The Impact of Attending a High-Mobility School on Children’s Reading and Mathematics Achievement in Chicago

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Introduction

We know that minority youth living in neighborhoods characterized by high levels of disadvantage (e.g., high concentrations of poverty, unemployment, welfare receipt, and single-parent households) tend to obtain comparatively low levels of achievement in reading and mathematics. If this effect is causal, one of the most plausible mechanisms that would account for it involves school quality. People who live near each other tend to attend similar schools, so residing in a high-risk neighborhood predicts attending a school with peers who also live in high-risk neighborhoods. We shall define such a school as a “high-risk” school, and we shall review some sociological research asserting that such high-risk schools tend to have low quality. (The strength of evidence supporting the widely-supported view that high-risk schools have low quality is much weaker than many would expect.)

An introductory part of our presentation will examine how these statistical associations work in Chicago. We will see that time-varying changes in neighborhood risk are statistically associated with time-varying changes in achievement – in the directions this literature will predict. We will also see that this association is largely “explained” by time-varying changes in the school risk. The association between time-varying school risk and time-varying achievement is strong.

In sum, we will test three hypotheses:

H1: Time-varying neighborhood risk is associated negatively with time-varying achievement
H2: Time-varying school-level risk is associated negatively with time-varying achievement
H3: Time-varying school-level risk “explains” the association between time-varying neighborhood risk and achievement

To understand these associations, it is essential to contend with a pervasive aspect of life among the inner-city poor: high rates of residential and school mobility. We know that families of urban children living in poverty frequently move, usually over short distances. Triggering such moves are widespread 

housing instability (transformation of rental units to condos, condemnation of deteriorating units or movement to escape those deteriorating units, demolition of public housing projects, opening up of new housing options via section 8 vouchers etc.); family instability (separation, cohabitation, changes in family size); and income instability (income loss, eviction and also upward occupational mobility leading to income gain). In many cases, such residential moves in turn trigger school moves. Moving across school catchment boundaries and moving comparatively long distances increase the likelihood that a residential move will trigger a school move. However, school moves also occur as families seek better schools or if children are expelled from their current school.

An essential aspect of high levels of residential and school mobility is that their effects are presumably not limited to the movers. A fairly substantial literature in sociology links high levels of residential instability to low levels of neighborhood cohesion and relatedly, low levels of informal school control – that is, low level’s of neighbors’ collective capacity to preserve public order and to achieve other common goals. A much smaller literature suggests similarly that high levels of student mobility undermine the capacity of educators to maintain high levels of school quality. Assessing the impact of such institutional mobility at the level of the school supplies the main (though not only) focus of this paper.

Literature on School-level Mobility

Sociologists have generated two primary explanations for why high school-level mobility would depress student learning. First, a large influx of new students disrupts instruction. If such mobile students are to be successful, teachers must take time help those students catch up with the rest of the class (if the new students are behind) or at least to become acclimated to the conceptual and pedagogical orientation of the class and its organization of time and student activity. Because the in-movers tend, on average, to be disadvantaged in various ways, we can anticipate that many of them will have comparatively low achievement and will need to catch up.

Notice that it is an influx of in-movers – especially during the year – that would generate this effect. In contrast, a large number of out-movers would not disrupt instruction in this way. Large out-migration would be a symptom rather than a cause of poor school quality, a fact that we shall exploit. The Consortium for Chicago School Research, which supplies our data, provides four measures of school mobility – intensity of inmovers during the year and between years and intensity of out-movers during the year and between years. This reasoning leads us to hypothesize
H4: High intensity of in-migration during the year has a negative impact on student achievement

H5: This result holds for mobile children as well as non-mobile children

H6: The effect is most pronounced for high-achievers

The rationale for H6 is that the tendency of in-movers to force teachers to review curricular content might not hurt (and might even help) the low-achievers, but it would tend to slow the pace of instruction, depressing the achievement of the high-achievers.

The second explanation is based on social network theory. We assume that educators and parents seek to generate and sustain pro-academic norms among students, a process that is facilitated by population stability and undermined by instability. Coleman’s notion of inter-generational closure – in which parents know each other and know each others’ children – and parents, teachers, and children know each other well – would be disrupted by high levels of student mobility. Moreover, large number of in-movers may be marginalized socially, undermining social cohesion and the capacity to engage in pro-academic social networks or at least social networks linked to school attendance.

This reasoning seems to imply

H8: The impact of school-level mobility will be greater for mobile students than for stable students.

Data

Our current analyses focus on 44,533 students attending approximate 565 Chicago schools between 1996-2005, generating 244,858 time-series observations. Most students are either African-American or Hispanic, with a minority of White or Asian background. Time-varying variables include

- Student level:
  - Concentration of poverty of block group of residence
  - Social status of block group
  - age and grade
  - reading and math achievement
  - mobility status of the student

- School level:
  - Concentration of poverty status of the school population
  - Social status of the school population
  - Ethnic composition
  - Percent Limited English Proficiency
  - Average class size
  - Charter or Magnet Status
  -- intensity of school-level mobility (in-movers during the year)
Exposure to School-Level Mobility

We shall describe which schools and which children are exposed to high levels of school mobility. This work involves:

a. Two-level hierarchical models in which time-varying school-level mobility is repeatedly observed for each school. We shall see that high-risk schools (schools characterized by high levels of concentration of poverty) and schools serving African American children exhibit sustained, high levels of mobility. Other schools have lower levels, and the trend for these over time is toward lower levels of student mobility.

b. Two-level models in which time-varying school-level mobility is repeatedly observed for students. We shall see that highly mobile students, African American students, and students in high risk neighborhoods are exposed to high levels of school mobility. Moreover, moves to high risk neighborhoods are linked to moves to high risk schools and to schools characterized by high levels of mobility.

Identification and Estimation of the Impact of School Level Mobility

a. Descriptive models. We shall estimate a series of models that identify the association between school-level mobility and achievement for children of varied background. These models are useful descriptively for characterizing the growth trajectories of several sub-populations and examining the statistical dependence of those trajectories on levels and changes in school-level mobility. We will then examine the functional form of the trajectories of change, the mean trajectory, individual variation around the mean, and correlates of growth.

b. “Fixed effects” models. We shall estimate models having fixed effects of students, time, and schools as well as students, time, and grades.

c. Models using “adaptive centering with random effects.” This approach (described in a previous paper by the first author) can replicate the fixed effects analyses in a computationally efficient manner while extending it to allow a) heterogeneity of impact of school-level mobility across schools; and b) to correctly incorporate school-level clustering within standard errors.

d. Models using stratification on the “prognosis score.” (see below)

e. Multilevel structural marginal means models (elaborated in the next section)

Methodological Innovations

The fixed effects approach is widely regarded as helpful in removing all time-invariant confounding – observed and unobserved – associated with the fixed effects dimensions (in our case students and schools or students and grades). An excellent example is in Hanushek, Rivkin, and Kain’s paper on school-level mobility in Texas. This appears to be the most important contribution to the specification to date of the impact of school-level mobility on student learning.
The approach is open to criticism on several dimensions, however.

1. **Over-simplification of the causal structure.** To understand the assumptions implicit in the fixed-effect specification, it helps to begin with a “saturated model” of the causal effects defineable in a study with \( t=1,\ldots,T \) time points where \( t=0 \) is the baseline condition (I attribute this primarily to work by Hong in 2006). For a repeated binary treatment \( Z_t \), one can identify \( 2^t \) potential outcomes at time \( t \) and \( 2^t - 1 \) causal effects at each time \( t \). For example, with \( t=2 \), we have, for \( t=1 \), the impact of time-1 treatment on time-1 outcome; and, for \( t=2 \), the main effect of time-1 treatment on time-2 outcome; the main effect of time-2 treatment on time-2 outcome; and the two-way interactive (or “synergistic”) effect of receiving the sequence of time-1 and time-2 treatments on time-2 outcome. So there are four causal effects in all. The fixed-effect specification imposes constraints that reduce these four causal parameters to one. For example, if we assume time-1 treatment on time-1 outcome to be equal to time-2 treatment on time-2 outcome, no synergistic effect, and no impact of time-1 treatment on time 2 outcome, we have what might be called the “constant ephemeral” effects model. However if time-1 treatment effect on time 2 outcome is equal to the effect of time-1 treatment on time-1 outcome and time-2 treatment on time-2 outcome, we have the “constant cumulative effects” model. Such as assumptions are rarely specified. For example, in models using gain scores as the outcome with a dummy variable for treatment and fixed effects of persons, the model is in effect a model assuming constant cumulative effects, though this assumption is often hidden. Intermediate models – not as simple as the single-parameter models and not as complex as the saturated model – are defensible and should generally be explored when there are repeated treatments. We shall consider several of these.

2. **Strong assumptions about time-varying confounding.** Fixed effects models that do not adjust for observable time-varying confounding assuming no time-varying confounding. Fixed effects models that do account for observable time-varying confounding assume that time-varying covariates controlled in the model cannot have been influenced by prior treatments.

3. **Functional form.** Fixed effects specifications typically assume either a) that inter-individual variation in growth rates is null or b) that inter-individual variation in growth rates are linear. (This is a criticism of practice but is not essential to the fixed effects specification).

To contend with these problems, we shall supplement our fixed effects (and adaptive centering with random effects) specification with a structural marginal means model as developed by Robins and extended to the multilevel setting by Hong and Raudenbush. The approach can identify a wide range of time-varying treatment scenarios (ranging from a one-parameter model to a saturated model) under the assumption of
sequential strong ignorability with inverse probability of treatment weighting ("IPTW"). The sequential strong ignorability assumption says that at time t, all unobserved covariates at play prior to time 2 are unrelated to treatment group assignment \( Z_t \) given the history of past treatments, outcomes, and observed covariates.

The key limitation in comparison to the fixed effects specification is that one cannot rule out unobserved time-invariant confounding. To cope with this problem, we estimate our models as follows. First, we estimate the impact of school-level mobility \( Z_T \) at time T, our last time point, controlling for the entire pre-T history. This means that we are controlling for the student’s entire pre-T outcome and treatment trajectory, as well as all prior time-invariant and time-varying covariates. Moreover, this specification can be compared to the fixed effects results for the same treatment effect. Next, we estimate the impacts of treatments \( Z_{T-1} \) and \( Z_T \) using IPTW. We compare the inferences about the impact of \( Z_T \) under this specification to the specification including only \( Z_T \). This process continues “backward” as long as results remain consistent. We shall explore a variety of causal effects structures using this approach, including the one-parameter structures possible under the fixed effects approach (that is the “constant ephemeral” and “constant cumulative” approaches) and more elaborate specifications. We believe this approach will address the issues associated with causal inference in fixed effects models as uncovered by Jesse Rothstein.

To cope with the problem of functional form, we specify a quadratic growth model with heterogeneous intercept, linear, and quadratic components, and we do this within 10 levels of a “prognosis score.” Suppose, for example, we estimate a model including data from \( t=1 \) to \( t=t^* \). Using this model, we estimate the conditional expected outcome at \( t^* \) given that model. We then stratify students in 10 levels of this conditional expected value, called the “prognosis score.” We allow the quadratic polynomial parameters to depend on fixed effects of these prognosis strata. We are then able to estimate the impact of school mobility on outcomes within these strata. This approach addresses, we believe, problems of metric, functional form, and lack of common support that tend to plague value added models, according to recent work by Reardon and Raudenbush.