American Educational Research Journal
http://aerj.aera.net

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Am Educ Res J 2013 50: 4 originally published online 23 October 2012
DOI: 10.3102/0002831212463813

American Educational Research Journal
February 2013, Vol. 50, No. 1, pp. 4–36
DOI: 10.3102/0002831212463813

How Teacher Turnover Harms Student Achievement

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Researchers and policymakers often assume that teacher turnover harms student achievement, though recent studies suggest this may not be the case. Using a unique identification strategy that employs school-by-grade level turnover and two classes of fixed-effects models, this study estimates the effects of teacher turnover on over 850,000 New York City fourth- and fifth-grade student observations over 8 years. The results indicate that students in grade levels with higher turnover score lower in both English language arts (ELA) and math and that these effects are particularly strong in schools with more low-performing and Black students. Moreover, the results suggest that there is a disruptive effect of turnover beyond changing the distribution in teacher quality.

KEYWORDS: student achievement, teacher turnover, retention

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Introduction

Teacher turnover rates can be high, particularly in schools serving low-income, non-White, and low-achieving student populations. Nationally, about 30% of new teachers leave the profession within 5 years, and the turnover rate is about 50% higher in high-poverty schools as compared to more affluent ones (Darling-Hammond & Sykes, 2003; Ingersoll, 2001, 2003).[1] Teacher turnover rates also tend to be higher in urban and lower-performing schools (Hanushek, Kain, & Rivkin, 1999).

Researchers and policymakers often assume that teacher turnover harms student learning. There are reasons to think it would, as institutional memory is lost and resources get used on the hiring process. On the other hand, the organizational management literature has demonstrated that some turnover may in fact be beneficial. Turnover, for example, can result in better person-job matches and infusion of new ideas into organizations (Abelson & Baysinger, 1984). To this point, Jackson (2010) demonstrates that poor person-job matches predict migration and that teachers tend to be more productive in their new schools. Moreover, turnover can have institutional benefits if the less effective employees leave.

Surprisingly little research has assessed the causal effect of teacher turnover on student achievement (Guin, 2004; Ingersoll, 2001). Most existing research on the relationship between teacher turnover and student achievement is correlational, revealing negative correlations. For example, Guin (2004) studies 66 elementary schools in a large urban district to look at the relationship between school-level turnover and the proportion of students meeting standards on statewide assessments in reading and math. Pearson correlations are significant and negative, indicating that schools with higher turnover also have lower achievement. These results are consistent with other correlational evidence (Boyd, Lankford, Loeb, & Wyckoff, 2005; Hanushek et al., 1999). Such evidence, though, is not necessarily indicative of a causal relationship, as a third factor (e.g., poverty, working conditions, or poor school leadership) may simultaneously cause both low achievement and higher turnover. Even if we assume the relationship is a causal one, its direction is unclear—teachers leaving may cause low achievement, but low achievement may also cause teachers to leave.

"Compositional" Explanations

One mechanism by which turnover may directly affect students is "compositional." That is, if there is a difference in quality between teachers who leave and those who replace them, then student achievement can change. When leaving teachers are, on average, worse than those who replace them, the compositional effect of turnover on student achievement is positive; if leaving teachers are better than the ones who replace them, the compositional effect is negative.

A growing body of evidence indicates that more effective teachers are at least as likely, and sometimes more likely, to stay in schools than their less effective peers and that this is true even in schools with historically underserved student populations (Boyd, Lankford, Loeb, Ronfeldt, & Wyckoff, 2011b; Goldhaber, Gross, & Player, 2007; Hanushek & Rivkin, 2010; Murnane, 1984). Boyd et al. (2011b) study data on teachers' applications for transfer to uncover which teachers are more likely to want to transfer from New York City (NYC) schools. They discover that teachers who produce higher achievement gains and those with more experience are less likely to apply for transfer.[2] This preference to stay held true even for teachers in the lowest performing schools. Earlier work by Murnane (1984) also finds evidence for selective attrition of less productive teachers, as signaled by principal ratings and prior student achievement, out of one large, urban district. Similarly, Hanushek and Rivkin (2010) show that in Texas, those who left a given school tended to be less effective than those who stayed.

Contrary to common assumptions, in the Hanushek and Rivkin (2010) study the relative effectiveness of stayers as compared to leavers is actually highest in schools with more low-achieving and Black students even though discussion about the harmful impact of teacher turnover often focuses on low-income, low-achieving, and high-minority schools (Carroll, Reichardt, & Guarino, 2000; Clotfelter, Ladd, Vigdor, & Wheeler, 2007; Hanushek et al., 2004; Ingersoll, 2001). In other words, the exiting teachers, at least compositionally, seem to benefit schools with historically underserved student populations the most.

In demonstrating that less effective teachers are more likely to leave than more effective counterparts, the studies described previously suggest turnover may be beneficial. However, none of these studies directly tested whether the teachers who filled vacancies in a given school were more effective on average than those they replaced. Darling-Hammond and Sykes (2003) argue that when teachers leave, low-income schools have a difficult time attracting new teachers and so end up hiring inexperienced and less prepared teachers. Without knowing the net distribution of quality that results from turnover, it is difficult to draw conclusions about the overall impact of turnover. Recognizing this point, Hanushek and Rivkin (2010) simulated the impact where only "rookie" teachers replaced exiting ones and found no overall effect of turnover on student achievement.

The results of the Hanushek and Rivkin (2010) simulation are an important challenge to the commonly held assumption that teacher turnover harms student achievement, especially that of low-performing, low-income, and non-White students. However, their findings have important limitations, even aside from being simulated, rather than observed, effects of new hires. Like all compositional accounts, the results assume that the only lever by which teacher turnover harms or helps student achievement is by adjusting the composition of teachers that make up a school's faculty. But turnover may impact student achievement beyond the relative effectiveness of those who stay as compared to those who leave.

"Disruptive" Explanations

The compositional explanations described previously assume that students benefit when their school hires teachers who are more effective than the ones who left. Effectiveness is thought to be something that individual teachers bring with them (or not). The overall effect of turnover depends on the resulting distribution in effectiveness of individual teachers. If leaving teachers are equally as effective as those who replace them, then there should be no net effect of turnover. In such compositional explanations, turnover effects are driven only by leavers and their replacements. The students of teachers who stay in the same school from one year to the next then are merely bystanders, unaffected by turnover.

Turnover, however, may have a broader organizational influence that reaches beyond leaving teachers, replacement teachers, and their students. Where turnover is considered to have a disruptive organizational influence, all members of a school community are vulnerable, including staying teachers and their students. In such disruptive accounts of turnover, even when leaving teachers are equally as effective as those who replace them, turnover can still impact students' achievement.

A substantial research base provides evidence that staff cohesion and community are related to student engagement and achievement (Bryk, Lee, & Holland, 1993; Bryk & Schneider, 2002; Johnson, Berg, & Donaldson, 2005; Little, 1982; Louis & Marks, 1998). According to Bryk and Schneider (2002), the quality of relationships and the trust between teachers, and between teachers and students, predicts student achievement. Likewise, Little (1982) finds "patterned norms" of interaction among colleagues that also predict student achievement. When teachers leave schools, previously held relationships and relational patterns are altered. To the degree that turnover disrupts the formation and maintenance of staff cohesion and community, it may also affect student achievement. Guin (2004) shows that teacher turnover indeed has a negative effect on faculty interactions and school climate. Likewise, a recent study by Hanselman, Grigg, Bruch, and Gamoran (2011) indicates that teacher and principal turnover has a disruptive effect on the "development and maintenance of social resources" (p. 27)—including staff collegiality, community, and trust—in a school. Moreover, these authors find the impact of turnover to be initially detrimental to "high resource" schools and initially beneficial to "low resource" schools. In other words, the disruptive influence of turnover can have either positive or negative effects depending on a school's initial conditions.

School instructional program coherence has also been shown to predict student achievement (Newman, Smith, Allensworth, & Bryk, 2001). Since staff turnover presents significant challenges to the successful and coherent implementation of such instructional programs (Guin, 2004), it also may harm student achievement. With leaving teachers goes organizational knowledge important to the effective implementation of such programs (Abelson & Baysinger, 1984). Moreover, newly hired teachers initially lack essential knowledge and skills to implement an unfamiliar instructional program, so must be brought up to speed before institutional progress can be made. The result in settings with persistent turnover then is that schools are continuously starting over rather than making progress on their programmatic agendas.

Turnover may have substantial impact on the financial and human resources in districts and schools as well. The recruiting, hiring, and training of new teachers requires significant financial costs (Barnes, Crowe, & Schaefer, 2007). These costs drain resources that might otherwise be spent on program improvement or working conditions (Barnes et al., 2007; Carroll et al., 2000; Darling-Hammond & Sykes, 2003). Such dynamics may harm schools with historically underserved student populations the most, as these schools tend to have more persistent turnover and in some cases have fewer overall resources to work with. In addition, new hires in underserved schools often are less experienced and so require more supports to improve (Carroll et al., 2000; Darling-Hammond & Sykes, 2003).

Contrary to compositional explanations that assume stayers to be unaffected by turnover, disruptive explanations indicate that stayers indeed may be affected. Because they bear much of the responsibility for mentoring new teachers about school expectations and programs, stayers can also be affected by turnover (Guin, 2004). Stayers must carry more of the instructional burden and have less professional development resources available to them, as available resources get used up on new hires (Shields et al., 1999, 2001). Persistent turnover may then have a debilitating impact on staying teachers and in turn their students.

We have provided a review of literature that describes many plausible mechanisms—both compositional and disruptive—by which teacher turnover may affect student achievement. Because prior research has not adequately established a direct, causal link between teacher turnover and student achievement, however, it is important first to establish that such a relationship exists before trying to explain why. Using a unique identification strategy and two classes of fixed-effects regression models, this study presents the cleanest estimates to date for a direct effect of teacher turnover on student achievement. After establishing evidence for a direct effect of turnover on student achievement, this article begins to explore possible mechanisms to account for the observed effect.

Three research questions guide the investigation:

Research Question 1: What is the average effect of teacher turnover on student achievement?
Research Question 2: Are the effects different for different kinds of schools?
Research Question 3: What explains the relationship between teacher turnover and student achievement?

To address the latter question, the study explores whether observed effects are compositional or disruptive in nature.

The article proceeds as follows. We first describe the data and methodological approach. We then present the results and conclude with a discussion of the implications of the findings.

Data

This study draws on extensive administrative data from the New York City Department of Education and the New York State Education Department. Analyses focus on approximately 850,000 observations of fourth- and fifth-grade students across all NYC elementary schools over eight academic years (2001–2002 and 2005–2010).[3] We are able to link student test scores in math and English language arts (ELA) to student, class, school, and teacher characteristics.

Table 1 describes student-year, teacher-year, and school-by-grade-by-year characteristics. During the years of this study, about 70% of students in fourth and fifth grades in NYC were either Black or Hispanic. Over one-third of students had a home language other than English, and 72% were on free or reduced priced lunch. Approximately 1% of students had been suspended in the previous year, while 9% had switched schools since the prior year. Finally, students were absent for an average of approximately 11 days in the previous year.

On average, 86% of teachers each year had stayed in the same school from the prior year (stayers). Approximately 4% of fourth- and fifth-grade teachers had transferred schools within NYC (movers), while 9% were first-year teachers. The fourth- and fifth-grade teachers in the district had, on average, 8 years of experience. Each fourth and fifth grade within each NYC school had, on average, 5 teachers, with a range from 1 to as many as 20 teachers. Figure 1 plots the distribution of teachers per grade in the sample schools.

Our identification strategy requires measuring school-by-grade level turnover in each year. Such measurement is not entirely straightforward. To illustrate, imagine a fourth grade within School A that had six teachers in year $t - 1$. Due to increasing enrollments, in year t there were seven fourth-grade teachers. Of these, five were stayers, one a mover, and one a first-year teacher. Teacher turnover could be estimated as the proportion of year $t - 1$ teachers that were no longer in the fourth grade in School A

Table 1
Student, Teacher, and School-by-Grade Characteristics

Student Characteristics	Mean
Proportion female	0.51
Proportion Hispanic	0.37
Proportion Black	0.32
Proportion Asian	0.14
Proportion other ethnic	0.00
Proportion Caucasian	0.16
Proportion free lunch	0.64
Proportion reduced lunch	0.08
Proportion home language English	0.62
Proportion suspended in prior year	0.01
Proportion changing schools from prior year	0.09
Average number of absences in prior year	10.66 (10.04)
Grade 4 observations (student-year)	431,341
Grade 5 observations (student-year)	432,765
Observations (student-year)	864,106
Teacher-Year Characteristics	**Mean**
Experience	8.36 (7.16)
Proportion stayers	0.86
Proportion movers	0.04
Proportion first years	0.09
Proportion unknown status	0.02
Observations (teacher-year)	42,170
Grade-by-Year-by-School Characteristics	**Mean**
Teachers	4.80 (2.32)
Turnover rate (lagged attrition)	0.11 (0.17)
Zero lagged attrition	0.58 (0.50)
Total lagged attrition	0.01 (0.08)
Turnover rate (proportion new to school)	0.13 (0.18)
Zero new to school	0.51 (0.50)
Total new to school	0.01 (0.09)
Observations (school-grade-year)	10,663

in year t (1/6 = 16.7%). On the other hand, turnover could be measured as the proportion of teachers that were new to the school-by-grade in year t—either first-year teachers or movers (2/7 = 28.6%). The first measure—"lagged attrition"—defines turnover as the proportion of teachers in a given grade level in year $t - 1$ who left the school by year t.[4] The second measure—"proportion new"—defines turnover as the proportion of teachers in a given

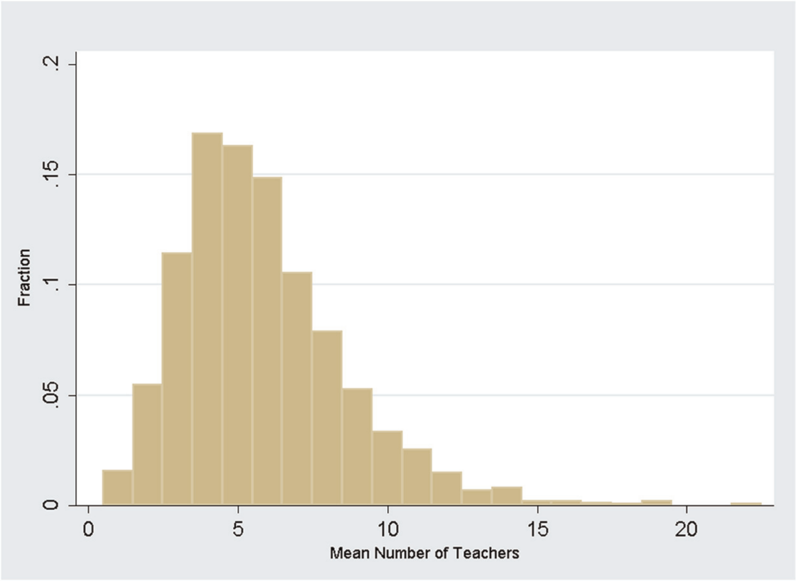

Figure 1. **Distribution of number of teachers per school by grade.**

grade level who are new (movers or first-year teachers) to the school in year *t*. We used both measures in all analyses to test whether results were robust across them; the distributions for school-by-grade lagged attrition (averaged over 8 years) can be seen in Figure 2 and for school-by-grade proportion new (averaged over 8 years) in Figure 3. The measures have similarly shaped distributions, bell shaped with a right skew.

The average teacher turnover rate in each grade in each school in each year was similar for both of the measures we developed: .11 for the lagged attrition measure and .13 for the proportion new measure. Thus, each year, approximately 1 out of every 10 fourth- and fifth-grade teachers in NYC left or came to a given grade level in a given school. At the school-grade-year level, the two measures have a correlation of $r = .27$.[5] Lagged attrition could result from teachers leaving the profession altogether or transferring to another school. This measure does not include the transfer of teachers from one grade to another within the same school. We chose not to include this behavior because in such cases, the expertise of teachers would remain within the same school.[6] About one-half of school-by-grades experienced no teacher turnover each year (between 51% and 58%). On the other hand, each year around 1% of fourth- and fifth-grade level teams had turnover rates of 100%.[7]

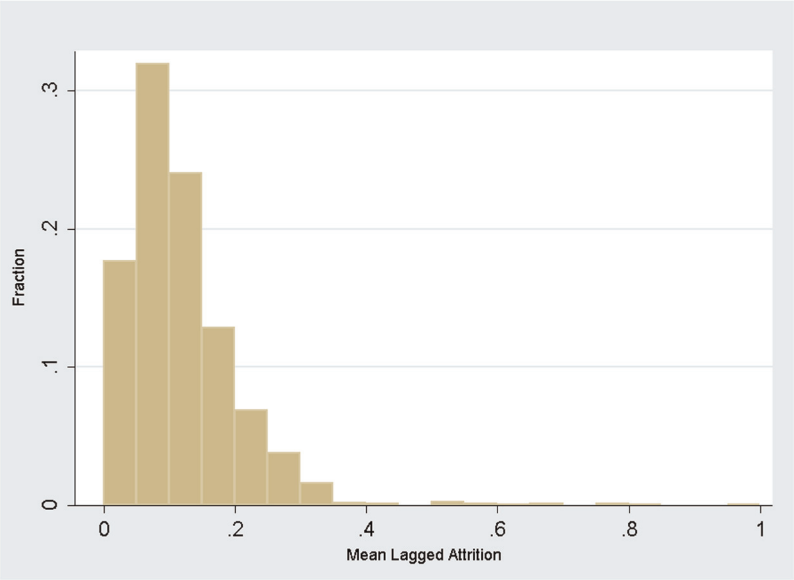

Figure 2. **Distribution of "lagged attrition" turnover measure.**

Methods

As described previously, three questions drive our analyses: What is the average effect of teacher turnover on student achievement? Are the effects different for different kinds of schools? And what explains the relationship between teacher turnover and student achievement?

What is the average effect of teacher turnover on student achievement? Typically teacher turnover is measured at the school level. However, high turnover rates in the sixth grade may have little impact on incoming fourth-grade students, especially when the fourth-grade level team stays intact. To get a more precise estimate of the effects of turnover, this study examines turnover at the school-by-grade-by-year level, rather than at the school or school-by-year level. Another benefit of examining school-by-grade-by-year level turnover is that we can adjust for school-by-grade or school-by-year level factors that could influence both student achievement and turnover. For example, if the school's principal leaves, then the transition could simultaneously affect both turnover and achievement. If we do not measure this effect, then our results would be biased, showing an association between turnover and achievement even if no causal relationship exists. Focusing on school-by-grade-by-year level turnover allows us to adjust for school-by-year level factors, both observed and not observed.

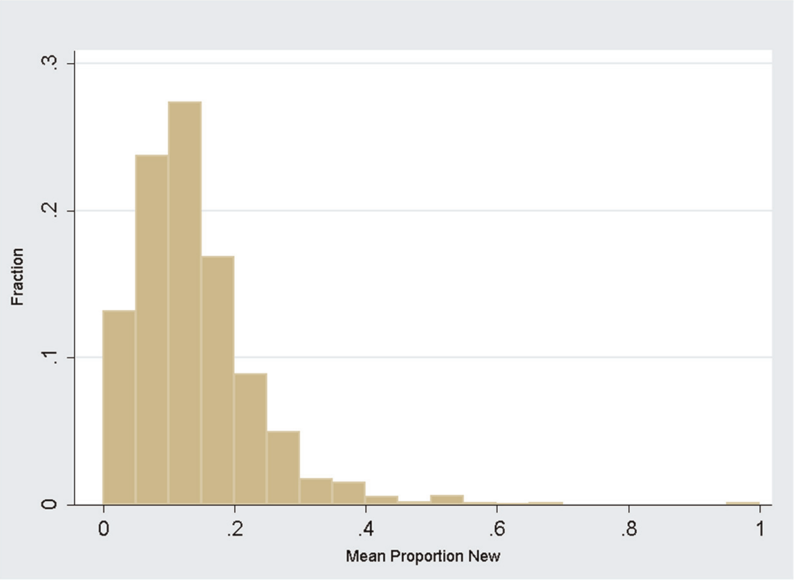

Figure 3. **Distribution of "proportion new" turnover measure.**

For each analysis we use two different estimation strategies to study the effects of school-by-grade-by-year level teacher turnover on student achievement. First, we use regression models with school-by-grade fixed effects to leverage variation in turnover across years within the same grade level and school. This allows us to examine whether students within the same grade level and within the same school had better or worse test score gains in a given year, as compared to other years when teacher turnover was at different rates. These models assume that the effects of turnover in the same school and grade level are comparable across years. These estimates can be affected by shocks that occur to a school in a particular year, such as a new principal, that may influence both teacher turnover and student achievement. To try to mitigate these influences and use more idiosyncratic variation, we add extensive controls—for prior student achievement and other student, class, school, grade, and teacher characteristics. Equation 1 summarizes the regression model used for these analyses:

$$A_{itgsy} = \beta_0 + \beta_1 A_{itgs(y-1)} + \beta_2 OtherA_{itgs(y-1)} + \beta_3 X_{itgsy} + \beta_4 C_{tgsy} + \beta_5 S_{sy} + \phi_y + \nu_{sy} + \beta_6 T_{gsy} + \varepsilon_{itgsy}. \quad (1)$$

The test performance of individual i, with teacher t, in grade g, in school s, in time y is a function of his or her test performance in that subject, A, and the other subject, *OtherA*, in the prior year, student background characteristics, X, time-varying classroom characteristics, C, time-varying school characteristics, S, year fixed effects, ϕ, grade-by-school fixed effects, ν, the grade-by-school-by-year turnover measure, T, and an error term, ϵ. To account for the nonindependence of turnover rates within a grade-by-school unit over time, we cluster the standard errors at the grade-by-school-by-year level.

In our second method of analysis, we use school-by-year, instead of school-by-grade, fixed effects to capitalize on turnover variation across grades within the same year and school. The advantage of the second method is that year-to-year variations—like bringing in a new principal, as described previously—cannot explain observed effects; however, the disadvantage is that it assumes turnover rates have comparable effects on student achievement at different grade levels. All models control for prior student achievement, but we also control for other student, class, school, grade, and teacher characteristics depending on the analysis. Equation 2 describes the second method of analysis:

$$A_{itgsy} = \beta_0 + \beta_1 A_{itgs(y-1)} + \beta_2 OtherA_{itgs(y-1)} + \beta_3 X_{itgsy} + \beta_4 C_{tgsy} + \beta_5 S_{sy} + \phi_y + \nu_{sy} + \beta_6 T_{gsy} + \varepsilon_{itgsy}. \quad (2)$$

The test performance of individual i, with teacher t, in grade g, in school s, in time y is a function of his or her test performance in that subject, A, and the other subject, *OtherA*, in the prior year, student background characteristics, X, time-varying classroom characteristics, C, time-varying school characteristics, S, grade fixed effects, ϕ, year-by-school fixed effects, ν, the grade-by-school-by-year turnover measure, T, and an error term, ϵ. To account for the nonindependence of turnover rates within a year-by-school unit across grade levels, we cluster the standard errors at the grade-by-school-by-year level.

A potential concern with the fixed-effect approaches is that there might not be enough variation in the turnover within the groups (e.g., within the grade in a particular school over time or across grades within a particular school in a particular year). However, we find that there is substantial variation within our groups. Almost three-quarters of the variation is within groups for both turnover measures when using school-by-grade fixed effects. Within-group variation is lower in models employing school-by-year fixed effects—42% for lagged attrition and 36% for proportion new.

The fixed effects models described previously are two of many possible approaches to estimating the effects of turnover on student achievement. One alternative is a repeated measures, multilevel analysis with student outcomes on the left-hand side of the equation and student-specific random intercept and growth terms on the right-hand side. One possible advantage of this alternative approach would be that the multilevel nature directly adjusts for the grouping of students within grade-by-school-by-year units, the level at which turnover is measured in our study. By clustering the standard errors at the school-by-grade-by-year level in our fixed-effects approach, we adjust for this nested structure; thus, an explicit multilevel structure would not provide more appropriate standard errors than our models. Another potential advantage of the alternative approach is that test scores, which are measured with error, do not appear on the right-hand side of the equation. Measurement error in these variables can bias the estimates on the coefficients for teacher turnover. Though our models do include test scores on the right-hand side, these include prior performance in both tested subjects (i.e., math and ELA), as well as time-varying classroom-level averages on these tests. Each of these measures is an imperfect signal for a student's incoming potential for achievement based on information from the previous year. By combining these variables to signal students' potential, we reduce the measurement error that we would have were we to include only one of these measures. An additional benefit of the fixed-effects approach we use is that repeated measures value-added models (VAMs) tend to be difficult to estimate with large samples. Fixed-effects models with least squares estimation often converge without difficulty under circumstances where maximum likelihood estimation of repeated measures VAMs is infeasible. Finally, in a study comparing models for estimating teachers' value-added to student test performance, McCaffrey, Lockwood, Koretz, Louis, and Hamilton (2004) compare fixed-effects and repeated measures approaches. In regards to a teacher's value-added, they find fault with the assumption that treatment effects fully persist, an underlying assumption of the repeated measures approach.

Another alternative to our approach is to model gain scores as the outcome. Compared to this alternative, an advantage of our approach is that it allows for performance in the other academic areas to affect learning in the focal area. Our approach also does not assume that students who start at different levels necessarily gain the same amount, on average, across time, a questionable assumption behind the alternative growth model. For example, if a student scores particularly well in one year, our approach accounts for the possibility that he or she may be more likely to have smaller gains the following year.

Are the effects of turnover different in different kinds of schools? To better understand the nature of observed effects, we examine whether the relationship between teacher turnover and student achievement varies in different kinds of schools. As described in the Introduction, many have suggested turnover to be a particularly pernicious problem in schools with historically underserved student populations, especially given that the turnover rates tend to be higher in these settings. To test this, we run models separately in low- versus high-performing schools and in low versus high percentage Black schools. In particular, we constrain our sample only to schools whose students averaged below the test score mean and then reproduce the analyses described previously. We then repeat this process with our sample constrained only to schools that had 20% or more Black students.[8] For comparison's sake, we also examine schools with students scoring at or above the mean on test scores and with Black student populations of less than 20%.

Additionally, during the period of this study, NYC opened a number of new schools, many of which were small and expanding. Given the unique challenges that new schools face, high rates of teacher turnover are more common (Hemphill, Nauer, Zelon, & Jacobs, 2009). National trends also indicate that small schools tend to have higher rates of teacher turnover (Ingersoll, 2001; Ingersoll & Rossi, 1995). We wondered whether the effects of turnover might then be particularly salient in new and small schools in NYC. Moreover, some have suggested school size to be related to staff cohesion and community (Bryk, Camburn, & Seashore Louis, 1999), which, as described in the Introduction, predict both teacher turnover and student achievement.

To explore whether the effects of turnover may vary in new and in small schools, we run models separately for large versus small schools and for new versus old schools. We classify "new" schools as not yet existing in 2001 and "old" schools as existing in or prior to 2001 and run models separately for each group. We classify "small" schools as having fewer than four teachers per grade level and "big" schools as having four or more teachers per grade level and run analyses separately for each group.

What explains the relationship between teacher turnover and student achievement? As described in the Introduction, there are many possible explanations for the effects of turnover that we estimate in Equations 1 and 2. Turnover may affect achievement because the teachers who replace those who left are either more or less effective (we refer to this as the "compositional" explanation). Alternatively, even where arriving and leaving teachers are equally effective, turnover may cause a broad disruption that impacts all students, including students of teachers who did not transition (we refer to this as the "disruption" explanation).

To examine the effect of differentially effective teachers (compositional explanation), we try controlling for different signals for teacher quality. A drawback to this approach of controlling for measured teacher characteristics is that there may be unmeasured characteristics of teachers that differ between new and remaining teachers that affect student performance. First, we add teacher experience indicator variables for the number of years of experience for each teacher in our data set (leaving out first-year teachers as the reference group) to see whether any observed turnover effects are driven by changes in the distribution of teachers' experience. We then add to our models an indicator variable for teachers who migrated from a different school in the previous year to test whether observed effects are driven by teachers who are new to schools being worse.

While there is no perfect way of measuring teacher effectiveness, regression-based, value-added measures are increasingly common. We also run models that control for teachers' average prior value-added to examine whether effects are driven by distributional changes in effectiveness resulting from teachers leaving and entering grade-level teams.[9] We can calculate average prior value-added scores for a subsample of teachers in the sample.[10] Due to missing data, our overall sample sizes are reduced substantially—from about 850,000 student observations to about 670,000 for both math and ELA.

As described in the Introduction, if only compositional, and not disruptive, effects are at work, we should not then see an effect of turnover on the students of teachers who were in the same grade-by-school group in the prior year (i.e., students of "stayers"). To test whether turnover has a disruptive force on student achievement beyond changing the distribution of teacher effectiveness, we rerun our analyses but only for students of stayers. More specifically, we constrain our sample only to teachers (and their students) who remained in the same grade and school from the previous year (stayers) and use models described in Equations 1 and 2 to estimate the effects of turnover on this subpopulation. In models with school-grade fixed effects, we compare the effects of turnover on the achievement of students of only stayers in a given grade level and school to the students of stayers in the same grade level and school but in different years. In models with school-year fixed effects, we compare the effects of turnover on the achievement of students of only stayers in a given year and school to the students of stayers in the same year and school but in a different grade level. For comparison's sake, we repeat this strategy by constraining our sample only to those teachers who stayed in NYC but migrated from a different school in the previous year (movers) and then by constraining the sample only to teachers (and their students) who are first-year (rookie) teachers.

Results

What Is the Average Effect of Teacher Turnover on Student Achievement?

Table 2 describes the results for estimates of the effects of teacher turnover on student achievement when comparing students within the same grade within the same school but in different years (grade-by-school fixed-effects models). Model 1 includes year fixed effects as well as school-by-grade fixed effects, while Model 2 adds in student-, class-, and school-level controls.[11] Note that each estimate in Table 2 comes from a separate estimation. The estimations vary in their outcome variable (math or ELA) and in their measure of turnover (proportion of new teachers or lagged attrition). The estimated coefficients are negative and significant for test

Table 2
Estimates of the Effects of Teacher Turnover on Student Achievement, Using School-by-Grade Fixed Effects

Test	Turnover Measure	Model 1	Model 2
Math	Lagged attrition	−.086**	−.082**
		(.011)	(.011)
	Proportion new to school	−.102**	−.096**
		(.01)	(.01)
ELA	Lagged attrition	−.049**	−.049**
		(.01)	(.01)
	Proportion new to school	−.060**	−.051**
		(.009)	(.009)
	School-by-grade fixed effects	x	x
	Year indicators	x	x
	Student, class, school controls		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
**$p < .01$.

scores in both ELA and math and for all model specifications, suggesting that the students of teachers in the same grade-level team in the same school do worse in years where teacher turnover rates are higher, as compared to years with less teacher turnover. Student math scores are 8.2% to 10.2% of a standard deviation lower in years when there was 100% turnover as compared to years when there was no turnover at all. For a year in which turnover increases by one standard deviation (.17 for lagged attrition), this corresponds with a decrease in math achievement by approximately 2% of a standard deviation. Effect sizes are somewhat smaller in ELA than in math, estimated at between 4.9% and 6.0% of a standard deviation decrease.

Across models, estimates are somewhat larger when signaling teacher turnover using the proportion of new teachers to a grade-level team as compared to the proportion of teachers who left a grade-level team in the prior year. We are not certain why this is the case but suspect it may be the result of differences in the sensitivity of measures to variation in turnover across years where there was growth or decline in the number of teachers within a particular grade-by-school. To illustrate, Table 3 summarizes three different scenarios—when there is an increase in the number of teachers in a hypothetical fourth grade in a hypothetical School A, when there is a decline in the number of teachers, and when the number of teachers stays the same. As the table demonstrates, the lagged attrition measure may be less sensitive to changes caused by turnover in growth years. On the other hand, in decline years, the proportion new measure may fail to detect changes due

Table 3
Examining Measures of Turnover in Growth, Decline, and Constant Years

Hypothetical: Grade 4 in School A	Example	Turnover Rate Using Lagged Attrition = (*N* Who Left in 2004–2005)/(Total *N* in 2004–2005)	Turnover Rate Using Proportion New = (*N* New in 2005–2006)/(Total *N* in 2005–2006)
Growth: increase in number of teachers	2004–2005: 6 teachers 2005–2006: 7 teachers (6 stayers, 1 mover)	Turnover rate = 0/6 Turnover rate = 0	Turnover rate = 1/7 Turnover rate = 0.14
Decline: decrease in number of teachers	2004–2005: 7 teachers 2005–2006: 6 teachers (6 stayers)	Turnover rate = 1/7 Turnover rate = 0.14	Turnover rate = 0/6 Turnover rate = 0
Constant: number of teachers is constant	2004–2005: 6 teachers 2005–2006: 6 teachers (5 stayers, 1 mover)	Turnover rate = 1/6 Turnover rate = 0.17	Turnover rate = 1/6 Turnover rate = 0.17

to turnover. In the 5-year period we studied in NYC, we found that grade-by-school teams experienced average increases in faculty size in Grades 4 and 5;[12] this average growth may explain why the lagged attrition estimates are relatively lower. Another possibility is that the proportion new measure may be more sensitive to the compositional effect of bringing in new, and likely less experienced and effective, teachers.

Table 4 describes the estimates for models using school-by-year fixed effects instead of school-by-grade fixed effects. Looking across models and measures, the results are similar. The consistently negative and statistically significant estimates again suggest that teacher turnover harms student achievement. More specifically, the results indicate that within the same school and within the same year, students in grade levels that experience 100% turnover have lower test scores by 7.4% to 9.6% of a standard deviation in math and by 6.0% to 8.3% of a standard deviation in ELA, as compared to grade levels with no turnover at all. As with models using school-by-grade fixed effects, estimates are consistently lower when signaling turnover with lagged attrition as compared to the proportion of new faculty.

To get a better sense about the magnitude of the effects, we examine the effects at different quartiles of teacher turnover. Table 5 describes grade-by-school-by-year level characteristics at different quartiles of teacher turnover. The bottom quartile (least turnover) is comprised of only grade levels in schools that experienced no teacher turnover. There is no second quartile because more than 50% of school-by-grades have zero turnover and therefore fall into the first quartile. In the third quartile, an average of 15% of teachers left; in the fourth quartile, an average of 37% left. As compared to school-by-grades in the top quartile of turnover, those in the bottom quartile

Table 4
Estimates of the Effects of Teacher Turnover on Student Achievement, Using School-by-Year Fixed Effects

Test	Turnover Measure	Model 1	Model 2
Math	Lagged attrition	−.074**	−.074**
		(.013)	(.013)
	Proportion new to school	−.096**	−.093**
		(.012)	(.012)
ELA	Lagged attrition	−.060**	−.064**
		(.013)	(.013)
	Proportion new to school	−.083**	−.082**
		(.012)	(.012)
	School-by-year fixed effects	x	x
	Grade indicators	x	x
	Student, class, school controls		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{**}p < .01$.

Table 5
School-Grade-Year Level Descriptive Statistics by Quartile of Lagged Attrition

Variable	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Lagged attrition	0.00		0.15	0.37
Math test score (standardized)	0.13		0.04	−0.04
Proportion free lunch	0.63		0.68	0.69
Proportion Hispanic	0.34		0.40	0.39
Proportion Black	0.33		0.34	0.39
Proportion Asian	0.14		0.12	0.09
Proportion “other” race/ethnicity	0.00		0.00	0.01
Proportion female	0.51		0.51	0.52
Lagged number of absences	10.73		11.18	11.67
Lagged proportion suspended	0.01		0.01	0.02

have more high-achieving and Asian students; fewer low-income, Black, and Hispanic students; and fewer student absences and suspensions.

Table 6 shows the estimates for the effects of teacher turnover on student ELA achievement by quartile of turnover; Table 7 summarizes results for math achievement. The first column displays estimates for models employing school-by-year fixed effects, while estimates in the second column

Table 6

Estimates of Effects of Teacher Turnover on Student Achievement in English Language Arts (ELA) by Quartile of Teacher Turnover (Bottom Quartile Is Reference Group)

Turnover Measures	Model 1	Model 2
Lagged attrition Q2		
Lagged attrition Q3	−.012**	−.012**
	(.005)	(.004)
Lagged attrition Q4	−.020**	−.017**
	(.005)	(.004)
Proportion new Q2		
Proportion new Q3	−.009*	−.000
	(.005)	(.004)
Proportion new Q4	−.029**	−.016**
	(.005)	(.004)
Student, class, school controls	x	x
School-by-year fixed effects	x	
Grade indicators	x	
School-by-grade fixed effects		x
Year indicators		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses.
*$p < .05$. **$p < .01$.

come from models with school-by-grade fixed effects. All models control for student, classroom, and school characteristics. Depending on the model and signal for turnover, students experiencing rates of teacher turnover in the fourth quartile have 2% to 4% of a standard deviation lower math achievement as compared to students experiencing the least (bottom quartile) teacher turnover. In a given grade level with five teachers (mean value), this would suggest that reducing teacher attrition from two teachers leaving (40% turnover) to none leaving corresponds with an increase in student math achievement of 2% to 4% of a standard deviation. This effect is small but meaningful and it applies to all students in the grade. As an example, the magnitude is approximately the same as the magnitude of the coefficient on the student indicator variable for being eligible for free or reduced price lunch (3%), our proxy for student poverty.[13] With our identification strategy, we are probably underestimating the true effect of turnover since we are identifying largely idiosyncratic turnover—variation across grades (within a school and year) or across years (within a grade and school) likely due to chance. There likely exist, however, particular schools with persistently high turnover due to larger, more systemic issues (e.g., gang activity in the community). Though such persistent turnover likely has additional negative

Table 7

Estimates of Effects of Teacher Turnover on Student Achievement in Math by Quartile of Teacher Turnover (Bottom Quartile Is Reference Group)

Turnover Measures	Model 1	Model 2
Lagged attrition Q2		
Lagged attrition Q3	−.009*	−.008*
	(.005)	(.004)
Lagged attrition Q4	−.026**	−.029**
	(.005)	(.004)
Proportion new Q2		
Proportion new Q3	−.014**	−.010*
	(.005)	(.004)
Proportion new Q4	−.036**	−.033**
	(.005)	(.004)
Student, class, school controls	x	x
School-by-year fixed effects	x	
Grade indicators	x	
School-by-grade fixed effects		x
Year indicators		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses.
*$p < .05$. **$p < .01$.

effects, our modeling approach does not account for these additional effects. Even though turnover rates may be persistently large across time for a given school-grade, we focus our analysis on year-to-year differences in turnover within the same school-grade. Though the former may exist for systemic reasons, the latter likely represents chance variation around more systemic effects.

Are the Effects Different for Different Kinds of Schools?

Prior literature suggests that the turnover rates are especially high in schools with more low-performing and minority students (Boyd et al., 2005, 2011b; Hanushek et al., 2004; Scafidi, Stinebrickner, & Sjoquist, 2003). Moreover, it is typically more challenging to fill vacancies in these kinds of schools with qualified teachers (Boyd et al., 2011a). Thus, many have argued that the effects of teacher turnover are probably most harmful to students in schools with underserved student populations. However, estimates in the recent study by Hanushek and Rivkin (2010) suggest the opposite to be true—that turnover may exert a lower cost on schools with higher populations of low-achieving and Black students as compared to schools with fewer of these student populations.

Table 8

Estimates of Effects of Teacher Turnover on Student Achievement at Different Kinds of Schools (Achievement and Race), Using School-by-Grade Fixed Effects

Test	Turnover Measure	High Achievement	Low Achievement	Low Black	High Black
Math	Lagged attrition	−.073**	−.085**	−.062**	−.094**
		(.018)	(.014)	(.018)	(.014)
	Proportion new	−.068**	−.119**	−.059**	−.128**
		(.016)	(.013)	(.016)	(.014)
ELA	Lagged attrition	−.059**	−.045**	−.053**	−.047**
		(.019)	(.012)	(.018)	(.013)
	Proportion new	−.026	−.073**	−.018	−.080**
		(.016)	(.011)	(.015)	(.012)
	School-by-grade fixed effects	x	x	x	x
	Year indicators	x	x	x	x
	Student, class, school controls	x	x	x	x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{**}p < .01$.

Table 9

Estimates of Effects of Teacher Turnover on Student Achievement at Different Kinds of Schools (Achievement and Race), Using School-by-Year Fixed Effects

Test	Turnover Measure	High Achievement	Low Achievement	Low Black	High Black
Math	Lagged attrition	−.060**	−.085**	−.047*	−.095**
		(.022)	(.016)	(.020)	(.017)
	Proportion new	−.055**	−.130**	−.048**	−.129**
		(.019)	(.015)	(.018)	(.016)
ELA	Lagged attrition	−.058**	−.072**	−.037+	−.087**
		(.022)	(.016)	(.021)	(.017)
	Proportion new	−.058**	−.112**	−.043*	−.114**
		(.020)	(.015)	(.018)	(.016)
	School-by-grade fixed effects	x	x	x	x
	Year indicators	x	x	x	x
	Student, class, school controls	x	x	x	x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{+}p < .10$. $p < .05$. $^{**}p < .01$.

Table 10

Estimates of Effects of Teacher Turnover on Student Achievement at Different Kinds of Schools (Age and Size), Using School-by-Year Fixed Effects

Test	Turnover Measure	New	Old	Small	Big
Math	Lagged attrition	−.101	−.074**	−.089**	−.041+
		(.067)	(.013)	(.016)	(.022)
	Proportion new	−.125*	−.091**	−.075**	−.122**
		(.063)	(.013)	(.014)	(.022)
ELA	Lagged attrition	−.085	−.063**	−.063**	−.062**
		(.053)	(.014)	(.017)	(.021)
	Proportion new	−.054	−.082**	−.076**	−.091**
		(.058)	(.012)	(.015)	(.021)
	School-by-grade fixed effects	x	x	x	x
	Year indicators	x	x	x	x
	Student, class, school controls	x	x	x	x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Table 11

Estimates of Effects of Teacher Turnover on Student Achievement at Different Kinds of Schools (Age and Size), Using School-by-Grade Fixed Effects

Test	Turnover Measure	New	Old	Small	Big
Math	Lagged attrition	−.090*	−.082**	−.084**	−.078**
		(.045)	(.012)	(.014)	(.019)
	Proportion new	−.107*	−.095**	−.094**	−.103**
		(.043)	(.011)	(.013)	(.018)
ELA	Lagged attrition	−.007	−.051**	−.052**	−.046**
		(.040)	(.011)	(.013)	(.017)
	Proportion new	−.033	−.053**	−.057**	−.046**
		(.036)	(.010)	(.012)	(.016)
	School-by-grade fixed effects	x	x	x	x
	Year indicators	x	x	x	x
	Student, class, school controls	x	x	x	x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{*}p < .05$. $^{**}p < .01$.

To examine this matter further, we analyzed whether the effects of teacher turnover were similar or different in schools with more low-achieving and Black students as compared to schools with fewer of these student populations (see Methods section for more details). Table 8 presents results for models using school-by-grade fixed effects, while Table 9 presents results for models using school-by-year fixed effects. Across math and ELA, and across measures for teacher turnover, the negative effect of teacher turnover on student achievement was larger in schools with higher proportions of low-achieving and Black students.

Tables 10 and 11 compare estimates for old (existed in 2001) versus new (did not exist in 2001) schools and for big (four or more teachers per grade level) versus small schools (fewer than four teachers per grade level). Across models, estimates are negative and mostly significant, suggesting that turnover has a harmful effect on student achievement across kinds of schools. Also, there are no clear differences in the magnitudes of the effects in big versus small or old versus new schools. These results indicate that new school reforms in NYC are not driving the negative effects of turnover described previously.

What Explains the Relationship Between Teacher Turnover and Student Achievement?

There are many possible mechanisms by which teacher turnover can harm student achievement. As described in the Introduction, prior literature often focuses on the relationships between teacher turnover and teacher quality to explain this effect. The assumed causal mechanism is that teacher turnover changes the average effectiveness of teachers in schools, which in turn changes student outcomes. More specifically, the effect of turnover is driven by the relative effectiveness of teachers who leave a school, as compared to those who replace them (compositional explanation). We include in our models two signals for teacher quality—experience and lagged value-added—to test whether changes in teaching experience or prior effectiveness at raising test scores explain the harmful effects of turnover on student achievement that we observe. Because the first year in a school may be especially difficult, even for experienced teachers, we also add a control for whether the teacher transferred from a different school. This allows us to test whether changes in distribution of movers may explain observed effects.

Tables 12 and 13 show estimates for models examining whether teaching experience and migration explain the effects of teacher turnover on student achievement. We begin with the base model in Model 1, add experience indicators in Model 2, and then add an indicator for whether a teacher transferred from another school (a mover) in Model 3. Table 14 describes results for models using school-by-grade fixed effects; Table 15 describes models using school-by-year fixed effects. In both tables, Model 2

Table 12

Examining Whether Teacher Experience and Migration Explains Effects of Turnover on Student Achievement, Using School-by-Grade Fixed Effects

Test	Turnover Measure	Model 1	Model 2	Model 3
Math	Lagged attrition	−.082**	−.065**	−.059**
		(.011)	(.011)	(.011)
	Proportion new to school	−.096**	−.055**	−.036**
		(.010)	(.011)	(.011)
ELA	Lagged attrition	−.049**	−.035**	−.031**
		(.010)	(.010)	(.010)
	Proportion new to school	−.051**	−.012	.000
		(.009)	(.010)	(.010)
	School-by-grade fixed effects	x	x	x
	Year indicators	x	x	x
	Student, class, school controls	x	x	x
	Experience indicators		x	x
	Mover indicator			x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$**p < .01$.

Table 13

Examining Whether Teacher Experience and Migration Explains Effects of Turnover on Student Achievement, Using School-by-Year Fixed Effects

Test	Turnover Measure	Model 1	Model 2	Model 3
Math	Lagged attrition	−.074**	−.063**	−.058**
		(.013)	(.013)	(.013)
	Proportion new to school	−.093**	−.052**	−.034**
		(.012)	(.012)	(.013)
ELA	Lagged attrition	−.064**	−.052**	−.048**
		(.013)	(.013)	(.013)
	Proportion new to school	−.082**	−.042**	−.029*
		(.012)	(.012)	(.012)
	School-by-year fixed effects	x	x	x
	Grade indicators	x	x	x
	Student, class, school controls	x	x	x
	Experience indicators		x	x
	Mover indicator			x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$*p < .05$. $**p < .01$.

Table 14

Examining Whether Prior Value-Added Explains Effects of Turnover on Student Achievement, Using School-by-Grade Fixed Effects

Test	Turnover Measure	All Schools		Low Achieving		High Achieving	
		Model 1	Model 2	Model 1	Model2	Model 1	Model 2
Math	Lagged attrition	−.059**	−.040**	−.067**	−.049**	−.044*	−.024
		(.013)	(.012)	(.016)	(.015)	(.021)	(.020)
	Proportion new to school	−.048**	−.034**	−.082**	−.065**	−.015	−.007
		(.012)	(.012)	(.016)	(.015)	(.019)	(.018)
ELA	Lagged attrition	−.033**	−.027*	−.035*	−.028*	−.031	−.025
		(.012)	(.012)	(.014)	(.014)	(.022)	(.021)
	Proportion new to school	−.004	.000	−.027*	−.023+	.018	.021
		(.011)	(.011)	(.014)	(.014)	(.018)	(.018)
	School-by-grade fixed effects	x	x	x	x	x	x
	Year indicators	x	x	x	x	x	x
	Student, class, school controls	x	x	x	x	x	x
	Average prior value-added		x		x		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Table 15

Examining Whether Prior Value-Added Explains Effects of Turnover on Student Achievement, Using School-by-Year Fixed Effects

Test	Turnover Measure	All Schools		Low Achieving		High Achieving	
		Model 1	Model 2	Model 1	Model2	Model 1	Model 2
Math	Lagged attrition	−.055**	−.034**	−.063**	−.049**	−.045+	−.016
		(.015)	(.013)	(.019)	(.017)	(.025)	(.021)
	Proportion new to school	−.045**	−.033**	−.101**	−.075**	.008	.008
		(.015)	(.013)	(.019)	(.017)	(.022)	(.019)
ELA	Lagged attrition	−.036*	−.034*	−.042*	−.041*	−.031	−.025
		(.016)	(.014)	(.018)	(.017)	(.027)	(.024)
	Proportion new to school	−.037*	−.024+	−.073**	−.058**	−.006	.006
		(.014)	(.013)	(.018)	(.016)	(.023)	(.020)
	School-by-year fixed effects	x	x	x	x	x	x
	Grade indicators	x	x	x	x	x	x
	Student, class, school controls	x	x	x	x	x	x
	Average prior value-added		x		x		x

Note. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

estimates are consistently lower than those in Model 1 but still statistically significant. These results indicate that changes in the distribution of teacher experience explain some of the effect of teacher turnover on student achievement, although a substantial amount of the effect remains unexplained. Compared to Model 2, Model 3 estimates are also somewhat smaller but still statistically significant. These results suggest that teachers who migrated from other schools were, on average, less effective and that this accounted for some of the harmful effects of teacher turnover on student achievement.[14] However, Model 3 estimates remained statistically significant, indicating that other factors, beyond teaching experience and migration, also explain the effects of teacher turnover on student achievement.

One of the most likely remaining explanatory factors is teachers' prior effectiveness at improving student achievement (Hanushek & Rivkin, 2010). Tables 14 and 15 show estimates for models using only the subsample of teachers for whom we have data on prior value-added. Model 1 includes estimates for the effect of teacher turnover on student achievement for this subsample; Model 2 controls for teachers' average prior value-added[15] to see if prior effectiveness explains any observed effects in Model 1. These tables show that even with the subsample of teachers for whom we have data on prior value-added, the estimates of the effects of teacher turnover on student achievement remain negative and mostly significant (Model 1, "All Schools"), though are somewhat smaller in magnitude as compared to the larger sample. After controlling for teachers' average prior value-added, estimate sizes reduce somewhat though remain statistically significant. These results suggest that changes in the distribution of teachers' effectiveness account for some of the observed relationship between teacher turnover and student achievement, though an effect remains beyond this compositional explanation. The remaining effect may be a result of limitations in our methods to account for the compositional explanation. Given more perfect signals for prior effectiveness, for instance, it is possible that no significant effect of turnover would remain. As described below, however, we find that turnover significantly impacts the achievement of the students of stayers (teachers who remain in the same grade and school), suggesting a disruptive effect will remain regardless of how well we measure and account for compositional effects.

Because we find the effects of teacher turnover to be especially deleterious in lower-achieving schools, we reproduce the value-added analyses separately in lower-achieving and higher-achieving schools. Tables 14 and 15 shows that with the reduced sample, the turnover effect is negative and significant in lower-achieving schools but that there is no significant effect in higher-achieving schools. Moreover, the effect of teacher turnover remains negative and in most cases statistically significant even after controlling for prior value-added. Thus, teachers' prior effectiveness does not appear to explain fully the harmful effects of turnover on student achievement in lower-achieving schools.

That the magnitudes for the effects of turnover are larger (even more negative) before controlling for average prior value-added suggests the compositional effect of turnover due to changes in the distribution of teacher effectiveness has a net negative effect. On average, students are harmed by the changing composition in teacher effectiveness that results from teacher turnover, primarily in lower-performing schools. These findings are consistent with studies that suggest underserved schools tend to fill vacancies with relatively less effective teachers.

Given that distributional changes in teacher experience, migration, and prior effectiveness do not fully explain the harmful effects of turnover on student achievement, particularly in lower-performing schools, what else might account for them? It is beyond the scope of this study to identify and test all possible mechanisms by which turnover may harm student achievement. However, we begin to identify how turnover impacts student achievement by examining whether the effects of teacher turnover accrue only to students who have teachers who are new to the grade-level team in their school or whether the effects of turnover are also felt by students whose teachers had remained. If the students of stayers are harmed by teacher turnover, it would cast further doubt on the hypothesis that turnover harms student achievement only through changing the relative effectiveness of the teachers who leave as compared to those that replace them. It would suggest instead that the rotation of teachers has a disruptive influence that reaches beyond just those students of teachers who were coming and going to negatively impact even the students who were assigned to teachers who stayed in the same school from year to year. To test this, we examine the effects of turnover separately for teachers who were stayers, movers, and rookies (first year) to see the extent to which the students of these groups of teachers experienced the effects of turnover differently. Given prior evidence that the effect of turnover manifests primarily in lower-achieving schools, we continue to analyze low- and high-achieving schools separately.

Table 16 shows the results for models using school-by-grade fixed effects while Table 17 shows results for models using school-by-year fixed effects. On the left are estimates for the effects of teacher turnover on math achievement—for all schools, for low-achieving schools, and for high-achieving schools; on the right are estimates on ELA achievement organized in the same way. Across models and measures, there is a consistent pattern—students of stayers perform significantly worse when turnover is greater, and the negative effects are mostly found in lower-performing schools.[16] For the students of movers, estimates trend negative (especially in school-by-grade fixed-effects models) but are generally nonsignificant and somewhat unstable. Given that only 4% of teachers in our sample are movers, we suspect that the reduced sample size and corresponding lack of power likely account for the

Table 16
Examining the Effect of Teacher Turnover on Stayers, Movers, and Leavers (School-by-Grade Fixed Effects)

		Math			ELA		
		All Schools	Low Performing	High Performing	All Schools	Low Performing	High Performing
Stayers	Lagged attrition	−.054**	−.053**	−.053**	−.035**	−.022	−.059**
		(.012)	(.015)	(.020)	(.011)	(.013)	(.021)
	Proportion new	−.030*	−.058**	−.000	.008	−.007	.022
		(.012)	(.016)	(.019)	(.011)	(.013)	(.019)
Movers	Lagged attrition	−.062	−.046	−.095	−.028	−.040	−.017
		(.040)	(.050)	(.060)	(.038)	(.043)	(.068)
	Proportion new	−.047	−.046	−.101	−.060	−.050	−.070
		(.040)	(.053)	(.062)	(.042)	(.052)	(.069)
Rookies	Lagged attrition	−.054*	−.082**	.014	.014	−.015	.068
		(.026)	(.031)	(.047)	(.026)	(.031)	(.045)
	Proportion new	−.008	.008	−.027	.025	.026	.018
		(.026)	(.031)	(.049)	(.024)	(.029)	(.041)
	School-by-grade fixed effects	x	x	x	x	x	x
	Year indicators	x	x	x	x	x	x
	Student, school, class controls	x	x	x	x	x	x

Note. Models estimating the effects of turnover on the students of stayers, movers, and first-year teachers were run separately for each group. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^*p < .05$. $^{**}p < .01$.

instability of estimates. The substantially larger standard errors and unusually large magnitudes on some coefficients are consistent with this explanation. Lastly, estimates for the effects of turnover on the achievement of students of first-year (rookie) teachers vary by model, turnover measure, school type, and subject being tested. Mostly estimates are nonsignificant, suggesting no significant effect of turnover on the students of rookies. Some estimates are significant and negative, suggesting a harmful effect. However, more research is needed, as the instability of estimates may again be due to the diminished sample (9% of teachers are rookies).

Discussion

This study finds some of the first empirical evidence for a direct effect of teacher turnover on student achievement. Results suggest that teacher turnover has a significant and negative impact on student achievement in both math and ELA. Moreover, teacher turnover is particularly harmful to the achievement of students in schools with large populations of low-performing and Black students.

Table 17

Examining the Effect of Teacher Turnover on Stayers, Movers, and Leavers (School-by-Year Fixed Effects)

		Math			ELA		
		All Schools	Low Performing	High Performing	All Schools	Low Performing	High Performing
Stayers	Lagged attrition	−.059**	−.069**	−.047+	−.056**	−.048**	−.074**
		(.014)	(.017)	(.024)	(.014)	(.017)	(.025)
	Proportion new	−.032*	−.090**	.026	−.030*	−.054**	−.016
		(.014)	(.019)	(.022)	(.014)	(.017)	(.023)
Movers	Lagged attrition	−.256**	−.056	−.509*	−.041	.069	−.213+
		(.094)	(.079)	(.215)	(.072)	(.097)	(.121)
	Proportion new	−.055	.044	−.098	−.065	.076	−.037
		(.090)	(.079)	(.154)	(.078)	(.103)	(.126)
Rookies	Lagged attrition	−.029	−.039	.027	−.068	−.115*	.067
		(.045)	(.055)	(.072)	(.045)	(.058)	(.060)
	Proportion new	−.054	−.127*	.062	−.060	−.124*	.051
		(.045)	(.051)	(.083)	(.043)	(.051)	(.072)
	School-by-year fixed effects	x	x	x	x	x	x
	Grade indicators	x	x	x	x	x	x
	Student, school, class controls	x	x	x	x	x	x

Note. Models estimating the effects of turnover on the students of stayers, movers, and first-year teachers were run separately for each group. Each column corresponds to a different model in the analysis; *x* indicates which controls and fixed effects were included in each model. Standard errors in parentheses. ELA = English language arts.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Much of the existing literature assumes that teacher turnover impacts student achievement by changing the distribution in quality of teachers in schools. That is, if the teachers who leave a school are worse than those who replace them, then turnover is assumed to have a net positive effect. In this view, stayers, and their students, are merely bystanders who do not affect and are not affected by turnover. Although this study finds evidence that changes in teacher quality explain some of the effect of turnover on student achievement, the results suggest there may be a disruptive impact of turnover beyond compositional changes in teacher quality. First, results show that turnover has a harmful effect on student achievement, even after controlling for different indicators of teacher quality, especially in lower-performing schools. Also, we find that turnover negatively affects the students of stayers—those who remain in the same school from one year to the next. Thus, turnover must have an impact beyond simply whether incoming teachers are better than those they replaced—even the teachers outside of this redistribution are somehow harmed by it.

Although this study does not identify the specific mechanism by which turnover harms students, it provides guidance on where to look. The findings indicate that turnover has a broader, harmful influence on student achievement since it can reach beyond just those students of teachers who left or of those that replaced them. Any explanation for the effect of turnover must possess these characteristics. One possibility is that turnover negatively affects collegiality or relational trust among faculty; or perhaps turnover results in loss of institutional knowledge among faculty that is critical for supporting student learning. More research is needed to identify the specific mechanism.

This study makes important methodological contributions. First, finding evidence for a disruptive influence beyond changing the distribution in quality of teachers calls into question research that draws inferences about the effects of teacher turnover based solely on compositional explanations. Future studies need to take a more comprehensive view on the mechanisms by which teacher turnover may influence student achievement. Second, we introduce a unique identification strategy and modeling approach that improves on prior efforts to estimate the effects of teacher turnover on student achievement. The effects of turnover are typically analyzed at the school level, an approach that makes the questionable assumption that the effects of turnover are comparable across different kinds of schools. Instead, we utilize two innovative modeling approaches that do not make this assumption. The first identifies turnover variation *across years within the same grade level and within the same school* to examine whether students had better or worse test score gains in a given year, as compared to other years when teacher turnover was at different rates. The second identifies turnover variation *across grade levels within the same year and within the same school* to examine whether students in grade levels with higher or lower turnover rates also had higher or lower achievement gains. Though an improvement over school-level analyses, both of these methods also make questionable assumptions. The former assumes the effects of turnover rates within the same grade and school are comparable across years; the latter assumes that turnover effects within the same school and year are comparable across grade levels. Despite concerns over potential bias introduced by these assumptions, findings were similar across methodological approaches, suggesting our analytic strategy to be valid and that we have detected a true effect.

Finally, the findings of this study have policy implications. Though there may be cases where turnover is actually helpful to student achievement, on average, it is harmful. This indicates that schools would benefit from policies aimed at keeping grade-level teams intact over time. One possibility might be to introduce incentive structures to retain teachers that might leave otherwise. Implementing such policies may be especially important in schools with large populations of low-performing and Black students, where turnover has the strongest negative effect on student achievement.

Acknowledgments

This research was made possible by generous financial support from a National Center for Analysis of Longitudinal Data in Education Research (CALDER) grant and an Institution of Education Sciences (IES) postdoctoral fellowship. CALDER is supported by IES Grant R305A060018 to American Institutes of Research. The views expressed in the article are solely those of the authors and may not reflect those of the funders. Any errors are attributable to the authors.

Notes

[1]These are approximate values based on somewhat inconsistent sources. Ingersoll (2003) uses year-to-year turnover rates (by level of experience) from nationally representative data to estimate that 46% of teachers leave teaching within 5 years. These estimates, however, include private school teachers who have substantially higher rates of turnover than public school teachers and ignore the fact that many who leave teaching end up returning. Using Ingersoll's estimates but adjusting for these factors, Darling-Hammond and Sykes (2003) calculate a 5-year cumulative attrition rate of about 30% for public school teachers. Henke, Chen, Geis, and Knepper (2000) estimate that about 20% of teachers leave the profession within 5 years. However, these findings are focused only on teachers who entered the profession immediately following college graduation, so are unlikely to represent the broader population of teachers.

[2]On the other hand, they found that teachers with better preservice qualifications (LAST scores, competitiveness of undergraduate institution) were more likely to apply for transfer.

[3]Altogether there were 864,451 student observations in English language arts (ELA) and 864,106 in math. Due to peculiarities in the New York City (NYC) administrative data collected in 2002–2003, we were unable to identify the grade levels of all teachers in NYC that year. Since our analyses depend on grade-level information across the district, we included only years for which we could confidently identify grade level.

[4]We use work-history information collected in October of each academic year to identify whether and where teachers are currently working. An anonymous reviewer suggested that midyear turnover might have a more substantial impact on student achievement. Though we are unable to confidently identify midyear turnover at this point, we believe the reviewer raises an important consideration that we hope to examine in the future.

[5]As described in the previous paragraph, our two methods for measuring turnover generate quite different values when the number of teachers in a given school and grade do not remain constant over time. Where there is no turnover according to one measure, for example, there can be substantial variation according to the other measure. As a result, the correlation between the two measures is not large.

[6]We also ran models that included indicators for whether teachers switched grade levels. Results were similar, suggesting the grade-level switching does not account for the effects of grade-level turnover on student achievement.

[7]We use many classroom- and school-level characteristics as controls in the regression models described in the following. Appendix Table S1 (in the online version of the journal) describes the variables used as school and classroom controls in analyses.

[8]We used 20% as the cutoff score as this was close to the median value. This assured we had similar number of observations in each group.

[9]We calculated teachers' average value-added by estimating students' test scores (in either math or ELA) as a function of lagged scores (in both math and ELA); time-variant and invariant student characteristics; time-variant classroom characteristics; time-variant school characteristics; indicators for teacher experience, year, and grade; and teacher fixed effects. The coefficient on a given teacher's effect is the estimate of his or her contribution to achievement gains across years—his or her "average value-added." In our analyses, we control only for teachers' average value-added in years prior to the one in which the

effects of turnover is being estimated, beginning in 2001—the earliest year for which we could calculate value-added. For example, when estimating the effects of turnover on student achievement in 2005, we control for teachers' average value-added from 2001 to 2004. We adjust the coefficients using Empirical Bayesian shrinkage to account for measurement error.

[10]All first-year teachers are dropped from this analysis because we do not have student test score data in prior years. For experienced teachers we were unable to estimate value-added for all prior years. To keep our sample as large as possible we decided to use the average of all prior value added estimates as a signal for prior effectiveness. The likelihood of having the data necessary to calculate any value-added estimate increases with experience. As a result, teachers for whom we had prior value-added estimates had substantially more experience (9.4 years), on average, than did teachers for whom we had no prior value-added estimates (5.0 years). We also found that a smaller percentage (55%) of teachers in the value-added sample worked in low-performing schools than did the no value-added sample (65%). Since less experienced teachers are more likely to work in low-performing schools, differences in average experience likely explain the observed differences between groups in the proportion working in low-performing schools.

[11]Table 1 describes the student controls used in these models; Appendix Table S1 describes the classroom and school controls.

[12]We examined grade-by-school level growth by creating a measure for the difference between years in the number of teachers per grade level per school: Difference = Number of teachers (n) – Number of teachers ($n - 1$). By averaging difference scores across years and school-by-grade levels we calculated a mean difference score of about .3 for our sample. This suggests an average yearly growth of .3 teachers within a grade level within a school.

[13]Here we use the coefficient on free or reduced priced lunch eligibility from the same models used to estimate the effect of turnover on student achievement. These models control for prior achievement, as well as other student characteristics, that captures much of the effect of qualifying for free and reduced lunch. Thus, estimates are smaller than they would be without such controls. That said, our estimates for the effects of teacher turnover on student achievement would also increase in magnitude were we not to control for prior achievement or other student characteristics. The effects of teacher turnover in previous years of schooling, for example, will be captured in prior achievement scores. Since we are examining the effects of idiosyncratic turnover, rather than looking at the cumulative effects of turnover, it seems more appropriate to compare the magnitudes of our estimates for turnover to estimates on free or reduced lunch that include controls for prior achievement and other student controls.

[14]The magnitude for turnover estimates decrease in Models 2 and 3, suggesting that the effects of turnover resulting from changing distributions in teacher experience and migration have negative net effects.

[15]A teacher's average prior value-added is the mean of his or her value-added across previous years. See note 9 for more detail on how we estimate teachers' value-added scores.

[16]One possible explanation for this result is that principals assign more difficult students to stayers rather than to rookies or migrating teachers. We try to account for this possibility in our modeling approach by controlling for prior achievement and prior suspension records, among many other observable student characteristics. Even so, we acknowledge the possibility that such sorting may be occurring on other nonobservable student characteristics. Furthermore, one of our reviewers speculated that more experienced teachers may be better able to "weather" the effects of turnover. To test this we reran analyses separately for stayers with 5 or fewer years of experience and for stayers with more than 5 years of experience. Estimates were similar for these two groups and are available upon request from the authors. These results indicate that more experienced stayers were no better or worse at weathering the effects than less experienced stayers; that is, students of stayers, regardless of experience, were harmed by turnover.

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Manuscript received July 1, 2011
Final revision received June 14, 2012
Accepted August 3, 2012