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Growing up Homeless: Student Homelessness and Educational Outcomes in Los Angeles

Soledad De Gregorio
University of Southern California

Tasminda K. Dhaliwal
University of Southern California

Ann Owens
University of Southern California

Gary Painter
University of Southern California

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Soledad De Gregorio

Tasminda K. Dhaliwal

Ann Owens

Gary Painter

University of Southern California

WORKING PAPER

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Correspondence concerning this paper should be addressed to Soledad De Gregorio, University of Southern California, 635 Downey Way, VPD 207. Los Angeles, CA. 90089, USA. Email: mdegrego@usc.edu.

Abstract

Homelessness is rising among public school students in large cities across the US. Using nine years of student-level administrative data, we examine how homelessness affects students' mathematics and attendance outcomes within the Los Angeles Unified School District, including the differential effects of homelessness based on duration and timing of their homeless experiences. Results using inverse probability of treatment weighting find that homeless students score 0.13 SD lower on math assessments and miss 5.8 additional days of school than students who never experience homeless. Results suggest that current homelessness has larger negative impacts on math achievement and attendance than former homelessness, and that transitory homelessness has larger negative impacts than persistent homelessness on the same outcomes.

Growing up Homeless in Los Angeles: Student Homelessness and Educational Outcomes

Homelessness has been steadily rising in major cities across the United States, with children under 18 comprising nearly a quarter of the homeless population (Henry et al., 2017). The economic fallout of the COVID-19 pandemic will likely result in more families facing homelessness, especially as eviction moratoriums expire. Consequently, large urban school districts across the country are challenged with identifying and serving an increasing number of homeless students –defined as living in a shelter, motel, car, campsite, on the street, or doubled up in another family's home due to los of housing or economic hardship– whose numbers surged to 1.5 million in the 2016-17 school year (National Center for Homeless Education, 2020; Jones & Willis, 2017; Shapiro, 2018). As school districts grapple with how to support homeless students and families, this study seeks to characterize the homeless student population in the Los Angeles Unified School District (LAUSD) and examine how the timing and duration of homelessness impacts educational outcomes.

Researchers have not yet reached a consensus on how homelessness impacts the students who experience it. While the majority of existing research finds that experiencing homelessness is associated with negative academic and behavioral outcomes (e.g., Cowen, 2017; Masten et al., 2012), other studies find no relationship between homelessness and achievement (Buckner et al., 2001), or find that the impacts of homelessness are mediated by attendance or school mobility (J. W. Fantuzzo et al., 2012; Tobin, 2016). The conflicting evidence on the effects of homelessness may stem from differences in the duration, timing, and contexts across studies, which influence the overall relationship between homelessness and achievement (Miller, 2011; Tierney & Hallett, 2010, 2012). Differences in analytical approaches may also contribute to the mixed effects of homelessness, with few studies employing methods to reduce selection bias.

In this article, we contribute to the existing literature on student homelessness by using longitudinal data from the country's second largest school district, LAUSD, to ask: what is the relationship between academic and behavioral outcomes and homeless status for LAUSD students? How does this relationship differ by the timing and duration of homelessness? To reduce sources of bias, we first generate inverse probability of treatment weights to control for differences between homeless and stably housed students, which are estimated using a range of third-grade student- and neighborhood-level demographic data. We then apply these weights to regression models that estimate outcomes in eighth grade. We find that students who experience homelessness between fourth and eighth grades score 0.13 standard deviations lower on math tests ($p<.01$) and miss 5.8 additional days of school ($p<.001$) in eighth grade. These effects are largest when students experience homelessness in the year the outcomes are measured (i.e., eighth grade). Additionally, we find that both transitory (1 or 2 years) and persistent (3 or more years) homelessness are associated with negative effects on math achievement and attendance, but the effects are larger for students who experience transitory homelessness. We conclude with implications for how school districts and social welfare organizations designate supports and resources for homeless students.

Background

The research on students experiencing homelessness is sparse but growing, as new attention is being placed on this vulnerable population. Existing studies have shown that homelessness is associated with negative consequences for student behavior and academic achievement. Homeless students are more likely to have behavioral issues (Kurtz et al., 1991) and engage in risky behaviors (Bantchevska et al., 2008; Greene et al., 1997; Oppong Asante et al., 2016). They also exhibit lower reading and math proficiency (Cowen, 2017; J. Fantuzzo et al., 2013; J. W. Fantuzzo et al., 2012; Masten et al., 2012), and lower math achievement growth (Cutuli et al., 2013). Perhaps relatedly, homeless students have lower attendance, are more likely to be grade retained (Deck, 2017; Perlman & Fantuzzo, 2010), and have higher school mobility (Cowen, 2017; Deck, 2017; Dhaliwal et al., 2021; J. W. Fantuzzo et al., 2012; Larson & Meehan, 2011; Miller & Bourgeois, 2013). However, some studies have failed to find a relationship between homelessness and achievement (Buckner et al., 2001), or have found that attendance and mobility mediate the impacts of being homeless (J. W. Fantuzzo et al., 2012; Tobin, 2016).

There is a subset of studies that control for student and school characteristics in more sophisticated ways using fixed effects or matching methods; however, these studies also yield mixed evidence. For instance, Cowen (2017) uses a student fixed-effects and finds that only math assessment gain scores (differences in scores between two years), and not achievement levels, are negative and continue to be significant when controlling for mobility. Thus, homelessness may alter test scores between two years, rather than altering the trajectory of achievement. Meanwhile, Tobin (2016) uses school fixed-effects and finds no difference between homeless and housed low-SES elementary students on math and language arts standardized test scores. Deck (2017) matches students in shelters to a comparable housed or doubled-up student using demographic characteristics (i.e., gender, race, grade and disability type) and finds that students in shelters have higher mobility and lower attendance but not statistically different reading and math test scores than both doubled-up and housed students. As pointed out by Miller (2011), this mixed evidence may be a product of differences across studies in the age of homeless youth studied, the contexts, and the duration of homeless experiences.

There is minimal research regarding the impacts of timing and duration of homelessness. Perlman & Fantuzzo (2010) find that homeless shelter experiences in infancy or as a toddler are strong predictors of second and third-grade academic achievement and attendance, suggesting that effects persist in the future or that other disruptive attributes persist even after exiting homelessness (e.g., poverty, instability). Studies on how the duration of homelessness impacts outcomes are lacking due to the dearth of longitudinal homeless data. Longer periods of homelessness may have more severe negative impacts on students due to longer exposure or because these students are the most vulnerable to begin with (see Michelmore & Dynarski, 2017 for evidence of the effects of persistent poverty), as students experiencing transitory homelessness (e.g., 1 or 2 years) are likely very different to those persistently homeless (e.g., 3 our more consecutive years) much like the literature on adult homelessness suggests (see Kuhn & Culhane, 1998).

Initial research suggests that students who experience homelessness for longer periods of time develop coping mechanisms or have more time to be identified and supported by schools, mitigating the negative impacts of homelessness on outcomes. Pavlakis et al. (2017) examine the relationship between math achievement growth and being a chronically homeless student (defined as two consecutive years of homelessness[1]), compared to being a chronically poor non-homeless student. They find no difference between these two groups after controlling for attendance, mobility, and lagged math achievement. In a different setting, researchers have also found that students experiencing four to five years of homelessness have higher school attendance than those who are homeless for shorter periods, suggesting that students may benefit from being identified as homeless for longer periods (Pavlakis et al., 2020).

LAUSD Context: Homeless Student Identification and Support Services

The federal McKinney-Vento Homeless Assistance Act dictates how schools should support homeless students. The Act defines homeless students as those who "lack a fixed, regular, and adequate nighttime residence”, including students residing in other persons’ homes (doubled-up); living in motels, hotels, trailers, in shelters, or students sleeping in “a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings” (42 U.S.C. §11434a(2), 2002). The breadth of the definition contrasts with definitions, including those used by the Department of Housing and Urban Development, that do not consider persons doubled-up as homeless.

Under the McKinney-Vento Act, districts must report the number of homeless students to the state annually and are required to have staff members responsible for supporting students. LAUSD families must fill out a student residency questionnaire (SRQ) each fall as part of the school’s registration paperwork. The survey asks whether students have a stable residence, and if not, what their current housing situation is. The SRQ may be updated during the school year as students move in or out of homelessness. Every school identifies a school homeless liaison onsite (such as a school counselor or attendance administrator) that is responsible for tracking and supporting homeless students (Gonzalez, 2016). Additionally, teachers and other school staff receive training on the homeless definition and how to help identify students/families who should update their SRQ. The district’s routinized process for identifying students attempts to improve homeless data accuracy.

Once students are identified as homeless, the LAUSD homeless education program team is charged with providing the supports guaranteed by law and is provided nominal funds under the McKinney-Vento act to do so (Tierney & Hallett, 2012). The district is required to provide the necessary supplies for school attendance (i.e., stationery, backpacks, uniforms) and allow students to enroll in school even if they are missing paperwork (i.e., immunization records, transcripts, residency documents) (Tierney & Hallett, 2012). To minimize disruption, homeless students are also permitted to continue attending their origin school if they move outside of the school's attendance boundaries, and districts are required to provide transportation from the student's residence to school, oftentimes supplying bus passes (Gonzalez, 2016).

In other work using LAUSD data (see Dhaliwal, et al. forthcoming), when compared to non-homeless students, homeless students are more likely to be marginalized on a variety of indicators (e.g., Black, Latinx, eligible for SPED services, immigrants) than non-homeless students. Students experiencing homelessness are clustered in schools and neighborhoods with higher concentrated disadvantage (e.g., lower achieving schools, higher proportions of students of color, students eligible for free- and reduced-price lunch [FRL]). These students also have higher levels of school and neighborhood mobility than students who are not homeless, including in the years they are homeless, and they are more likely to exit the district when homeless (Dhaliwal et al., 2021).

Data

Our data are drawn from LAUSD administrative data sets from the 2008-2009 to the 2016-2017 school years for students enrolled in K through 8th grade. We focus on a longitudinal sample of LAUSD students who were enrolled in 8th grade during the 2015-2016 and the 2016-2017 school years and who were also enrolled in 3rd grade during the 2010-2011 and 2011-12 school years. The outcome variables of interest are eighth grade student achievement measured by math test scores and student attendance measured by days attended. Beginning with test scores, we observe standardized math test scores for eighth graders in the 2015-16 and 2016-17 school years and when these students were third graders in the 2010-2011 and 2011-12 school years . We standardize math test scores by grade and year to allow comparisons across years and assessments.[3] For student attendance, we use a raw measure of total days the student attended to account for the fact homeless students may enroll late, which we observe for eighth graders in the 2015-16 and 2016-17 school years and when these students were third graders in the 2010-11 and 2011-12 school years.

The key "treatment" for this study is homelessness, which we decompose into 5 different treatment variables. As previously mentioned, homeless status is recorded by the school district during each school year.[2] First, we use homeless status data to construct a binary variable indicating if students experienced homelessness at any time between 4^{th} and 8^{th} grade or were never homeless during that period. Second, we generate two binary variables for timing: if students experienced homelessness in 8^{th} grade (current homelessness), and if they experienced homelessness between 4^{th} and 7^{th} grades (past homelessness). Finally, for the duration of homelessness, we calculate the total number of years each student was homeless and generate two binary variables: homeless for 1 or 2 years (transitory homelessness), and homeless for three or more years (persistent homelessness). To allow for a more straightforward interpretation of the results, the control groups for all five treatment variables are never homeless students. This avoids for example, comparing students who experience homelessness transitorily to a control group comprised of both never homeless and persistently homeless students. See Figure 1 for a list of the treatment variables and key definitions.

The data includes student demographic characteristics, which are used as controls and in the estimation of inverse probability of treatment weights. The demographic characteristics include binary variables for students of color (Asian, Black, Hispanic, Filipino, Native American, or Pacific Islander), eligibility for special education services (SPED), limited English proficiency, gender, and FRL eligibility. Based on the work of Michelmore and Dynarski (2017), we also generate a series of poverty measures identifying students as persistent (i.e., up to third grade they are eligible every year), transitory (i.e., eligible only some years), or never FRL if, only some years, or never eligible, respectively. We also observe student addresses which are geocoded to the census tract level.

Finally, we complement the student data with publicly available census tract-level data from the US Census Bureau's American Community Survey (ACS) five-year estimates, which are used as controls and in the estimation of inverse probability of treatment weights.[4] We observe census tract median household income, variables for the percent of: Hispanic/Latino and Black residents, residents with a college degree or above, families with income below the federal poverty level, owner-occupied households, residents employed, residents employed in professional occupations (professional, scientific, and technical service sectors), female-headed households, severely rent-burdened households (spending more than 50% of their income on rent and utilities), and overcrowded households (living with more than one person per bedroom).

Sample. Our analysis focuses on the two cohorts of LAUSD students who were in eighth grade during the 2015-2016 and the 2016-2017 school years and enrolled in third grade in the 2010-11 and 2011-12 school years. Combining two cohorts of students provides a large enough sample to estimate each of our treatment variables. We further restrict out sample to students who have outcome data in both grades and who had not experienced homelessness before fourth grade (for reasons explained in the Methods section). After implementing these restrictions, the sample is comprised of 54,950 unique students.

As shown in Table 1 column 1, of the students in our sample, 90% are students of color (i.e., Asian, Black, Hispanic, Filipino, Native American, or Pacific Islander), 50% are female, 8% have limited English proficiency, 8% are eligible for special education services (SPED), 10% are never eligible for free- and reduced-price lunches (FRL), 36% are FRL-eligible some years, and 54% are FRL-eligible every year they are present. In terms of eighth-grade outcomes, the average math score is 0.1 standard deviations above the district mean, and the average student attended 173 days out of 180 instructional days.

Methods

Studies estimating the “effect” of homelessness have to contend with the fact that homelessness does not occur randomly. Consequently, studies that use descriptive statistical techniques to identify an effect of homelessness on student outcomes may be detecting the direct effect of homelessness on student outcomes but their results are likely biased by differences between homeless and non-homeless students before experiencing homelessness, referred to as baseline or selection bias (Morgan & Winship, 2014). Selection bias is likely, since students who experience sustained, deep poverty may be more likely to become homeless, and these students may face other disadvantages that can influence their academic and behavioral outcomes (e.g., lack of parental support, lack of access to high-quality schools).

To attempt to eliminate selection bias, we employ regression methods using inverse probability of treatment weighting (IPTW) to estimate the effect of each of our five treatments on student achievement and attendance outcomes. The use of regression with IPTW allows us to compare students who experience homelessness (as defined by the respective treatment) to a set of students who are comparable but did not experience homelessness. If the IPTW control for observable and unobservable differences between students, we can interpret differences between students as causal effects of homelessness. The generation of IPTW requires two steps. First, we estimate propensity scores, or the likelihood that each student experiences each of the five treatments based on baseline characteristics. We include mathematics test scores and attendance, and demographic and neighborhood characteristics as baseline covariates in third grade. Second, we use these propensity scores to generate IPTW. Finally, to arrive at causal estimates, we apply the IPTW to a regression model that estimates the effects of our five treatments on student achievement and attendance outcomes, respectively. The regression models with IPTW use a doubly robust method where we include the same covariates used to estimate the propensity scores as controls.[5]

Propensity score estimation. The first step for IPTW is estimating the propensity scores. We use third grade as the baseline year because it is the first tested grade and one of the outcomes of interest is student achievement. We select the covariates for the models through descriptive analysis where we identify the initial student-level variables that are related to each of our five treatment variables (ever homeless, past, current, transitory, and persistent homelessness) (Imbens & Rubin, 2015). The covariates are student and neighborhood-level characteristics at the baseline (3rd grade). At the student-level we include identifiers for student of color (non-white), Limited English Proficiency, Special Education Eligibility, FRL persistence, Math Score, and Attendance; and at the neighborhood level we include Median Income, and percent of the population that is/has: Hispanic/Latino, Black, college degree or above, employed, working in professional fields, female headed households, severely rent burdened, and overcrowded. Next, we estimate propensity scores using logistic regression. Propensity scores are the likelihood of treatment (experiencing homelessness) for each student, given their own characteristics and their neighborhood's characteristics. Because we have five different treatment variables, we estimate five different propensity scores for each students (see Figure 1 for the treatments).

We then assess the balance between treatment and control groups conditional on the estimated propensity scores (Imbens & Rubin, 2015). To avoid having estimates driven by a few observations with extremely large weights, we trim the samples by disregarding control observations whose propensity scores are smaller than the minimum score for treated observations (i.e., very close to zero), and disregarding treatment observations whose scores are larger than the maximum score for control observations. Next, for the trimmed sample, we repeat the first steps to estimate new propensity scores only for the remaining observations.

We complete this process to generate the final propensity scores for each student for each one of the five treatments. As mentioned earlier, the control group for each treatment consists only of students who have never experienced homelessness, to avoid for example, comparing currently homeless students to a control group of never homeless and past homeless students. Because we trim observations depending on the estimated propensity scores for each treatment, this also means that the final sample for each treatment is slightly different.

Inverse probability of treatment weights (IPTW). Using the estimated propensity scores, we generate IPTW using the equations below. Equations 1 and 2 represent the weights applied to treated and control observations, respectively:

$$(1) \qquad w_i = \frac{1}{P_i(D=1)}$$

$$(2) \qquad w_i = \frac{1}{1-P_i(D=1)}$$

where $P_i(D = 1)$ is the probability that student *i* experiences the treatment D and $1 - P_i(D = 1)$ is the probability that the student does not experience the treatment.

To assess the balance, we visually examine if there is sufficient overlap in the distribution of estimated propensity scores for treatment and control observations (Appendix Figure A1). After confirming that there is overlap with most of the distribution of scores having both treated and control observations, we estimate a series of regressions with and without the estimated weights. Each regression contains the treatment variable as the outcome and one of the covariates used in the propensity score estimation model as the predictor. Table 2 displays the unweighted regressions for the full sample and shows that without weights, all the covariates are unbalanced (with p-values lower than 0.05 in all cases). Once we account for IPTW, we see that the baseline characteristics no longer predict treatment (except for the percentage of neighborhood residents in professional occupations), which is the case for all treatments. The weighted regression suggests that the inverse probability of treatment weights account for selection bias on observables. Table 2 presents the results for the regressions for the first treatment (ever homeless between 4th and 8th grade), the results for the other treatments are very similar.

Main analysis. Once balance is confirmed, we estimate weighted regressions including the baseline covariates as controls to further reduce estimation bias, referred to as double robust regressions (Iacus et al., 2012). The student-level model predicts the student outcomes on each of the homeless treatment variables, controlling for a set of student covariates:

$$(3) \qquad Y_i = \beta_0 + \beta_1 homeless_i + \beta_2 X_i + \varepsilon_i$$

where Y_i is the outcome (standardized math scores or days attended school) for student i. The variable $homeless_i$ represents each of the treatment statuses: whether a student is ever homeless between 4th and 8th grade, whether the experience is transitory or persistent, and whether it is current (i.e., in 8th grade) or in the past. We interpret β_1 as the difference in outcomes that can be attributed to the treatment, after accounting for X_i , a set of student-level demographic covariates used to estimate the propensity scores. We cluster all standard errors at the school level, correcting for correlation in outcomes among students from the same school.

While our study aims to make important contributions, the causal claims are reliant on the inverse probability of treatment weights adequately controlling for other important observable and unobservable differences between the homeless and housed population. We rely on third-grade baseline characteristics to account for important differences between homeless and non-homeless students before they experience homelessness for the first time. We examine diagnostics that show appropriate overlap and balance in the propensity scores (making the treatment independent of the covariates included), but we cannot discard that other unobservable or unmeasured characteristics may bias the results. Although we may not perfectly isolate the effects of homelessness and housing insecurity, the fact that they are such complex situations suggests that being able to isolate the pure effect of homelessness may be unrealistic, and possibly even unhelpful.

Results

To characterize homelessness within our sample of LAUSD students, we examine what characteristics are associated with homelessness and the duration and timing of homelessness. Of the 54,950 eighth-graders in our sample, 2% were homeless at some point between 4^{th} and 8^{th} grade and 38% of those ever homeless were homeless in 8^{th} grade (see Table 1, column 3). Students who experienced homelessness are identified as homeless 1.9 years on average. Almost 1 in 4 of these students experienced persistent homelessness, spending three or more years homeless during the period between 4^{th} and 8^{th} grade.

Students who experienced homelessness differ noticeably from those who never experienced homelessness in terms of demographic characteristics, as previous research suggests (Table 1, columns 2 and 3). Two salient differences are that students of color (Asian, Black, Hispanic, Filipino, Native American, or Pacific Islander) are disproportionately represented in the homeless population, and that students who experience homelessness live in more disadvantaged neighborhoods in 8^{th} grade than students who do not experience homelessness. Students who experience persistent homelessness live in even more disadvantaged neighborhoods according to these indicators. There appear to be no notable differences between students who have different homeless experiences, for example between students who experience current versus past homelessness, or persistent versus transitory homelessness (Table 1).

Our main research question examines the causal relationship between student outcomes and homeless status. Tables 3 and 4 present results from the double robust regression models described above in which we predict the relationship between each one of our treatment variables and student outcomes (math scores and attendance).

Being homeless at least once between 4^{th} and 8^{th} grades has a negative effect on math test scores of 0.13 standard deviations ($p<0.01$) (Table 3, column 1). This represents one-third of the 0.397 standard deviations gap between students who experience homelessness at least once and students who never experience homelessness in our sample, meaning that homelessness itself explains one-third of the gap and two-thirds remain unexplained. Experiencing homelessness also hurts attendance, with homeless students attending 5.8 fewer days of school (Table 4, column 1). The average eighth-grader in the sample misses 7 days of school, thus homelessness adds almost six additional days absent in a 180-day school year (an 80% increase).

Next, we turn to the results estimating the differential effects of homelessness on eighth-grade math scores by timing and duration of homelessness. For timing, we find that being currently homeless in eighth grade has a larger negative effect ($\beta=-0.168$, $p<0.01$) on math scores than being homeless in the past between 4^{th} and 7^{th} grade ($\beta=-0.125$, $p<0.05$) (Table 3, columns 2 and 3). Concerning the duration of homelessness, while we find no significant effect of persistent homelessness (3 or more years) on math scores, transitory homelessness (1 or 2 years) has large significant negative effects ($\beta=-0.140$, $p<0.01$) (Table 3, column 4). In sum, being homeless at least once between 4^{th} and 8^{th} grade has sizable negative effects on eighth-grade math scores.

The effects of homelessness on eighth-grade attendance also differ by the timing and duration of homelessness (see Table 4). Both being homeless before eight grade (past) and being homeless in eight grade (current) have statistically significant negative effects on eighth-grade attendance, but current homelessness has a larger effect than past homelessness (β=-10.790, $p<0.001$, compared to β=-5.003, $p<0.001$) (Table 4, columns 2 and 3). Duration also has distinct effects. Transitory homelessness has a larger effect than persistent homelessness (β=-6.808, $p<0.001$, compared to β=-2.308, $p<0.05$) (Table 4, columns 4 and 5). Similar to the effects on math scores, we find that homelessness has strong negative effects on eighth-grade attendance.

Robustness Checks

Following Imbens & Rubin (2015), we trim the observations that have extremely high or extremely low probabilities of being treated, and weight all other observations to create representative and similar treatment and control groups. We trim between 741 and 4,937 control observations depending on the treatment variable (between 1.4 and 9.3% of control observations) and only one treatment observations for one treatment (past homelessness). As a robustness check, we run the analysis on the non-trimmed full sample for all five treatments. We find that balance is obtained, and the results do not differ significantly from trimmed sample results. We also run the analysis for an alternative control group for each treatment status, such that the control group includes the other types of homelessness, for example, transitory homeless students could be compared to both never homeless and persistently homeless students. Results are similar, with slightly smaller estimates when using alternative control groups. Finally, to determine how much the results may be due to the specific methodology we chose, we ran the analysis using a related method—coarsened exact matching—and obtain remarkably similar results. These results are available upon request.

Discussion

We add to the growing research base on student homelessness by exploring the characteristics of homeless students in LAUSD and providing new evidence of the effects of homelessness and the heterogeneity in homeless experiences. Even after accounting for important sources of selection bias, in line with existing research, we find a strong negative relationship between homelessness and math achievement and attendance. Overall, we believe our findings support the idea of a gradient of vulnerability where students experiencing homelessness are in a situation of higher vulnerability than their poor but housed peers.

Our findings regarding the duration and timing of homelessness uncover nuance in these results. We observe the largest negative impacts on math achievement and attendance for students who are currently experiencing homelessness, while students who have been homeless in the past show smaller negative effects on these outcomes. The significant effects of past homelessness on both outcomes suggest that the impacts of homelessness are not short-lived, but also lessen over time. Educational supports that continue after exiting homelessness, can help mitigate the short-term impacts faster, with likely effects on long-term impacts as well. Districts can flag homeless students to follow their progress even after they are housed, and identify if students need special supports or not. Also, considering that homeless students have higher rates of school mobility, schools and districts can work with each other as students transition from one school or district to another. Communication between schools and districts can allow to more quickly identify students as currently homeless or having exited homelessness, and continue providing them with additional supports.

Interestingly, we find that transitory homelessness has larger negative effects on math scores and attendance than persistent homelessness. Transitory disruptions and housing instability seem to be more detrimental than more permanent situations, and students benefit from being identified as homeless longer. This finding highlights the need for districts to increase their identification efforts in order to avoid missing students who may be homeless for short periods of time. Districts should expand the education of relevant school staff and personnel (from teachers, counselors to bus drivers), their engagement with community partners (laundromats, food banks, shelters, motels, etc.), and more swiftly reach out to families and youth that may be experiencing homelessness. Furthermore, because there are policies already in place through the McKinney-Vento Homeless Assistance Act, future research should probe these results and examine how particular policies impact students experiencing homelessness, and how they can be improved to better identify and support students.

Our results also raise many new questions. Future research should examine the effects of particular types of homeless residences, by building on the single study (Deck, 2017) that investigates differential impacts of living doubled-up (i.e., living in the home of family or friends) versus other unstable housing arrangements on educational outcomes. Also, because neighborhoods where children grow up impact their outcomes, including health and psychological well-being, as well as their educational outcomes (Carlson & Cowen, 2015; Galster, 2012; Owens, 2010), future research should also consider the relationship between neighborhoods, schools, and homelessness to offer new insights about the mechanisms that put youth at-risk or insulate them from the potential negative impacts of being homeless.

NOTES

[1] This definition does not coincide with the Department of Housing and Urban Development's or McKinney-Vento's definition of chronic homelessness which also require the head of household to have a disability

[2] Underreporting of homeless students could introduce mismeasurement bias into the treatment variables. If there were misreporting, the most likely scenario is that current reports are undercounting homeless students, thus our estimated effects would be biased towards zero since our control groups would include unidentified homeless students.

[3] The state of California changed its assessment program during the time frame we study due to changes in the state's content standards as a result of the common core state standards. The assessment program in the 2015-16 and 2016-17 school years was California Assessment of Student Performance and Progress (CAASPP) System, and then assessment program in the 2010-11 and 2011-12 school years was the Standardized Testing and Reporting (STAR) program.

[4] We assign each school year to the midpoint of the ACS five-year estimate, using the first semester of the school year. For example, school year 2009-2010 is considered 2009 and assigned to the ACS 2011 five-year estimates, which cover from 2007 to 2011.

[5] Because our weighted regressions balance treatment and control groups across all the included covariates at baseline, the regression estimates for these covariates (omitted from the tables) are not informative of their relationship with the outcomes. Appendix tables A1 and A2 present results from OLS regressions to shed light on the relationship between the covariates and the outcomes. The regressions include school fixed effects to account for school-level differences that may impact both the likelihood of homeless identification and student outcomes.

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Figure 1 – *Treatment Variables and Definitions*

McKinney Vento Act	Federal Law first published in 1987 and most recently reauthorized in 2015 as part of the Every Student Succeeds Act. Subtitle VII-B of the McKinney-Vento Homeless Assistance Act, titled Education for Homeless Children and Youths, defines homelessness and provides guidelines for homeless student identification and protection.
Homeless students	Students who “lack a fixed, regular, and adequate nighttime residence”, including students residing in other persons’ homes (doubled-up); living in motels, hotels, trailers, in shelters, or students sleeping in “a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings” (42 U.S.C. §11434a(2), 2002).
Treatment Variables	
Homeless Ever	Students who identify as homeless at any time between 4th and 8th grade.
Timing: Current Homeless	Students who identify as homeless during 8th grade (the tested grade).
Timing: Past Homeless	Students who identify as homeless between 3rd and 7th grade (before the tested grade).
Duration: Transitory Homeless	Students who identify as homeless during one or two school years (consecutive or not).
Duration: Persistent Homeless	Students who identify as homeless during three or more school years (consecutive or not).

Table 1 – *Sample Characteristics 8th graders in 2015-16 and 2016-17 cohorts*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
					Duration of Homelessness				Timing of Homelessness			
Variable	All eighth graders	Never homeless 4-8 gr	Homeless between 4-8 gr	Difference	Transitory (1-2 years)	Difference	Persistent (3+ yrs)	Difference	Past	Difference	Current	Difference
Share of sample	1.00	0.98	0.02		0.01		0.00		0.01		0.01	
Share of homeless			1.00		0.77		0.23		0.64		0.76	
Minority (non-white)	0.90	0.90	0.98	-0.07 ***	0.97	-0.07 ***	0.99	-0.08 ***	0.99	-0.09 ***	0.96	-0.05 ***
Hispanic	0.76	0.76	0.81	-0.05 ***	0.79	-0.02	0.86	-0.10 ***	0.82	-0.06 *	0.76	0.00
Black	0.06	0.06	0.14	-0.08 ***	0.15	-0.09 ***	0.11	-0.04 **	0.15	-0.09 ***	0.16	-0.10 ***
Asian	0.05	0.05	0.01	0.04 ***	0.01	0.04 ***	0.00	0.05 ***	0.00	0.04 **	0.00	0.04 ***
White	0.10	0.10	0.02	0.07 ***	0.03	0.07 ***	0.01	0.08 ***	0.01	0.09 ***	0.04	0.05 ***
Female	0.50	0.50	0.53	-0.03 *	0.54	-0.04 *	0.51	-0.01	0.52	-0.02	0.55	-0.05
Limited English Prof.	0.08	0.08	0.11	-0.03 ***	0.11	-0.03 ***	0.10	-0.02	0.09	-0.01	0.14	-0.06 ***
SPED Eligible	0.08	0.08	0.12	-0.04 ***	0.11	-0.03 ***	0.14	-0.06 ***	0.10	-0.02	0.12	-0.05 ***
FRL never	0.10	0.10	0.00	0.10 ***	0.00	0.10 ***	0.00	0.10 ***	0.00	0.10 ***	0.00	0.10 ***
FRL transitorily	0.27	0.27	0.25	0.02	0.29	-0.02	0.12	0.15 ***	0.22	0.05	0.33	-0.06 **
FRL persistently	0.63	0.63	0.75	-0.12 ***	0.71	-0.08 ***	0.88	-0.25 ***	0.78	-0.15 ***	0.67	-0.04
Math Score	0.10	0.11	-0.29	0.40 ***	-0.31	0.41 ***	-0.20	0.30 ***	-0.20	0.31 ***	-0.36	0.47 ***
Attended days	172.70	172.89	163.28	9.61 ***	161.78	10.91 ***	168.26	4.46 ***	165.69	7.09 ***	156.75	16.14 ***
Attendance (%)	0.97	0.97	0.94	0.03 ***	0.94	0.03 ***	0.94	0.02 ***	0.95	0.02 ***	0.93	0.04 ***
Neighborhood Characteristics												
White	0.17	0.17	0.11	0.06 ***	0.11	0.06 ***	0.10	0.07 ***	0.09	0.08 ***	0.12	0.06 ***
Black	0.07	0.07	0.09	-0.01 ***	0.09	-0.02 ***	0.08	-0.01	0.09	-0.02 **	0.09	-0.02 **
High school grad +	0.22	0.22	0.24	-0.02 ***	0.24	-0.02 ***	0.24	-0.02 ***	0.24	-0.02 ***	0.24	-0.02 ***
College grad +	0.15	0.15	0.11	0.04 ***	0.11	0.03 ***	0.11	0.04 ***	0.10	0.04 ***	0.11	0.033 ***
Median Income	53064	53200	45100	8160 ***	45700	7490 ***	42800	10400 ***	43200	9970 ***	45300	7940 ***
Families in poverty	0.20	0.20	0.24	-0.04 ***	0.23	-0.03 ***	0.25	-0.05 ***	0.25	-0.06 ***	0.23	-0.04 ***
Owner Occupied hh	0.38	0.38	0.35	0.04 ***	0.35	0.027 **	0.32	0.06 ***	0.33	0.05 **	0.34	0.042 ***
Employed	0.65	0.65	0.64	0.01 ***	0.64	0.01 ***	0.65	0.01 ***	0.65	0.01	0.64	0.012 ***
Professional Occs	0.12	0.12	0.12	0.00 *	0.12	0.00 *	0.12	0.00	0.12	0.01	0.12	0.00
Female headed hh	0.19	0.19	0.22	-0.02 ***	0.21	-0.02 ***	0.22	-0.03 ***	0.23	-0.03 ***	0.21	-0.02 ***
Rent burdened hh	0.60	0.60	0.63	-0.03 ***	0.63	-0.03 ***	0.63	-0.03 ***	0.64	-0.04 ***	0.62	-0.02 ***
Severe rent burd hh	0.33	0.33	0.35	-0.02 ***	0.35	-0.02 ***	0.35	-0.02 **	0.36	-0.03 ***	0.34	-0.01 *
Overcrowded hh	0.20	0.20	0.23	-0.03 ***	0.22	-0.02 ***	0.24	-0.04 ***	0.24	-0.04 ***	0.22	-0.02 ***
Total Years Homeless	0.04	0.00	1.86	-1.86 ***	1.40	-1.40 ***	3.42	-3.42 ***	1.89	-1.89 ***	1.01	-1.01 ***
Number of Obs	54,905	53,851	1,054		812		242		256		379	

** p<0.05, **p<0.01, ***p<0.001 indicates statistical significance from ttest differences between each treatment and never homeless students.*

Table 2 – *Balance of Covariates on Propensity Weights*

Dependent Variable: Homeless at least once between 4th and 8th grade

	Full sample Unweighted Regressions			Trimmed sample Weighted Regressions		
Baseline Covariates (all 3rd gr)	Coefficient	Standard Errors	P-Value	Coefficient	Standard Errors	P-Value
Minority (non-white)	0.074***	(0.01)	0.000	0.000	(0.02)	0.984
Limited English Proficiency	0.047**	(0.01)	0.001	0.008	(0.02)	0.677
SPED Eligible	0.009	(0.01)	0.199	0.006	(0.01)	0.681
FRL Persistence	0.192***	(0.02)	0.000	-0.001	(0.05)	0.977
Math Score	-0.382***	(0.03)	0.000	0.012	(0.05)	0.813
Attendance days	-4.988***	(0.38)	0.000	-0.01	(0.34)	0.976
Median Income	-6593.6***	(725.01)	0.000	-452.9	(1199.8)	0.706
White %	-0.073***	(0.01)	0.000	-0.002	(0.01)	0.858
Black %	0.023***	(0.00)	0.000	-0.001	(0.00)	0.845
College grad or more %	-0.036***	(0.00)	0.000	-0.005	(0.00)	0.332
Owner Occupied hh %	-3.534***	(0.75)	0.000	0.636	(1.23)	0.606
Families in poverty %	0.039***	(0.00)	0.000	0.001	(0.01)	0.850
Employed %	-0.008***	(0.00)	0.000	-0.004	(0.00)	0.167
Professional Occupations %	-0.008***	(0.00)	0.000	-0.005*	(0.00)	0.018
Female-headed hh %	0.026***	(0.00)	0.000	0.003	(0.00)	0.386
Severe rent-burdened hh %	0.019***	(0.00)	0.000	0.005	(0.00)	0.317
Overcrowded households %	0.033***	(0.00)	0.000	0.000	(0.01)	0.982
Number of Observations	54950			53514		

** p<0.05, **p<0.01, ***p<0.001 indicates statistical significance.*

Table 3

Impact of Homelessness on Math Scores by timing and duration of Homelessness

Dependent Variable: Eighth-grade Math scores

	(1)	(2)	(3)	(4)	(5)
		Timing		Duration	
	Ever	Current	Past	Transitory	Persistent
Homeless at least once (4-8 gr)	-0.130**				
	(0.041)				
Current (8 gr)		-0.168**			
		(0.050)			
Past (by 7 gr)			-0.125*		
			(0.053)		
Transitory (1-2 years)				-0.140**	
				(0.046)	
Persistent (3+ years)					-0.053
					(0.049)
R-sqr	0.389	0.386	0.386	0.406	0.377
Obs	53514	50769	50741	53896	49130

*$*$ p<0.05, **p<0.01, ***p<0.001 indicates statistical significance.*
Standard errors clustered at the school level are reported in parentheses.
Note: The sample size for each treatment is slightly different because we run the models and trim observations for the likelihood of each treatment separately. Covariates included and not presented include student and neighborhood-level characteristics at the baseline (3rd grade). Student: minority (non-white), Limited English Proficiency, Special Education Eligibility, FRL persistence, Math Score, and Attendance. Neighborhood: Median Income, % Hispanic/Latino, % Black, % with college degree or above, % employed, % working in professional fields, % female headed households, % severely rent burdened, % overcrowded.

Table 4

Impact of Homelessness on Attendance by timing and duration of Homelessness

Dependent Variable: Eighth-grade Attendance (total days attended)

	(1)	(2)	(3)	(4)	(5)
		Timing		Duration	
	Ever	Current	Past	Transitory	Persistent
Homeless at least once (4-8 gr)	-5.776***				
	(0.665)				
Current (8 gr)		-10.790***			
		(1.486)			
Past (by 7 gr)			-5.003***		
			(1.075)		
Transitory (1-2 years)				-6.808***	
				(0.827)	
Persistent (3+ years)					-2.308*
					(0.984)
R-sqr	0.102	0.149	0.130	0.112	0.106
Obs	53514	50769	50741	53896	49130

** p<0.05, **p<0.01, ***p<0.001 indicates statistical significance.*
Standard errors clustered at the school level are reported in parentheses.
Note: The sample size for each treatment is slightly different because we run the models and trim observations for the likelihood of each treatment separately. Covariates included and not presented include student and neighborhood-level characteristics at the baseline (3rd grade). Student: minority (non-white), Limited English Proficiency, Special Education Eligibility, FRL persistence, Math Score, and Attendance. Neighborhood: Median Income, % Hispanic/Latino, % Black, % with college degree or above, % employed, % working in professional fields, % female headed households, % severely rent burdened, % overcrowded.

Appendix

Figure A1 – *Overlap of Propensity Scores - Trimmed sample*

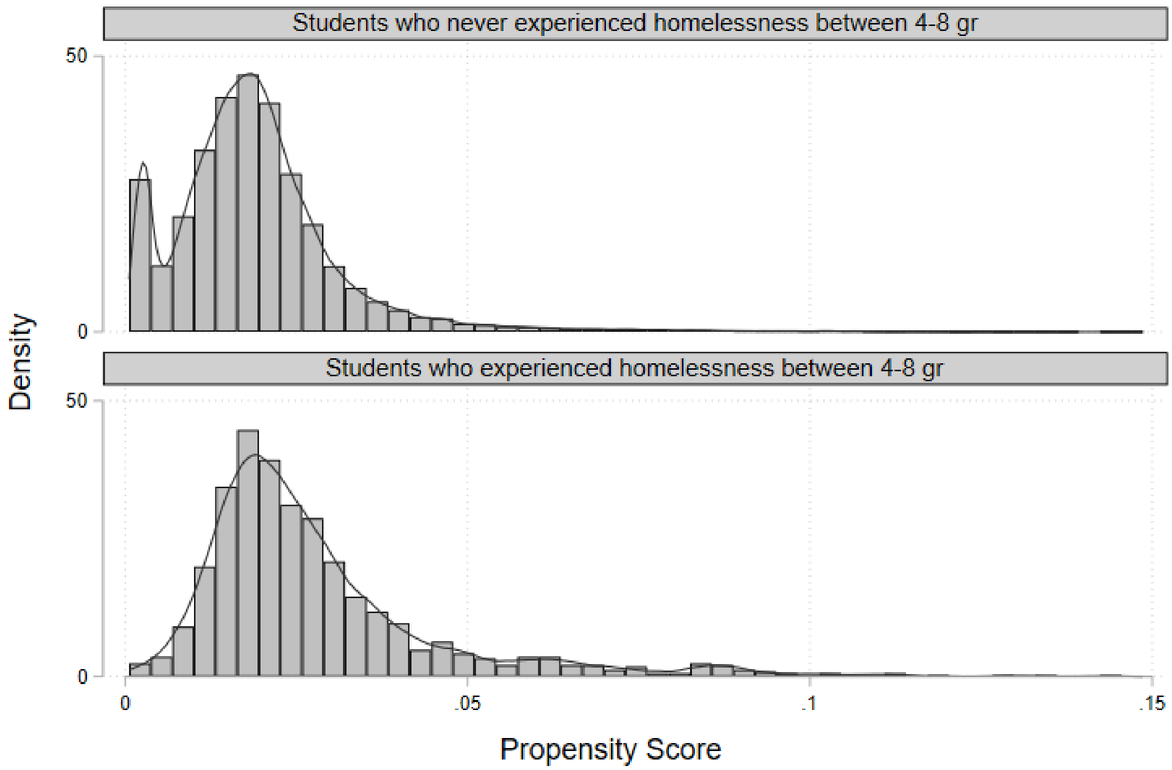

Table A1 – *OLS Estimates, Dependent Variable: Eighth grade Math scores*

		Timing		Duration	
	Ever	Current	Past	Transitory	Persistent
Homeless at least once (4-8 gr)	-0.085***				
	(0.020)				
Current (8 gr)		-0.129***			
		(0.040)			
Past (by 7 gr)			-0.021		
			(0.040)		
Transitory (1-2 years)				-0.106***	
				(0.025)	
Persistent (3+ years)					-0.014
					(0.045)
Minority (non-white)	-0.094***	-0.093***	-0.094***	-0.094***	-0.094***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Limited English Proficiency	-0.494***	-0.495***	-0.495***	-0.495***	-0.497***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
SPED Eligible	-0.325***	-0.322***	-0.323***	-0.323***	-0.325***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Transitory FRL	-0.263***	-0.262***	-0.263***	-0.262***	-0.262***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Persistent FRL (every year)	-0.300***	-0.300***	-0.301***	-0.300***	-0.300***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Math Score 3rd gr	0.460***	0.460***	0.460***	0.460***	0.460***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Attendance days 3rd gr	0.001**	0.001**	0.001**	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Neighborhood Characteristics (3rd gr)					
Median Income (log)	0.011	0.013	0.012	0.014	0.011
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
White %	0.018	0.02	0.016	0.017	0.018
	(0.039)	(0.040)	(0.039)	(0.039)	(0.040)
Black %	-0.046	-0.04	-0.044	-0.04	-0.044
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
College grad or more %	0.225***	0.225***	0.229***	0.227***	0.227***
	(0.073)	(0.074)	(0.074)	(0.073)	(0.074)
Families in poverty %	-0.131**	-0.119**	-0.125**	-0.118*	-0.134**
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Owner Occupied Households %	0.001*	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employed %	-0.211***	-0.207***	-0.214***	-0.212***	-0.211***
	(0.067)	(0.068)	(0.068)	(0.068)	(0.068)
Professional Occupations %	0.114	0.117*	0.112	0.112	0.118*
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
Female headed households %	-0.027	-0.027	-0.028	-0.03	-0.02
	(0.061)	(0.062)	(0.062)	(0.061)	(0.062)
Rent burdened hh % (severe)	-0.024	-0.026	-0.025	-0.026	-0.023
	(0.037)	(0.038)	(0.038)	(0.037)	(0.038)
Overcrowded households %	0.038	0.029	0.031	0.033	0.035
	(0.056)	(0.056)	(0.056)	(0.056)	(0.057)
constant	0.372	0.335	0.354	0.337	0.342
	(0.250)	(0.250)	(0.250)	(0.249)	(0.250)
R-sqr	0.378	0.379	0.378	0.378	0.378
Obs	54872	54202	54455	54630	54061

** p<0.05, **p<0.01, ***p<0.001 indicates statistical significance. Fixed effects at the school level.*

Table A2 – *OLS Estimates, Dependent Variable: Eighth-grade Attendance (total days attended)*

		Timing		Duration	
	Ever	Current	Past	Transitory	Persistent
Homeless at least once (4-8 gr)	-11.019***				
	(0.487)				
Current (8 gr)		-17.774***			
		(0.783)			
Past (by 7 gr)			-9.513***		
			(0.972)		
Transitory (1-2 years)				-12.668***	
				(0.549)	
Persistent (3+ years)					-5.332***
					(0.993)
Minority (non-white)	1.279***	1.276***	1.292***	1.316***	1.305***
	(0.299)	(0.296)	(0.299)	(0.298)	(0.293)
Limited English Proficiency	-1.668***	-1.618***	-1.604***	-1.687***	-1.583***
	(0.276)	(0.275)	(0.278)	(0.276)	(0.273)
SPED Eligible	-0.105	-0.143	-0.149	-0.133	-0.213
	(0.276)	(0.275)	(0.278)	(0.276)	(0.273)
Transitory FRL	-2.286***	-2.241***	-2.348***	-2.252***	-2.252***
	(0.310)	(0.306)	(0.310)	(0.309)	(0.303)
Persistent FRL (every year)	1.443***	1.398***	1.389***	1.424***	1.294***
	(0.317)	(0.314)	(0.317)	(0.316)	(0.310)
Math Score 3rd gr	1.602***	1.563***	1.631***	1.586***	1.570***
	(0.081)	(0.080)	(0.081)	(0.080)	(0.079)
Attendance days 3rd gr	0.203***	0.205***	0.207***	0.202***	0.200***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Neighborhood Characteristics (3rd gr)					
Median Income (log)	-0.777	-0.727	-0.741	-0.741	-0.748
	(0.548)	(0.545)	(0.550)	(0.548)	(0.539)
White %	-1.746*	-1.706*	-1.715*	-1.816**	-1.658*
	(0.906)	(0.900)	(0.908)	(0.904)	(0.890)
Black %	-4.298***	-4.472***	-4.495***	-4.352***	-4.325***
	(0.954)	(0.949)	(0.957)	(0.952)	(0.940)
College grad or more %	1.462	1.447	1.105	1.3	1.295
	(1.685)	(1.674)	(1.691)	(1.682)	(1.656)
Families in poverty %	-2.014	-2.003	-2.08	-1.989	-2.275*
	(1.379)	(1.371)	(1.384)	(1.377)	(1.357)
Owner Occupied Households %	0.020***	0.020***	0.020***	0.019***	0.018**
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
Employed %	1.741	1.519	1.944	1.879	1.369
	(1.553)	(1.544)	(1.559)	(1.551)	(1.528)
Professional Occupations %	-0.417	-0.585	-0.684	-0.58	-0.424
	(1.621)	(1.613)	(1.628)	(1.620)	(1.596)
Female headed households %	-3.206**	-3.518**	-3.156**	-3.471**	-3.347**
	(1.408)	(1.401)	(1.414)	(1.407)	(1.386)
Rent burdened hh % (severe)	2.504***	2.526***	2.635***	2.496***	2.598***
	(0.861)	(0.855)	(0.864)	(0.859)	(0.846)
Overcrowded households %	0.918	0.879	0.616	0.971	0.661
	(1.288)	(1.283)	(1.294)	(1.288)	(1.268)
constant	142.580***	141.836***	141.290***	142.280***	143.205***
	(5.711)	(5.676)	(5.729)	(5.704)	(5.620)
R-sqr	0.059	0.059	0.052	0.059	0.049
Obs	56366	55643	55923	56108	55467

** p<0.05, **p<0.01, ***p<0.001 indicates statistical significance. Fixed effects at the school level.*