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Patterns in Student Assignment to Elementary School Classrooms

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Abstract: In an effort to better understand aggregate patterns in the way elementary school students are assigned to classes, we conduct a careful analysis of observed classroom assignment outcomes in the 5th grade in North Carolina elementary schools. First, we model the probability that a pair of students are classmates as a function of the characteristics of that pair of students. This novel methodological technique enables us to directly observe the degree to which actual assignment patterns differ from what might be expected under random assignment for a wide variety of student characteristics. Second, we analyze patterns in classroom assignment and discuss the implications of these patterns. We show that classroom assignments tend to deviate from random assignment in a way that tends to group similar students and that these deviations tend to be greatly magnified in Magnet schools. Importantly, we find evidence that administrators sort students based on attributes not normally observable by researchers. These findings have important implications for researchers using value-added modeling (VAM) techniques. Finally, we find that classroom assignment patterns are generally stable across the racial, income, and geographic characteristics of schools.
Keywords: classroom composition; teacher assignment; value-added modeling

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Patrones de asignación de estudiantes en aulas de escuelas primarias
Resumen: En un esfuerzo por comprender mejor los patrones agregados sobre la manera en que se asignan los estudiantes a determinadas clases, llevamos a cabo un análisis detallado de los resultados de asignación a aulas de 5 º grado en las escuelas primarias de Carolina del Norte. En primer lugar, se creo un modelo sobres la probabilidad de que un par de los estudiantes sean compañeros de clase en función de las características de ese par de estudiantes. Esta novedosa técnica metodológica nos permite observar directamente el grado en que los patrones de asignación reales difieren de lo que cabría esperar con una asignación al azar para una amplia variedad de características de los estudiantes. En segundo lugar, analizamos los patrones de asignación de clase y discutimos las implicaciones de estos patrones. Se demuestra que las asignaciones a ciertas aulas tienden a desviarse de la asignación aleatoria de una manera que tiende al grupo de estudiantes similares y que estas desviaciones tienden a ser ampliada en gran medida en las escuelas *magnet.* Es importante destacar, que encontramos evidencia de que los administradores asignaban estudiantes utilizando atributos que normalmente no son atendidos por investigadores. Estos resultados tienen consecuencias importantes para los investigadores que utilizan técnicas de modelado de valor agregado (VAM). Por último, encontramos con que los patrones de asignación a aulas son generalmente estables tomando las características raciales, de ingresos, y geográficas de las escuelas.
Palabras clave: composición de aulas; asignación de docentes; modelos de valor agregado

Padrões de matricula de estudantes em salas de aula do ensino fundamental
Resumo: Em um esforço para compreender melhor os padrões globais de como os alunos são assinados às aulas, realizamos uma análise detalhada dos resultados da alocação nas salas de aula da 5 ª série em escolas primárias da Carolina do Norte. Primeiro, criamos um modelo na probabilidade de que um par de estudantes sejam companheiros de aula de acordo com as características desses dois alunos. Esta nova técnica metodológica permite observar diretamente do grau em que os padrões de distribuição reais diferem daquilo que seria de esperar com uma atribuição aleatória de uma grande variedade de características dos estudantes. Em segundo lugar, analisamos os padrões de atribuição de classe e discutir as implicações destes padrões. Nós mostramos que certas assinações na sala de aula tendem a desviar-se da atribuição aleatória de forma que os estudantes tendem a agrupar semelhantes e que estes desvios tendem a ser ampliados em escolas *magnet.* Importante, encontramos evidências de que os administradores das escolas assinam aos alunos usando atributos que normalmente não são vistos pelos pesquisadores. Estes resultados têm consequências importantes para os pesquisadores que usam técnicas de modelagem de valor adicionado. Finalmente, verificou-se que os padrões de matricula de salas de aula são geralmente estáveis, tendo em conta as caraterísticas raciais, de renda e geográficas das escolas.
Palavras-chave: composição das salas de aula; a alocação de professores; modelos de valor agregado

Introduction[1]

A resource-constrained elementary school administrator seeking to improve educational outcomes has a difficult task. The administrator's problem is especially difficult given that the interests of various students, parents, and teachers may compete for resources and that efficiency and fairness concerns may conflict. For example, an administrator may wish to assign more students

[1] We are grateful for helpful support from the North Carolina Education Research Data Center and for helpful comments from my colleagues at Utah State University. Any errors are the authors'.

to the best teachers, but may also feel that such a policy would be unfair. In the absence of additional resources and with a fixed staff and curriculum, an administrator's options may be limited to choosing which students to assign to which classrooms. Given that research suggests that both teacher and peer effects can be important determinants of educational outcomes, we might expect that conscientious administrators will make these assignments carefully.

Increased pressure to improve test scores might lead to assignment patterns designed to maximize efficiency in instruction. Research suggests that classroom instruction may be more efficient in relatively homogeneous classrooms (Bosworth & Caliendo, 2007; Lazear, 2001), giving administrators the incentive to group similar students. However, administrators may also need to consider fairness to students, teachers, and parents. One possible assignment procedure is to simply randomly assign students to classrooms. This procedure may be viewed as fair because it (*ex-ante*) treats all students equally. However, given that some students may be expected to perform better with some teachers or classmates than with others, equity-conscious administrators may choose to use a non-random assignment procedure to ensure the success of some students.

There are good reasons to expect that random assignment may not be used in practice, even if administrators value fairness (Burns & Mason, 1995). Random allocation may be fair *ex-ante*, but may still produce classroom assignments that are unfair *ex-post*. For example, administrators may feel that classrooms that are unbalanced with respect to race or gender characteristics are unacceptable, even if the assignment procedure was fair *ex-ante*. Students might be assigned to classrooms strategically for pedagogical reasons (e.g., grouping academically similar students for efficient instruction), for fairness (e.g., evenly distributing difficult students across classroom to avoid overburdening a particular teacher) or in response to parental requests. It is important to note that a conflict may exist between the separate goals of efficient instruction and fairness.

Understanding classroom assignment procedures and the resulting patterns is important because these procedures affect educational outcomes through class size effects, teacher quality effects, and peer effects. Moreover, researchers seeking to understand the effects of these various educational inputs on educational outcomes may find their estimates to be biased if the models employed do not properly account for classroom composition. Researchers have shown that estimates of the effects of class size and teacher quality can be biased if classroom assignment is non-random (Clotfelter, Ladd, & Vigdor, 2006; Hoxby, 2000a). For example, Rothstein (2009) shows that estimates of teacher effectiveness based on value-added modeling (VAM) may be biased if students are not randomly assigned to classrooms. Moreover, Koedel and Betts (2011) argue that even when value-added models take observed student composition characteristics into account, bias may result from classroom assignment based on unobserved characteristics.

To better understand classroom assignment patterns, we conduct a careful analysis of observed classroom assignment outcomes in the 5^{th} grade in North Carolina elementary schools for the year 2004. Detailed records are available for students in all public elementary schools in North Carolina. Because we expect that different school environments might lead to different classroom assignment procedures and patterns, the diversity of school types in North Carolina provides an ideal setting for our study. Importantly, North Carolina has a wide range of school types in terms of income, racial composition, and population density, as well as a large number of Magnet schools. Magnet schools in North Carolina first began to appear in the 1970's as part of North Carolina's desegregation efforts. The first Magnet schools were self-contained gifted and talented programs. Magnet schools have historically been designed to reduce racial isolation by attracting students of heterogeneous racial and ethnic backgrounds and they continue to be designed to do so. However, Magnet schools in North Carolina also usually focus on a theme such as the arts, science and mathematics, or a foreign language. Magnet schools in North Carolina generally have 50% or more minority enrollment. For background on the history of Magnet schools in North Carolina see Flood (1978). For information on the academic achievement and sociological effects of Magnet schools generally see, for example, Archbald (2004), Saporito and Sohoni (2006), and Metz (1986).

The first key contribution of this study is to introduce a novel methodological technique for analyzing classroom assignment patterns that may be useful to researchers in other settings: We model the probability that a pair of students are classmates as a function of the characteristics of that pair of students. This technique enables us to directly observe the degree to which actual assignment patterns differ from what might be expected under random assignment for a wide variety of student characteristics. This innovative research method is designed to uncover patterns in classroom assignments and provide insight to the processes used by elementary school administrators. This technique can be used within a single school or used, as in this study, to examine aggregate patterns in within-school sorting. Given that the reliability of value-added models can be influenced by the degree of student-teacher sorting, this simple-to-implement technique can be a valuable tool for practitioners or researchers seeking to understand the nature and extent of non-random assignment in a particular setting.

A second key contribution is to illustrate the technique by analyzing patterns in classroom assignment in North Carolina elementary schools. We also investigate how these patterns vary across different types of schools. In particular, we investigate differences in classroom assignment patterns in Magnet and traditional elementary schools in the North Carolina public school system. We show 1) that classroom assignments tend to deviate from random assignment in particular patterns, 2) that these deviations tend to be greatly magnified in Magnet schools, and 3) there is strong evidence that administrators sort students based on attributes not normally observable by researchers. These findings have important implications for researchers using value-added modeling techniques. Finally, we find that classroom assignment patterns are remarkably stable across the racial, income, and geographic characteristics of schools.

Related Literature

Researchers have uncovered substantial evidence that students are not generally assigned to classrooms in a random fashion. Qualitative evidence from studies of the classroom assignment process at various schools suggests that the assignment process is influenced by a wide variety of factors. For example, Burns and Mason (1995) find that principals generally value randomization and classroom diversity; however, Burns and Mason (1995) also find that principals are sometimes willing to deviate from initial (possibly random) assignments based on parental requests, teacher requests, or other factors. Burns and Mason (1998) also find that more difficult-to-teach multi-grade classrooms were generally assigned better students. The same authors also find that classroom assignment procedures are sometimes purposefully used to create desired classroom compositions (Burns & Mason, 2002). Other qualitative studies have also found variety across schools in the assignment process (Dills & Mulholland, 2010; Kraemer, Worth, & Meyer, 2011; Praisner, 2003) and that assignment decisions can be a "team-based process" involving input from administrators, teachers, and other sources (Kraemer, Rhodes, Steele, & Meyer, 2012). Monk (1987) shows that principals tend to be more involved in the assignment process when school socio-economic status is low.

Researchers have also shown that classroom composition is statistically related to learning outcomes. For example, peer effects and classroom composition have been shown to be empirically linked to educational outcomes (Bosworth, 2011; Burke & Sass, 2008; Dar & Resh, 1986; Dreeben & Barr, 1988; Figlio, 2007; Hattie, 2002; Hoxby, 2000b; Luyten, Schildkamp, & Folmer, 2009;

McEwan, 2003) and teacher assignment practices (Clotfelter, et al., 2006; Kalogrides, Loeb, & Beteille, 2011). Moreover, theoretical work predicts that classroom composition will influence learning (Bosworth & Caliendo, 2007; Lazear, 2001).

Importantly, non-random assignment of students to classrooms has the potential to bias the effects estimated via value-added models. For example, researchers have argued that classroom assignment based on unobservable student attributes can bias estimates of teacher quality in value-added models ((Koedel & Betts, 2011; Jesse Rothstein, 2009; J. Rothstein, 2010). Other researchers have discussed various limitations of value-added modeling (Ballou, Sanders, & Wright, 2004; Darling-Hammond, Amrein-Beardsley, Haertel, & Rothstein, 2012; Harris, 2009; McCaffrey, Lockwood, Koretz, Louis, & Hamilton, 2004; Rubin, Stuart, & Zanutto, 2004). For examples of applications of value-added modeling see Adcock and Phillips (2000) and Doran and Izumi (2004). Meyer (1997) discusses the conceptual foundations of value-added modeling. See Braun (2005) for a non-technical introduction of value-added modeling.

Despite the importance of understanding classroom assignment procedures and outcomes, few empirical studies exist on the topic. Recognizing the paucity of research in this area, Steele, Kraemer, and Meyer (2012) recently created a survey for the purpose of better understanding the procedures used to assign students to classrooms. Noting that "[f]ew studies have focused on student-teacher assignment" and that "[m]ost of these studies have relied on observations, interviews, and focus groups to gather data", Steele, Kraemer, and Meyer (2012) argue that student-teacher assignment is not well understood across schools and districts. The research reported in this paper is intended complement these qualitative studies by investigating aggregate patterns in classroom assignment outcomes. Comparisons between aggregate empirical studies and localized qualitative studies can show whether or not the patterns and outcomes observed at individual locations appear to be typical or unusual.

Data

The data for this research have been provided by the North Carolina Education Research Data Center (NCERDC)[2]. The data center was established in 2000-01 to provide researchers with access to large stores of data collected by the North Carolina Department of Public Instruction and other agencies. The NCERDC is housed in the Center for Child and Family Policy at Duke University and contains district, school, teacher, classroom, and student level information. Importantly, the data contains information on demographic and academic characteristics (in the form of End-of-Grade (EOG) test results) for each student.

We construct our dataset as follows: First, using the data on 5th graders in the year 2004, we use the school, teacher, and student identifiers provided by the NCERDC to create an observation for each possible pair of students assigned to regular (i.e. not special education) classrooms.[3] We consider a pair of students to be a possible pair if they are in the same school, grade, and year. Because the process of creating an observation for each possible pair of students is computationally intensive and creates an almost overwhelmingly large dataset, we restrict our analysis to just one grade-year (grade 5, year 2004). This means we create an observation for each pair of students who

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[2] NCERDC data are not available to the general public but academic researchers can apply for access. Detailed information on the data available from the NCERDC can be found on their website: http://www.pubpol.duke.edu/centers/child/ep/nceddatacenter/index.html.

[3] For this study, we restrict the analysis to classrooms with at least 15 students. Classrooms smaller than 15 students generally contain high proportions of students categorized as having one or more learning disabilities.

could have been (or were) classmates in the 5th grade in 2004. For this year and grade, we have 89,619 students in 1,081 schools. This process yields about 4.5 million possible pairs of students in our statewide dataset. A simple example may help illustrate the technique: Suppose there are four students in a grade-school-year: a, b, c, and d. We would create an observation for each of the following pairs: ab, ac, ad, bc, bd, and cd. We then create an indicator that is equal to 1 if the pair were actually classmates and zero if they were not.

Table 1 reports means and descriptions of the variables describing each pair of students. The indicator variables for "Same Gender", "Same Race", and "Same Gender and Race" are self-explanatory. We create the "Same Gender and Race" variable to allow for the possibility that classroom assignment patterns with respect to race may vary by gender, or, equivalently, that gender assignment patterns may vary by race. If both students in the pair are on free or reduced price lunch the variable "Both Free Lunch" is equal to one. Likewise, the variable "Neither Free Lunch" is equal to one if neither student is on free or reduced price lunch. The variable "Top Pair" indicates a pair of students who were both in the top 25% of their 4th grade EOG exams in both reading and mathematics. Likewise, "Middle Pair" and "Bottom Pair" indicate pairs of students who have both scored in the middle 50% or bottom 25%, respectively, on both the 4th grade EOG exams in both reading and mathematics. "Parent High Education" indicates a pair of students who both have parents with more than a high school education.

Table 1: Summary Statistics

Variable	Mean*	Description
Student Pair Variables		
Same Gender	0.501	=1 if students are the same gender
Same Race	0.563	=1 if students are the same race
Same Gender & Race	0.282	=1 if students are the same race and same gender
Both Free Lunch	0.168	=1 if both of the students are on Free or Reduced Price Lunch
Neither Free Lunch	0.350	=1 if neither of the students are on Free or Reduced Price Lunch
Top Pair	0.124	=1 if both students were in the top 25% of 4th grade EOG exams
Middle Pair	0.191	=1 if both students were in the middle 50% of 4th grade EOG exams
Bottom Pair	0.068	=1 if both students were in the bottom 25% of 4th grade EOG exams
Parent High Education	0.252	=1 if both students have a parent with more than a high school education (4th grade records)
Classmates Last Year	0.183	=1 if the pair of students were classmates the previous year (4th grade)
School Variables		
Magnet	0.058	=1 if school is a Magnet school
Race		
Majority Black	0.189	=1 if the majority of students are classified as African-American
Few Black	0.260	=1 if fewer than 10% of the students are classified as African-American
Income		
Low Income	0.182	=1 if more than 55% of the students are on Free or Reduced Price Lunch
High Income	0.335	=1 if less than 25% of the students are on Free or Reduced Price Lunch
Population Density		
Rural	0.402	=1 if school is in a rural community
Town	0.148	=1 is school is in a town
Suburb	0.215	=1 is school is in a suburb
City	0.235	=1 if school is in a city

*For Student Pair Variables, this indicates average value among all student pairs in our sample (5th grade, 2004).

For School Variables, means indicate average values for schools in our sample.

Parental Education levels are constructed using information recorded by the student's 4th grade (rather than 5th grade) teacher to avoid teacher-specific correlations in this variable. Finally, "Classmates Last Year" indicates a pair of students who were classmates the previous year. Note that each of these dummy variables is constructed to indicate whether or not the pair of students are similar in an observable way.

Table 1 also reports means and descriptions for our school-level variables. The variable "Magnet" indicates a Magnet school. The other school-level variables describe the racial, income, or population density of the schools. The variable "Majority Black" indicates a school where more than 50% of the students are classified as African-American and the variable "Few Black" indicates a school where less than 10% of the student population is African-American. An African-American student population of 10% represents about the 25th percentile in terms of the distribution of the percentage of African-American students across the schools in our data. The variables "Low Income" and "High Income" indicate schools with, respectively, more than 55% or fewer than 25% of the student population on free or reduced price lunch. These cutoffs represent approximately the 25th and 75th percentiles of the distribution of the proportion of students on free or reduced price lunch across schools in our data. Finally, the variables "Rural", "Town", "Suburb", and "City" indicate the population density of the region where the school is located.

Table 2 reports pairwise correlations among our predictor variables. Because variables that are highly collinear may impede confident inference of individual effects, we are interested to know of any unusually strong associations among the variables in our model. Unsurprisingly, the variables "Same Gender" and "Same Race" are strongly correlated (r=0.626 and r=0.552) with the variable "Same Race and Gender". However, none of the other correlations exceed 0.406 in absolute value.

Table 2: Pairwise Correlations

	Same Gender	Same Race	Same Race & Gender	Both Free Lunch	Neither Free Lunch	Top Pair	Bottom Pair	Middle Pair	Parents High Educ.
Same Gender	1								
Same Race	0.0003	1							
Same Race and Gender	0.626	0.552	1						
Both Free Lunch	0.000	-0.033	-0.018	1					
Neither Free Lunch	0.000	0.235	0.130	-0.330	1				
Top Pair	0.0003	0.0656	0.0365	-0.117	0.227	1			
Bottom Pair	0.0014	-0.002	-0.000	0.194	-0.150	-0.102	1		
Middle Pair	0.001	0.019	0.010	-0.028	-0.006	-0.183	-0.132	1	
Parents High Education	0.000	0.129	0.072	-0.214	0.406	0.155	-0.111	0.016	1
Classmates Last Year	-0.006	0.0244	0.008	-0.009	0.026	0.030	0.006	0.018	0.053

Empirical Model

We model the probability that a pair of students are classmates as a function of the characteristics of that pair. Let $Y_{ij} = 1$ if student *i* and student *j* are classmates and equal zero if they are not. Let X_{ij} represent a vector of characteristics describing pair *ij* and let the probability that pair *ij* are classmates be a function of a linear combination of these characteristics:

$$\text{Prob}(Y_{ij} = 1 \mid X_{ij}) = f(\beta' X_{ij}) \quad (0)$$

In its simplest form, this equation can be estimated directly using a linear probability model (LPM), as shown in equation (2).

$$Y_{ij} = \beta' X_{ij} + \varepsilon_{ij} \quad (0)$$

The probability that a pair of students are classmates will also depend on characteristics unique to the school. To control for these effects, we introduce a set of school-level fixed effects that capture the average effect of a particular school on the probability that students are assigned to the same classroom. We therefore model the probability that pair *ij* in school *k* are classmates with a school-specific fixed effect as follows:

$$Y_{ijk} = \beta' X_{ij} + \alpha_k + \varepsilon_{ijk} \quad (0)$$

Given that the LPM will have a heteroscedastic error term and has the potential for fitted values outside the (0,1) interval, a logit or probit model is often the more appropriate modeling choice. However, the LPM also has a number of advantages that are particularly relevant and helpful in this context. First, it is essential to our estimation that the vector *X* contains school fixed effects because the characteristics of the school will likely play an important role in the probability that a given pair of students are classmates. For example, two randomly chosen students in a small school are obviously more likely to be classmates than two randomly chosen students in a large school. The use of school-level fixed effects enables us to control for any (observed or unobserved) school-specific effects on the probability of a pair of students being classmates. Unlike logit and probit models, the linear probability model has the advantage of being able to handle the very large number of school fixed effects in our dataset without the well-known theoretical and practical problems encountered in non-linear models with fixed effects. (W. Greene, 2004). Second, our technique of creating an observation for each possible pair of students creates an extremely large sample (about 4.5 million observations). Non-linear models can require extremely large amounts of time and computing resources to estimate with very large data sets.[4] Finally, the estimated parameters of the LPM are simple to interpret and do not require the computation of marginal effects to provide meaningful magnitudes. Recent examples of the use of linear probability models include Klaassen & Magnus (2003) and Betts & Fairlie (2001).

Despite the advantages of the LPM, it is important to address the relevant weaknesses of the LPM. For a discussion of these weaknesses, see Gujarati and Porter (2003) or Greene (1997). While Maddala (1986) has shown that the LPM provides consistent parameter estimates, the use of a dummy dependent variable indicates that the error term will be heteroscedastic and non-normally distributed. Heteroscedastic error terms can lead to biased estimates of the standard errors. We

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[4]Despite these difficulties, we have managed to estimate some simple versions of the models reported herein using probit and logit models with school characteristics as controls, rather than our preferred method of using school-level fixed effects. We find that our general results are robust to these alternative modeling techniques. These results are available from the authors upon request.

address this issue by using White's heteroscedasticity-robust standard errors (Long & Ervin, 2000). It is important to note that these standard errors are robust to both known and unknown forms of heteroscedasticity. Another weakness of the LPM is the potential for the model to predict probabilities outside the (0,1) interval. We show, however, that our models do not produce fitted values outside the (0,1) interval. Finally, we note that although we follow convention and report R^2 for each of our models, traditional measures of goodness-of-fit have less meaning in the case of a dummy dependent variable (Train, 2009).

Empirical Results

Our empirical results are organized as follows: We first show the results of models that pool data from all 5th grade cohorts in 2004 in public elementary schools in North Carolina. Given that we might expect alternative administrative arrangements to influence classroom assignment patterns, we then compare these results to models based on a sub-set of the data from Magnet schools only. Finally, we check for variation in classroom assignment patterns by estimating models based on sub-sets of the data according to the racial, income, or geographic characteristics of the school population.

Baseline Models: All Schools and Magnet Schools

As a baseline hypothesis, suppose that students are assigned to classes randomly. If this hypothesis were true, we would expect that none of the characteristics exhibited by a pair of students will influence the probability that they are classmates (after controlling for school-specific effects.) Model 1, labeled "All Schools" in Table 3, clearly shows that we can reject this baseline hypothesis of random assignment. This model pools data from all 5th grade students in public elementary schools in North Carolina in 2004 and shows that each and every included characteristic is a statistically significant predictor of whether or not a pair of students are classmates. In general, we find that students that are similar on observable characteristics are statistically more likely to be classmates. The coefficients on the variables "Same Race", "Both Free Lunch", "Neither Free Lunch", "Top Pair", "Bottom Pair", "Middle Pair", "Parents High Education", and "Classmates Last Year" are all statistically significantly positive, indicating that students who share these characteristics are more likely to be classmates. Of notable exception to this general pattern of grouping similar students are the negative coefficients on the variables "Same Gender" and "Same Gender and Race", indicating that administrators seek to avoid gender imbalanced classrooms. Students of the same gender and race are even less likely to be classmates than those of the same gender but with different racial characteristics. Alternately stated, students of the same race are less likely to be classmates if they are of the same gender. We also note that the "Same Race" variable is statistically significantly different from zero at only the 10% level in Model 1, suggesting that racial characteristics may be less important, statistically, than other observable attributes in predicting whether or not students are classmates.

Table 3: Linear Probability Models with School Level Fixed Effects[a]

VARIABLES	(1) All Schools	(2) Magnet Schools	(1A) All Schools	(2A) Magnet Schools
Same Gender	-0.0045***	-0.0024	-0.0040***	-0.0003
	(0.001)	(0.002)	(0.001)	(0.003)
Same Race	0.0011*	0.0040*	0.0025***	0.0055**
	(0.001)	(0.002)	(0.001)	(0.003)
Same Gender & Race	-0.0061***	-0.0083**	-0.0054***	-0.0085**
	(0.001)	(0.003)	(0.001)	(0.004)
Both Free Lunch	0.0068***	0.0210***	0.0074***	0.0354***
	(0.001)	(0.003)	(0.001)	(0.003)
Neither Free Lunch	0.0045***	0.0084***	0.0019***	-0.0188***
	(0.001)	(0.002)	(0.001)	(0.003)
Top Pair	0.0130***	0.0068***	0.0083***	0.0038
	(0.001)	(0.002)	(0.001)	(0.003)
Bottom Pair	0.0128***	0.0160***	0.0143***	0.0279***
	(0.001)	(0.004)	(0.001)	(0.005)
Middle Pair	0.0065***	0.0026	0.0074***	0.0030
	(0.001)	(0.002)	(0.001)	(0.003)
Parents High Education	0.0046***	-0.0038*	-0.0018***	-0.0042*
	(0.001)	(0.002)	(0.001)	(0.002)
Classmates Last Year	0.0368***	0.1775***	0.0290***	0.1472***
	(0.001)	(0.002)	(0.001)	(0.005)
…*Same Gender	--	--	-0.0030*	-0.0105*
			(0.002)	(0.006)
…*Same Race	--	--	-0.0088***	-0.0109*
			(0.002)	(0.006)
…*Same Gender & Race	--	--	-0.0031	0.0039
			(0.002)	(0.008)
…*Both Free Lunch	--	--	-0.0045***	-0.0943***
			(0.002)	(0.007)
…*Neither Free Lunch	--	--	0.0136***	0.1089***
			(0.001)	(0.005)
…*Top Pair	--	--	0.0223***	0.0145***
			(0.002)	(0.006)
…*Bottom Pair	--	--	-0.0059***	-0.0443***
			(0.002)	(0.010)
…*Middle Pair	--	--	-0.0035**	0.0027
			(0.001)	(0.006)
…*Parents High Education	--	--	0.0311***	-0.0049
			(0.001)	(0.005)
Constant	0.2111***	0.1990***	0.2125***	0.2051***
	(0.000)	(0.002)	(0.001)	(0.002)
Observations	4525138	264116	4525138	264116
R-squared	0.051	0.065	0.051	0.070

[a]School fixed effects not shown to save space. One, two, and three asterisks indicate the coefficients are statistically different from zero at 10%, 5%, and 1% confidence levels, respectively. Standard errors are in parentheses.

Figure 1 shows the distribution of predicted probabilities from Model 1 for all student pairs in the data. While the coefficients in Model 1 are statistically significant they are, individually, generally small in magnitude. For example, our model suggests that the probability that a pair of students who are a "Top Pair" are classmates is 0.013 larger than an otherwise identical pair who are not both top students, all else equal. However, it is unclear from the model coefficients alone how much difference these individually small, though statistically significant, effects may make in terms of aggregate classroom heterogeneity. Figure 1 suggests that these predicted probabilities deviate substantially from what might be expected under a naïve model of random student assignment. For example, random assignment would suggest that probabilities for a cohort with two classrooms would equal one-half while random assignment to three classrooms would indicate probabilities of about one-third.[5] Figure 1 shows that there are indeed visible portions of the distribution that cluster around these numbers. However, there is also noticeable variation around these values. It is also worth noting that none of the predicted probabilities lie outside the (0,1) interval, suggesting that this potential weakness of the LPM is not problematic in this context.

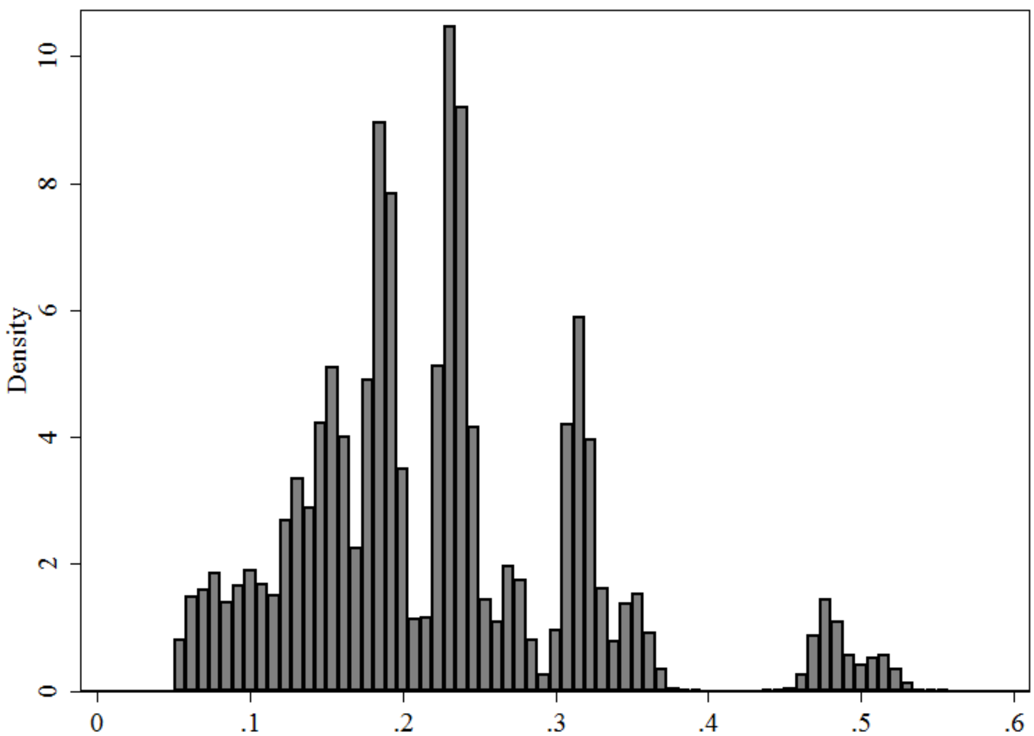

Figure 1: Model 1 Predicted Probabilities (All student pairs)

We focus special attention on the variable "Classmates Last Year" because it allows us to test for the influence of unobserved factors on the classroom assignment process. Unlike the other variables, which identify whether or not students share an easily observable characteristic, this variable merely identifies the fact that the students were classmates the previous year. If students were randomly assigned to classes, we would of course expect that *none* of our variables would have a statistically significant effect on the probability that they are classmates. However, if students were

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[5] These probabilities are not quite exact and will depend on the number of students and number of classes. For example, if a cohort has 50 students to be randomly assigned to two equally sized classes, the exact probability that a given student is assigned to the same class as another is actually 24/49=0.4898.

sorted only on observable characteristics, we would expect that, after controlling for the influence of these variables, the variable "Classmates Last Year" would have no effect on the probability that they are classmates this year. If, however, the variable "Classmates Last Year" does have a significant effect, it would provide evidence that including observable student and classroom characteristics in value-added models is not sufficient to control for variation in classroom composition.

Interestingly, the variable "Classmates Last Year" does have a statistically significant effect. Moreover, the coefficient on this variable is by far the largest coefficient in absolute magnitude in Model 1. This model indicates that students who were classmates the previous year are more likely to be classmates; the magnitude of the effect of this variable (probability increase=0.037) is easily the largest among the variables included the model. Figures 1A and 1B illustrate the influence that this variable has on the predicted probabilities from Model 1. In Figure 1A, the distribution of predicted probabilities for students who were not classmates the previous year is shown. The mean of this distribution is 0.191. Figure 1B shows the analogous distribution for students who were classmates the previous year. The mean of this distribution is 0.272, much larger than the mean of the distribution of predicted probabilities for students who were not classmates the previous year. We return later to this topic with an in-depth analysis of the "Classmates Last Year" variable in the next section.

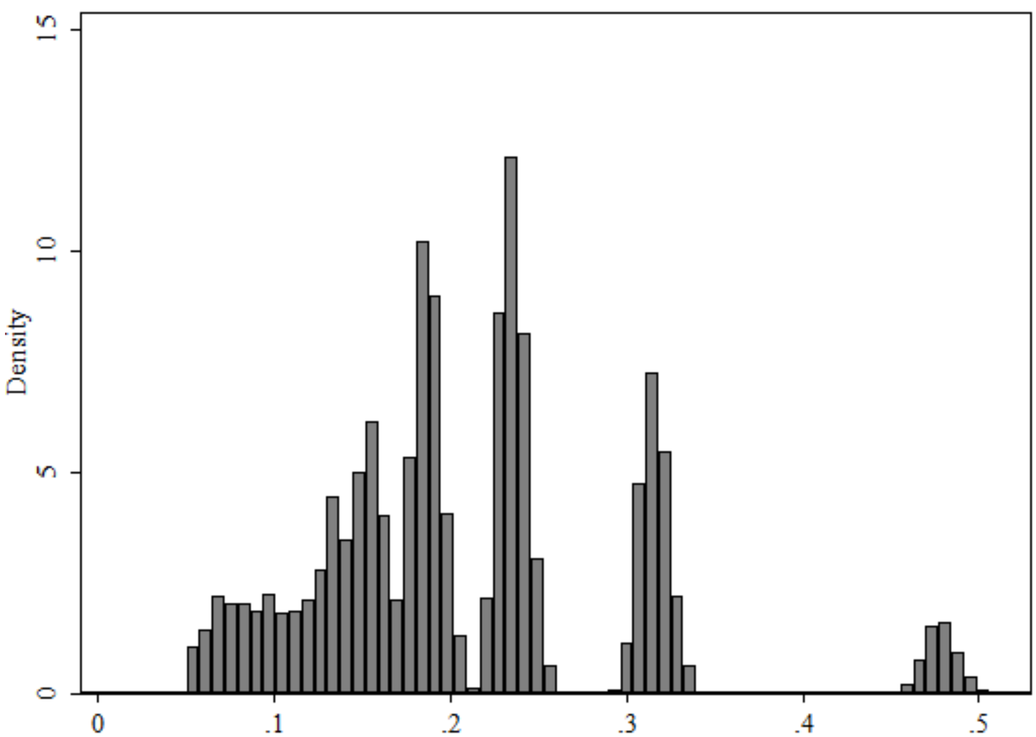

Figure 1A: Model 1 Predicted Probabilities (Classmates Last Year=0)

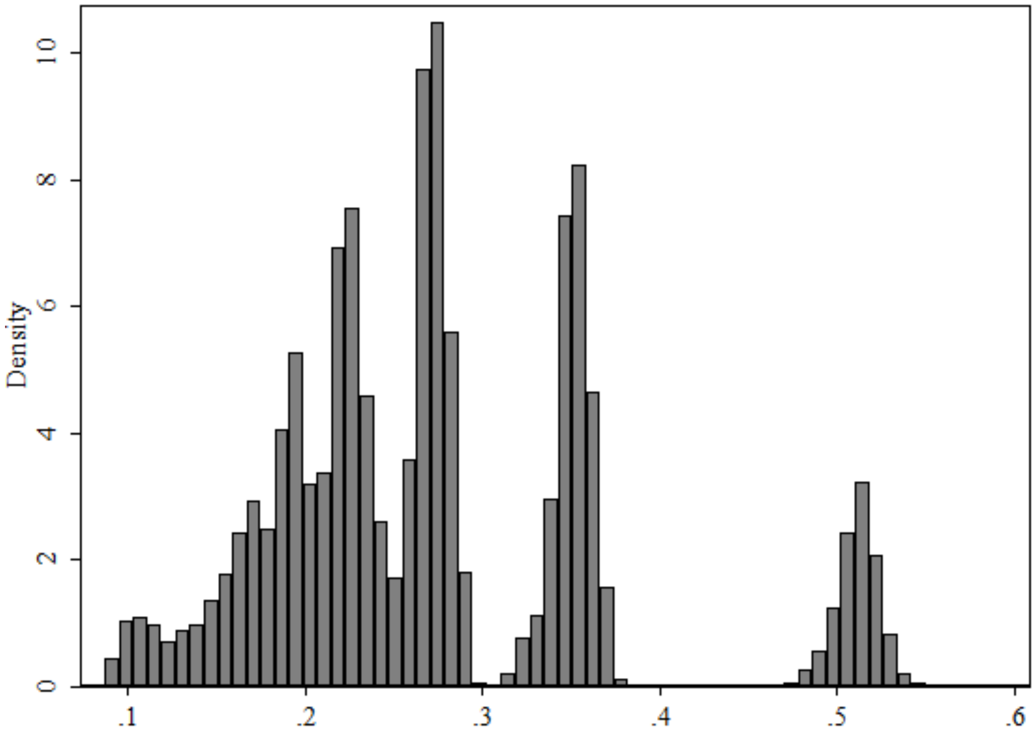

Figure 1B: Model 1 Predicted Probabilities (Classmates Last Year=1)

Model 2 reports the results of an identical model applied only to Magnet schools. The most striking feature of this model is that the coefficient on "Classmates Last Year" is very large—much larger than the analogous parameter in Model 1 (0.178 compared to 0.037). Model 2 indicates that pupils in Magnet schools who were classmates the previous year are much more likely to be classmates in the current period. Figure 2 shows the distribution of predicted probabilities for Magnet schools.

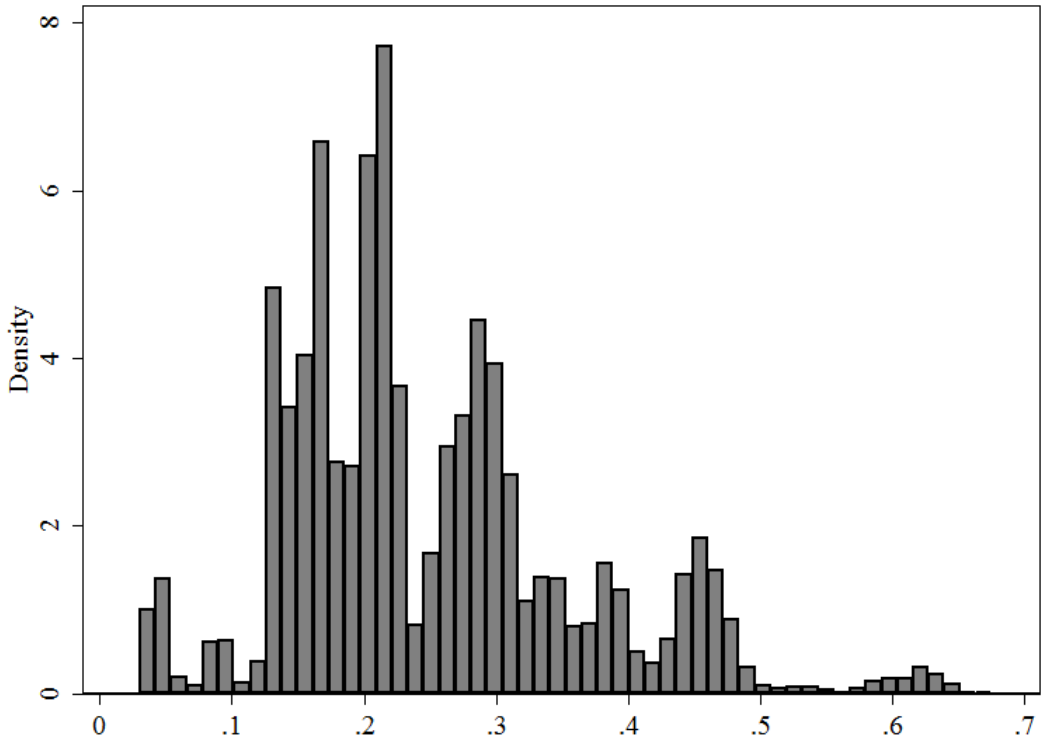

Figure 2: Model 2 Predicted Probabilities (Magnet school pairs)

In Model 2, we also observe substantially larger coefficients on the variables "Same Race", "Both Free Lunch", and "Neither Free Lunch", suggesting that Magnet schools are more likely to sort students based on these characteristics. We also observe that the coefficient on "Parents High Education" is negative for Model 2, suggesting that Magnet schools are actually less likely to sort students based on parental education levels; however, we note that average reported parental education levels are substantially higher for Magnet schools. In our dataset, the mean of the "Parents High Education" variable is about 0.471 for Magnet schools, compared to 0.252 for all schools.

Classmates Last Year

We include the variable "Classmates Last Year" as a test of sorting on unobserved characteristics. The ability to include this variable in our models is an important feature of our analysis and is possible only because our modeling strategy specifies that each observation represents a pair of students, rather than an individual student.

Our baseline hypothesis, which we strongly reject, is that students are assigned to classes randomly. A secondary hypothesis may be that students are sorted only on easily observable characteristics such as academic performance, race, gender, or income. If this hypothesis is true, the fact that students were classmates the previous year should not influence the probability that they are classmates in the current year, after controlling for the effects of normally observable characteristics. If this hypothesis is false, however, it indicates that other unobserved factors influence the probability that students are classmates. Moreover, it implies that the normally available variables used as controls in value-added modeling may be insufficient to control for the effects of non-random assignment to classrooms.

In fact, in both Models 1 and 2 we see that the "Classmates Last Year" variable has the largest coefficient among all included variables, suggesting that whatever unobserved factors influenced the previous year's class assignment decision are also important in the current year, even after controlling for observables.[6] One implication of this result is that the effect of normally unobserved factors on the assignment process may be large relative to the effect of observed factors.

In an effort to better understand the effect of the "Classmates Last Year" variable, we introduce a set of interaction terms that allow the coefficient on the "Classmates Last Year" variable to vary systematically according to the other observable characteristics. The coefficients on these interaction terms can provide insight into which types of students are more likely to be paired together in consecutive years. These results are shown in Models 1A (All Schools) and 2A (Magnet Schools) in Table 3.

In Model 1A, we find that the effect of the indicator "Classmates Last Year" varies significantly. This variation can be summarized by observation that the tendency for students to be repeat classmates appears stronger for more successful and advantaged students and weaker for less successful and less advantaged students. For example, the propensity for students who were classmates the previous year to be classmates again is stronger for pairs of students who are a "Top Pair", who have highly educated parents, or who are not on free on reduced lunch. However, this effect works in the opposite direction for students on free or reduced lunch, and for students from the bottom or middle of the academic distribution. It is also interesting to note that the baseline effect of "Parents High Education" turns negative once the interaction effect between classmates last year and highly educated parents is included in the regression. This suggests that, on average, students with highly educated parents are actually less likely to be classmates, unless they were classmates the previous year. One possible explanation for these results is that administrators may be more inclined to repeat successful student pairings (and avoid unsuccessful pairings) based on information gleaned from teachers and parents over the previous year.

The Model 2A, we repeat the specification in Model 1A with our subset of Magnet schools. With the exception of the "Parents High Education" variable, the coefficients on the interaction terms in the Magnet school sub-sample carry the same sign and level of statistical significance as in Model 1A. However, we observe much larger magnitudes for some variables. In particular, we see that the effect of the "Classmates Last Year" variable is dramatically lower (-0.094) for pairs of students on free or reduced lunch and dramatically higher (0.109) for pairs who are not on free or reduced lunch. Given that the coefficients on these dummy variables can be interpreted as probability changes, this means that pairs of students (who previously were classmates) who are not on free or reduced lunch have a probability of being classmates that is higher by about 0.2 than an (otherwise similar) pair who are on free or reduced lunch. In general, these relatively large magnitude coefficients suggest substantial deviation from what might be expected under random assignment in Magnet school. One explanation for this finding is that administrators at Magnet schools are more actively involved in constructing custom classroom assignments (Metz, 1986; West, 1994).

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[6] As observed by an anonymous reviewer, one possible explanation for this result would be the practice of "looping"—students and teachers remaining together for more than one year. However, this practice appears extremely rare in our data, even in Magnet schools. In the full sample, classrooms where fewer than 35% of students were classmates the previous year constitute over 95% of the observations and classrooms where less than 86% were classmates the previous year constitute over 99% of the observations. To check that our results are not influenced by a small number of unusual observations we have also re-estimated our key models with any classrooms where more than 86% of the students were classmates the previous year excluded as observations. These results are not materially different than those reported in the text. Full results are available from the authors upon request.

Variation by School Type

We now investigate models that estimate our student sorting models on various subsets of the data. The purpose of this exercise is to investigate the consistency of sorting patterns across school types. For this exercise, our baseline hypothesis is that the factors that influence student assignment are similar in all school types. Our alternative hypothesis is that these patterns vary with school attributes.

Racial and Income Composition

Using the variables "Majority Black" and "Few Black" we estimate the models described above for schools that are predominantly African-American and for schools with fewer than 10% African-American students. In general, the patterns displayed in Table 4 are remarkably stable across variation in school type by race characteristics. We find that in both "Majority Black" and "Few Black" Schools, the general pattern of grouping students who are similar on observable characteristics holds and that the magnitudes of the coefficients are similar to the aggregate results shown in Table 3. We also note that the variable "Same Race" is only statistically significant in the "Majority Black" sub-sample. However, we refrain from making inferences of different administrator behavior given that schools with a majority of African-American students are more racially heterogeneous than other schools. Schools with little racial heterogeneity will obviously have little opportunity for sorting based on racial characteristics.

Table 4: Linear Probability Models
with School Level Fixed Effects[b] (Subsets by Race and Income)

VARIABLES	(3) Majority Black	(4) Few Black	(5) Low Income	(6) High Income
Same Gender	-0.0036***	-0.0085***	-0.0039***	-0.0060***
	(0.001)	(0.002)	(0.001)	(0.001)
Same Race	0.0091***	-0.0004	0.0021	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Same Gender & Race	-0.0064***	-0.0012	-0.0058***	-0.0034**
	(0.002)	(0.002)	(0.002)	(0.001)
Both Free Lunch	0.0092***	0.0056***	0.0044***	0.0085***
	(0.001)	(0.002)	(0.001)	(0.002)
Neither Free Lunch	0.0122***	0.0027***	0.0143***	0.0009
	(0.001)	(0.001)	(0.002)	(0.001)
Top Pair	0.0293***	0.0059***	0.0200***	0.0100***
	(0.002)	(0.001)	(0.002)	(0.001)
Bottom Pair	0.0124***	0.0059***	0.0132***	0.0144***
	(0.001)	(0.002)	(0.001)	(0.002)
Middle Pair	0.0082***	0.0043***	0.0088***	0.0063***
	(0.001)	(0.001)	(0.001)	(0.001)
Parents High Education	0.0101***	0.0015	0.0057***	0.0015**
	(0.001)	(0.001)	(0.002)	(0.001)
Classmates Last Year	0.0422***	0.0238***	0.0292***	0.0481***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.2121***	0.2298***	0.2168***	0.2032***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	853043	1175043	822017	1515207
R-squared	0.053	0.043	0.074	0.041

[b]School fixed effects not shown to save space. One, two, and three asterisks indicate the coefficients are statistically different from zero at 10%, 5%, and 1% confidence levels, respectively. Standard errors are in parentheses.

Remarkably, the same patterns shown in Tables 3 and 4 also hold in Models 5 and 6, shown in Table 4: Both "Low Income" and "High Income" schools tend to group similar students, with the clear exception of gender characteristics. The magnitudes of the coefficients are also similar to the aggregate results shown in Table 3. One small difference is that the "Same Race" variable is not statistically significant for these sub-samples.

Population Density

Models estimated on different sub-samples for Rural, Town, Suburb, and City environments (Table 5) also display remarkable similarity to the aggregate results shown in Table 3 in terms of coefficient sign, magnitude, and statistical significance. However, we observe that the variable "Same Race" is statistically significant only in the City schools sub-sample. Given that these schools tend to be much more racially heterogeneous, and hence have much more opportunity for sorting, we caution against interpreting this as general evidence of differences in classroom assignment patterns or procedures in City schools.

Table 5: Linear Probability Models
with School Level Fixed Effects[c] (Subsets by Population Density)

VARIABLES	(7) Rural	(8) Suburb	(9) Town	(10) City
Same Gender	-0.0047***	-0.0050***	-0.0034***	-0.0047***
	(0.001)	(0.001)	(0.001)	(0.001)
Same Race	-0.0003	0.0015	0.0019	0.0026**
	(0.001)	(0.001)	(0.001)	(0.001)
Same Gender & Race	-0.0058***	-0.0056***	-0.0063***	-0.0069***
	(0.001)	(0.002)	(0.002)	(0.002)
Both Free Lunch	0.0064***	0.0080***	0.0052***	0.0089***
	(0.001)	(0.001)	(0.001)	(0.001)
Neither Free Lunch	0.0053***	0.0029***	0.0061***	0.0039***
	(0.001)	(0.001)	(0.001)	(0.001)
Top Pair	0.0159***	0.0124***	0.0161***	0.0075***
	(0.001)	(0.001)	(0.002)	(0.001)
Bottom Pair	0.0152***	0.0131***	0.0109***	0.0112***
	(0.001)	(0.002)	(0.002)	(0.002)
Middle Pair	0.0070***	0.0078***	0.0064***	0.0044***
	(0.001)	(0.001)	(0.001)	(0.001)
Parents High Education	0.0047***	0.0027**	0.0091***	0.0032***
	(0.001)	(0.001)	(0.001)	(0.001)
Classmates Last Year	0.0189***	0.0438***	0.0255***	0.0710***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.2282***	0.2101***	0.1547***	0.2190***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1818749	974308	670344	1061737
R-squared	0.049	0.035	0.072	0.044

[c]School fixed effects not shown to save space. One, two, and three asterisks indicate the coefficients are statistically different from zero at 10%, 5%, and 1% confidence levels, respectively. Standard errors are in parentheses.

Variation by School Type: Discussion

In general, the statistical patterns in the probability that a pair of students are classmates are remarkably stable with respect to school racial composition, income, and population density. One possible reason for this result is that, in general, school administrators follow similar procedures for class formation across different schools. For example, we find that that in all sub-samples, administrators avoid grouping students by gender, but are willing to group students (at the margin) by other characteristics. We observe that former classmates are more likely to be classmates in all sub-samples and that this tendency is especially pronounced for more advantaged students.

Findings and Implications

In this study, we model the probability that a pair of students are classmates as a function of the characteristics of those students. Importantly, we allow the probability that a pair of students were classmates to vary according to whether or not they were classmates the previous year. We use this methodological technique to better understand how elementary students are assigned to classrooms and, importantly, to assess the degree to which statistical models of teacher quality, class size effects, and other educational metrics are able to control for the effects of non-random assignment to classrooms. The technique we use can be easily implemented by researchers or practitioners seeking to understand sorting patterns in a particular school or district.

Modeling the probability that a pair of students are classmates is unusual, but we adopt this innovative technique because it allows us to test whether or not the fact that students were previous classmates has any effect on the probability that they are classmates again. If students who were past classmates are more likely to be assigned to the same class again, even after controlling for other observable characteristics, then ordinarily available student characteristics may not be sufficient to control for classroom composition effects in value-added models.

The key results of this study show that, after controlling for school-specific effects, students with similar indicators for income, academic performance, and parental education level are more likely to be classmates than students who are not similar on these observable characteristics. Moreover, even after controlling for a wide variety of observable characteristics, students who were classmates the previous year were more likely to be classmates again. The magnitude of this latter effect is large relative to the effect of the other variables, suggesting that factors that are normally not observed by researchers play a significant role in classroom assignment decisions. We also show that this tendency for a pair of students to be classmates again is especially strong for students who are advantaged in terms of academics, income, or parental education levels.

Although our results show that, in general, similar students are more likely to be classmates, a clear exception to this rule is gender. Administrators appear reluctant to sort students on gender: same gender pairs are less likely to be repeat classmates and this is especially true for same-gender pairs of the same race.

Finally, we find that the tendency to group similar students is especially strong in Magnet schools, suggesting that these schools have systematically different classroom formation procedures. This finding suggests that research investigating differences in outcomes across school types should be interpreted with caution. Although it is possible that differences in outcomes are attributable to differences in school inputs, these differences may also be due to differences in school procedures such as classroom formation processes. With the exception of Magnet schools, however, we find that aggregate statistical patterns in classrooms assignment outcomes are broadly similar across different school types.

These results have important implications for both researchers and policy makers. Research using statistical models that rely, explicitly or implicitly, on the assumption that students are randomly assigned to classrooms is unlikely to provide reliable results—our models suggest strong patterns in student assignment to classrooms. However, even the use of more sophisticated models that attempt to control for non-random assignment by using normally observed classroom composition characteristics may be unreliable. The fact that a pair of students are more likely to be classmates if they have been classmates previously, even after controlling for a wide variety of observed characteristics, suggests that classroom assignment decisions may be based on characteristics that are not normally observable to the researcher. Thus, even models that attempt to control for non-random assignment via control variables may still be unreliable. Policy makers should therefore use caution in using the results of statistical analyses of teacher quality, class size, or other effects to make policy or resource allocation decisions.

Conclusions

Understanding the manner in which students are assigned to classrooms is important because 1) classroom assignment has a direct impact on student learning outcomes through teacher effects and peer effects, 2) classrooms assignment practices and patterns have implications for the reliability of statistical techniques such as value-added modeling, and 3) the results of these statistical analyses may be used as the basis for educational policy changes. As noted by Koedel and Betts (2011), "the success of the value-added approach will depend largely on data availability and the underlying degree of student-teacher sorting in the data (much of which may be unobserved)". We show that the degree of student-teacher sorting in our data is indeed non-trivial and, importantly, we find strong evidence that much of the sorting is likely to be based on characteristics which are unobserved. This evidence suggests that policymakers should use caution in interpreting and applying the results of statistical analyses of teacher quality effects, class size effects, and other educational metrics. If students are assigned to classes based on characteristics that are unobserved or difficult to control for, as suggested by this study, statistical inferences may be unreliable or misleading.

In addition to implications for the use and interpretation of statistical analyses, our study yields some other results that may be of direct interest to researchers and policymakers. First, the fact that students are not randomly assigned to classrooms is interesting because it implies that local administrators must be following some other procedure. As noted in this study, these procedures and their implications are not well understood (Steele, Kraemer, and Meyer, 2012) and represent an opportunity for important new research. Second, classroom assignment procedures may have important implications for fairness and for efficient use of educational resources. For example, our study suggests that more advantaged students in terms of income, academic performance, and parental education level are more likely to be classmates. While some research indicates that grouping similar students may be more efficient, grouping advantaged students may also be viewed as unfair or inequitable.

The quantitative and aggregate nature of this study may also provide some indication of fruitful areas for future research. Although this study shows clear results regarding the assignment of students to classrooms, we are unable to comment on how students may be sorted *within* classrooms (also known as ability grouping). Future qualitative research may be able to investigate the extent to which ability grouping practices are influenced by classroom assignment procedures. Finally, because little is known about how the processes of classroom assignment procedures vary across schools, we are unable to comment on how these practices and the observed outcomes might change in response to new rules, guidelines, and laws. Future research on this topic may be able to shed light on this important question.

References

Adcock, E. P., & Phillips, G. W. (2000). Accountability Evaluation of Magnet School Programs: A Value-Added Model Approach.

Archbald, D. A. (2004). School Choice, Magnet Schools, and the Liberation Model: An Empirical Study. *Sociology of Education, 77*(4), 283-310. doi: 10.1177/003804070407700402

Ballou, D., Sanders, W., & Wright, P. (2004). Controlling for student background in value-added assessment of teachers. *Journal of educational and behavioral statistics, 29*(1), 37-65.

Betts, J. R., & Fairlie, R. W. (2001). Explaining ethnic, racial, and immigrant differences in private school attendance. *Journal of Urban Economics, 50*(1), 26-51.

Bosworth, R. (2011). Class size, class composition, and the distribution of student achievement. *Education Economics*, 1-25. doi: 10.1080/09645292.2011.568698

Bosworth, R., & Caliendo, F. (2007). Educational production and teacher preferences. *Economics of Education Review, 26*(4), 487-500. doi: 10.1016/j.econedurev.2005.04.004

Braun, H. I. (2005). *Using student progress to evaluate teachers: A primer on value-added models*: Educational Testing Service Princeton, NJ.

Burke, M. A., & Sass, T. (2008). Classroom Peer Effects and Student Achievement. *SSRN eLibrary*. doi: 10.2139/ssrn.1260882

Burns, R. B., & Mason, D. A. (1995). Organizational Constraints on the Formation of Elementary School Classes. *American Journal of Education, 103*(2), 185-212.

Burns, R. B., & Mason, D. A. (1998). Class Formation and Composition in Elementary Schools. *American Educational Research Journal, 35*(4), 739-772. doi: 10.3102/00028312035004739

Burns, R. B., & Mason, D. A. (2002). Class Composition and Student Achievement in Elementary Schools. *American Educational Research Journal, 39*(1), 207-233. doi: 10.3102/00028312039001207

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2006). Teacher-Student Matching and the Assessment of Teacher Effectiveness. *Journal of Human Resources, XLI*(4), 778-820. doi: 10.3368/jhr.XLI.4.778

Dar, Y., & Resh, N. (1986). Classroom Intellectual Composition and Academic Achievement. *American Educational Research Journal, 23*(3), 357-374. doi: 10.3102/00028312023003357

Darling-Hammond, L., Amrein-Beardsley, A., Haertel, E., & Rothstein, J. (2012). Evaluating teacher evaluation. *Phi Delta Kappan, 93*(6), 8-15.

Dills, A. K., & Mulholland, S. E. (2010). A comparative look at private and public schools' class size determinants. *Education Economics, 18*(4), 435-454. doi: 10.1080/09645290903546397

Doran, H. C., & Izumi, L. T. (2004). Putting education to the test: A value-added model for California. *San Francisco: Pacific Research Institute.*

Dreeben, R., & Barr, R. (1988). Classroom Composition and the Design of Instruction. *Sociology of Education, 61*(3), 129-142.

Figlio, D. N. (2007). Boys Named Sue: Disruptive Children and Their Peers. *Education Finance and Policy, 2*(4), 376-394. doi: 10.1162/edfp.2007.2.4.376

Flood, D. E. (1978). *The Magnet School Concept in North Carolina.*

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *Econometrics Journal, 7*(1), 98-119. doi: 10.1111/j.1368-423X.2004.00123.x

Greene, W. H., & Zhang, C. (1997). *Econometric analysis* (Vol. 3): Prentice hall Upper Saddle River, NJ.

Gujarati, D. N., & Porter, D. (2003). Basic Econometrics Mc Graw-Hill International Edition.

Harris, D. N. (2009). Would accountability based on teacher value added be smart policy? An examination of the statistical properties and policy alternatives. *Education Finance and Policy, 4*(4), 319-350.
Hattie, J. A. C. (2002). Classroom composition and peer effects. *International Journal of Educational Research, 37*(5), 449-481. doi: 10.1016/s0883-0355(03)00015-6
Hoxby, C. M. (2000a). The Effects of Class Size on Student Achievement: New Evidence from Population Variation. *The Quarterly Journal of Economics, 115*(4), 1239-1285. doi: 10.1162/003355300555060
Hoxby, C. M. (2000b). Peer Effects in the Classroom: Learning from Gender and Race Variation. *National Bureau of Economic Research Working Paper Series, No. 7867*.
Kalogrides, D., Loeb, S., & Beteille, T. (2011). *Power Play? Teacher characteristics and class assignments*. CALDER Working Paper No. 59. The Urban Institute, Washington D.C.
Klaassen, F. J. G. M., & Magnus, J. R. (2003). Forecasting the winner of a tennis match. *European Journal of Operational Research, 148*(2), 257-267.
Koedel, C., & Betts, J. R. (2011). Does student sorting invalidate value-added models of teacher effectiveness? An extended analysis of the Rothstein critique. *Education Finance and Policy, 6*(1), 18-42.
Kraemer, S., Rhodes, S., Steele, C., & Meyer, R. H. (2012). A Team-Based Model of Classroom Assignment *American Education Finance and Policy 37th Annual Conference*. Boston MA.
Kraemer, S., Worth, R., & Meyer, R. H. (2011). *Classroom Assignment Practices in Urban School Districts Using Teacher Level Value-Added Systems*. Paper presented at the Association for Education Finance and Policy Annual Conference, Seattle WA.
Lazear, E. P. (2001). Educational Production. *The Quarterly Journal of Economics, 116*(3), 777-803. doi: 10.1162/00335530152466232
Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician, 54*(3), 217-224.
Luyten, H., Schildkamp, K., & Folmer, E. (2009). Cognitive development in Dutch primary education, the impact of individual background and classroom composition. *Educational Research and Evaluation, 15*(3), 265-283. doi: 10.1080/13803610902955333
Maddala, G. S. (1986). *Limited-dependent and qualitative variables in econometrics* (Vol. 3): Cambridge University Press.
McCaffrey, D. F., Lockwood, J., Koretz, D., Louis, T. A., & Hamilton, L. (2004). Models for value-added modeling of teacher effects. *Journal of educational and behavioral statistics, 29*(1), 67-101.
McEwan, P. J. (2003). Peer effects on student achievement: evidence from Chile. *Economics of Education Review, 22*(2), 131-141. doi: 10.1016/s0272-7757(02)00005-5
Metz, M. H. (1986). *Different by Design. The Context and Character of Three Magnet Schools*: Routledge & Kegan Paul Inc., 29 West 35th Street, New York, NY 10001 ($20.00).
Meyer, R. H. (1997). Value-added indicators of school performance: A primer. *Economics of Education Review, 16*(3), 283-301.
Monk, D. H. (1987). Assigning Elementary Pupils to Their Teachers. *Elementary School Journal, 88*(2), 167-187.
Praisner, C. (2003). Attitudes of Elementary School Principals Toward the Inclusion of Students With Disabilities. *Exceptional Children, 69*(2), 135-145.
Rothstein, J. (2009). Student Sorting and Bias in Value-Added Estimation: Selection on Observables and Unobservables. *Education Finance and Policy, 4*(4), 537-571. doi: 10.1162/edfp.2009.4.4.537

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *The Quarterly Journal of Economics, 125*(1), 175-214.

Rubin, D. B., Stuart, E. A., & Zanutto, E. L. (2004). A potential outcomes view of value-added assessment in education. *Journal of educational and behavioral statistics, 29*(1), 103-116.

Saporito, S., & Sohoni, D. (2006). Coloring outside the Lines: Racial Segregation in Public Schools and Their Attendance Boundaries. *Sociology of Education, 79*(2), 81-105.

Steele, C., Kraemer, S., & Meyer, R. H. (2012). *Measuring the Unknown: Creating a Survey about Student-Teacher Assignment.* Value-Added Research Center; Wisconsin Center for Education Research; University of Wisconsin - Madison.

Train, K. E. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). Cambridge: Cambridge University Press.

West, K. C. (1994). A Desegregation Tool That Backfired: Magnet Schools and Classroom Segregation. *The Yale Law Journal, 103*(8), 2567-2592.

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