance over time is important for several reasons. There is some evidence that test scores exert an independent effect on earnings; if performance of immigrant students worsens over time, those students will fare less well in the labor market and possibly be less productive as well (Neal and Johnson, 1996; Murnane et al., 1995; Joensen and Nielsen, 2009) . In addition, the potential for immigrants to exert positive peer effects will be transitory if only recent immigrants outperform native-born students. Finally, convergence downward will contribute yet another challenge for urban districts to overcome, adding to an already full agenda. Thus the question addressed in this paper - what is the time path of immigrant performance - is important to both future labor market productivity and current resource demands.

We make use of a panel of individual-level data on third through eighth graders, who remain in New York City public schools and proceed one year at a time (roughly 34,000 students in each year) over a six year period beginning in 1995-96, tracking the students as they move through grades and schools. The centerpiece of our research is a student-level model of education performance that reinterprets the convergence hypothesis in terms of the Solow growth model. The intent is to estimate the dependence of the time path of academic performance on initial levels of achievement and to consider the evidence for 'convergence' to the native-born academic performance.

Our results suggest that immigrants do not converge to the academic achievement of their native-born peers. Furthermore, the better performance of foreign-born students is not determined by the ethnic composition of this group. By ethnicity, foreign-born students maintain their advantage through time and perform better compared to the native-born students of the same ethnic group.

2 Literature Review on Immigrant Academic Assimilation

Two different perspectives have been raised in the literature on immigrant assimilation. The first is the possibility that assimilation is a natural process by which immigrants adapt to the host country culture and reach economic outcomes similar to the natives (*straight-line assimilation*). The second allows for different patterns of assimilation that depend on a wide range of ethnic, cultural and socio-economic factors (*segmented assimilation*).

From the broad literature on immigrant assimilation, we briefly review quantitative analyses of elementary and secondary school performance. The first characteristic shared by these studies is the comparison of student academic performance across generations. The second shared characteristics is that evidence of a significant impact of years in the U.S. and ethnicity on performance is usually interpreted to mean that immigrant academic performance depends on the 'context of acceptance '. In other words, sometimes the 'context of acceptance' is invoked as the reason behind this segmented assimilation.

For example, Kao and Tienda (1995) in a study of 8th grade students using National Educational Longitudinal Survey data (NELS-88), compare the academic performance of first and second-generation immigrants and native-born third and higher generation students. They find that immigrants of both first and second generations outperform native-born students. This finding holds for Asians, Hispanic and black students, although which generation (first or second) scores highest varies across race/ethnicities. Kao (1999) turns to psychological well-being and educational achievement, again using NELS-88, and again finds a pattern of better academic performance of immigrants versus native-born students, across all racial groups, with especially strong results for blacks and Asians. A study by Portes and MacLeod (1996) of 8th and 9th grade children of immigrants in Florida and California finds that family and school socio-economic status affect test score achievement, but that the particular origin of the immigrant parent(s) exerts an independent effect as well. The authors associate differences across national origins – early Cuban as well as Vietnamese immigrants exhibit higher academic achievement compared to Haitian, Mexican and later Cuban immigrants – to differences in the context in which the immigrant group was incorporated into the U.S. (welcomed political refugee or discriminated economic immigrant). They also find some evidence that second generation "disadvantaged"immigrants in inner cities perform about the same as native-born students.

Glick and White (2003) employ production function theory, which makes explicit the importance of school resources and past performance as control variables in order to ensure unbiased estimates of how being an immigrant matters to the way schooling affects performance. They use High School and Beyond (HSB) and NELS data to look at the assimilation of high school students in two different cohorts (1980 and 1990), over generations of immigrants. They find that the effect of an immigrant's generation on "baseline"(i.e. level) scores is statistically and substantively significant, but that the effect on "trajectories"or value-added scores almost disappears. More specifically, they report that for baseline scores, 10th grade immigrants in 1980 performed worse that third or later generation native-born pupils, but in 1990 immigrants out-performed native-born students. On the other hand, immigrant status made no difference in either decade for scores that controlled for past performance (trajectories in the authors' parlance).

In summary, the evidence across studies on the whether immigrants perform better or worse than native-born students over time is mixed. When using levels of scores, immigrants sometimes outperform natives. Studies that use value added scores find that the positive effect of immigration is often eliminated. When the country or region of the world from which the student migrated can be identified, there are, again, mixed results and the segmented version or at least a more nuanced version of the time path of immigrant performance emerges.

The problem of convergence has not only been a concern in the study of academic achievement but has received considerable attention in the area of economic growth as well. Cross-country convergence has long been debated in macroeconomics, since the seminal studies by Solow (1956) and Swan (1956). In this area, empirical work has focused on whether poor countries tend to grow faster than rich countries and therefore catch up in terms of income levels. The terminology of straight-line convergence translates here into absolute convergence. Under absolute convergence all countries are predicted to converge to some common level of economic output, in a similar way as immigrants are predicted to converge to native-born academic achievement. Segmented convergence, instead, has some common features with the concept of conditional convergence. The latter predicts that differences in income levels are due to the economic fundamentals and not to initial conditions. For this reason, independently of the initial level of output, countries that share the same institutions and production technology will converge to a similar long run level of output. In studying academic achievement, this translates into the role that ethnicity and socioeconomic status have on long run performance.

Our study differs from the previous literature in the approach used and in the data employed. First, the similarities between the concepts developed in economic growth and in the education literature suggest that the neoclassical growth model might constitute a natural starting point for the study of human capital accumulation and convergence across individuals with different starting levels of cognitive achievement, such as native-born and immigrant. Human capital can be conceptualized as being produced using cognitive achievement in the same way as output is produced using capital. The quest for the evolution of the 'nativity gap' can be translated therefore to the quest for the nature of convergence in academic achievement across all individuals or across groups of individuals using the techniques developed in the growth literature. We construct a structural model of human capital accumulation and cognitive achievement development and we employ it to analyze convergence. Second, we address academic convergence of the first generation of immigrants. The data used in the analysis collect information on foreign-born and native-born student performance, demographic and economic characteristics in third through eight grade.

3 The Solow Model Revisited

In this section we present a model of human capital and cognitive achievement evolution. This framework is used to rethink models of convergence in academic achievement.

Much of the economic analysis of education outcomes relies on the concept of an education production function (Hanushek, 1979): cognitive achievement is produced with inputs such as school and family resources. Often the literature has focused on explaining achievement at a particular point in time as a function of resources used at that point in time. The need to account for the cumulative nature of achievement in absence of data on the entire histories of resources used has induced the literature to use past achievement values as a proxy for these histories. Todd and Wolpin (2003) show conceptually how different specifications of education production functions used in empirical work can be derived from different assumptions about the way in which the history in the past resources are transformed into achievement.

Our analysis builds on the education production function literature, with two main contributions. First, we distinguish between human capital production and cognitive achievement production. Second, the model is dynamic, that is we study the change in human capital and cognitive achievement over time.

The interest of both individuals and policy makers in education is due in large part to the role that human capital plays in the production of economic value. From a microeconomic perspective, human capital is directly related to earnings (Mincer, 1974). From a macroeconomic perspective, human capital enters the aggregate production function of a country and is a determinant of GDP (Hanushek and Woessmann, 2008). It is standard to view human capital as being determined by many factors, including family and school resources and individual ability.

In this paper we indicate with $H_{ij}(t)$ the stock of human capital obtained by individual i in school j at time t. We indicate with $R_{ij}(t)$ the vector of resources used in the production of human capital and with $A_i(t)$ an individual's ability. Further, in our model, human capital is produced using cognitive achievement (and not proxied by it). Intuitively, additions to cognitive achievement give the individual new skills that can be used in the production of human capital. For example, a third grader might be required to know the year the Declaration of Independence was signed. The process of acquiring this knowledge in turn requires the acquisition of particular skills that result in the formation of human capital, such as the ability to acquire, use and retain relevant information. Even though cognitive achievement and human capital move together, they are conceptually distinct. We indicate with $K_{ij}(t)$ the stock of cognitive achievement of individual i in school j at time t. To summarize, human capital is a function of cognitive achievement, family and school resources and individual ability:

$$H_{ij}(t) = f\Big(K_{ij}(t), R_{ij}(t), A_i(t)\Big).$$

For simplicity, we assume that the human capital production function takes the specific form:

$$H_{ij}(t) = A_i R_{ij} f\Big(K_{ij}(t)\Big), \tag{1}$$

where $f(\cdot)$ satisfies the Inada conditions[1] and exhibits decreasing returns to scale and, for purpose of the convergence analysis, note that A_i and R_{ij} (ability and resources) are fixed over time.

Two observations are worth noting. First, the literature has often treated cognitive achievement as a proxy for human capital subject to measurement error. In other words, cognitive achievement is treated as a direct measure of human capital. Our approach is different in that human capital is a *function of* cognitive achievement, but not necessarily a direct function. Instead, human capital formation may involve other variables and/or may be a nonlinear function of cognitive achievement. Second, in our formulation both individual ability and resources are exogenously fixed. This differs from the treatment in Todd and Wolpin (2003), where the authors assume that resources evolve as functions of cognitive achievement, permanent wealth and optimal decision rules set by parents and principals.

As noted, the second contribution of the analysis is the introduction of dynamic behavior of

[1] $f(0) = 0, \quad f'(K) > 0, \quad f''(K) < 0, \quad \lim_{K\to 0} f(k) = \infty, \quad \lim_{K\to\infty} f(k) = 0.$

human capital and knowledge formation. Since ability and resources are set to be exogenously fixed, the dynamic evolution of human capital is completely determined by the dynamic behavior of the remaining independent variable, cognitive achievement $(K_{ij}(t))$. Note that future analysis may fruitfully modify these fixed variables. We return to this in the results section. In the model we present, not only is the stock of human capital closely related to the stock of cognitive achievement, but also its evolution is directly linked to the evolution of academic performance.

What are the determinants of cognitive development? First, we postulate that the evolution of cognitive achievement is a function of the investment in human capital undertaken at time t. Continuing the previous example, once the third grader learns the year of the Declaration of Independence, he might have learned also how to select important information in a book. This investment in human capital in third grade is used in fourth grade for understanding more advanced texts, although the actual knowledge of an important date does not directly affect new cognitive achievement. Part of the skills acquired through time turn obsolete, however due to competencies that become inappropriate with time or competencies that the individual forgets and this has a negative effect on the evolution of cognitive achievement. We indicate the instantaneous change in cognitive achievement for individual i in school j at time t with $\dot{K}_{ij}(t)$. Then $\dot{K}_{ij}(t)$ is derived from the present stock of human capital $H_{ij}(t)$ at rate s: $sH_{ij}(t)$. In addition, the evolution of cognitive achievement is partially offset by the changes due to depreciation of the previous stock of knowledge at rate δ: $\delta K_{ij}(t)$. Thus cognitive achievement changes as it is added to from previous human capital and subtracted from by depreciation of previous knowledge, or:

$$\dot{K}_{ij}(t) = sH_{ij}(t) - \delta K_{ij}(t) = sA_i R_{ij} f\Big(K_{ij}(t)\Big) - \delta K_{ij}(t). \tag{2}$$

This equation is not new in the literature. Todd and Wolpin (2003) present a version of it, which in our notation would be written as $\dot{K}_{ij}(t) = f_t\Big(R(t), A_i\Big)$, where $R(t) = R_t\Big(K(t), W, A_i\Big)$ and W represents family's permanent resources. Compared to Todd and Wolpin, we assume that resources are exogenously fixed (i.e. do not change over time) and we impose a linear and multiplicative structure to the way in which resources enter the production function. These assumptions are kept throughout the paper. We will see, however, how this model still translates into the most common empirical regression functions used to estimate the education production function.

The model presented is a redefinition of the Solow growth model (Solow, 1956; Swan, 1956), where the production of output is now production of human capital and the main input is cognitive achievement. Figure 1 gives a graphical representation of the model

The Figure shows how cognitive achievement determines the stock of human capital. Knowledge will grow as long as the investment in human capital is 'profitable', i.e. additions to knowledge are not smaller than depreciation of knowledge. The optimal level of cognitive achievement is represented by K^*_{ij}. When K^*_{ij} is reached, the growth rate of cognitive achievement is zero and beyond K^*_{ij} the growth rate of cognitive achievement is negative. When cognitive achievement equals K^*_{ij} human capital no longer evolves over time. Let K^*_{ij} and H^*_{ij} denote the *steady state* values of knowledge and human capital obtained once cognitive achievement and human capital are not evolving. In other words, K^*_{ij} is the level of knowledge at which $\dot{K}_{ij}(t) = 0$ and similarly H^*_{ij} is the level of knowledge at which $\dot{H}_{ij}(t) = 0$. The steady state values can be interpreted

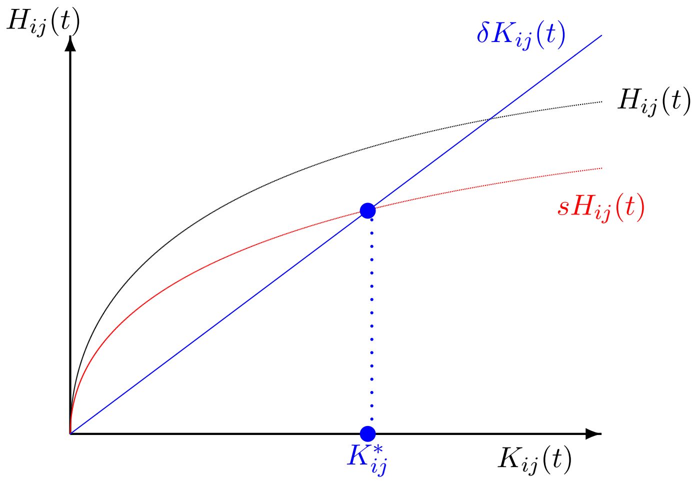

Figure 1: Graphical representation of the Solow model, where K^*_{ij} is the steady state level of cognitive achievement.

as the total amount of human capital and knowledge accumulated through investment in education but also through all those investments in human capital that form the individual ability to perform labor and produce economic value.

To fix ideas, if we assume that $f\Big(K_{ij}(t)\Big) = K^{\alpha}_{ij}(t)$, the steady state value of cognitive achievement is:

$$K^*_{ij} = \Big(\frac{sR_{ij}A_i}{\delta}\Big)^{\frac{1}{1-\alpha}}, \tag{3}$$

and the steady state of human capital is:

$$H^*_{ij} = \Big(\frac{sR_{ij}A_i}{\delta}\Big)^{\frac{\alpha}{1-\alpha}}. \tag{4}$$

Equations 3-4 show how resources and individual ability have a positive impact on the steady state values of cognitive achievement and human capital.

Due to the properties of $f(\cdot)$, s, and δ, the Solow model represented with equation 1 and 2 predicts that individuals with lower initial cognitive achievement will have faster growth rates compared to individual with higher initial cognitive achievement. Graphically this can be shown noticing that the growth rate of cognitive achievement is given by the vertical distance between the human capital investment ($sH_{ij}(t)$) and the depreciation of cognitive achievement ($\delta K_{ij}(t)$). The assumptions on $f(\cdot)$ guarantee that this distance is reducing as cognitive achievement reaches its steady state value. Therefore, students with lower initial $K_{ij}(t)$ will have higher growth rates compared to students starting at higher achievement levels. Mathematically, it is a standard exercise to show that the percentage change in cognitive achievement is decreasing in the level of cognitive achievement.[2]

To assess the speed of convergence, i.e. the rate at which cognitive achievement evolves toward the steady state, one can linearize equation 2 around the steady state to achieve a more tractable version. Denoting the deviations from the respective steady state values as $\hat{K}$, the linearized equation takes the form:

$$\dot{\hat{K}}_{ij}(t) = -\lambda \hat{K}_{ij}(t), \tag{5}$$

where λ indicates the speed of convergence.[3]

The previous is a differential equation that has the solution:

$$\hat{K}_{ij}(t) = \hat{K}_{ij}(0)e^{-\lambda t} \tag{6}$$

Rewriting the previous equation in terms of level change instead of percentage change yields:

$$K_{ij}(t) - K_{ij}(0) = K_{ij}(0)(e^{-\lambda t} - 1) + (1 - e^{-\lambda t})K^*_{ij}. \tag{7}$$

Equation 7 is the fundamental equation in our analysis: it shows that the change in performance is inversely related to initial achievement.

A similar argument holds for the evolution of human capital:

$$\dot{H}_{ij}(t) = A_i R_{ij} f'(K_{ij}(t))\Big[\dot{K}_{ij}(t)\Big] \tag{8}$$

After linearizing around the steady state, human capital converges to its steady state value according to (see Appendix on page 18):

$$\dot{\hat{H}}_{ij}(t) = -\lambda A_i R_{ij} \hat{H}_{ij}(t)$$

Given that R_{ij} and A_i are fixed, human capital and cognitive achievement evolve at proportional speed until they reach the steady state. Therefore, any statement on the speed of convergence of cognitive achievement will hold also for the speed of convergence of human capital. This sheds light on why we are interested in both variables. First, there is a close relationship between human capital and productivity. Given the explained relationship between human capital and

[2]In other words;

$$\frac{\partial \dot{K}_{ij}(t)/K_{ij}(t)}{\partial K_{ij}(t)} < 0.$$

[3]From equation 2, the evolution of cognitive achievement is a function of the level of achievement, i.e. $\dot{K}_{ij}(t) = \dot{K}_{ij}(K_{ij})$. Since in steady state $\dot{K}_{ij} = 0$, then a first order Taylor series approximation of $\dot{K}_{ij}(K_{ij})$ around $K_{ij}(t) = K^*_{ij}$ yields:

$$\dot{\hat{K}}_{ij}(t) \simeq \Big[\frac{\partial \dot{K}_{ij}(K_{ij})}{\partial K_{ij}(t)}\Big|_{K_{ij}(t)=K^*_{ij}}\Big]\hat{K}_{ij}(t).$$

where

$$\frac{\partial \dot{K}_{ij}(K_{ij})}{\partial K_{ij}(t)}\Big|_{K_{ij}(t)=K^*_{ij}} = \delta - sA_iR_{ij}f'\Big(K_{ij}(t)\Big) = \delta - \delta\frac{K^*_{ij}}{f(K^*_{ij})}f'\Big(K_{ij}(t)\Big) = -(1-\eta)\delta = -\lambda.$$

Here η is the elasticity of human capital with respect to cognitive achievement and $\lambda > 0$.

cognitive achievement, we are able to link theoretically the relevance of cognitive achievement to productivity and labor market outcomes. While our model gives theoretical justification to such a relationship, work by Murnane et al. (Murnane et al., 1995; Tyler et al., 1999) and recently by Joensen and Nielsen (2009) has explored the empirical validity of this link. Second, since human capital is a latent variable it is often difficult to make any statement about its dynamic behavior. Standard work in the literature has used schooling as an approximation. We are able to show that although human capital is not directly observable, it evolves in the same way as cognitive achievement. Therefore, studying cognitive achievement will also provide information on how human capital is produced and behaves over time. In sum, although the rest of the analysis focuses on measures of the evolution of cognitive achievement, the theoretical model presented allows us to generalize any statement on cognitive achievement to human capital behavior.

4 From Theory to Empirics

Equation 7 can be transformed into an empirical specification that tests for convergence in cognitive achievement across individuals. Note that cognitive achievement is measured by test performance. Let $TS_{ij}(t)$ be the test score of individual i in school j at time t. Then substituting $T_{ij}(t)$ for $K_{ij}(t)$, yields:

$$TS_{ij}(t) - TS_{ij}(0) = \beta_0 + \beta_1 TS_{ij}(0) + \epsilon_{ij}(t), \tag{9}$$

where $\beta_0 = (1 - e^{-\lambda t})K^*_{ij}$, $\beta_1 = (e^{-\lambda t} - 1)$ and the disturbance is assumed to be white noise. The fundamental parameter in the study of convergence is β_1, which determines the speed of adjustment towards the steady state A positive value of this parameter will indicate divergence, while a negative value will indicate convergence across students. Intuitively, if initial test scores are inversely related to the growth rate, students will converge to some common level of achievement. The type of convergence represented in equation 9 is called *absolute convergence* in growth theory and has a similar interpretation to the *straight-line* assimilation theory. Here β_0 represents the common steady state achievement value reached by all individuals in the long run.

Absolute convergence relies on the assumption that all variables that determine the steady state value of cognitive achievement are the same across individuals. Clearly, this is not only counterintuitive but also inconsistent with the theory. In fact, K^*_{ij} is implicitly defined by the equation $sA_iR_{ij}f(K^*_{ij}) = \delta K^*_{ij}$ and for this reason is a function of the fundamental variables in the model. To make explicit the role of resources, ability and production function parameters, we can rewrite equation 7 as:

$$K_{ij}(t) - K_{ij}(0) = K_{ij}(0)(e^{-\lambda t} - 1) + (1 - e^{-\lambda t})K^*_{ij}(s, \delta, A_i, R_{ij}) \tag{10}$$

The estimating equation that comes out of equation 10 is:

$$TS_{ij}(t) - TS_{ij}(0) = \beta_0 + \beta_1 TS_{ij}(0) + \beta_2 X_{ij}(t) + \epsilon_{ij}(t), \tag{11}$$

where X a vector of demographic, socio-economic and school characteristics and $\beta_2 X$ is approximating $(1 - e^{-\lambda t})K^*_{ij}(s, \delta, A_i, R_{ij})$[4]. The significance of β_2 will indicate whether certain characteristics are working as shifters of the steady state value for students (and implicitly represent s, δ, A_i, R_{ij}). A test on the negativity of β_1 will indicate if individuals converge conditional on specific characteristics. This form of evolution is called *conditional convergence*. A graphical representation of conditional convergence is given in Figure 2. In the figure, individuals are grouped into two groups: the foreign-born have a 'high' value of s (s_{fb}) and the native-born have a 'low' value of s (s_{nb}). Only individuals who share the same inputs in the production of human capital (s, A, R, δ) will converge to the same steady state. Convergence is therefore conditional on certain characteristics and in the figure below foreign-born individuals will converge to higher levels of achievement and human capital.

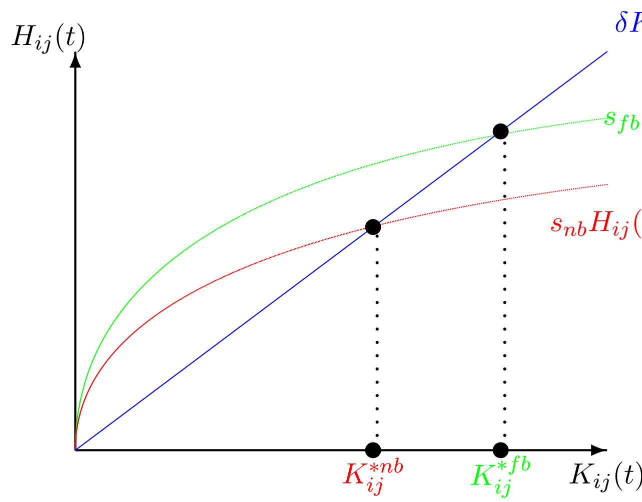

Figure 2: Graphical representation of conditional convergence

In sum, equation 9 is a test of the hypothesis that there is convergence to a common achievement level (straight-line assimilation), while equation 11 is a test of the hypothesis that convergence happens only inside nativity groups and therefore is subject to segmented assimilation.[5]

Two final observations are worth making. First, the theoretical model translates to an empirical specification that comes very close to the estimation of a value-added production function model. If the dynamic component of the model is the correct specification, however, then the dependent variable must be a change in test scores. A simple regression of $TS_{ij}(t)$ on $TS_{ij}(0)$ will not permit a correct interpretation of the parameter β_1. Further, the model is misspecified if the regression does not control for past performance. Second, we stress again that the results that hold for cognitive achievement will hold also for the evolution of human capital, other things being equal. Therefore, the convergence (if any) in academic achievement for foreign-born

[4]Note that we cannot directly measure either s or δ. We assume that the characteristics available capture also these two parameters.

[5]It has been argued (Allison, 1990; Becker, 2004; Becker et al., 1990; Becker and Salemi, 1977) that the regression of the change in test scores on the lagged test score gives biased estimates on β_1. To check if our results are biased, we run all models in levels, i.e. $TS_{ij}(t) = \gamma_0 + \gamma_1 TS_{ij}(0) + \epsilon_{ij}(t)$. In all regressions we failed to reject the null that $\gamma_1 = 1 + \beta_1$. We interpret this result as evidence of the absence of serious bias in the estimation of β_1. In order to be more consistent with the theoretical model, we present results for the regression reported in equation 9 and 11.

students should be followed by convergence in human capital accumulation. If we were able to follow students until their entrance in the labor market we would be able to observe if the relationship between cognitive achievement, human capital accumulation and wage determination is as expected.

5 The Data

Data on individual student socioeconomic, education and academic characteristics were provided by the New York City Department of Education (NYCDOE) for all students attending first through eighth grade in a New York City public school, for six consecutive schools years, 1995-96 through 2000-01. Students in full-time special education are excluded from our analyses because often they do not take citywide tests and because often their education programs differ from the rest of the students. School-level data were obtained from NYCDOE Annual School Reports (ASR) and School Based Expenditure Reports (SBER). Student performance on standardized tests is reported for a citywide test in reading (CTB/McGraw Hill Test of Basic Skills or New York State English Language Assessment) and mathematics (California Achievement Test or CAT or New York State Math Assessment) for third through eighth grade. To make tests scores comparable across grades and years, we convert them to standardized z-scores, with mean zero and standard deviation of one.

Our analyses focus on understanding the evolution of performance of the cohort of students attending third grade in 1995-96. We choose this group for two reasons. First, this is the first year for which we were able to obtain data and, second, third is the first grade for which standardized test-score data are available.

We further restrict the sample to the continuous test takers, in order to have all the data available on test scores. Because our data extends to 2000-01, we are able to construct a panel of students and follow them through the end of their primary school years, tracking performance of 33,870 students through the eighth grade. Table 1 provides descriptive statistics for the third graders in 1995-96.

More than 33 thousand third graders, nearly 4 thousand of whom were born outside of the United States, attended New York City public schools in 1995-96. New York City school children are ethnically and racially diverse - more than a third are black, more than a third are Hispanic, roughly a tenth are Asian and roughly 17% are white. Poverty is common - around 70% qualify for free lunch and another 8% for reduced price lunch. Many students - almost 40% - come from a home in which a language other than English is spoken; roughly 7% have taken the Language Assessment Battery (LAB) to assess their eligibility for programs to address Limited English Proficiency (LEP), and 5% do poorly enough to be LEP-eligible. The foreign-born and native-born populations differ from one another in several ways. The foreign-born are disproportionately Asian at nearly a third of the group, while blacks are far less common among the foreign-born- less than 25%. Unsurprisingly, most of the foreign-born students come from homes in which English is not the primary language (more than 64%) and around 8% are Limited English Proficient. With regard to academic performance, in reading the average test scores among foreign-born students fell slightly below the average test scores of the native-born students by about 0.03 standard deviation. In third grade, foreign-born outperform native-born students in math: the average test score of foreign-born in the CAT is 0.013 standard deviations higher than the average test score for native-born students.

Table 2 displays the average test score over time. The first two columns show the average test score in reading, while the fourth and fifth column show the average test score in math. The average changes are shown by nativity. In reading, foreign-born students perform worse than native-born students in 1996 but their average test score increases over time. On the contrary, the performance of native-born students deteriorates: for example, the average change in reading scores from 1997 compared to 1996 for native-born was a 0.096 decrease in the score compared to a stable test score for foreign-born. In math, foreign-born students perform better than native-born students in 1996 and maintain their advantage through time. These differences between foreign-born and native-born students performance are captured in columns 3 and 6 by the evolution of the nativity gap. On average, both in reading and in math, the nativity gap is increasing over time, due also to the increasingly poor performance of native-born. By 2001, in reading native-born students score on average 0.124 standard deviation below their original score in 1996, while foreign-born students score 0.155 standard deviations above their original score in 1996. The pattern of achievement in math is similar. This implies that the change in the nativity gap between 2001 and 1996 is as large as 0.278 standard deviations in reading and 0.289 standard deviations in math. Table 2 is indicative of the possibility that foreign-born are growing faster than native-born and, given the divergent behavior of the two groups, foreign-born and native-born students might be converging to different long run levels of achievement.

With Table 3 we descriptively inspect the possibility that foreign-born performance converges to the performance of their own ethnic group. The table shows the average reading and math scores by ethnicity and nativity. Also by ethnicity, foreign-born performance improves, while native-born performance decreases over time. The nativity gaps persist over time. In most cases, foreign-born students start at lower levels of performance, catch up with their peers and finally outperform them by 2001. Black and Asian students are an exception to this general trend. The nativity gap for Black students evolves in a non-linear way, although its positivity persists over time. The performance of Asian foreign-born students follows a non-linear path as well. Both in reading and in math, these students are improving through time, although in the last two years of school the average test scores decline, compared to the peak of achievement reached by fifth grade. Asian foreign-born students perform worse than Asian native-born students in all grades. The nativity gap for Asian students is negative. The change in achievement between 2001 and 1996 is higher for the foreign-born students than for the native-born students, however. This implies that although they start at lower levels of achievement they are growing faster and might eventually catch up with their peers. At last, it should be noted that the change in the nativity gap between 2001 and 1996 is small for Asian students compared to all other ethnicities.

There is some evidence that the evolution of academic performance is very different across nativity groups. Further, the disparities in cognitive development are persistent also looking at each ethnicity, with the exception of Asian students. This seems to suggest that foreign-born do not assimilate at the lower performance of native-born students and they do not converge to the performance of their own ethnic group. In the rest of this paper, we estimate the theoretical model presented earlier to analyze appropriately the evolution of cognitive achievement.

6 Empirical Results

We estimate the models in equations 9 and 11 using pooled OLS. The base year test score used is the z-score in reading and math in 1996. The final year test score used is the z-score in reading and math in 2001.

Results obtained from the estimation of equation 9 are presented in Table 4. The first column displays results for reading, the second column for math. In both reading and math the coefficient on the initial test score (third grade test score) is strongly negative and significant. This suggests that students with low initial achievement tend to grow faster and to 'catch up' with their peers who had higher initial scores. Therefore, under the assumption that all students share the same production technology and the same variables that affect the steady state, the model predicts that there is convergence across individuals to a common steady state level of cognitive achievement. Based on the structural model, using $t = 5$ and $\beta_1 = -(1 - \exp(-5\lambda))$, the first panel of Table 7 shows implications derived from the absolute convergence regression. The first two columns report the implied convergence speed (λ) in reading and math.[6] The model predicts that the rate at which the gap between actual achievement and long run achievement close is 6% in reading and 5.5% in math for each year. The third and fourth columns display the time (in years) it takes to move half way to the steady state,[7] which, given the convergence speed, is over 11 years in reading and over 12 years in math. In other words, the model predicts that convergence will not occur during the compulsory school period and differences in achievement are expected to persist over time. The last two columns of table 7 show the implied steady state achievement level by the regression,[8] which is a test score of -0.05 for reading and -0.054 for math.

As already discussed, a shortcoming associated with the absolute convergence model is the assumption of common production technology and inputs shared by all individuals. These characteristics are not likely to be the same as they are error prone proxies for resources, abilities s and δ. If this assumption is not satisfied, omitted variable bias is present in our estimate of β_1. Familial and individual characteristics are different across students and the education production literature has shown how they have a significant impact on cognitive achievement. For this reason, we estimate equation 11 to control for differences in production inputs and to determine if these characteristics also impact cognitive development. Table 5 reports the results from these regressions. We report results of three different models in both reading and math. The first model (column 1 and 4) uses a full set of demographic, socioeconomic, language and school characteristics but does not control for time fixed effects and school fixed effects. The second model (column 2 and 5) adds time fixed effects and the third model (column 3 and 6) adds school fixed effects. Across all models the coefficients on all regressors remain stable in magnitude and sign, indicating that the different specifications adopted are not substantially affecting the results. For this reason we discuss only the specification using the full set of regressors (column 3 and 6).

[6] These calculations are based on the regression with time effects.

[7] Calculation based on the fact that

$$\frac{K_{ij}(t_{0.5}) - K_{ij}^*}{K_{ij}(0) - K_{ij}^*} = 0.5 = e^{-\lambda t_{0.5}}$$

.

[8] Here we use the fact that $\beta_0 = (1 - e^{-\lambda t})K_{ij}^*$.

In column 3 and 6, the coefficient on the initial achievement level is negative and strongly significant, with an increased magnitude compared to the results on absolute convergence from Table 4. This indicates that the previous regression suffers from omitted variable bias. There are many regressors that have an impact on achievement change, some of which are reported in Table 5. For example, nativity, ethnicity, socio-economic status and gender, previously excluded from the regression, do play an important role in understanding achievement.

Second, the interpretation of the remaining coefficients is more meaningful when they are interpreted as proxy measures of the structural parameters A_i, R_{ij}, s, δ, which determine K^*_{ij} in equation 10. That is, significant coefficients can be interpreted as indicating characteristics that determine the steady state level of achievement.

Being a foreign-born individual positively affects the long run achievement level. In particular, the long run change in foreign-born achievement is 0.177 standard deviations higher in reading and 0.20 standard deviations higher in math compared to the change in achievement of native-born. In other words, a foreign-born low-performing student in 1996 will score in reading in 2001 0.177 standard deviations higher compared to the test score performance of a native-born peer who is equally low performing in 1996. For this reason a foreign-born student will converge to higher steady state value of achievement. The steady state value of cognitive achievement are affected by other characteristics, as well. Black students have lower achievement compared to white peers (the change in performance between 2001 and 1996 will be an 0.25 standard deviations decrease in reading and a 0.212 standard deviations decrease in math compared to white students). Asian students experience a 0.173 higher change in the 5 year time compared to white born peers in reading and improve their initial scores by 0.247 compared to white students in math. Hispanic students experience a negative change in test scores, with a decrease of 0.137 in reading and a decrease of 0.82 in math. Other important determinants of steady state achievement are gender, English proficiency and socioeconomic status. Females score higher in both reading and math (0.242 and 0.214). Interestingly, limited English proficiency does not have any impact in reading but has a positive impact on performance in math. For example, a native-born white individual who scores below the 40th percentile in the LAB and has low test score in 1996 will have a 0.396 higher test score in math in 2001 compared to a native-born white individual who scored above the 40th percentile in the LAB. Poverty has a negative impact on achievement. Individuals with reduced or free lunch reach a lower long run equilibrium compared to non-poor individuals (-0.211, -0.124 in reading and -0.154, -0.84 in math). At last, it should be noted that all the school fixed effects are individually and jointly significant at any standard significance level.[9] This implies that achievement is also determined by the school attended.

The significant effect of these observable characteristics indicates that convergence still occurs (as represented by the negative sign on past achievement) but individuals converge to specific steady state values depending on their demographic, socio-economic and school characteristics (as in Figure 2). The first two columns of the second panel of Table 7 show the speed at which ethnic groups converge to their respective steady state values. The gap between current achievement and long run achievement closes by 10% in reading and 9% in math in a five year span. This implies that it takes almost 7 years for these students to get half way to their long run achievement in reading and almost 8 years in math.

Table 5 indicates that foreign-born individuals converge to higher long run achievement com-

[9]The F-statistic is 52.34 in reading and 14.73 in math

pared to native-born or that convergence occurs conditional on nativity. The nativity gap captured by raw measures does not fade over time, based on the significant coefficient on the foreign-born indicator. But we might also ask if foreign-born students are converging to the same long run achievement within their own ethnicity. We have seen in Table 5 that ethnicity plays an important role in determining the long run achievement level of students. In reading, compared to white students, black and Hispanic students have a lower long run achievement by 0.25 and 0.137 standard deviations respectively, while Asian students perform better by 0.173 standard deviations. In math, compared to white students, black and Hispanic students have a lower long run achievement by 0.212 and 0.08 standard deviations respectively, while Asian students perform better by 0.247 standard deviations. The impact of ethnicity is never enough to reduce the positive impact of nativity, however. For example, consider a low performing white native-born and a low performing Asian foreign-born. Based on the results presented in columns 3 and 6 of Table 5, being foreign-born still pushes performance up, net of the negative effect associated with the specific ethnicity of the individual. The nativity advantage is reduced by 0.121 in reading and 0.154 in math compared to the nativity advantage experienced by foreign-born whites. These differences in cognitive development of Asian students have been captured also by the descriptive findings in Table 3 commented in the previous section. The regression analysis in Table 5 suggests that these differences are significant, however despite their lower performance, in the long run both black and Asian foreign-born students are predicted to converge to higher levels of achievement.

The last assessment on the possibility that foreign-born converge to their ethnic group is made in Table 6. Here we run the full model by ethnic group. This allows us to assume that each ethnic group faces a completely different achievement process, i.e. different coefficients in the production function. If foreign-born are indeed converging to a higher steady state value of achievement, the coefficient of the nativity indicator should be positive and significant, *ceteris paribus*. Table 6 displays results from this regressions (column 1 to 4 for reading and column 4 to 8 for math). In all cases foreign-born perform better compared to the native-born peers and therefore reach higher steady state values of performance. It should be noted that the lowest nativity advantage is experienced by Asian students, as we expected from the descriptive evidence in Table 3. Evidence of different steady state values reached by nativity and ethnicity is shown in Table 7. The last two column of Table 7 show the steady state level of achievement. We report the long run level of achievement for males, English proficient and not poor students of different nativity and ethnicities. As already highlighted, foreign-born maintain their advantage and across all ethnicities converge to higher values of performance.

We conclude that foreign-born outperform native-born and their advantage does not fade over time. Further, evidence from both pooled regressions and regressions by ethnicity suggest that foreign-born converge to higher levels of achievement and not to the level of achievement of their ethnicity. Student's long run performance is determined, however, by other factors as well, such as gender, socio-economic status, and the school the student attends.

A natural question is: why is there a nativity gap? The structural model implies the following answer: because of s, R_{ij}, A_i, δ and λ. In other words, foreign-born use a different production technology or different inputs. It is of particular interest if foreign-born grow at a different rate than native-born. In fact, the coefficient λ is a function of the previous parameters and of the human capital elasticity to cognitive achievement and human capital. Different λ across nativity groups indicate that foreign-born react more to changes in cognitive achievement, that is a positive increase in cognitive achievement will have a bigger impact on human capital accumulation. To show this we present results of conditional convergence by nativity in Table 8. The two convergence rates are statistically different from each other at 5% significance level.[10] The table is also informative on the role of ethnicity. While across native-born students ethnicity determines long run achievement, across foreign-born only being a black student affects the long run level of performance. All other ethnicities cannot be distinguished from white academic performance.[11]

7 Empirical Results: Students Innate Ability

Until now we have assumed that observable characteristics such as language spoken, socio-economic variables and school program participation (such as LEP) well captured the variables that determine the steady state, R_{ij}, A_i, s, δ. Although the previous regressors may be good representation of resources R_{ij}, s and δ, they do not necessarily well approximate innate ability as represented by the term A_i. To control for innate ability it is necessary to introduce student fixed effects.

To maintain the focus on the long run academic performance and still be able to estimate a model with fixed effects, we divide the data into four-year spans. We then use as dependent variable the difference between the the last year of the span and the first year of the span (Islam, 1995).[12] Since both nativity and ethnicity are time-invariant characteristics, the analysis of their impact on the long run achievement level of students in a student fixed effects model will be carried in the following way. To understand if the nativity gap fades over time, we estimate a model with the full set of time variant characteristics separately by nativity status. Similarly, to understand if foreign-born students converge to their ethnicity long-run achievement level, we run separate regressions by ethnicity. Although it is not possible to directly assess the role played by nativity as we did in the previous section, the constant term and the speed of convergence across nativity group are informative on the long-run achievement level of foreign-born students compared to native-born students as explained below.

Table 9 shows results for the regression by nativity with individual fixed effects (column 1 and 3 for native-born and column 2 and 4 for foreign-born). Overall, the introduction of the fixed effects does not invalidate the previous results of convergence by nativity. Students converge at a faster speed, however (-0.97 compared to a coefficient that never went beyond -0.43 in the previous section). This indicates that innate ability is positively related to initial achievement level and the analysis that excludes the student fixed effects from the regression is upward biased. The different intercepts between foreign-born and native-born students show the long run achievement level reached by the two groups, *ceteris paribus*. Further evidence is presented in the bottom panel of Table 7. Across nativity, it takes about a year to go half way to the steady state in reading for both foreign-born and native-born. In math, the half-times correspond to half a year for native-born students and around 9 months for foreign-born students. As already found in the previous section, foreign-born students are predicted to converge to higher level of achievement compared to native-born students in both reading and math (between 0.30 and

[10]The t-statistic is 1.88

[11]Note that this is not in contrast with the results in Table 5 since in that regression the reference group was being a white native-born student.

[12]Given the data, this implies that we have two observations per student, the difference between the test scores in 2001-1997 and in 2000-1996.

0.40 standard deviations higher).

Table 10 shows results for a regression with student fixed effects by nativity and ethnicity. This table sheds light on the possibility that foreign-born students converge to the performance level of their own ethnic group. The higher intercept that foreign-born students have indicate that there is convergence at higher level of performance also across ethnicities. The two exceptions are the academic achievement of Hispanic students in reading and the academic achievement of Asian foreign-born students in math. In these cases it seems that foreign-born students do not converge to statistically higher level of achievement. These results are confirmed by the last panel of Table 7. As before, the convergence speed is higher across all ethnicities and nativity groups compared to the pooled model results. This implies that the time it takes to get half way to the steady state is much less and goes from a minimum of 6 months (white native-born students in reading) to a maximum of a year and a half (black foreign-born students in reading). Across all ethnic groups foreign-born students outperform native-born students. Foreign-born Hispanic students in both reading and math and Asian students in math have a similar performance to native-born students.

To summarize, the introduction of the student fixed effects does not invalidate the previous results. On average the nativity gap does not fade over time. Foreign-born students catch up with their peers as in the case of Asian and Hispanics who start disadvantaged but converge in the long run to a similar achievement level. In case of other ethnicities like white and black, foreign-born students not only catch-up but converge to a higher level of performance. In general, ethnicity does not seem to play a fundamental role in the determination of long run cognitive achievement.

8 Conclusions

In the paper we have presented a framework to study the evolution of cognitive achievement and the theoretical impact that this has on human capital accumulation. The theoretical model provided a framework to study convergence in academic achievement of immigrants. We estimated a structural model of convergence using data on individual student socioeconomic, education and academic characteristics that were provided by the New York City Department of Education (NYCDOE) for all students attending third through eighth grade in a New York City public school, for six consecutive schools years, 1995-96 through 2000-01. Despite some pessimism in the literature on the possibility that the nativity gap fades over time, we find that immigrants maintain their advantage. Not only they do not assimilate downward, but they do not seem to converge also across ethnicity. We do not find evidence of segmented assimilation.

Clearly, more analysis is necessary. First, we have carried the analysis on a specific sub-sample of the data, the continuous test takers and have not corrected for sample selection. Second, we have not explained the reason of the existence and persistence of the nativity gap. We still need to open the black box to explore specifications of A_i, R_{ij}, δ and s.

A Convergence of Human Capital

Recall from equation 8 that human capital evolves according to: $\dot{H}_{ij}(t) = A_i R_{ij} f'(K_{ij}(t))\dot{K}_{ij}(t)$. For clearness, we omit the time dependence of the variables and all the subscripts. In what follows $\dot{H} = \dot{H}_{ij}(t)$, $A = A_i$, $R = R_{ij}$, $K = K_{ij}(t)$ and K^*, H^* indicate the steady state values of human capital and cognitive achievement.

Substituting equation 2 into equation 8 and expressing K as an implicit function of H, $K = K(H)$ yields:

$$\dot{H} = ARf'\Big(K(H)\Big)\Big[sARf\Big(K(H)\Big) - \delta K(H)\Big] = G(H)$$

A first-order Taylor expansion around the steady state gives:

$$\dot{\hat{H}} \simeq \Big[\frac{\partial \dot{G}(H)}{\partial H}\Big|_{H=H^*}\Big]\hat{H}$$

We need to calculate the partial derivative of $G(H)$ with respect to H, evaluated at the steady state value of human capital. By differentiating $G(H)$, we obtain:

$$\frac{\partial \dot{G}(H)}{\partial H}\Big|_{H=H^*} = AR\Big[sAR\Big(f''(K)f(K)K'(H)+f'(K)^2K'(H)\Big)-\delta\Big(f''(K)K'(H)K+f'(K)K'\Big)\Big]$$

Applying the inverse function theorem $K'(H) = 1/f'(K)$. Substituting into the previous equation yields:

$$\frac{\partial \dot{G}(H)}{\partial H}\Big|_{H=H^*} = AR\Big[sAR\Big(\frac{f''(K)f(K)}{f'(K)} + f'(K)\Big) - \delta\Big(\frac{f''(K)K}{f(K)} + 1\Big)\Big]$$

Rearrange terms to obtain:

$$\frac{\partial \dot{G}(H)}{\partial H}\Big|_{H=H^*} = AR\Big[\frac{f''(K)}{f'(K)}\Big(sARf(K) - \delta K\Big) + sARf'(K) - \delta\Big]$$

Since we are linearizing around the steady state $sARf(K) = \delta K$. This implies that $(sARf(K) - \delta K) = 0$ and that $sAR = \delta K/f(K)$. Therefore, the previous equation can be re-written as:

$$\frac{\partial \dot{G}(H)}{\partial H}\Big|_{H=H^*} = AR\Big[sARf'(K) - \delta\Big] = AR\Big[\frac{\delta K f'(K)}{f(K)} - \delta\Big] = -AR\lambda,$$

where $\lambda = \delta(1 - \eta)$ and η is the elasticity of human capital to cognitive achievement.

B Tables

Table 1: Mean Characteristics of 3rd grade students, Continuous Test Takers, 1995-1996 School Year

	All Students	Native-Born	Foreign-Born
White	0.215	0.216	0.207
Black	0.338	0.352	0.232
Asian	0.124	0.104	0.273
Hispanic	0.324	0.328	0.288
Female	0.531	0.533	0.519
Non-English Speaking at Home	0.393	0.360	0.647
Free Lunch	0.693	0.686	0.746
Reduced Lunch	0.081	0.080	0.092
Have Meal Data	0.963	0.961	0.980
Reading Z-Score	0.306	0.310	0.275
Math Z-Score	0.310	0.308	0.321
LAB percentile	2.279	1.877	5.361
Took the LAB	0.074	0.065	0.151
Limited English Proficient (LEP)	0.050	0.045	0.086
Observations	33,870	29,963	3,907
(%)	(100%)	(88.465%)	(11.535%)

Eligibility for free lunch is calculated only for students with non-missing data.
Foreign-born students are students not born on U.S. soil.
Limited English Proficient students are those students who score less than or equal to the 40th percentile on their Language Assessment Battery (LAB) exam.
Continuous test takers are those students in Standard Academic Progress cohort (students that progress one year at time) whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 2: Native-Born and Foreign-Born: Average Test Scores, over time

	Reading Score			Math Score		
Year	Native-Born	Foreign-Born	Nativity Gap	Native-Born	Foreign-Born	Nativity Gap
Year	Native Born	Foreign Born	Nativity Gap	Native Born	Foreign Born	Nativity Gap
1996	0.310	0.275	-0.035	0.308	0.321	0.013
1997	0.214	0.275	0.061	0.269	0.370	0.101
1998	0.222	0.356	0.134	0.238	0.389	0.150
1999	0.228	0.367	0.139	0.244	0.433	0.190
2000	0.201	0.396	0.195	0.214	0.442	0.228
2001	0.186	0.429	0.244	0.182	0.482	0.300
Change 2001-1996	-0.124	0.155	0.279	-0.126	0.162	0.288

The nativity gap is here defined as the difference in test scores between foreign-born and native-born.
The change in performance between 2001 and 1996 is calculated as the difference between the average test scores in 2001 and the average test score in 1996.
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress cohort (students that progress one year at time) whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 3: Native-Born and Foreign-Born Average Test Scores over Time, by Ethnicity

	White			Black			Hispanic			Asian		
	Natives	Foreigns	Nativity Gap	Natives	Foreigns	Nativity Gap	Natives	Foreigns	Nativity Gap	Natives	Foreigns	Nativity Gap
	Average Reading Score											
1996	0.707	0.562	-0.145	0.210	0.186	-0.025	0.098	0.074	-0.024	0.486	0.344	-0.142
1997	0.691	0.648	-0.043	0.041	0.121	0.081	0.009	0.032	0.023	0.451	0.378	-0.073
1998	0.650	0.712	0.062	0.051	0.215	0.164	0.019	0.112	0.093	0.548	0.462	-0.086
1999	0.633	0.683	0.050	0.048	0.171	0.123	0.038	0.123	0.086	0.596	0.551	-0.044
2000	0.640	0.735	0.096	-0.022	0.133	0.155	0.006	0.174	0.168	0.661	0.597	-0.063
2001	0.658	0.909	0.251	-0.069	0.094	0.163	-0.030	0.138	0.169	0.748	0.657	-0.091
Change 2001-1996	-0.050	0.347	0.396	-0.280	-0.092	0.188	-0.128	0.065	0.193	0.262	0.313	0.050
	Average Math Score											
1996	0.725	0.670	-0.055	0.143	0.125	-0.019	0.090	0.069	-0.020	0.688	0.487	-0.201
1997	0.717	0.788	0.071	0.046	0.095	0.049	0.033	0.043	0.009	0.832	0.630	-0.202
1998	0.668	0.789	0.121	-0.016	0.067	0.083	0.032	0.107	0.075	0.856	0.655	-0.201
1999	0.636	0.832	0.196	-0.018	0.056	0.075	0.067	0.182	0.114	0.869	0.716	-0.153
2000	0.608	0.984	0.376	-0.070	0.038	0.108	0.041	0.173	0.132	0.915	0.745	-0.170
2001	0.600	0.870	0.269	-0.136	0.009	0.145	-0.017	0.169	0.185	0.997	0.833	-0.164
Change 2001-1996	-0.124	0.200	0.324	-0.280	-0.115	0.164	-0.106	0.100	0.206	0.310	0.346	0.037
N	6483	810		10533	906		9832	1124		3115	1067	

The nativity gap is here defined as the difference in test scores between foreign-born and native-born.
The change in performance between 2001 and 1996 is calculated as the difference between the average test scores in 2001 and the average test score in 1996.
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress cohort whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 4: Absolute Convergence, NYC Public School Continuos Test Takers, Change in Test Score between 2001 and 1996

	(1) Reading	(2) Math
Reading Z-score in 1996	-0.258***	
	(0.0143)	
Math Z-score in 1996		-0.240***
		(0.0153)
Constant	-0.0129	-0.0188
	(0.0180)	(0.0172)
Observations	33870	33870
F	324.3	244.0

Clustered robust standard errors in parentheses.
Additional regressors not shown are language spoken variables and school characteristics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 5: Conditional Convergence, NYC Public Schools Continuous Test Takers, Change in Test Score between 2001 and 1996

	(1) Reading	(2) Reading	(3) Reading	(4) Math	(5) Math	(6) Math
Reading Z-score in 1996	-0.351***	-0.351***	-0.387***			
	(0.00989)	(0.00989)	(0.00849)			
Math Z-score in 1996				-0.337***	-0.333***	-0.364***
				(0.0108)	(0.0112)	(0.0101)
Foreign Born	0.229***	0.229***	0.177***	0.250***	0.247***	0.200***
	(0.0439)	(0.0439)	(0.0401)	(0.0399)	(0.0400)	(0.0358)
Black	-0.260***	-0.260***	-0.250***	-0.213***	-0.258***	-0.212***
	(0.0303)	(0.0303)	(0.0225)	(0.0244)	(0.0244)	(0.0192)
Asian	0.169***	0.169***	0.173***	0.238***	0.222***	0.247***
	(0.0373)	(0.0373)	(0.0334)	(0.0403)	(0.0421)	(0.0306)
Hispanic	-0.124***	-0.124***	-0.137***	-0.0697***	-0.103***	-0.0816***
	(0.0234)	(0.0234)	(0.0225)	(0.0216)	(0.0222)	(0.0205)
Black Foreign Born	-0.0557	-0.0557	0.00164	-0.103**	-0.0944**	-0.0505
	(0.0546)	(0.0546)	(0.0496)	(0.0459)	(0.0466)	(0.0414)
Asian Foreign Born	-0.178***	-0.178***	-0.121**	-0.211***	-0.213***	-0.154***
	(0.0561)	(0.0561)	(0.0503)	(0.0482)	(0.0493)	(0.0426)
Hispanic Foreign Born	-0.0272	-0.0272	0.0239	-0.0573	-0.0457	-0.0187
	(0.0485)	(0.0485)	(0.0440)	(0.0443)	(0.0449)	(0.0396)
Female	0.252***	0.252***	0.242***	0.0326***	0.0327***	0.0214***
	(0.00927)	(0.00927)	(0.00878)	(0.00741)	(0.00740)	(0.00721)
LEP	0.354***	0.354***	0.210	0.455***	0.443***	0.396***
	(0.134)	(0.134)	(0.143)	(0.142)	(0.141)	(0.145)
Free Lunch	-0.267***	-0.267***	-0.211***	-0.194***	-0.218***	-0.154***
	(0.0198)	(0.0198)	(0.0171)	(0.0165)	(0.0176)	(0.0125)
Reduced Lunch	-0.151***	-0.151***	-0.124***	-0.0967***	-0.105***	-0.0844***
	(0.0205)	(0.0205)	(0.0181)	(0.0189)	(0.0193)	(0.0162)
Observations	33870	33870	33870	33870	33870	33870
R^2	0.206	0.206	0.274	0.220	0.213	0.289
F	133.1	133.1	195.9	86.37	100.9	114.3
School Fixed Effects	No	No	Yes	No	No	Yes

Clustered robust standard errors in parentheses

Additional regressors not shown are language spoken variables and school characteristics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The sample includes only continuous test takers, i.e. those students in Standard Academic Progress whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 6: Conditional Convergence, by Ethnicity, NYC Public School Continuous Test Takers, Change in Test Score between 2001 and 1996

	(1) White	(2) Black	(3) Hispanic	(4) Asian	(5) White	(6) Black	(7) Hispanic	(8) Asian
Reading Z-score in 1996	-0.346***	-0.405***	-0.439***	-0.305***				
	(0.0134)	(0.0143)	(0.0110)	(0.0221)				
Math Z-score in 1996					-0.303***	-0.394***	-0.419***	-0.284***
					(0.0143)	(0.0173)	(0.0124)	(0.0227)
Foreign Born	0.147***	0.169***	0.191***	0.0906***	0.173***	0.144***	0.175***	0.0703**
	(0.0391)	(0.0303)	(0.0198)	(0.0312)	(0.0363)	(0.0189)	(0.0204)	(0.0293)
Female	0.263***	0.254***	0.202***	0.279***	0.00698	0.0637***	-0.000475	-0.0119
	(0.0224)	(0.0138)	(0.0126)	(0.0273)	(0.0182)	(0.0117)	(0.0114)	(0.0212)
LEP	0.640	-0.254	0.169	0.715	1.783**	0.253	0.345**	2.268***
	(0.578)	(0.594)	(0.127)	(0.536)	(0.894)	(0.371)	(0.139)	(0.818)
Free Lunch	-0.271***	-0.150***	-0.127***	-0.228***	-0.201***	-0.0941***	-0.0914***	-0.189***
	(0.0288)	(0.0260)	(0.0288)	(0.0400)	(0.0217)	(0.0212)	(0.0261)	(0.0418)
Reduced Lunch	-0.180***	-0.0717**	-0.0190	-0.115***	-0.123***	-0.00764	-0.0147	-0.110**
	(0.0309)	(0.0293)	(0.0347)	(0.0414)	(0.0213)	(0.0263)	(0.0354)	(0.0516)
Observations	7293	11439	10956	4182	7293	11439	10956	4182
R^2	0.245	0.273	0.298	0.213	0.251	0.265	0.309	0.235
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered robust standard errors in parentheses
Additional regressors not shown are language spoken variables and school characteristics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 7: Implied Convergence Speeds and Long Run Cognitive Achievement Level

	Implied Convergence Speed (per year)		Half-Time (years)		Long Run Achievement Level	
	Reading	Math	Reading	Math	Reading	Math
Absolute Convergence	0.060	0.055	11.614	12.629	-0.050	-0.054
Conditional Convergence	0.098	0.091	7.082	7.658		
White Natives	0.084	0.073	8.221	9.525	0.000	0.000
White Foreigns	0.100	0.067	6.919	10.331	0.458	0.549
Black Natives	0.101	0.100	6.851	6.919	-0.647	-0.687
Black Foreigns	0.125	0.104	5.524	6.697	-0.188	-0.138
Hispanic Natives	0.113	0.106	6.146	6.547	-0.354	-0.224
Hispanic Foreigns	0.138	0.128	5.029	5.395	0.104	0.325
Asian Natives	0.072	0.065	9.678	10.595	0.446	0.678
Asian Foreigns	0.078	0.072	8.918	9.601	0.592	0.805
	Conditional Convergence with Student Fixed Effects					
Native-Born	0.754	1.243	0.919	0.558	0.059	0.117
Foreign-Born	0.715	0.921	0.969	0.753	0.343	0.543
White Natives	0.628	0.813	1.103	0.853	0.532	0.554
White Foreigns	0.549	0.429	1.263	1.617	1.215	0.948
Black Natives	0.872	0.845	0.795	0.820	-0.216	-0.281
Black Foreigns	0.475	0.590	1.459	1.175	0.000	0.000
Hispanic Natives	0.788	1.331	0.879	0.521	0.000	0.000
Hispanic Foreigns	0.524	0.862	1.324	0.805	0.000	0.354
Asian Natives	0.493	0.814	1.405	0.851	0.617	1.237
Asian Foreigns	0.611	0.616	1.135	1.125	0.955	0.990

The long run achievement level for white native-born students was not statistically different from zero and it is therefore reported as zero.
Convergence speed by ethnicity and nativity are calculated from regression not reported in the paper. Results are available from the authors upon request.
In the regression with student fixed effects to calculate the speed of convergence we used the upper limit of the 95% confidence interval for β_1 due to its closeness to the absolute value of 1.
Whenever β_0 was not significant, the cognitive achievement level is reported as zero.

Table 8: Conditional Convergence, by Nativity, NYC Public Schools Continuous Test Takers Change in Test Score between 2001 and 1996

	(1) Reading - NB	(2) Reading - FB	(3) Math - NB	(4) Math - FB
Reading Z-score in 1996	-0.382***	-0.424***		
	(0.00857)	(0.0206)		
Math Z-score in 1996			-0.363***	-0.368***
			(0.0100)	(0.0192)
Black	-0.255***	-0.162*	-0.214***	-0.217***
	(0.0229)	(0.0913)	(0.0198)	(0.0825)
Asian	0.182***	0.0833	0.265***	0.0798
	(0.0345)	(0.0858)	(0.0336)	(0.0731)
Hispanic	-0.137***	-0.0600	-0.0809***	-0.0463
	(0.0237)	(0.0865)	(0.0210)	(0.0822)
Female	0.241***	0.249***	0.0249***	-0.0127
	(0.00931)	(0.0238)	(0.00754)	(0.0238)
LEP	0.177	0.291	0.422***	0.249
	(0.149)	(0.288)	(0.152)	(0.298)
Free Lunch	-0.200***	-0.267***	-0.146***	-0.207***
	(0.0178)	(0.0464)	(0.0131)	(0.0379)
Reduced Lunch	-0.117***	-0.173***	-0.0750***	-0.147***
	(0.0195)	(0.0489)	(0.0167)	(0.0485)
Observations	29963	3907	29963	3907
R^2	0.262	0.339	0.277	0.336
School Fixed Effects	Yes	Yes	Yes	Yes

Clustered Robust standard errors in parentheses.
Additional regressors not shown are language spoken variables and school characteristics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress whose test scores in either reading or math are available for all the years between 1996 and 2001.

Table 9: Conditional Convergence with Student Fixed Effects, NYC Public Schools Continuous Test Takers Change in Test Score by Nativity between 1996 and 2001

	(1) Reading - NB	(2) Reading - FB	(3) Math - NB	(4) Math - FB
Initial Z-Score	-0.977***	-0.972***		
	(0.0108)	(0.0247)		
Initial Z-Score			-0.998***	-0.990***
			(0.00895)	(0.0275)
Constant	0.0563	0.323**	0.116*	0.529***
	(0.0749)	(0.156)	(0.0678)	(0.146)
Observations	59926	7814	59926	7814
R^2	0.788	0.786	0.822	0.819

Standard errors in parentheses
Additional regressors not shown are socio-economic and school characteristics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Conditional Convergence, by Ethnicity and Nativity, NYC Public Schools Continuous Test Takers, Change in Test Scores between 1996 and 2001

	(1) White NB	(2) White FB	(3) Black NB	(4) Black FB	(5) Hispanic NB	(6) Hispanic FB	(7) Asian NB	(8) Asian FB
Initial Z-Score	-0.961***	-1.001***	-1.002***	-0.963***	-0.990***	-0.959***	-0.932***	-0.999***
	(0.0214)	(0.0573)	(0.0166)	(0.0574)	(0.0167)	(0.0419)	(0.0362)	(0.0438)
Constant	0.489***	1.080**	-0.209**	-0.353	-0.0815	-0.111	0.531***	0.872***
	(0.151)	(0.444)	(0.0942)	(0.387)	(0.0897)	(0.338)	(0.184)	(0.284)
R^2	0.764	0.752	0.797	0.797	0.797	0.820	0.759	0.773
				Math				
Initial Z-Score	-1.002***	-0.961***	-0.993***	-0.991***	-1.021***	-1.043***	-0.993***	-0.977***
	(0.0208)	(0.0720)	(0.0138)	(0.0436)	(0.0132)	(0.0382)	(0.0315)	(0.0620)
Constant	0.533***	0.777***	-0.231***	-0.174	-0.0774	0.343*	1.189***	0.906**
	(0.121)	(0.212)	(0.0736)	(0.239)	(0.0889)	(0.188)	(0.174)	(0.399)
Observations	12966	1620	21066	1812	19664	2248	6230	2134
R^2	0.804	0.771	0.818	0.839	0.840	0.875	0.779	0.781

Standard errors in parentheses
Additional regressors not shown are socio-economic and school characteristics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The sample includes only continuous test takers, i.e. those students in Standard Academic Progress whose test scores in either reading or math are available for all the years between 1996 and 2001.

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