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The Impacts of Homelessness Prevention and Rapid Rehousing on Homeless and Highly Mobile Students

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ABSTRACT

Despite the recent dramatic rise in student homelessness in the U.S., little research evidence exists on the effects of homelessness programs and interventions on students and young people. This paper examines the effects of a homelessness prevention and rapid rehousing program—which combines temporary rental subsidies with light-touch case management—on homeless and highly mobile students in a large urban school district. By linking detailed district administrative data with programmatic data, I create a novel dataset that allows me to estimate impacts to students in the immediate weeks and months following exposure to the rehousing intervention. Specifically, I use generalized and event study difference-in-differences models to estimate within-student differences in district and school mobility, attendance, and behavioral outcomes before and after beginning participation in the program. I find that the treatment improves student behavior, significantly reducing the likelihood of students having multiple behavioral incidents in a month, but increases students' absence rates and chronic absenteeism, particularly for students who are rehoused outside the city proper but remain enrolled in the central district. These results highlight both the positive impacts of this type of intervention, as well as unintended consequences, raising questions around the priorities and inherent tradeoffs of rehousing programs.

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Abstract

Despite the recent dramatic rise in student homelessness in the U.S., little research evidence exists on the effects of homelessness programs and interventions on students and young people. This paper examines the effects of a homelessness prevention and rapid rehousing program—which combines temporary rental subsidies with light-touch case management—on homeless and highly mobile students in a large urban school district. By linking detailed district administrative data with programmatic data, I create a novel dataset that allows me to estimate impacts to students in the immediate weeks and months following exposure to the rehousing intervention. Specifically, I use generalized and event study difference-in-differences models to estimate within-student differences in district and school mobility, attendance, and behavioral outcomes before and after beginning participation in the program. I find that the treatment improves student behavior, significantly reducing the likelihood of students having multiple behavioral incidents in a month, but increases students' absence rates and chronic absenteeism, particularly for students who are rehoused outside the city proper but remain enrolled in the central district. These results highlight both the positive impacts of this type of intervention, as well as unintended consequences, raising questions around the priorities and inherent tradeoffs of rehousing programs.

1. Introduction

K-12 education in the United States is fundamentally linked to families' residential location, and decades of research have documented the multi-dimensional connections between schooling and housing (see, for example, Schwartz and Stiefel, 2014). Housing impacts students' educational outcomes not only by determining their access to various schools, but also by influencing factors such as neighborhood characteristics, housing conditions, and housing affordability—all of which contribute to the home environment and the contexts in which students live and learn. Housing policy broadly affects all students, but the impacts are particularly acute for homeless and highly mobile students who lack stable housing and are directly affected by policies aimed at reducing homelessness and promoting housing stability. This population of students is growing rapidly. In the 2017-18 school year, 1.5 million students were identified as homeless, up 15 percent from just two years earlier (National Center for Homeless Education, 2020). In New York City, 10 percent of public-school students were homeless at some point during the 2018-19 school year (Amin, 2019); in Los Angeles, 17,500 students attending LA Unified School District were identified as homeless, an increase of almost 2,000 students from just two years prior (Swaak, 2019). Despite this troubling growth, the research on the impact of housing policies on the educational experiences of this subgroup of students is notably thin.

In the city where this study takes place, homelessness has become a high-profile concern driven in part by the city's high housing costs, limited affordable housing, and increasingly visible homeless encampments. There, the numbers are less dramatic yet still troubling. In the 2015-16 school year, approximately 4 percent, or around 2,500 students, were identified by the school district as homeless or highly mobile, which is almost certainly an undercount of the actual number of school-age children experiencing homelessness or unstable housing during that academic year. To help address the needs of this population, the city government, in partnership with the school district and a local non-profit organization serving homeless families (referred to throughout as "NGO") launched an initiative aimed at housing the city's homeless families through a homelessness prevention and rapid rehousing program.

While academic research has largely established that homeless and highly mobile (HHM) students are at high risk for negative health, socio-emotional, and academic outcomes (e.g. Obradovic et al. 2009; Cutuli et al. 2013), much less is known about the effectiveness of policies and interventions aimed at helping homeless children and youth. In particular, we know little about how these vulnerable young people respond to gaining housing stability. One of the few sources of data on such interventions is the multi-site randomized trial known as the Family Options Study; however, existing research on this study has focused either on a limited number of student outcomes starting a year-and-a-half after the intervention took place (Gubits et al., 2018), or on outcomes that can only be measured annually (Cutuli and Herbers, 2019). In this paper, I expand upon this research base by using detailed, highly granular administrative data to examine homelessness prevention and rapid rehousing's impact on outcomes relating to students' behavior, engagement, and enrollment, starting in the immediate weeks and months following their involvement with the services provided by NGO. In doing so, I am able to shed light on students' experiences during a critical period of transition, as well as examine the dynamic nature of the program's impacts in the short- and medium-term.

The goal of homelessness prevention and rapid rehousing programs (HPRPs) is to minimize households' time spent homeless or, ideally, prevent it altogether. Rapid rehousing, the more prominent and common component of these programs, prioritizes placing households in stable homes as quickly as possible, typically pairing temporary rent subsidies with light-touch case management and housing search assistance. Homelessness or eviction prevention, which is sometimes but not always included as another component, is similar but without the need for housing search assistance. HPRPs are intended to be relatively cost-effective, scalable interventions, particularly when compared to the primary alternatives of transitional housing, which involves more intensive case management and programming, or emergency shelter. The underlying logic of these programs is that the placement of households into stable housing situations is the most effective and efficient way to promote their self-sufficiency (Cunningham and Batko, 2018).

There are a number of ways in which an HPRP could feasibly impact students. The experience of homelessness is tied to an array of negative risk factors for children, and HHM students tend to have worse academic, behavioral, and health outcomes than their peers. Research by Piña and Pirog (2018) finds that school districts located in areas with HPRP funding tend to have lower rates of homelessness among students, suggesting that such programs do in fact have some success with regard to their primary goal. For students whose families do participate in such programs, the benefit of housing stability, as well as the financial assistance and emotional support from case managers and staff, could reduce stress in the home environment, make it easier for students to get to school regularly, and help families meet the basic needs required for students to thrive.

However, the experience of rapid rehousing itself brings with it a number of challenges. Searching for a new place to live can be stressful and logistically difficult, even with assistance, and even for families who successfully locate a new home, a move might come with a loss of community, a longer commute, or a sense of displacement. This is particularly the case in areas with limited affordable housing, where families might have to travel far to find an affordable apartment to rent. Families may have to make difficult decisions about moving their children to new schools or even new districts during what is likely already a difficult period of transition. Finally, it is also possible that for families who are already struggling to the point that they need the HPRP services, the light-touch support and temporary resources might do little to alter students' experiences or their trajectories in schools.

At the outset, it is not clear how these various plausible effects play out. Given the lack of research on students' experiences during and immediately following the period of transition associated with receiving HPRP services, I address the following research questions:

1. What are the short- and medium-term effects of homelessness prevention and rapid rehousing on HHM students' likelihood of departing the school district, intra-district school mobility, school attendance, and behavior at school?
2. Are the effects of the program heterogeneous with regard to the particular services students' families receive— specifically, rapid rehousing in a new home as compared to eviction prevention in their existing home?
3. What role does the location of students' new homes play with regard to these educational impacts?

To study these research questions, I create a novel dataset linking student-level administrative data, including daily attendance records, from the school district with data on rehoused families from NGO. The programmatic data include details such as families' date of intake to the program and their location of rehousing. I use generalized difference-in-differences (DD) models with student fixed effects to estimate the within-student differences in outcomes before and after their families begin participating in the homelessness prevention and rapid rehousing program, leveraging the longitudinal nature of the student administrative data and the quasi-random variation with regard to the exact dates on which families apply or are referred for services. These DD models allow me to compare the pre-/post-treatment changes in treated students to the contemporaneous changes observed among a comparable control group of students. I also use event study specifications to examine the dynamic nature of impacts to students over time. I focus on student outcomes that are recorded continuously throughout the year. The frequency of these data provides considerable statistical power to detect impacts related to students' entry into the program.

I find that, although the population of students who received HPRP services were more mobile on average than their peers, participation in the program itself did not have a clear impact on students' overall likelihood of leaving the school district or of switching schools within the district. However, analyses of heterogeneous effects indicate that rehoused students are more likely than both non-rehoused students and untreated students to leave the district for good following participation in the program. Additionally, I find that participating in the program actually had a negative impact on treated students' school attendance, particularly in the period beginning 5 to 6 months following intake. Heterogeneous models indicate that the increase in absences is limited to those students who are rehoused, particularly those who move far away but continue attending the city's public schools. Finally, I find positive impacts of the program on student behavior, with measurable reductions in the likelihood of students having multiple behavioral incidents in a month, regardless of whether they were rehoused or where the new housing was located. These findings highlight both the positive impacts and drawbacks of HPRPs and raise questions about the tradeoffs to rapid rehousing, which I discuss in the concluding remarks.

2. Background on Homelessness Prevention and Rapid Rehousing Programs

2.1 Policy background

In 2009, as part of the American Recovery and Reinvestment Act, Congress approved the allocation of $1.5 billion to a new HUD program now known as the Homelessness Prevention and Rapid Re-Housing Program (HPRP). The creation of the HPRP was motivated by the economic downturn and aimed to assist those individuals and families impacted by the recession who would, in the absence of support, become homeless. The reauthorization of the McKinney-Vento Homeless Assistance programs, the federal government's signature homeless assistance law, followed soon thereafter. Known as the HEARTH Act, the reauthorization expanded the eligible activities funded by the program beyond its previous focus on emergency shelter and outreach to include homelessness prevention and rehousing.

Collectively, HPRP and the HEARTH Act signaled a shift in the government's policy priorities toward addressing homelessness, expanding the populations targeted for assistance and increasing focus on longer-term solutions that would prevent homelessness or help position the homeless to become stably housed. Although HPRP was only a three-year program, most grantee communities remained committed to continuing these new forms of homeless assistance following its conclusion (Piña and Pirog, 2018; Fiore et al., 2015). This continued commitment is reflected in the sustained growth of homelessness prevention and rapid rehousing programs across the United States. According to the 2019 HUD Annual Homeless Assessment Report, the number of beds dedicated to permanent housing for people formerly experiencing homelessness (which includes rapid rehousing beds) outnumbered those intended for temporary shelter for the third consecutive year. Additionally, the national inventory of rapid rehousing beds increased about 20 percent from 2017 (HUD, 2019; 2018).

Homelessness prevention and rapid rehousing programs have a fair amount of latitude in how they structure and target their services. During the period of HPRP's funding, HUD required grantees to accept households with incomes up to 50 percent of Area Median Income (AMI), though grantees were allowed to use stricter parameters. Additionally, the details of how grantees would pick their target populations and appropriately assist them, whether by focusing on preventing the loss of current housing or on resolving literal homelessness, were at the discretion of the prevention programs themselves. HUD guidelines recommended that programs serve individuals and households who they believed would become or remain literally homeless "but for" the assistance. On the other hand, a number of grantees adopted criteria for program participation that emphasized the likely *sustainability* of participants' status as housed. Variation in how programs chose to balance these competing factors resulted in a considerable range in how programs designed and implemented their services (Fiore et al., 2015).

Despite the variation, these programs generally consist of a particular set of components, namely, housing search services, short-term financial assistance for housing-related expenses, and case management services (Cunningham, Gillespie, and Anderson, 2015). Rapid rehousing typically prioritizes reducing the amount of time that people are homeless. The approach focuses on placing families in permanent housing before turning to the issue of maintaining their stability there, rather than the other way around. Homelessness prevention, simply put, focuses on preventing at-risk households from ever becoming homeless to begin with.

2.2 Homelessness prevention and rapid rehousing services in the city of study

In city of study (hereafter referred to as "the City"), where the cost of living is exceptionally high, the homeless service provider, "NGO," has operated a housing services program since 2006 that incorporates both rapid housing placement for families who are already homeless and eviction prevention for at-risk families. The rapid rehousing arm of the program distributes temporary rental subsidies, case management, housing search services, and, in some cases, job search assistance and provides families with some combination of these services and supports for up to a year after they are placed in permanent housing. The homelessness prevention arm similarly provides temporary financial assistance, case management, and if needed, legal services to help ward off eviction. According to NGO's own analysis from 2012-15, over 90% of families participating in the rapid re-housing program retained their housing and did not become homeless again.

Families' participation in NGO's rapid rehousing program begins when they apply to or are referred to the program. Referrals to the program come from a range of sources. Since 2014, NGO has partnered with the school district to establish a "hotline" between the two entities, enabling teachers, social workers, nurses, and counselors who become aware of a student's housing problems to refer them directly to the NGO. Families may also be referred to the rapid rehousing program through other charitable organizations, healthcare organizations, and homeless service providers throughout the city, including the emergency shelter and transitional housing run by the NGO itself. Once referred, or once a family submits an application, participation in the rapid rehousing program is based on the family's eligibility (i.e. they must be below the income limit and be homeless or at-risk of losing their home to eviction), interest, and the resources the NGO currently has available. Priority is given to families who are literally homeless, experiencing domestic violence, or are at imminent risk of losing housing (for example, have rental costs that exceed 70 percent of their income).[1]

2.3 Additional supports for homeless and highly mobile students in the city of study

In addition to non-profit homeless service providers and city agencies, the City's unified school district (hereafter referred to as "USD") also operates programs to support its HHM students and their families. These supports generally fall under the requirements of the McKinney-Vento Homeless Assistance Act, which mandates that school districts identify homeless and highly mobile students and provide them with basic services, including expedited enrollment, tutoring, and mental and physical health referrals. The law also provides students experiencing homelessness with the right to either continue attending their original school or to enroll in a new public school based on their new housing address. For students who continue to attend their original school and continue to live within district boundaries, USD is required to provide and arrange transportation to and from school. If students move to another district but continues to attend a USD school, the two LEAs must agree upon a method and means of splitting the cost and responsibility to transport students to and from school.

It is worth noting that the McKinney-Vento provision around flexible school enrollment may impact students and families differently in USD than it does in school districts where school assignment is based on residential address. USD—the only public school district in the City—has an open enrollment policy based around school choice. In most cases, students are assigned

[1] In early 2019, after the time period of this study, the City rolled out a new "coordinated entry" system meant to centralize the provision of homeless services, reduce inefficiencies, and enable a tracking system of the homeless population to understand people's personal histories and which treatments or services have or have not worked for them in the past. Under the new system, homeless individuals and families register through "access points" to the city's Department of Homelessness and Supportive Housing, which then coordinates with city agencies and service providers to connect people to the programs and treatments they need. Consequently, the referral process for NGO has become more systematic, and families no longer apply for services directly to the organization.

to schools based on their ranked preferences, rather than their residential address, and it is not uncommon for students to attend schools outside their neighborhood, regardless of their HHM status.

3. Relevant Literature

3.1 Impacts of homelessness and mobility on students

Past research on children experiencing homelessness has found that they tend to have lower test scores and academic performance (Cowen, 2017; Cutuli et al., 2013; Obradovic et al., 2009; Herbers et al., 2012; Fantuzzo et al., 2013), lower classroom engagement (Fantuzzo et al., 2012), and worse school attendance than their peers (Institute for Children, Poverty, and Homelessness, 2015). Tobin (2016) finds that housing status is predictive of test scores in math and reading (controlling for student demographics), but not meaningfully so when absence rates are added to the model, suggesting that attendance is a major mediator of the effect of homelessness on academic outcomes. Additionally, studies have found that these children are at higher risk than their peers for health problems (Buckner, 2008) and tend to demonstrate more behavioral problems (Kurtz, Jarvis, and Kurtz, 1991). Despite being at a high risk for a range of negative outcomes, research has also shown that homeless students can demonstrate considerable academic and emotional resilience in the face of their difficult situations (Obradovic et al., 2009; Cutuli et al., 2013; Huntington, Buckner, and Bassuk, 2008).

The majority of research on the effects of homelessness has been correlational or descriptive in nature. Isolating causal impacts of homelessness is particularly challenging for a number of reasons. HHM students have, somewhat by definition, high levels of mobility. Additionally, identifying students experiencing homelessness generally relies on families' engagement with homeless services or self-identification with schools and agencies. One of the most challenging aspects of identifying homelessness' causal effects is disentangling it with other critical risk factors that impact young people's educational, behavioral, and health outcomes—the most salient one being poverty. Some scholars posit the theory that homelessness can best be contextualized by a continuum of risk, with HHM students facing a number of co-occurring risks that overlap with the experience of poverty and that can cumulatively have a greater negative impact on educational outcomes (e.g. Brumley et al., 2015). Consistent with this account of a risk gradient are findings from Cutuli et al. (2013) showing that HHM students have lower levels of achievement than low-income, housed students, who in turn perform lower than their higher income peers.

Relatedly, the extent to which the relationship between homelessness and adverse effects is driven by acute risk (i.e. the actual time spent being homeless) or chronic risk (i.e. poverty) remains an open question. Cutuli et al. (2013) find that homelessness is more disruptive to achievement during the period of time that students are actually experiencing homelessness, while more recent work (Cutuli and Herbers, 2019; Cowen, 2017) has found evidence that once demographic characteristics and school and residential mobility are taken into account, the experience of becoming homeless in a given year yields no greater risk of adverse outcomes.

Adding further complication to the study of homelessness is that it is not a singular experience. How children experience homelessness and the specifics of their housing situation—whether in shelters, transitional housing, doubled up, in cars or motels—can vary widely, as do the policy landscapes influencing the programs and supports available to HHM families (Pavlakis, 2017). Moreover, the experience of homelessness carries not only logistical challenges and barriers, but also the stress responses to those situations, both of which can impact educational outcomes in distinct and interrelated ways (Cutuli and Herbers, 2019).

As already alluded to, the issue of homelessness is also inextricably tied to that of mobility. Several studies demonstrate that levels of residential mobility, school mobility, and district mobility are higher among HHM students (Cowen, 2017; Fantuzzo et al. 2012; Miller and Bourgeois, 2013). And research shows that mobility in and of itself has negative impacts on students. Voight et al. (2012) show that residential moves in early elementary years have a negative relationship with academic achievement in 3rd grade and that the gap is not made up over time. Metzger et al. (2015) find that even residential moves to less-poor neighborhoods are linked to lower high school graduation rates. Meanwhile, a sizeable body of research suggests that school mobility is linked to lower test scores, higher rates of grade retention, and school dropout (see Welsh, 2017, for review). Much of this literature distinguishes between structural school mobility—when the change is expected based on schools' grade span or school closures—and nonstructural moves motivated by students' families (whether voluntary and strategic, or involuntary and reactive) (Rumberger et al., 1999). Although identifying causal effects of mobility is challenging, recent work by Schwartz et al. (2017) uses student fixed effects models and instrumental variables analysis to estimate the effects of structural and non-structural school moves, finding that structural moves are harmful for student performance in both the short- and medium-term. Cordes et al. (2019) builds on this work to estimate the effects of residential mobility—again, using student fixed effects and instrumental variables so as not to conflate residential and school mobility— and finds that long-distance moves negatively impact student performance while short-distance moves have positive effects.

3.2 Impacts of homelessness interventions on students

While much is known about the adverse risks to children of homelessness and high mobility, considerably less is known regarding the effects of programs to address or mitigate these experiences. Successful interventions to help resolve homelessness are generally still elusive, and the research base regarding the impacts of various programs to children and families, as well as the specifics of effective implementation, is still developing (Apicello 2010). Certain services and school-based efforts have showed promise. For example, Shinn et al. (2015) show that case management services that facilitate access to community resources have a positive impact on middle-school students' achievement, attendance and behavior in school. Additionally, O'Malley et al. (2015) provide evidence that for homeless students, positive school climates can act as a moderator between the impacts of their home environments and academic achievement. However, broadly speaking, research on interventions is hindered by the challenge of studying a population with high levels of mobility and attrition (Herbers and Cutuli, 2014).

Arguably the most compelling and comprehensive recent study on interventions for homeless families is the Family Options Study (FOS), a multi-site randomized trial that examined three different housing and service interventions: long-term rent subsidies, community-based rapid rehousing, and project-based transitional housing. The control group in the study had access only to the "usual care," which is to say, access to existing community resources but no priority access to the three treatment interventions. The study analyzed impacts to housing stability, family preservation, adult well-being, child well-being (including school mobility, absences, behavior problems, and overall health), and self-sufficiency (Gubits et al. 2018). The long-term subsidies paid the difference between 30 percent of families' incomes and their housing costs and were combined with housing search assistance but few other services.

The community-based rapid rehousing included short-term rent subsidies lasting up to 18 months and case management, supportive services, and other short-term financial assistance—services aimed at helping families to increase their self-sufficiency and minimize the "acute risk" of homelessness. Lastly, transitional housing consisted of supervised housing paired with intensive case management that could last up to two years. Researchers measured impacts at 20 months and 37 months after random assignment and found that long-term subsidies were the most effective in improving all outcomes for homeless families, particularly housing stability. Rapid rehousing was largely ineffective in improving outcomes for families relative to the control group; however, they did significantly reduce children's school absences and significantly increased total family income.

Although the FOS offers some insight into the effects of a rapid rehousing program similar to that of NGO, it offers little visibility into the immediate impacts to students going through the rehousing process, with outcomes first measured approximately a year and a half later. Additionally, the FOS relies on parent self-report regarding student attendance and parents' assessments of their child's behavior and attitudes toward school. Cutuli and Herbers (2019) have since built on the initial FOS findings by linking data from one particular site of the randomized experiment—Hennepin County, MN— with school records from Minneapolis Public Schools. The authors compare outcomes for students in each of the randomized treatment arms, along with a matched group of low-income housed students, across four years, using annual measures of school mobility, attendance, and reading and math achievement as the outcomes. The study finds that outcomes were no better for students in the rapid rehousing or long-term subsidy groups than they were for those in usual care. While this study benefits from the incorporation of administrative data, it is limited by the coarseness of its outcome measures and consequently cannot offer insight on the immediate and short-term effects of rapid rehousing, or on the dynamic nature of the impacts in time periods smaller than a year. My research is the first to my knowledge to examine homelessness prevention and rapid rehousing services' impacts on students using highly granular, longitudinal administrative data on student enrollment, attendance, and behavior that can speak to these research gaps.

4. Data

4.1 Data sources and sample construction

I use administrative data on all school-age children who participated in NGO's homelessness prevention and rapid rehousing program from January 2014 through September 2017. The data from NGO include a broad range of variables including the date of families' application or referral (which I refer to generally as "intake"), the start dates of their housing search and rental subsidies, their lease date of their new home, their previous permanent address, their new address, and their housing status at entry and exit from the program. The data also include personally identifiable data on students such as their full names and birthdates and the names of their parents or guardians.

The distribution of students' rapid rehousing intake dates, shown in Figure 1, help illustrate the fact that, although NGO operated a rapid rehousing program for a number of years prior to the start of this analysis, participation in this program began to increase considerably beginning near the start of 2015. Intake dates were more common during the spring semester (n=175) than the fall semester (n=81) or the summer months (n=41). According to officials at NGO, this temporal unevenness is likely due to the NGO's own funding calendar and the higher levels of outreach that the program tends to conduct in the spring months, rather than differential levels of need on the part of families.

Using combinations of students' names, birthdates, and parents' names, I link NGO's data to administrative data from USD on all students TK-12 from 2013-14 through 2017-18. The district administrative data include, among other variables, student demographic information[2], school of attendance, daily attendance records, and records of office referrals for behavioral incidents. The district data also include information on whether a student participated in various city agencies' programs helping homeless families, which I use to create an indicator for whether a student was ever identified as homeless during the five-year period.

Between January 2014 through September 2017, 443 school-age children participated in the HPRP. 413 of these students match to attendance records during the five school years for which I have data, 408 of which have a non-missing NGO intake date. To construct my primary analytical sample, I identify the school-grade-year of treated students at a baseline point prior to the start of the participation in the rapid rehousing program, which I define as 3 months prior to the month of their intake. Based on this baseline point in time, I identify all students who were in the same school-grade-year as the treated students—these grade-mates collectively make up my control group. Using this approach for sample construction, I arrive at an analytic sample that includes 24,099 students across all grades TK-12 across the five years of data. 301 of these students were treated students, i.e. they participated in the homelessness prevention and rapid rehousing program and, importantly, began to do so during the time in which they were enrolled in USD. These students also were enrolled in USD at the "baseline" point of 3 months prior to their intake. While the total number of students in the analytical sample may seem surprisingly

[2] Note that demographics in this case include gender and race/ethnicity. USD did not share data on students' free and reduced-price lunch eligibility, or any other indicator of income level.

large, it is worth noting that the students participating in NGO's program were well distributed across grades and schools throughout the district, attending 114 different schools during the time that they appear in the 5-year window of district data. The analytical sample consequently represents students from all grades across a total of 168 schools (which include special education programs, TK's, and alternative schools in addition to traditional schools), as control students remain in the sample if they originally shared a school-grade with a treated student but ultimately changed to a different school over the course of the five-year window.

In addition to this primary analytic sample, I construct a secondary sample made up of all 301 treated students along with students who were ever identified as homeless by the district, i.e. students whose families had participated in city programs helping the homeless. These "ever homeless" students collectively make up the control group in this alternative sample, though it is worth noting that there is some overlap between the group of NGO-treated students and the "ever homeless" group (n=112). Using this approach, I arrive at an analytic sample of 3,726 students, representing all grades across a total of 159 schools. While the "ever homeless" group makes up a reasonably comparable control group to NGO-treated students, there are almost certainly a number of homeless and highly mobile students in the school district that are not identified as such by this mechanism. Given that there is some selection into this control group, I prioritize the larger grade-mates control group described above and use this secondary analytic sample in supplemental models to assess the robustness of my results.

4.2 Outcomes

The student outcomes I examine are students' departure from the school district, their school mobility, monthly measures of school attendance, and counts of behavioral incidents over the course of a month. To measure students' departure from the district, I construct a fully balanced panel based on the analytic sample in question, in which there is an observation for each of the 24,099 students (or 3,726 students) across the 51 instructional months (i.e. months in which USD had at least one instructional day) of the 2013-14 through 2017-18 school years. In other words, I create blank observations for months in which a student has no attendance record. In this panel, I impute student grades for all observations with missing data, assuming that students progress from grades K through 12 without skipping grades or being retained.[3] I identify a student departure in any given month if the student had an attendance record in the previous month and has no record in the month in question (for example, if a student has attendance data in March 2015 and none in April 2015, she is marked as having departed from the district in April 2015). Because, in some cases, students leave for a period of time and then return to the district, it is possible for departures to be either temporary or permanent over the course of the five-year window and it is possible for a single student to have multiple district leaves. I distinguish between all district leaves, permanent district leaves, those that take place mid-year versus between school years, and those due to 12th grade graduation.

For all other outcomes, I use an unbalanced data panel where the number of student-month observations varies in accordance with their actual administrative data records, up to a maximum of 51 months. Note that only instructional months are included in the panel, though summer months are accounted for when calculating the temporal distance between an observation and a students' program intake date. For example, if a treated student's intake takes place in July, there are no observations for her month of intake, but enrollment, attendance, and

[3] Student-month observations for which the imputed grade is undefined (because it is earlier than kindergarten or after 12th grade) are dropped from this balanced panel dataset.

behavior outcomes for the following October will be considered as 3-month lagged outcomes relative to her intake.

For school mobility outcomes, I identify three different types of intra-district school moves: a) school switches occurring between school years, regardless of grade level, b) school switches occurring between school years that are specifically non-structural, and c) mid-year school switches (which are necessarily non-structural). In USD, the standard grade range for elementary schools is K-5, for middle schools is 6-8, and for high schools is 9-12; for simplicity, I define non-structural mobility as any moves that that are *not* between 5th and 6th grade or between 8th and 9th grade.

For measures of school attendance, I calculate monthly absence rates as the number of days a student was marked absent for any reason divided by the number of instructional days the student was enrolled in USD that month. Chronic absence is an indicator variable equalling one if the monthly absence rate is greater than or equal to 0.10, in accordance with USD's own definition of chronic absenteeism.

Finally, behavioral incidents are measured by the number of out-of-classroom referrals made as a result of the following potential types of student misbehavior: bullying, cheating, damage, disruption, non-disciplinary reasons, noncompliance, sexual harassment, class skip, substance possession, theft, threats, verbal aggression, violence, walkout, weapons, and other. The most common reason for out-of-classroom referrals is disruption (accounting for 45 percent of incidents recorded in the sample), followed by noncompliance (15 percent), walkout (11 percent), and violence (9 percent). To understand impacts of the rapid rehousing services on both the intensive and extensive margins of student behavioral issues, I estimate models using both the count of referrals recorded each month, as well as indicators of students having one or more, two or more, or three or more referrals in a month.

Table 1 shows summary statistics describing the students in the primary analytic sample in terms of gender, race, grade, average outcome measures, and—for the subsample of treated students—their status at entry, whether they were rehoused or treated with eviction prevention services only, whether they moved outside of the City during their time in the program, and the number of days between their intake and placement in a new apartment. Because the outcome measures are at the level of the month, each observation in Table 1 is a student-month.[4] As this description shows, treated students are considerably more likely to be Black or Hispanic than the overall sample of grade-mates. The average grade level of control students is slightly higher than that of treated students; because students in higher grades have larger numbers of grade-mates, the older students are over-represented in the control group.[5] On average, treated students have higher absence rates, are more likely to be chronically absent, and have more behavioral incidents than their peers. Over 50 percent of treated students are literally homeless upon program intake. 79 percent are rehoused and for 41 percent, the new housing location is outside of the City. The average amount of time between intake and moving into a new apartment is approximately 4 months, although that length of time varies widely.

[4] See Appendix Table A1 for a comparable descriptive statistics table showing time-invariant descriptors at the student-level and Appendix Table A2 for descriptive statistics of the alternative analytic sample.
[5] Note that this does not affect the internal validity of the study, as grade fixed effects are included in all models.

5. Methods

5.1 Empirical Strategy

To estimate the causal impact of NGO's homelessness prevention and rapid rehousing program on students' short- and medium-term outcomes, I use a panel-based research design that effectively compares changes in outcomes of treated students to contemporaneous changes of un-treated students and students who have yet to begin participation in the rapid rehousing program. I estimate models of the following form:

$$Y_{it} = \alpha_i + \gamma_t + \theta D_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

Here, Y_{it} is the dependent variable of interest for student *i* in time period *t* (where time period is a month). α_i are student fixed effects, γ_t are month-year fixed effects, and ε_{it} is a mean-zero error term with clustering at the student level. Including student-level fixed effects accounts for time-invariant characteristics of each student, while month-year-level fixed effects account for common relationships across all students between time and the outcome of interest. D_{it} is an indicator taking a value of 1 when an observation is from a treated student in the month of or any subsequent months after intake to the rapid rehousing program. θ is therefore the coefficient of interest, representing the causal impact of the HPRP services. X_{it} is a vector of covariates that varies within student over time—in most cases, X_{it} represents grades, though in models estimating impacts to behavioral referrals, I additionally control for the monthly absence rate.

It is worth noting that this model, which determines "treated months" based on students' intake date, estimates the effect of participation in the HPRP, rather than the effect specifically of, say, being placed in a new home. Once a family is entered into the rapid rehousing program, the specifics of their case management are determined based on their particular situation. As such, whether a family is rehoused or kept in their existing home, or the length of time it takes for them to be rehoused, is endogenous. One could imagine, for example, that a family could decide to more emphatically pursue a new apartment lease once the head of household gets a new job, or once a student starts doing better (or worse) in school. By maintaining the start of treatment as the intake date, rather than, say, their new lease date, I avoid conditioning on any characteristics of the family or the particulars of their case. In other words, all students who participate in the HPRP overall make up the "intent-to-treat" sample; the specifics of their treatment are endogenous to their specific situation. The estimated treatment effects can therefore be interpreted as reduced form effects.

However, to better understand how treatment effects differ for different subsets of students, I consider heterogeneous effects for various categories of participants; specifically, I examine whether results differ for students who were rehoused versus those who were not, and for students who were moved outside the city of San Francisco versus those who stayed. To do so, I use a similar model of the following form:

$$Y_{it} = \alpha_i + \gamma_t + \theta^{RH} D_{it}^{RH} + \theta^{noRH} D_{it}^{noRH} + \beta X_{it} + \varepsilon_{it} \qquad (2)$$

Here, D_{it}^{RH} is an indicator valued at one for observations from a student who received rapid rehousing services in the month of or any subsequent months after intake to the rapid rehousing program. D_{it}^{noRH} is similarly an indicator for observations from a student who received eviction prevention services. This model therefore allows me to estimate reduced form treatment effects for recipients of the two types of services within the HPRP. I use comparable models to estimate differential treatment effects of the program on students who move outside the City (distinguishing between those who moved to nearby versus faraway cities) and those who remained in the City.

The models described in equations (1) and (2) estimate treatment effects that are constant across time, which is in itself a strong assumption. The mean number of days between intake and a rehoused family's new lease is 120 days. It seems highly unlikely that for rehoused students, responses to the HPRP would be consistent before and after moving into new stable housing. Additionally, one might expect that an adjustment period could take place, as families respond to receiving new services and support, or to a new home or neighborhood. To allow for dynamic treatment effects that can vary non-parametrically over time, I also estimate models of the following form, where separate indicator variables for individual months (or intervals of months) before and after intake allow for distinct effects in different time periods around the start of participation in the rapid rehousing program:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\tau=1}^{4} \delta_{-\tau} D_{i,t-\tau} + \sum_{\tau=0}^{18+} \delta_{\tau} D_{i,t+\tau} + \beta X_{it} + \varepsilon_{it} \quad (3)$$

Equation (3) represents a fully dynamic model. I also estimate semi-dynamic models that include only the separate indicator variables for months after intake occurs. The fully dynamic model offers the added benefit of testing the internal validity of the estimation strategy. Because the DD approach relies on a parallel trends assumption that within-student changes in outcomes in a given month are a reasonable counterfactual to changes for treated students, in a fully dynamic specification, the coefficients on the indicators for months prior to intake should ideally be insignificant.[6]

[6] As described in Section 4.1, I construct my data sample using the requirement that all treated students are enrolled in USD at least 3 months prior to their HPRP intake in order to limit the sample of treated students to those who are "stable" attendees of USD schools. Note that the effects of this sample construction are evident in the results of the fully dynamic event study models I estimate, particularly with regard to models of district leave and missingness.

As discussed previously, I estimate all models using both the primary analytic sample—in which NGO-treated students' grade-mates make up the control group—and the alternative analytic sample—in which students ever identified as homeless make up the control group—to assess the robustness of my findings.

5.2 Missingness

One concern with a panel-based research design is the problem of differential attrition, or missingness. This is especially a concern here, given the plausibility that NGO-treated students would be more likely to move outside of the City and to switch to another school district, therefore disappearing from the panel. In addition to the concern of moving away, the nature of a panel based on school district data is that students necessarily graduate out of the panel, or enter into it only when they are old enough for TK or Kindergarten, making the panel itself particularly fluid.

To test for differential missingness, which would threaten the internal validity of the research design, I use the same fully balanced panel with imputed grades described in Section 4 that I use to examine impacts to students' departure from the district. This panel includes an observation for each of the 24,099 (3,726) students in the primary (secondary) analytic sample across 51 instructional months, with the exception of observations where the imputed grade is undefined because it is earlier than kindergarten or after 12th grade. I then create a missing variable that is equal to 1 for student-month observations with no USD attendance record. Using

The results (as expected) show that treated students are less likely to be missing or not enrolled in the district up to three months prior to program intake; in other words, by design, the coefficients on the indicators for pre-treatment months are negative and significant in these particular models. See Appendix for the results of all fully dynamic models.

missingness as the outcome of interest, I estimate DD models of the form described above to test for differential attrition as a result of treatment.

The results are shown in Appendix Table A3. The non-dynamic model indicates that there is no differential attrition for treated students. The semi-dynamic and dynamic models shows that, for both the primary and secondary samples, treated students are only more likely to be missing in the time period of 18 or more months post-intake. As such, for the semi-dynamic and dynamic results I discuss throughout, I privilege estimated effects for the time periods between intake and 18 months after. Additionally, as a robustness check, I estimate supplemental models for impacts on school mobility, attendance, and behavior using only the subsample of treated and control students who have no missing outcome data across the 51 instructional months. These balanced panel models restrict the sample size to 11,015 students in the primary analytic sample, with 108 treated students. The findings from the balanced panel models are substantively consistent with those of the main models (see Appendix Tables A9 and A13 for results).

The issue of data missingness is distinct from, but clearly related to, that of student departures from USD, for which I consider the timing of when students leave the district and whether they do so permanently or not. While the examination of data missingness speaks to the internal validity of the research design, the examination of types of district departure speak to the ways in which students leave the district and the impact that HPRP participation has on their likelihood to leave. I discuss these patterns of district departure and the DD estimation results in the following section.

6. Results

6.1 District leave

Consistent with past research on homeless and highly mobile students (Cowen, 2017), levels of district mobility are descriptively higher among the NGO-treated students than among their counterparts. The upper panel of Table 2 shows summary statistics of types of district departure for students in the rapid rehousing program and for the control groups in the primary and secondary analytic samples. Treated students are less likely to graduate from USD high schools than their grademates or than the ever homeless group. They are more likely to leave the district – temporarily or permanently—than their peers. Indeed, treated students are over twice as likely to leave the district for any length of time mid-year than their grademates. They are also more likely to leave the district permanently than students in the control groups. This is particularly true for mid-year departures, as the difference in likelihood of leaving permanently between school years is only statistically significant when compared to the ever homeless group.

Because students in the ever homeless group likely face many of the same challenges that the treated students do, it is notable that all types of non-graduation district departure are more likely for the treated group than for the secondary control group. One possible explanation for this is that on a continuum of risk, those families who are referred to or actively apply for NGO's rapid rehousing services are in a more disadvantaged position than those students ever identified by the district as homeless. Another possible explanation is that participation in the HPRP itself increases students' likelihood of leaving the district. Descriptively, only 37 of the 301 treated students depart USD permanently (not due to high school graduation) within 6 months or less of their program intake. However, it seems that waiting until the end of the school year plays a factor for some treated students, particularly those who are rehoused (n=221). 28 treated students depart USD permanently over the summer (not due to graduation), 27 of whom were rehoused. 16 of these students depart USD over the first summer following their intake, 15 of whom were rehoused. For rehoused families, the timing of new apartment leases also seem to be relevant. Of the rehoused students, 25 left the district permanently between the time of their program intake and the month of their new lease.[7] 22 students left the district permanently within 7 months of their new lease. 8 students left permanently over the first summer following their new lease.

While these descriptive summaries illustrate the higher levels of district mobility of treated students, they do not indicate whether participation in the rapid rehousing program actually caused changes in treated students' district leave behavior. To assess the causal impact, I estimate the regression models described in Section 5. Table 3 shows the results of the non-dynamic and the semi-dynamic models using the primary analytic sample, where the outcome variables are the different types of non-graduation district leave (see Appendix Table A4 for results of the full dynamic model). All specifications include student, month, and grade fixed effects. Column 1 shows that treated students are more likely to leave the district mid-year for any length of time following their program intake, although the impact is not statistically significant and the magnitude of the impact is small (about a 1.5 percent increase over the mean of the full sample). Column 2, which shows the the results of the semi-dynamic model of the same outcome, indicates that program participation leads to a decrease in the likelihood of departure in the month of intake and positive but non-significant increases in the months that follow. The results for leaves beginning over the summer follow similar patterns (columns 3-4), with some indication that treatment leads to a decrease in summer leaves in later months.

[7] All but one of these students were rehoused in cities other than the City.

Columns 5-8 show results for models where the outcome is specifically permanent leaves from the district. Here, the results are similar but somewhat more robust. Treated students are significantly more likely to permanently depart after treatment mid-year (about a 2 percent increase over the mean), though in the semi-dynamic specification, the increase is not statistically significant until the final time period. Note, however, that the significance of the non-dynamic result is not robust to alternative sample construction, as findings from the secondary analytic sample indicate (see Appendix Table A5). Additionally, the results for permanent leaves beginning over the summer offer little evidence for a causal increase in student departure, instead showing some indication that treatment leads to a decrease in the likelihood of students permanently leaving USD between school years.

In sum, the results suggest that the rapid rehousing program did not have a clear, substantive impact on overall treated students' tenure in USD, nor is there a clear trend that emerges over time. However, these main models may cloud heterogeneous effects to students. Appendix Table A6 shows the results of models described by Equation 2, estimating separate effects for rehoused and non-rehoused (i.e. eviction prevention) students, and for those students who moved outside of the City versus those who remained. These results suggest that when it comes to permanent district departures, rehoused students and students who move outside the City are more likely to leave USD. F-tests of the non-dynamic estimates show that the impact is significantly different for rehoused versus non-rehoused students, particularly for mid-year moves. Additionally, in semi-dynamic models, impacts to mid-year moves are generally negative for non-rehoused students and positive (though not statistically signficant) for rehoused students. Impacts are also significantly different for students who move outside the City, for both mid-year and summertime departures. These supplemental findings show that although the HPRP did not have a conclusive impact on the full sample of participating students, perhaps unsurprisingly, positive effects on the likelihood of district leave are concentrated among students who are rehoused and who subsequently move to another city.

6.2 School mobility

The lower panel of Table 2 shows descriptive comparisons of school mobility across treated students and students in the two control groups. While there are no significant differences across groups for all school switches between school years (i.e. summer moves), for specifically non-structural summer moves, treated students have mobility rates that are about twice as large as their grademates, and almost 50 percent higher than non-treated students who were ever homeless. For non-structural moves that take place mid-year, treated students again have higher mobility rates, although only the difference between treated students and their grademates is statistically significant.

Again, these descriptive comparisons provide useful context but cannot speak to the causal impact of the homelessness prevention and rapid rehousing program on treated students. Table 4 shows the estimated treatment effects on school mobility that result from the regression models described in Section 5 (see Appendix Table A7 for results from the full dynamic model). All models include student, month, and grade fixed effects. These results indicate that although school mobility rates are higher among the treated population of students, participating in the program had no measurable causal effect on students' likelihood of switching schools. The non-dynamic estimated treatment effects are not significant for any of the three types of school moves. The results do show that in the month of program intake, treated students are less likely to make a non-structural summer move, or in other words, to start the school year at a different elementary, middle, or high school than they previously attended (column 4). This data point, however, applies specifically to students whose families begin treatment at the start of the school year, and it is difficult to draw any conclusions from that singular coefficient. A broader view of the estimates from the various model specifications indicates that there is no evidence that HPRP participation meaningfully affected school mobility for treated students who remained in USD.[8]

On its surface, this finding might seem surprising. However, USD's open enrollment policy is likely particularly relevant here. It is not uncommon for families to send their children to a school that is not particularly close to where they live, so it is likely that for families who wish to remain in the district, housing transitions will not motivate them to change their school enrollment. It is also possible that such families, in order to minimize the amount of instability their children must face, purposefully try to avoid school-related transitions. While the McKinney-Vento law mandates that districts allow HHM students to remain in their original school if they so desire, it is possible that the external validity of this finding is limited and that impacts of rapid rehousing programs in districts without open enrollment might differ.

6.3 Absences

Table 5 shows the estimated treatment effects of HPRP services on students' monthly absence rates and monthly indicators for chronic absence. The non-dynamic model results indicate that the rapid rehousing program leads to an approximately 2 percentage point increase in monthly absence rates and an approximately 5 percentage point increase in the likelihood of

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[8] I also estimate supplemental models using the secondary analytic sample, the fully balanced panel limited to students with non-missing data across the 51 instructional months, and models estimating heterogeneous effects by service type of by location of new housing. The findings are largely consistent with the main models, indicating no clear treatment effect with respect to intra-district school mobility. If anything, there is suggestive evidence of a reduction in non-structural summer moves in the months following program intake for non-rehoused students, and a reduction in mid-year moves for rehoused students, though a consistent and clear trend in estimates does not emerge. See Appendix Tables A8-A10 for results.

being chronically absent. The semi-dynamic model similarly shows that, although there is suggestive evidence that absences are reduced in the month that intake occurs, over time treated students are significantly more absent from school.[9] Indeed, the magnitude of impacts to student absences jumps considerably 5 to 6 months following program intake and the effects remain consistently significant throughout the remaining window of time that students are visible in the data. Figure 2 shows the results of the dynamic models graphically, with within-student effects estimated relative to a reference point of 5 months prior to intake.

These findings appear initially to contradict past literature demonstrating the relationship between housing instability and student attendance (e.g. Cowen, 2017). Indeed, one might expect that financial and case management support, along with placement in permanent housing, would add stability to students' daily lives and help them attend school more consistently, rather than less. However, the increase in absences that these results show appear to be critically linked to the patterns of students' rehousing. As noted earlier, the average time between intake and rehousing for those students who are rehoused is 120 days, or approximately four months. It is highly plausible that the increased absences seen 5 to 6 months following intake are linked to the adjustment that takes place when students move into their new home. Additionally, I estimate supplemental models using the date of the new apartment lease as the treatment "event," rather than the date of program intake (the timing of which is admittedly more likely to be endogenous). The results of these models further support the hypothesis that students' absences are linked to students' move to their new home, as significant increases occur immediately following the new lease date (see Appendix Table A13 for results).

[9] Estimates from the fully dynamic models arrive at consistent findings. Estimates from the fully balanced panel also are generally consistent, although the balanced panel indicates a more significant effect of having fewer absences specifically in the month of intake. See Appendix Tables A12-A13 for results. Results from supplemental models using the secondary analytic sample, which also generate consistent estimates, are available upon request.

The results from models estimating heterogeneous treatment effects further support this theory. Table 6 shows estimated treatment effects for rehoused and non-rehoused students. While there are clear increases in both absence rates and chronic absenteeism for rehoused students beginning 5 to 6 months post-intake, for non-rehoused students, the effects are of much smaller magnitude and are not statistically signficant. It should be noted, however, that the number of non-rehoused students is comparatively small (n=80). Additionally, while an F-test of joint significance of the two treatment effects indicates that they are jointly significant, an F-test of the equivalence of the two effects shows that we cannot reject the null that the effects for rehoused and non-rehoused students are the same.

Models of heterogeneous treatment effects based on the location of students' new housing show similar trends. Table 7 shows the results of these models, where I estimate separate treatment effects for students who remain in the City (this includes both non-rehoused students and students who were placed in new housing in the city proper), for students who move to cities less than 30 miles from the City (n=78), and for students who move to cities greater than 30 miles away (n=63).[10] Students who moved further away from the City saw greater increases in monthly absence rates compared to those who moved to closer neighboring cities (a 5.9 percentage point increase compared to a 3.7 percentage point increase, according to the non-dynamic models) and compared to those who stayed in the City, who saw no change in absences. Meanwhile, the estimated treatment effects on chronic absenteeism (i.e. the extensive margin of student absences) are consistent across the two groups of movers; students who stayed in the City again saw no change in chronic absence rates. F-tests of joint significance rule out the null

[10] I measure distance to the City as the minimum driving distance according to Google maps from the destination city to the City, using the cities themselves as the start and end points.

hypothesis that all treatment effects are equal to zero, as well as the null that the treatment effects are all equal to each other.[11] See Figure 3 for graphical representations of these results.

One potential concern regarding these findings is that students whose families relocate to faraway cities but remain enrolled in USD schools may be more likely to have high recorded absence rates for unobservable reasons unrelated to their rehousing. For example, the higher absence rates I observe for this subgroup of students could result if these particular households lack the time or capacity to officially disenroll their children from USD, despite effectively removing them from the City's school system and no longer sending them to USD schools. To ensure this is not the case, I estimate supplemental models where I exclude outlier observations that could result from this scenario. Specifically, I exclude all students who have multiple months where their absence rate is equal to 100 percent, as well as all student-month observations where the absence rate is at least 75 percent. I also estimate models using more stringent restrictions, where all student-month observations with absence rates of at least 50 percent are excluded, and/or where I additionally drop any treated students from the sample if they *ever* had a 100 percent monthly absence rate post intake. Estimates from these models are generally consistent with my main models, indicating that this scenario is not driving my results. See Appendix B for more detail.

The heterogeneity of impacts that I find offers a clearer picture of the relationship between rapid rehousing and student attendance. The City is a notoriously difficult place to find affordable housing, so it is unsurprising that a number of rehoused families would have to venture outside—in some cases, far outside—the city to find a permanent home. The larger

[11] See Appendix Tables A12-A13 for results from the fully dynamic models of student attendance and behavior and for models using the fully balanced panel. Results for models using the secondary analytic sample, which arrive at consistent results, are available upon request.

metropolitan area in which the City is located is plagued with traffic problems and delays in public transportation and as families search increasingly far away to find an affordable place to live, the logistical difficulties that come with their new home are a likely mechanism for explaning the increase in students' absence rates. These findings suggest an unintended consequence of the rapid rehousing approach, one which is particularly salient in a high cost area such as this one. Additionally, the magnitude of the impact could potentially be meaningful for students' success. For example, a 5.9 percentage point increase in monthly absences corresponds to approximately 120 percent of the mean monthly absence rate for the full analytic sample, or about 0.5 of a standard deviation. Even relative to treated students only, this increase corresponds to 64 percent of the mean absence rate, or about 0.4 of a standard deviation.

6.4 Behavior

Table 8 shows the estimated effects of rapid rehousing on student behavior. The models used to estimate these effects have the same specifications as the previous models described, with the exception that they additionally control for students' monthly absence rates because absenteeism results in fewer opportunities for a student to receive an out-of-classroom referral. Columns 1-2 show non-dynamic and semi-dynamic treatment effects on the number of behavioral incidents (i.e. referrals) in a month, while columns 3-8 show effects on the likelihood of having one or more, two or more, or three of more incidents in a month.

The results show consistently negative, but typically not statistically significant, effects on the number of referrals a student receives each month. Further, the results indicate that rapid rehousing has no discernible effect on the likelihood of one or more referrals, but has significant negative effects on the likelihood of having 2 or more, or 3 or more referrals. The semi-dynamic results show that evidence for this decrease becomes significant in the 3 to 4 months post-intake when the outcome is two or more incidents; when the outcome is three or more incidents, the effect is immediate. There does not, however, appear to be a clear monotonic pattern with regard to the impact over time. Figure 4 shows the results of the full dynamic model graphically.[12]

As with absences, I estimate models that compare the treatment effects on student behavior for rehoused versus non-rehoused students, and for those who move out of the City versus those who stay. The results are shown in Appendix Table A14. The findings suggest that both rehoused and non-rehoused students benefit from the rapid rehousing program with regard to improved behavior when measured as having at least 2 or at least 3 incidents. The non-dynamic estimated treatment effect is only significant for rehoused students; however, an F-test fails to reject the null hypothesis that the two coefficients are equal to each other. Similarly, the treatment reduces students' chances of having multiple behavioral incidents regardless of whether they stay in or move out of the City. The non-dynamic estimate is again only significant for students who move out of the City, but the F-test fails to reject the null that the two coefficients are equal. For both rehoused and non-rehoused groups, and for residents inside and outside of the city proper, the semi-dynamic estimates are consistently negative but do not follow a clear monotonic trend in reductions over time.

These results indicate that the HPRP treatment has a positive impact on student behavior. The fact that there is no apparent effect on the likelihood of having one or more incidents, but significant effects on the likelihood of having multiple incidents, suggests that this positive impact is specific to those students who already tend to have behavioral problems, or for whom

[12] Appendix Table A13, which uses a fully balanced panel, arrives at substantively similar but slightly less robust results.

receiving an office referral is not a one-off occurrence. Generally speaking, the rate of behavioral problems across students is fairly low. The mean number of referrals for the full analytic sample is 0.047 and for the treated students specifically is 0.075. However, the variation across students is comparatively wide, with SDs of 0.412 and 0.535 for the full sample and treated students, respectively. Many students facing housing instability do not demonstrate behavioral problems in school, but for those who do, the additional support and stability that come with the rapid rehousing treatment appear to have a meaningful positive impact. Indeed, a decrease of 0.0065 in the likelihood of having two or more behavioral incidents (Table 8, column 5) corresponds to a 50 percent decrease relative to the treated student mean.

7. Discussion

The experience of homelessness can be extremely disruptive for children and youth, affecting their educational and socioemotional wellbeing. As such, the benefits of minimizing— or eliminating— at-risk families' time spent homeless are difficult to dispute. However, it is critically important to examine the impacts that homelessness prevention and rapid rehousing efforts have on students, particularly during the period of acute risk that these programs aim to mitigate. Understanding the benefits and risks that these programs cause can help schools and districts make informed decisions about how to best support HHM students going through housing transitions, as well as inform HPRP program design and impelementation. These insights are particularly relevant given the growth in homelessness and housing instability that the US is facing and the need for scaled up public interventions to address these problems.

The findings from this study indicate that, even with a relatively small sample of treated students, there are measurable benefits as well as risks that result from HPRP services. Perhaps surprisingly, participating in the HPRP did not, by and large, have a significant impact on students' likelihood of departing the school district for the overall population of treated students. While a non-negligible number of students do leave at some point following their family's intake to the program, when taking into account students' previous likelihood of moving in and out of the district and the likelihood of departure for control students in contemporaneous months, the effects of the treatment are generally insignificant. With regard to permanent departures from the district, there is evidence of an increase in mid-year leaves following treatment—an increase driven primarily by rehoused students and those moving out of the City. However, the magnitude of these increases are small (and not significant in all but the non-dynamic specifications). Indeed, the majority of treated students remain USD students, even when their new housing is a long commute away.

The reasons behind this finding are not readily explainable using the data at hand, which unfortunately cannot shed light on families' motivations. Conversations with USD officials and NGO staff suggest that many families who move away may choose to maintain connections with the City because that is the location of their social or support networks, or the community resources with which they are most familiar. Many parents may also be employed in the City and find it logistically simpler to keep their children enrolled there as well. Families may also think that the educational opportunities are better for their children in the City than in their new city, or believe that it is best for their children to maintain the same teachers and groups of friends, understanding the challenges and academic risks for students inherent to all types of mobility.

To some extent, the limited level of district departure is encouraging. This evidence, coupled with the finding that treatment does not increase intra-district school mobility (if anything, there is suggestive evidence that it decreases it), suggests that HPRP services do not add further disruption to students' education. However, it also highlights the challenges that families facing housing instability continue to face even with the support of HPRP interventions. The tradeoffs that come with the decision to stay enrolled in USD even when rehoused outside the district are apparent from the findings regarding impacts to student attendance. This study demonstrates that monthly absence rates increase considerably for these students, that the increase likely corresponds to families' moves into new housing, and that the impact is greater the further students move from the district. Chronic absenteeism, which has been shown to predict lower test scores and higher dropout rates (e.g. Gottfried, 2014; Smerillo et al., 2018), also increases for students rehoused outside the city. These findings raise the possibility that the academic benefits for certain students of gaining stable housing might be attenuated by the reduction in time actually spent in school.

That said, the findings regarding changes in student behavior are cause for optimism. Treated students are significantly less likely to receive multiple out-of-classroom referrals for behavioral incidents following their intake into the HPRP. These positive impacts are seen for both rehoused and non-rehoused students, regardless of where their new (or maintained) housing is located. These results offer evidence to suggest that the stability and support that come with homelessness prevention and rapid rehousing services lead to a reduction in negative stressors for children and youth, measurably impacting those students who struggle the most. Additionally, the evidence of positive impacts to behavior suggests that the concurrent increase in absences are a result more of logistical difficulties than of student disengagement from school.

An important caveat of my overall findings relates to the issue of external validity. I unfortunately do not have any outcome data from other school districts for students who ultimately leave USD. As such, the results of my analysis regarding school mobility, attendance, and behavior apply specifically to those students who decide to stay enrolled in the City's public schools. Additionally, the City and its public school district offer a fairly unique environment in which to study the impacts of homelessness prevention and rapid rehousing. The high costs of living, not only in the city proper but also in much of the surrounding cities, as well as the district's open enrollment policy, likely play a role in families' housing choices and the decisions they make about where to send their children to school. Additionally, the City is a major urban center within a larger metropolitan area. In less regionally connected areas, households might be less inclined to maintain connections (educational or otherwise) with their city of origin if they are rehoused in another locality.

Despite the unique conditions of the City, this study offers important lessons that are relevant to schools and policymakers all around the country. HPRP services, and rapid rehousing in particular, has real benefits for students, but it is not without tradeoffs. As cities and states weigh different strategies to address homelessness in their communities, it is worthwhile to consider the priorities inherent to their policy choices. Are there ways to make student commutes easier, or for schools to support students who might struggle to make it to class every day? Should school districts and homeless service providers encourage families to enroll in their new school district? More broadly speaking, are investments in efforts to quickly rehouse families in existing housing the best use of resources? How might families be better served with greater investment in the construction of affordable housing within city limits, or in the closest cities neighboring urban centers? While this research cannot speak to these larger questions, the more we understand about the experiences of families and students directly affected by homelessness prevention programs, the better equipped we will be to make informed policy decisions.

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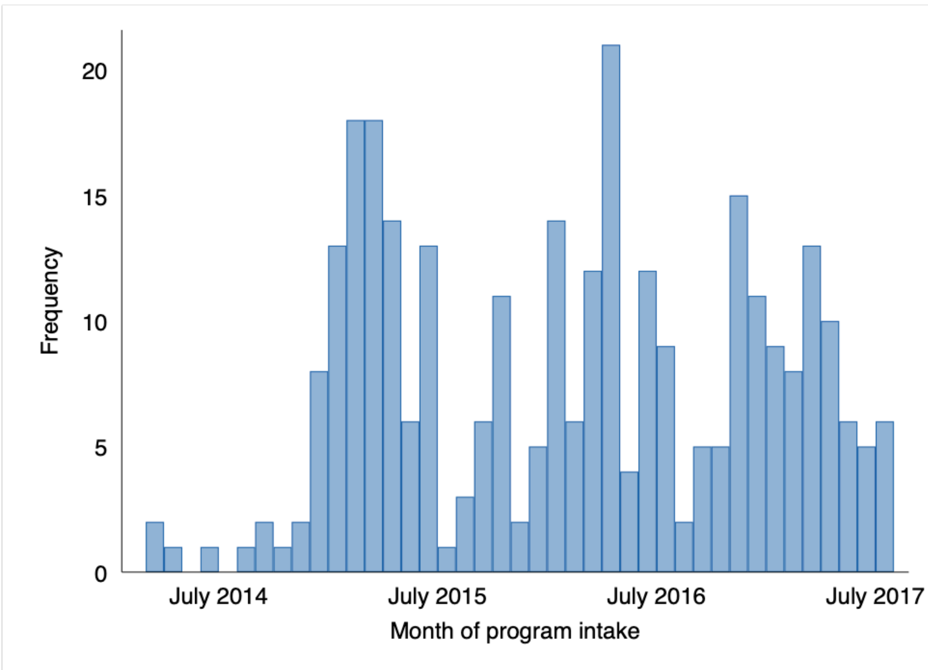
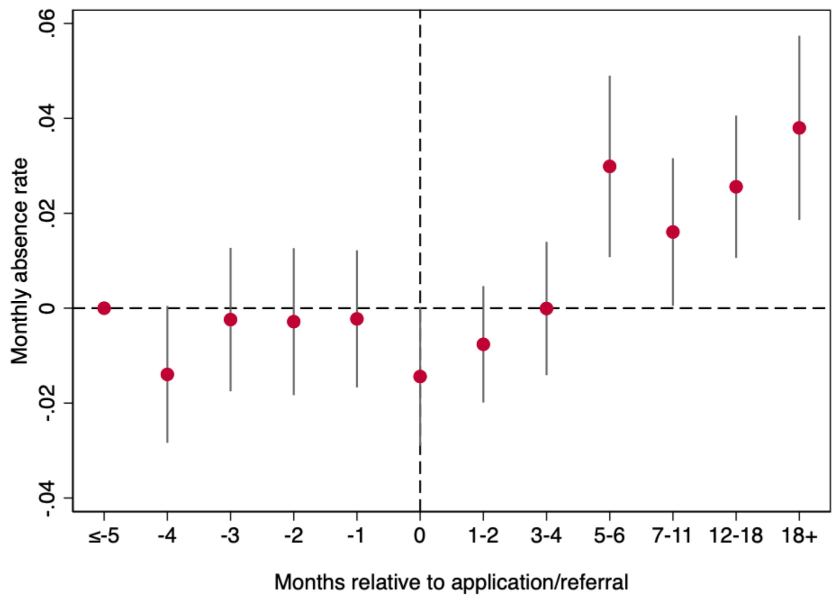
Figure 1 – Dates of students' intake to homelessness prevention and rapid rehousing program



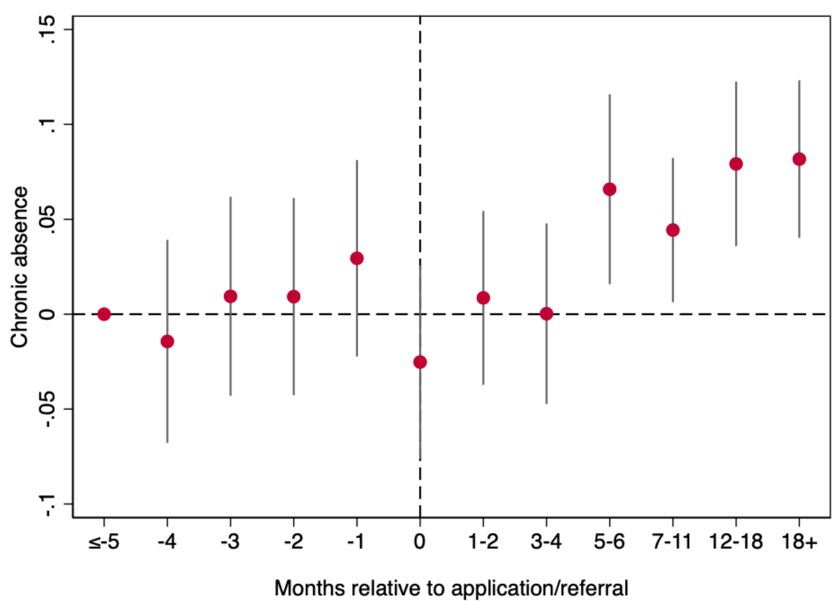
Notes: Histogram represents all treated students in the analytic sample (n=301).

Figure 2 – Estimated dynamic effects of HPRP services on student attendance

A. Monthly absence rate



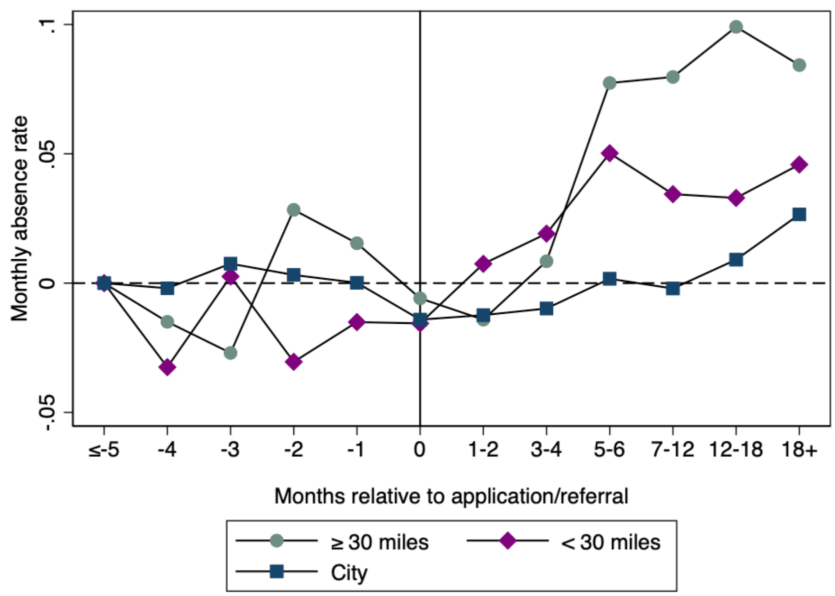
B. Chronic absenteeism



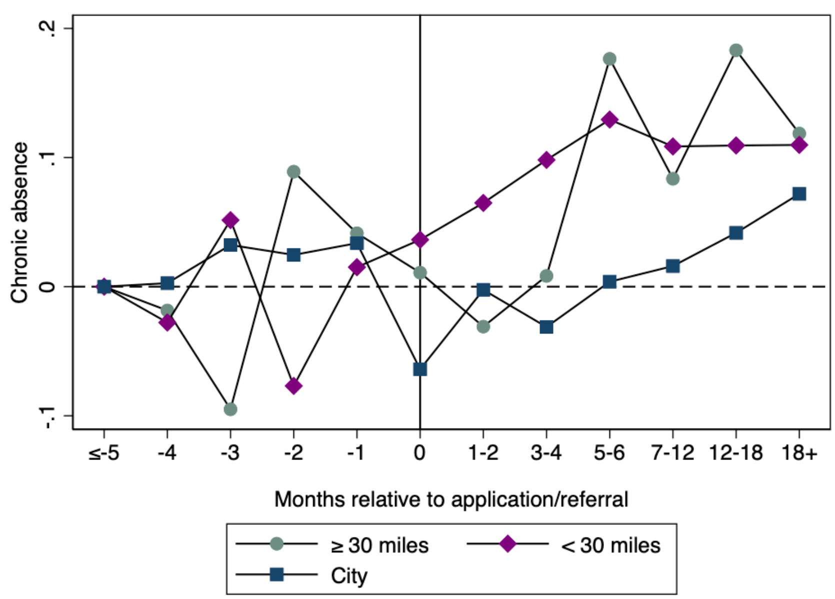
Notes: Estimates from models using the primary analytic sample (n=24,099). All models include student, month-year, and grade fixed effects. The reference period is 5 or more months prior to program intake.

Figure 3 – Estimated dynamic effects of HPRP services on student attendance, by location of new housing

A. Monthly absence rate



B. Chronic absenteeism



Notes: Estimates from models using the primary analytic sample (n=24,099). All models include student, month-year, and grade fixed effects. The reference period is 5 or more months prior to program intake. Distance refers to driving distance from city of new housing to the City.

Figure 4 – Estimated treatment effects of HPRP services on student behavior

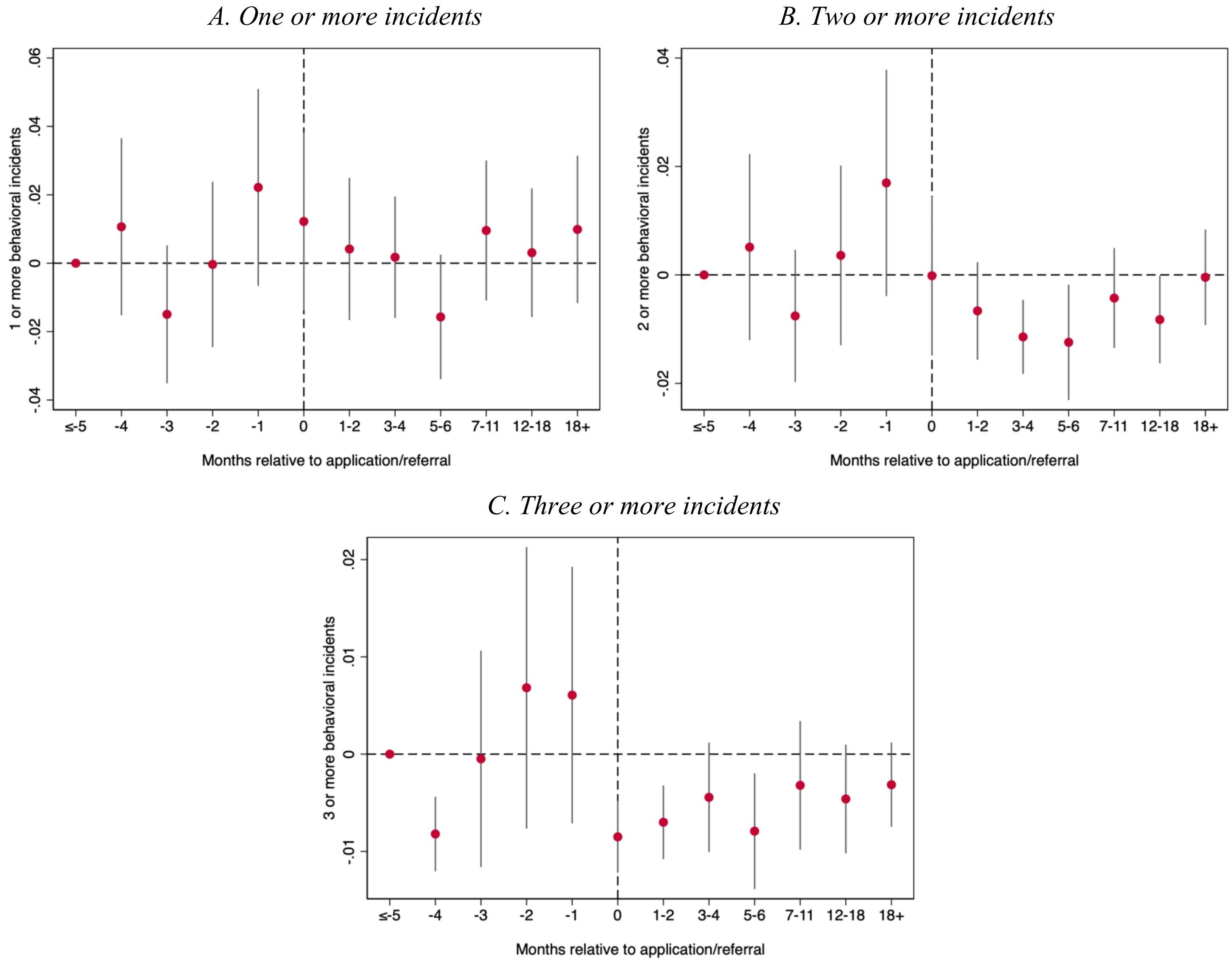


Table 1 - Descriptive statistics

	Mean	SD	Min	Max	N
Full analytic sample					
Race					
Black	0.094	-	0	1	916,369
Hispanic	0.329	-	0	1	916,369
Asian/Pacific Islander	0.358	-	0	1	916,369
White	0.087	-	0	1	916,369
Female	0.474	-	0	1	916,486
Grade	6.376	3.471	0	13	966,947
Monthly absence rate	0.048	0.111	0	1	967,005
Chronic absence (by month)	0.162	-	0	1	967,005
Number of behavioral incidents (per mo.)	0.047	0.412	0	34	967,005
1 or more behavioral incidents (per mo.)	0.025	-	0	1	967,005
2 or more behavioral incidents (per mo.)	0.009	-	0	1	967,005
3 or more behavioral incidents (per mo.)	0.004	-	0	1	967,005
Treated students					
Race					
Black	0.240	-	0	1	10,622
Hispanic	0.468	-	0	1	10,622
Asian/Pacific Islander	0.080	-	0	1	10,622
White	0.065	-	0	1	10,622
Female	0.492	-	0	1	10,626
Grade	4.851	3.365	0	12	11,143
Monthly absence rate	0.092	0.150	0	1	11,145
Chronic absence (by month)	0.317	-	0	1	11,145
Number of behavioral incidents (per mo.)	0.075	0.535	0	21	11,145
1 or more behavioral incidents (per mo.)	0.044	-	0	1	11,145
2 or more behavioral incidents (per mo.)	0.013	-	0	1	11,145
3 or more behavioral incidents (per mo.)	0.005	-	0	1	11,145
Status at entry: Literally homeless	0.530	-	0	1	11,145
Rehoused	0.687	-	0	1	11,145
Moved outside the City	0.407	-	0	1	11,145
Days between intake and new lease (rehoused students only)	120.202	96.418	0	405	6,762

Notes: Each observation is a student-month. Analytic sample is made up of all students treated by NGO and their school-grade-year peers (total n=24,099).

Table 2: Summary statistics of district departure and school mobility

	RRH student mean	Control group means: Gradmates (C1)	Control group means: Ever homeless (C2)	Difference (C1 - RRH)	Difference (C2 - RRH)
District departure					
Graduated	0.05	0.12	0.09	0.07***	0.04**
Left district: mid-year	0.26	0.12	0.19	-0.14***	-0.07*
Left district: over summer (no grad)	0.17	0.11	0.11	-0.06**	-0.05*
Left district permanently: mid-year	0.18	0.09	0.12	-0.08***	-0.06*
Left district permantly: over summer (no grad)	0.09	0.07	0.05	-0.02	-0.03*
School mobility					
School switch over summer, structural and non-structural	0.56	0.54	0.51	-0.02	-0.06
School switch over summer, non-structural only	0.26	0.13	0.18	-0.13***	-0.07**
Mid-year school switch	0.20	0.12	0.16	-0.08***	-0.04
Observations	301	23,798	3,425	24,099	3,726

* p<0.05 ** p<0.01 *** p<0.001

Table 3 - Effect of HPRP services on student departure from district

	All non-graduation leaves				Permanent non-graduation district leaves			
	Mid-year		Over summer		Mid-year		Over summer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post application/referral	0.0019		0.00022		0.0024***		0.00047	
	(0.0011)		(0.00055)		(0.00072)		(0.00038)	
Month of app/referral		-0.0024***		-0.00030		-0.00058		0.000080
		(0.00071)		(0.00039)		(0.00031)		(0.00013)
1-2 month lag		0.0021		-0.0012**		-0.00033		-0.00040**
		(0.0030)		(0.00041)		(0.00027)		(0.00014)
3-4 month lag		0.0025		0.00069		0.0019		0.0017
		(0.0035)		(0.0025)		(0.0026)		(0.0025)
5-6 month lag		0.0041		0.0048		0.0061		0.0038
		(0.0041)		(0.0041)		(0.0040)		(0.0034)
7-11 month lag		0.00029		0.00018		0.0016		0.00017
		(0.0019)		(0.0013)		(0.0016)		(0.00093)
12-18 month lag		0.0017		-0.0014**		0.0026		-0.00060***
		(0.0020)		(0.00042)		(0.0017)		(0.00013)
18+ month lag		0.0028		0.00045		0.0034*		0.00050
		(0.0019)		(0.00093)		(0.0013)		(0.00073)
N	1,042,563	1,042,563	1,042,563	1,042,563	1,042,563	1,042,563	1,042,563	1,042,563
R^2	0.029	0.029	0.037	0.037	0.025	0.025	0.033	0.033

Standard errors clustered at student level. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data).

* p<0.05 ** p<0.01 *** p<0.001

Table 4: Effect of HPRP services on intra-district school mobility

	Summer move		Summer move - non-structural		Mid-year move	
	(1)	(2)	(3)	(4)	(5)	(6)
Post application/referral	0.0041		0.00035		-0.0012	
	(0.0023)		(0.0017)		(0.0024)	
Month of app/referral		-0.0064		-0.0083***		0.0097
		(0.0033)		(0.0018)		(0.0089)
1-2 month lag		-0.0024		-0.0041		-0.00020
		(0.0058)		(0.0040)		(0.0042)
3-4 month lag		0.0092		0.0024		-0.0014
		(0.0083)		(0.0057)		(0.0049)
5-6 month lag		0.0090		0.0056		-0.0031
		(0.0087)		(0.0064)		(0.0048)
7-11 month lag		0.0019		0.00063		-0.0048
		(0.0040)		(0.0029)		(0.0028)
12-18 month lag		0.0046		-0.0018		-0.0051*
		(0.0037)		(0.0019)		(0.0023)
18+ month lag		0.0067		0.0026		0.0023
		(0.0034)		(0.0026)		(0.0040)
Observations	966,947	966,947	966,947	966,947	966,947	966,947
R^2	0.23	0.23	0.066	0.066	0.060	0.060

Standard errors clustered at student level. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data). Non-structural summer moves are school switches that occur over the summer but not between grades 5 and 6 or between grades 8 and 9.

* p<0.05 ** p<0.01 *** p<0.001

Table 5: Effect of HPRP services on monthly absence rates and chronic absence

	Monthly absence rate		Chronic absence	
	(1)	(2)	(3)	(4)
Post application/referral	0.022***		0.053***	
	(0.0054)		(0.015)	
Month of app/referral		-0.013		-0.025
		(0.0069)		(0.025)
1-2 month lag		-0.0060		0.0086
		(0.0058)		(0.022)
3-4 month lag		0.00069		0.0022
		(0.0071)		(0.024)
5-6 month lag		0.029**		0.066**
		(0.0093)		(0.025)
7-11 month lag		0.018*		0.044*
		(0.0077)		(0.018)
12-18 month lag		0.027***		0.073***
		(0.0076)		(0.021)
18+ month lag		0.041***		0.085***
		(0.0097)		(0.021)
N	966,947	966,947	966,947	966,947
R^2	0.33	0.33	0.27	0.27

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data). Absence rates are calculated as the number of days per month a student is marked absent divided by the number of days per month for which a student has an attendance record. Chronic absence is a variable indicating a student's absence rate ≥0.10 in any given month.

* p<0.05   ** p<0.01   *** p<0.001

Table 6 - Effect of HPRP services on monthly absence rates and chronic absence by service type

	Monthly absence rate				Chronic absence			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rehoused	Non-rehoused	Rehoused	Non-rehoused	Rehoused	Non-rehoused	Rehoused	Non-rehoused
Post application/referral	0.027***	0.013			0.061***	0.035		
	(0.0067)	(0.0091)			(0.017)	(0.027)		
Month of app/referral			-0.0093	-0.021			-0.017	-0.043
			(0.0084)	(0.012)			(0.030)	(0.048)
1-2 month lag			-0.0035	-0.011			0.0095	0.011
			(0.0072)	(0.0089)			(0.027)	(0.039)
3-4 month lag			0.0056	-0.0095			0.027	-0.052
			(0.0089)	(0.011)			(0.029)	(0.040)
5-6 month lag			0.039***	0.0058			0.10***	-0.023
			(0.011)	(0.016)			(0.031)	(0.043)
7-11 month lag			0.025**	0.0045			0.053*	0.027
			(0.0095)	(0.013)			(0.022)	(0.032)
12-18 month lag			0.031***	0.021			0.083**	0.053
			(0.0089)	(0.014)			(0.025)	(0.038)
18+ month lag			0.044***	0.035*			0.083***	0.095*
			(0.012)	(0.017)			(0.024)	(0.040)
p-value: (H_0:β_1=β_2)	0.207				0.415			
p-value: (H_0:β_1=β_2=0)	0.000				0.001			

Standard errors clustered at student level. Columns 1 and 2, 3 and 4, 5 and 6, etc. each come from the same model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=6 months prior data). 221 of these students were rehoused, 80 received some form of eviction prevention only. P-values shown are for F-tests of the null hypotheses that the coefficients for rehoused and non-rehoused students are equivalent, and that they are both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001

Table 7 - Effect of HPRP services on monthly absence rates and chronic absence by location of new home

	Monthly absence rate						Chronic absence					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	City	< 30 miles	≥ 30 miles	City	< 30 miles	≥ 30 miles	City	< 30 miles	≥ 30 miles	City	< 30 miles	≥ 30 miles
Post application/referral	0.0069	0.037***	0.059***				0.024	0.10***	0.090*			
	(0.0065)	(0.0092)	(0.018)				(0.019)	(0.027)	(0.038)			
Month of app/referral				-0.014	-0.011	-0.0062				-0.068*	0.039	0.0092
				(0.0094)	(0.0089)	(0.021)				(0.033)	(0.049)	(0.061)
1-2 month lag				-0.013	0.012	-0.015				-0.0066	0.068	-0.033
				(0.0066)	(0.010)	(0.019)				(0.029)	(0.045)	(0.055)
3-4 month lag				-0.0100	0.024	0.0080				-0.035	0.10	0.0066
				(0.0079)	(0.016)	(0.021)				(0.028)	(0.055)	(0.063)
5-6 month lag				0.0015	0.055**	0.077***				-0.00027	0.13**	0.18**
				(0.010)	(0.020)	(0.023)				(0.032)	(0.049)	(0.063)
7-11 month lag				-0.0021	0.039*	0.080*				0.012	0.11**	0.083
				(0.0082)	(0.015)	(0.032)				(0.022)	(0.039)	(0.050)
12-18 month lag				0.0094	0.038**	0.099**				0.038	0.11**	0.18**
				(0.0086)	(0.014)	(0.032)				(0.026)	(0.042)	(0.064)
18+ month lag				0.027*	0.052**	0.085**				0.068*	0.11**	0.12*
				(0.012)	(0.016)	(0.032)				(0.027)	(0.038)	(0.056)
p-value: (H_0:β_1=β_2=β_3)		0.002						0.030				
p-value: (H_0:β_1=β_2=β_3=0)		0.000						0.000				

Standard errors clustered at student level. Columns 1, 2, and 3; 4, 5 and 6; 7, 8, and 9, etc. each come from the same model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data). 158 of these students remained living in the City, 79 moved to cities within 30 miles of the City, 63 moved to cities greater than 30 miles from the City, and 1 student's new home city is unknown. P-values shown are for F-tests of the null hypotheses that the coefficients for all three categories of students are equivalent, and that they are all both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001

Table 8 - Effect of HPRP services on number of behavioral incidents in a month

	Count of incidents		1 or more incidents		2 or more incidents		3 or more incidents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post application/referral	-0.025		0.0041		-0.0065**		-0.0051**	
	(0.013)		(0.0058)		(0.0024)		(0.0016)	
Month of app/referral		-0.021		0.012		-0.00062		-0.0084***
		(0.018)		(0.013)		(0.0070)		(0.0018)
1-2 month lag		-0.032		0.0043		-0.0072		-0.0068***
		(0.021)		(0.010)		(0.0041)		(0.0017)
3-4 month lag		-0.027		0.0016		-0.012**		-0.0044
		(0.016)		(0.0088)		(0.0036)		(0.0030)
5-6 month lag		-0.046*		-0.013		-0.0100*		-0.0063*
		(0.019)		(0.0089)		(0.0046)		(0.0029)
7-11 month lag		-0.013		0.010		-0.0052		-0.0033
		(0.020)		(0.0097)		(0.0039)		(0.0029)
12-18 month lag		-0.029		0.0036		-0.0080*		-0.0054*
		(0.018)		(0.0086)		(0.0035)		(0.0023)
18+ month lag		-0.023		0.0037		-0.0049		-0.0048*
		(0.017)		(0.010)		(0.0036)		(0.0019)
N	966,947	966,947	966,947	966,947	966,947	966,947	966,947	966,947
R^2	0.21	0.21	0.22	0.22	0.18	0.18	0.14	0.14

Standard errors clustered at student level. All models containt student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have ≥3 months prior data). Incidents (i.e. out-of-classroom referrals) can be a result of the following student behaviors: bullying, cheating, damage, disruption, non-disciplinary reasons, noncompliance, sexual harassment, class skip, substance possession, theft, threats, verbal aggression, violence, walkout, weapons, and other.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

APPENDIX A: Supplemental Tables

Table A1 - Descriptive statistics for time-invariant student-level observations

	Mean	SD	Min	Max	N
Full analytic sample					
Race					
Black	0.095	-	0	1	13,870
Hispanic	0.345	-	0	1	13,870
Asian/Pacific Islander	0.288	-	0	1	13,870
White	0.086	-	0	1	13,870
Female	0.474	-	0	1	13,890
Grade	-	-	-	-	-
Monthly absence rate	-	-	-	-	-
Chronic absence (by month)	-	-	-	-	-
Number of behavioral incidents (per mo.)	-	-	-	-	-
1 or more behavioral incidents (per mo.)	-	-	-	-	-
2 or more behavioral incidents (per mo.)	-	-	-	-	-
3 or more behavioral incidents (per mo.)	-	-	-	-	-
Treated students					
Race					
Black	0.227	-	0	1	198
Hispanic	0.424	-	0	1	198
Asian/Pacific Islander	0.066	-	0	1	198
White	0.045	-	0	1	198
Female	0.543	-	0	1	199
Grade	-	-	-	-	-
Monthly absence rate	-	-	-	-	-
Chronic absence (by month)	-	-	-	-	-
Number of behavioral incidents (per mo.)	-	-	-	-	-
1 or more behavioral incidents (per mo.)	-	-	-	-	-
2 or more behavioral incidents (per mo.)	-	-	-	-	-
3 or more behavioral incidents (per mo.)	-	-	-	-	-
Status at entry: Literally homeless	0.598	-	0	1	301
Rehoused	0.734	-	0	1	301
Moved outside the City	0.472	-	0	1	301
Days between intake and new lease (rehoused students only)	118.805	96.646	0	405	200

Notes: Each observation is an individual student. Analytic sample is made up of all students treated by NGO and their school-grade-year peers (total n=24,099).

Table A2 - Descriptive statistics for analytic sample using "ever homeless" control group

	Student-month observations					Individual student observations				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Full analytic sample										
Race										
Black	0.151	-	0	1	123,831	0.157	-	0	1	2,474
Hispanic	0.491	-	0	1	123,831	0.430	-	0	1	2,474
Asian/Pacific Islander	0.210	-	0	1	123,831	0.178	-	0	1	2,474
White	0.026	-	0	1	123,831	0.030	-	0	1	2,474
Female	0.467	-	0	1	123,850	0.481	-	0	1	2,478
Grade	5.814	3.502	0	12	129,857	-	-	-	-	-
Monthly absence rate	0.079	0.148	0	1	129,938	-	-	-	-	-
Chronic absence (by month)	0.259	0.438	0	1	129,938	-	-	-	-	-
Number of behavioral incidents (per mo.)	0.077	0.534	0	31	129,938	-	-	-	-	-
1 or more behavioral incidents (per mo.)	0.041	0.198	0	1	129,938	-	-	-	-	-
2 or more behavioral incidents (per mo.)	0.015	0.122	0	1	129,938	-	-	-	-	-
3 or more behavioral incidents (per mo.)	0.008	0.087	0	1	129,938	-	-	-	-	-
Treated students										
Race										
Black	0.240	-	0	1	10,622	0.227	-	0	1	198
Hispanic	0.468	-	0	1	10,622	0.424	-	0	1	198
Asian/Pacific Islander	0.080	-	0	1	10,622	0.066	-	0	1	198
White	0.065	-	0	1	10,622	0.045	-	0	1	198
Female	0.492	-	0	1	10,626	0.543	-	0	1	199
Grade	4.851	3.365	0	12	11,143	-	-	-	-	-
Monthly absence rate	0.092	0.150	0	1	11,145	-	-	-	-	-
Chronic absence (by month)	0.317	-	0	1	11,145	-	-	-	-	-
Number of behavioral incidents (per mo.)	0.075	0.535	0	21	11,145	-	-	-	-	-
1 or more behavioral incidents (per mo.)	0.044	-	0	1	11,145	-	-	-	-	-
2 or more behavioral incidents (per mo.)	0.013	-	0	1	11,145	-	-	-	-	-
3 or more behavioral incidents (per mo.)	0.005	-	0	1	11,145	-	-	-	-	-
Status at entry: Literally homeless	0.530	-	0	1	11,145	0.598	-	0	1	301
Rehoused	0.687	-	0	1	11,145	0.734	-	0	1	301
Moved outside the City	0.407	-	0	1	11,145	0.472	-	0	1	301
Days between intake and new lease (rehoused students only)	120.202	96.418	0	405	6,762	118.805	96.646	0	405	200

Notes: Analytic sample is made up of all students treated by NGO and all students ever flagged for being homeless by the school district (total n=3,726).

Table A3 - Effect of HPRP services on missingness, conditional on having 3 month's data pre application/referral

	Sample 1: Grademates control group			Sample 2: Ever homeless control group		
	(1)	(2)	(3)	(4)	(5)	(6)
Post application/referral	0.0038			0.0077		
	(0.014)			(0.014)		
4 month lead			-0.053***			-0.048**
			(0.015)			(0.015)
3 month lead			-0.066***			-0.060***
			(0.015)			(0.016)
2 month lead			-0.068***			-0.066***
			(0.016)			(0.016)
1 month lead			-0.061***			-0.062***
			(0.016)			(0.016)
Month of app/referral		-0.049***	-0.063***		-0.049***	-0.063***
		(0.013)	(0.016)		(0.013)	(0.016)
1-2 month lag		-0.045***	-0.059***		-0.043***	-0.057***
		(0.013)	(0.015)		(0.013)	(0.016)
3-4 month lag		-0.033*	-0.046**		-0.033*	-0.046**
		(0.014)	(0.017)		(0.015)	(0.017)
5-6 month lag		-0.027	-0.041*		-0.023	-0.037*
		(0.015)	(0.017)		(0.015)	(0.017)
7-11 month lag		-0.015	-0.028		-0.0068	-0.020
		(0.016)	(0.018)		(0.016)	(0.018)
12-18 month lag		0.0050	-0.0082		0.013	-0.00023
		(0.018)	(0.020)		(0.019)	(0.020)
18+ month lag		0.054**	0.040		0.061**	0.046*
		(0.021)	(0.022)		(0.021)	(0.022)
N	1042563	1042563	1042563	139614	139614	139614
R^2	0.52	0.52	0.52	0.48	0.48	0.48

Standard errors clustered at student level. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers (Sample 1) or 3,726 unique student ID numbers (Sample 2). 301 students received homelessness prevention services while enrolled in USD and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data). To impute grades for missing observations, students are assumed to progress from K to 12 without skipping grades or retention. Student-month observations for students whose imputed grade is undefined (i.e. outside the span of K through 12) are not included in analysis.

* p<0.05 ** p<0.01 *** p<0.001

Table A4 - Full dynamic effects of HPRP services on student departure from district

	All non-graduation district leaves		Permanent non-graduation district leaves	
	(1)	(2)	(3)	(4)
	Mid-year	Over summer	Mid-year	Over summer
4 month lead	0.0010	-0.0011*	-0.00079*	-0.00018
	(0.0041)	(0.00053)	(0.00039)	(0.00016)
3 month lead	-0.0023**	-0.0011*	-0.00055	-0.00012
	(0.00081)	(0.00051)	(0.00039)	(0.00015)
2 month lead	0.0012	-0.00095	-0.00071*	-0.000084
	(0.0038)	(0.00050)	(0.00033)	(0.00015)
1 month lead	0.0013	-0.00066	-0.00068*	0.000078
	(0.0036)	(0.00049)	(0.00033)	(0.00013)
Month of app/referral	-0.0024**	-0.00052	-0.00073	0.000064
	(0.00077)	(0.00048)	(0.00038)	(0.00015)
1-2 month lag	0.0022	-0.0014**	-0.00049	-0.00042**
	(0.0030)	(0.00049)	(0.00033)	(0.00015)
3-4 month lag	0.0026	0.00048	0.0017	0.0017
	(0.0035)	(0.0025)	(0.0026)	(0.0025)
5-6 month lag	0.0042	0.0046	0.0060	0.0037
	(0.0041)	(0.0041)	(0.0040)	(0.0034)
7-11 month lag	0.00036	-0.000027	0.0014	0.00016
	(0.0020)	(0.0014)	(0.0016)	(0.00093)
12-18 month lag	0.0018	-0.0016**	0.0025	-0.00061***
	(0.0021)	(0.00050)	(0.0017)	(0.00014)
18+ month lag	0.0029	0.00023	0.0032*	0.00048
	(0.0020)	(0.00099)	(0.0014)	(0.00073)
N	1,042,563	1,042,563	1,042,563	1,042,563
R^2	0.029	0.037	0.025	0.033

Standard errors clustered at student level. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data).

* p<0.05 ** p<0.01 *** p<0.001

Table A5 - Effect of HPRP services on student departure from district (ever homeless control group)

	All non-graduation district leaves				Permanent non-graduation district leaves			
	(1) Mid-year	(2) Mid-year	(3) Over summer	(4) Over summer	(5) Mid-year	(6) Mid-year	(7) Over summer	(8) Over summer
Post application/referral	0.0012		0.000077		0.0013		0.00037	
	(0.0011)		(0.00058)		(0.00073)		(0.00042)	
Month of app/referral		-0.0026***		-0.00037		-0.00083*		-0.00020
		(0.00073)		(0.00042)		(0.00033)		(0.00019)
1-2 month lag		0.0016		-0.0014**		-0.00089**		-0.00067**
		(0.0030)		(0.00048)		(0.00029)		(0.00022)
3-4 month lag		0.0023		0.000084		0.0014		0.0014
		(0.0034)		(0.0025)		(0.0025)		(0.0025)
5-6 month lag		0.0039		0.0045		0.0055		0.0038
		(0.0040)		(0.0039)		(0.0039)		(0.0033)
7-11 month lag		-0.00028		0.00070		0.00062		0.00082
		(0.0019)		(0.0015)		(0.0015)		(0.0012)
12-18 month lag		0.00093		-0.0019***		0.0014		-0.0010***
		(0.0019)		(0.00051)		(0.0017)		(0.00027)
18+ month lag		0.0018		0.00024		0.0017		0.00018
		(0.0019)		(0.00096)		(0.0013)		(0.00075)
N	139,614	139,614	139,614	139,614	139,614	139,614	139,614	139,614
R^2	0.032	0.032	0.041	0.042	0.030	0.030	0.036	0.036

Standard errors clustered at student level. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 3,726 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data).

* p<0.05 ** p<0.01 *** p<0.001

Table A6 - Effect of HPRP services on student departure from district by service type and by location of new home

Panel A: By service type - rehoused (RH) or eviction prevention services only (non-RH)

	All non-graduation district leaves								Permanent non-graduation district leaves							
	Mid-year only				Over summer only				Mid-year only				Over summer only			
	(1) RH	(2) Non-RH	(3) RH	(4) Non-RH	(5) RH	(6) Non-RH	(7) RH	(8) Non-RH	(9) RH	(10) Non-RH	(11) RH	(12) Non-RH	(13) RH	(14) Non-RH	(15) RH	(16) Non-RH
Post application/referral	0.0027	-0.000020			0.00056	-0.00056			0.0035***	0.000034			0.00080	-0.00030		
	(0.0015)	(0.0012)			(0.00076)	(0.00045)			(0.00097)	(0.00071)			(0.00053)	(0.00026)		
Month of app/referral			-0.0025**	-0.0019			-0.00042	0.00021			-0.00046	-0.00053**			0.00012	0.00011
			(0.00091)	(0.0010)			(0.00049)	(0.00057)			(0.00042)	(0.00017)			(0.00015)	(0.00030)
1-2 month lag			0.0032	-0.00067			-0.0011*	-0.0013			-0.00021	-0.00039*			-0.00024	-0.00076*
			(0.0040)	(0.00072)			(0.00050)	(0.00068)			(0.00037)	(0.00017)			(0.00016)	(0.00033)
3-4 month lag			0.0044	-0.0019			-0.0017**	0.0066			0.0029	-0.00059**			-0.00046	0.0070
			(0.0049)	(0.0011)			(0.00061)	(0.0083)			(0.0036)	(0.00021)			(0.00026)	(0.0084)
5-6 month lag			0.0032	0.0067			0.0076	-0.0022**			0.0056	0.0077			0.0058	-0.0014**
			(0.0047)	(0.0084)			(0.0057)	(0.00084)			(0.0046)	(0.0083)			(0.0047)	(0.00046)
7-11 month lag			0.0012	-0.0017			0.00089	-0.0013*			0.0026	-0.00060***			0.00066	-0.00085*
			(0.0028)	(0.00099)			(0.0019)	(0.00055)			(0.0023)	(0.00017)			(0.0013)	(0.00033)
12-18 month lag			0.0019	0.0016			-0.0016**	-0.00071			0.0042	-0.00075**			-0.00062***	-0.00047
			(0.0025)	(0.0032)			(0.00055)	(0.00053)			(0.0024)	(0.00025)			(0.00013)	(0.00029)
18+ month lag			0.0041	-0.00073			0.0011	-0.0012			0.0049**	-0.00071*			0.0012	-0.0014
			(0.0025)	(0.00052)			(0.0012)	(0.00092)			(0.0018)	(0.00030)			(0.00092)	(0.00091)
p-value: (H_0:β_1=β_2)	0.157				0.201				0.004				0.062			
p-value: (H_0:β_1=β_2=0)	0.195				0.338				0.002				0.163			

Panel B: By location of new home

	All non-graduation district leaves								Permanent non-graduation district leaves							
	Mid-year only				Over summer only				Mid-year only				Over summer only			
	(1) Non-City	(2) City	(3) Non-City	(4) City	(5) Non-City	(6) City	(7) Non-City	(8) City	(9) Non-City	(10) City	(11) Non-City	(12) City	(13) Non-City	(14) City	(15) Non-City	(16) City
Post application/referral	0.0035	0.00066			0.0011	-0.00048			0.0044**	0.00099			0.0016	-0.00036*		
	(0.0022)	(0.00094)			(0.0012)	(0.00025)			(0.0014)	(0.00065)			(0.00085)	(0.00015)		
Month of app/referral			-0.0023	-0.0023**			-0.00085	0.00034			0.000071	-0.00099**			0.00012	0.00016
			(0.0012)	(0.00081)			(0.00073)	(0.00035)			(0.00053)	(0.00036)			(0.00021)	(0.00017)
1-2 month lag			0.0069	-0.0014*			-0.0014	-0.00087*			0.000024	-0.00063			-0.00023	-0.00051*
			(0.0065)	(0.00069)			(0.00074)	(0.00041)			(0.00042)	(0.00033)			(0.00020)	(0.00020)
3-4 month lag			0.0039	-0.0024**			-0.0032**	0.0033			0.0059	-0.0010**			-0.00087*	0.0035
			(0.0063)	(0.00084)			(0.00096)	(0.0042)			(0.0062)	(0.00038)			(0.00040)	(0.0042)
5-6 month lag			0.0065	0.0026			0.012	-0.0018***			0.0093	0.0035			0.0093	-0.0011***
			(0.0070)	(0.0046)			(0.0086)	(0.00053)			(0.0068)	(0.0046)			(0.0071)	(0.00030)
7-11 month lag			0.0023	-0.00085			0.0021	-0.0011***			0.0035	0.00022			0.0016	-0.00077***
			(0.0041)	(0.0017)			(0.0033)	(0.00032)			(0.0032)	(0.0015)			(0.0023)	(0.00019)
12-18 month lag			-0.00095	0.0039			-0.0027**	-0.00045			0.0016	0.0033			-0.00091***	-0.00039*
			(0.0023)	(0.0029)			(0.00090)	(0.00030)			(0.0024)	(0.0024)			(0.00020)	(0.00016)
18+ month lag			0.0056	0.00090			0.0019	-0.00067			0.0068*	0.00066			0.0023	-0.00086*
			(0.0039)	(0.0013)			(0.0020)	(0.00041)			(0.0027)	(0.0010)			(0.0015)	(0.00039)
p-value: (H_0:β_1=β_2)	0.244				0.196				0.029				0.024			
p-value: (H_0:β_1=β_2=0)	0.229				0.101				0.003				0.010			

Standard errors clustered at student level. Columns 1 and 2, 3 and 4, 5 and 6, etc. each come from the same model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data). 221 of these students were rehoused, 80 received some form of eviction prevention only. 143 of these students were rehoused outside of the City, 158 remained living in the City. P-values shown are for F-tests of the null hypotheses that the coefficients for the two categories of students are equivalent, and that they are both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001

Table A7: Full dynamic effects of HPRP services on intra-district school mobility

	(1) Summer Move	(2) Summer Move - Non-structural	(3) Mid-Year Move
4 month lead	-0.012	-0.0083	-0.0039
	(0.0066)	(0.0046)	(0.0043)
3 month lead	0.000021	-0.012***	0.011
	(0.0074)	(0.0023)	(0.0085)
2 month lead	0.0020	-0.0084*	0.017
	(0.0078)	(0.0038)	(0.0092)
1 month lead	-0.0038	-0.0035	0.0033
	(0.0056)	(0.0054)	(0.0067)
Month of app/referral	-0.0072*	-0.010***	0.011
	(0.0036)	(0.0022)	(0.0091)
1-2 month lag	-0.0032	-0.0060	0.0015
	(0.0060)	(0.0041)	(0.0042)
3-4 month lag	0.0085	0.00048	0.00035
	(0.0084)	(0.0057)	(0.0049)
5-6 month lag	0.0083	0.0038	-0.0014
	(0.0088)	(0.0065)	(0.0049)
7-11 month lag	0.0011	-0.0012	-0.0032
	(0.0042)	(0.0030)	(0.0029)
12-18 month lag	0.0038	-0.0036	-0.0035
	(0.0038)	(0.0021)	(0.0023)
18+ month lag	0.0059	0.00062	0.0040
	(0.0036)	(0.0027)	(0.0041)
Observations	966,947	966,947	966,947
R^2	0.23	0.066	0.060

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data). Non-structural summer moves are school switches that occur over the summer but not between grades 5 and 6 or between grades 8 and 9.
* p<0.05 ** p<0.01 *** p<0.001

Table A8: Effect of HPRP services on intra-district school mobility (ever homeless control group)

	Summer Move		Summer Move - Non-structural		Mid-Year Move	
	(1)	(2)	(3)	(4)	(5)	(6)
Post application/referral	0.0025		-0.00049		-0.0017	
	(0.0024)		(0.0017)		(0.0025)	
Month of app/referral		-0.0083*		-0.0084***		0.0089
		(0.0035)		(0.0020)		(0.0087)
1-2 month lag		-0.0030		-0.0046		-0.00068
		(0.0059)		(0.0040)		(0.0041)
3-4 month lag		0.012		0.0061		-0.0012
		(0.0088)		(0.0065)		(0.0048)
5-6 month lag		0.0065		0.0018		-0.00032
		(0.0084)		(0.0062)		(0.0051)
7-11 month lag		-0.00068		-0.0011		-0.0050
		(0.0041)		(0.0029)		(0.0028)
12-18 month lag		0.0015		-0.0030		-0.0057*
		(0.0037)		(0.0020)		(0.0023)
18+ month lag		0.0055		0.0021		0.00074
		(0.0035)		(0.0026)		(0.0040)
Observations	129,857	129,857	129,857	129,857	129,857	129,857
R^2	0.23	0.23	0.086	0.086	0.065	0.065

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 3,726 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data). Non-structural summer moves are school switches that occur over the summer but not between grades 5 and 6 or between grades 8 and 9.
* p<0.05 ** p<0.01 *** p<0.001

Table A9: Effect of HPRP services on intra-district school mobility, fully balanced panel

	Summer Move			Summer Move - Non-structural			Mid-Year Move		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post application/referral	0.0046			0.00032			-0.00064		
	(0.0026)			(0.0016)			(0.0019)		
4 month lead			0.00030			0.0068			-0.0025*
			(0.015)			(0.011)			(0.00099)
3 month lead			0.014			-0.0034*			-0.0024*
			(0.014)			(0.0014)			(0.00094)
2 month lead			0.016			-0.0029			0.017
			(0.012)			(0.0015)			(0.013)
1 month lead			0.0041			-0.0020			0.0080
			(0.0048)			(0.0014)			(0.0100)
Month of app/referral		-0.00045	0.00098		-0.0024	-0.0025		0.0078	0.0086
		(0.0057)	(0.0059)		(0.0013)	(0.0014)		(0.011)	(0.011)
1-2 month lag		0.0033	0.0047		-0.0031*	-0.0032*		-0.0020	-0.0012
		(0.0088)	(0.0089)		(0.0013)	(0.0015)		(0.0012)	(0.0010)
3-4 month lag		0.019	0.020		0.0096	0.0095		0.0035	0.0044
		(0.013)	(0.013)		(0.0087)	(0.0087)		(0.0065)	(0.0065)
5-6 month lag		0.0060	0.0073		0.0018	0.0017		0.0029	0.0037
		(0.014)	(0.014)		(0.0063)	(0.0064)		(0.0066)	(0.0066)
7-11 month lag		-0.0033	-0.0019		0.0030	0.0029		-0.0033**	-0.0025**
		(0.0056)	(0.0057)		(0.0037)	(0.0038)		(0.0011)	(0.00091)
12-18 month lag		0.0068	0.0083		-0.0030*	-0.0030*		-0.0026*	-0.0017
		(0.0049)	(0.0050)		(0.0012)	(0.0014)		(0.0012)	(0.0010)
18+ month lag		0.0056	0.0073*		-0.00034	-0.00044		-0.00011	0.00086
		(0.0033)	(0.0036)		(0.0020)	(0.0022)		(0.0025)	(0.0023)
N	561,765	561,765	561,765	561,765	561,765	561,765	561,765	561,765	561,765

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 11,015 unique student IDs who are represented across all 51 instructional months. 108 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data). Non-structural summer moves are school switches that occur over the summer but not between grades 5 and 6 or between grades 8 and 9.
* p<0.05 ** p<0.01 *** p<0.001

Table A10 - Effect of HPRP services on intra-district school mobility by service type and by location of new home

Panel A: By service type

	Summer Move				Non-Structural Summer Move				Mid-Year Move			
	(1) Rehoused	(2) Non-rehoused	(3) Rehoused	(4) Non-rehoused	(5) Rehoused	(6) Non-rehoused	(7) Rehoused	(8) Non-rehoused	(9) Rehoused	(10) Non-rehoused	(11) Rehoused	(12) Non-rehoused
Post application/referral	0.00484	0.00256			0.00112	-0.00131			-0.00382	0.00451		
	(0.00302)	(0.00313)			(0.00228)	(0.00188)			(0.00319)	(0.00341)		
Month of app/referral			-0.0103*	0.00488			-0.0106***	-0.00125			0.00354	0.0257
			(0.00418)	(0.00438)			(0.00240)	(0.00191)			(0.00969)	(0.0203)
1-2 month lag			-0.000313	-0.00796			-0.00356	-0.00507*			-0.00541	0.0130
			(0.00704)	(0.00954)			(0.00539)	(0.00205)			(0.00423)	(0.0103)
3-4 month lag			0.00617	0.0167			0.00338	0.000380			-0.00884*	0.0152
			(0.00959)	(0.0164)			(0.00718)	(0.00884)			(0.00441)	(0.0123)
5-6 month lag			0.00922	0.00881			0.0117	-0.00883***			-0.00627	0.00381
			(0.0106)	(0.0149)			(0.00901)	(0.00256)			(0.00552)	(0.00934)
7-11 month lag			0.00581	-0.00630			0.00339	-0.00507**			-0.00771*	0.000784
			(0.00518)	(0.00594)			(0.00413)	(0.00180)			(0.00363)	(0.00444)
12-18 month lag			0.00449	0.00504			-0.00306	0.00124			-0.00739*	-0.000568
			(0.00466)	(0.00611)			(0.00251)	(0.00280)			(0.00305)	(0.00300)
18+ month lag			0.00739	0.00513			0.00258	0.00299			0.00184	0.00251
			(0.00450)	(0.00415)			(0.00336)	(0.00310)			(0.00541)	(0.00320)
p-value: (H_0:β_1=β_2)	0.600				0.410				0.074			
p-value: (H_0:β_1=β_2=0)	0.200				0.695				0.202			

Panel B: By location of new home

	Summer Move				Non-Structural Summer Move				Mid-Year Move			
	(1) Non-City	(2) City	(3) Non-City	(4) City	(5) Non-City	(6) City	(7) Non-City	(8) City	(9) Non-City	(10) City	(11) Non-City	(12) City
Post application/referral	0.00578	0.00292			0.00194	-0.000764			-0.00546	0.00257		
	(0.00411)	(0.00264)			(0.00325)	(0.00170)			(0.00358)	(0.00319)		
Month of app/referral			-0.0132*	0.0000270			-0.0139***	-0.00284			-0.0136***	0.0314
			(0.00540)	(0.00388)			(0.00341)	(0.00153)			(0.00300)	(0.0167)
1-2 month lag			-0.00717	0.00180			-0.00581	-0.00261			-0.00693	0.00580
			(0.00815)	(0.00809)			(0.00741)	(0.00406)			(0.00550)	(0.00607)
3-4 month lag			0.0181	0.00309			0.0106	-0.00319			-0.0130***	0.00680
			(0.0160)	(0.00886)			(0.0123)	(0.00468)			(0.00304)	(0.00782)
5-6 month lag			-0.00154	0.0182			0.0135	-0.000996			-0.00500	-0.00110
			(0.0127)	(0.0119)			(0.0118)	(0.00640)			(0.00810)	(0.00548)
7-11 month lag			0.00750	-0.00167			0.000138	0.000822			-0.00782	-0.00207
			(0.00642)	(0.00509)			(0.00468)	(0.00360)			(0.00541)	(0.00312)
12-18 month lag			0.00494	0.00443			-0.00191	-0.00186			-0.00843*	-0.00199
			(0.00652)	(0.00446)			(0.00405)	(0.00184)			(0.00388)	(0.00266)
18+ month lag			0.0129*	0.00229			0.00572	0.000375			0.00177	0.00372
			(0.00643)	(0.00370)			(0.00499)	(0.00267)			(0.00684)	(0.00473)
p-value: (H_0:β_1=β_2)	0.558				0.461				0.094			
p-value: (H_0:β_1=β_2=0)	0.203				0.757				0.226			

Standard errors clustered at student level. Columns 1 and 2, 3 and 4, 5 and 6, etc. each come from the same model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=3 months prior data). 221 of these students were rehoused, 80 received some form of eviction prevention only. 143 of these students were rehoused outside of the City, 158 remained living in the City. P-values shown are for F-tests of the null hypotheses that the coefficients for the two categories of students are equivalent, and that they are both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001

Table A11 - Estimated effect of new apartment lease on attendance for rehoused students

	Monthly absence rate		Chronic absence	
	(1)	(2)	(3)	(4)
Post new apartment lease	0.040***		0.088***	
	(0.0085)		(0.019)	
Month of new lease		0.027*		0.049
		(0.012)		(0.035)
1-2 month lag		0.048***		0.10***
		(0.013)		(0.030)
3-4 month lag		0.030***		0.10***
		(0.0091)		(0.029)
5-6 month lag		0.028		0.034
		(0.015)		(0.032)
7-11 month lag		0.042***		0.11***
		(0.010)		(0.026)
12-18 month lag		0.034**		0.079**
		(0.011)		(0.027)
18+ month lag		0.049***		0.094***
		(0.014)		(0.027)
N	963461	963461	963461	963461

Standard errors clustered at student level. Each column is a different model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,005 unique student IDs. Sample of treated students is restricted to those who were rehoused and who have lease dates that appear to be accurate based on programmatic data (N= 207). Absence rates are calculated as the number of days per month a student is marked absent divided by the number of days per month for which a student has an attendance record. Chronic absence is a variable indicating a student's absence rate ≥0.10 in any given month.

* p<0.05 ** p<0.01 *** p<0.001

Table A12: Full dynamic effects of HPRP services on attendance and incidence of behavioral referrals

	Attendance measures		Behavioral measures			
	(1)	(2)	(3)	(4)	(5)	(6)
	Monthly absence rate	Chronic absence	Count of behavioral incidents	1 or more incidents	2 or more incidents	3 or more incidents
4 month lead	-0.014	-0.013	-0.019	0.011	0.0053	-0.0081***
	(0.0074)	(0.027)	(0.028)	(0.013)	(0.0088)	(0.0020)
3 month lead	-0.0020	0.010	-0.046	-0.015	-0.0075	-0.00045
	(0.0077)	(0.027)	(0.027)	(0.010)	(0.0062)	(0.0057)
2 month lead	-0.0017	0.011	0.020	-0.000091	0.0037	0.0069
	(0.0079)	(0.027)	(0.049)	(0.012)	(0.0085)	(0.0074)
1 month lead	-0.0017	0.029	0.029	0.024	0.018	0.0068
	(0.0074)	(0.027)	(0.032)	(0.015)	(0.011)	(0.0068)
Month of app/referral	-0.014	-0.023	-0.022	0.014	0.00064	-0.0080***
	(0.0075)	(0.026)	(0.020)	(0.014)	(0.0076)	(0.0018)
1-2 month lag	-0.0070	0.011	-0.033	0.0055	-0.0060	-0.0064***
	(0.0062)	(0.024)	(0.025)	(0.011)	(0.0046)	(0.0019)
3-4 month lag	-0.00037	0.0046	-0.028	0.0028	-0.011**	-0.0040
	(0.0072)	(0.025)	(0.018)	(0.0092)	(0.0034)	(0.0029)
5-6 month lag	0.028**	0.068**	-0.046*	-0.011	-0.0088	-0.0060*
	(0.0094)	(0.026)	(0.022)	(0.0090)	(0.0049)	(0.0028)
7-11 month lag	0.017*	0.046*	-0.014	0.011	-0.0041	-0.0029
	(0.0081)	(0.020)	(0.023)	(0.010)	(0.0044)	(0.0030)
12-18 month lag	0.026***	0.076***	-0.029	0.0048	-0.0069	-0.0051*
	(0.0077)	(0.022)	(0.021)	(0.0093)	(0.0036)	(0.0024)
18+ month lag	0.040***	0.087***	-0.024	0.0050	-0.0037	-0.0044*
	(0.010)	(0.021)	(0.020)	(0.011)	(0.0040)	(0.0021)
Observations	966,947	966,947	966,947	966,947	966,947	966,947
R^2	0.33	0.27	0.21	0.22	0.18	0.14

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student IDs. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data).

* p<0.05 ** p<0.01 *** p<0.001

Table A13 - Estimated effect of HPRP services on attendance and incidence of behavioral referrals, fully balanced panel

	Attendance measures				Behavioral measures					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Monthly absence rate		Chronic absence		1 or more behavioral incidents		2 or more behavioral incidents		3 or more behavioral incidents	
Post application/referral	0.017**		0.054**		0.0093		-0.0037		-0.0050*	
	(0.0062)		(0.019)		(0.0085)		(0.0034)		(0.0023)	
Month of app/referral		-0.014*		-0.079*		0.022		0.0030		-0.0090***
		(0.0060)		(0.035)		(0.021)		(0.014)		(0.0025)
1-2 month lag		-0.0064		0.023		0.0034		-0.0023		-0.0062***
		(0.0045)		(0.033)		(0.016)		(0.0071)		(0.0017)
3-4 month lag		0.0027		0.011		-0.0050		-0.018***		-0.0085**
		(0.0063)		(0.029)		(0.013)		(0.0047)		(0.0028)
5-6 month lag		0.026*		0.038		-0.011		-0.0074		-0.0100***
		(0.011)		(0.035)		(0.016)		(0.0087)		(0.0028)
7-11 month lag		0.012		0.028		0.012		-0.0026		-0.0015
		(0.0079)		(0.024)		(0.014)		(0.0068)		(0.0050)
12-18 month lag		0.023**		0.077**		0.013		-0.0055		-0.0065*
		(0.0079)		(0.028)		(0.013)		(0.0051)		(0.0030)
18+ month lag		0.027*		0.086**		0.012		-0.0010		-0.0039
		(0.011)		(0.026)		(0.014)		(0.0048)		(0.0025)
N	561,765	561,765	561,765	561,765	561,765	561,765	561,765	561,765	561,765	561,765

Standard errors clustered at student level. Dataset covers five school years (2013-14 through 2017-18) of data on 11,513 unique student IDs who are represented across all 51 instructional months.108 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have≥3 months prior data).
* p<0.05 ** p<0.01 *** p<0.001

Table A14 - Effect of HPRP services on incidence of behavioral referrals by service type and location of new home

	1 or more referrals				2 or more referrals				3 or more referrals			
Panel A: By service type												
	(1) Rehoused	(2) Non-rehoused	(3) Rehoused	(4) Non-rehoused	(1) Rehoused	(2) Non-rehoused	(3) Rehoused	(4) Non-rehoused	(7) Rehoused	(8) Non-rehoused	(9) Rehoused	(10) Non-rehoused
Post application/referral	0.0083	-0.0049			-0.0067*	-0.0061			-0.0059**	-0.0034		
	(0.0072)	(0.0094)			(0.0028)	(0.0043)			(0.0019)	(0.0032)		
Month of app/referral			-0.00070	0.051			-0.0040	0.0087			-0.0084***	-0.0089**
			(0.014)	(0.031)			(0.0065)	(0.019)			(0.0021)	(0.0033)
1-2 month lag			0.0094	-0.0083			-0.011**	0.0030			-0.0074***	-0.0055*
			(0.011)	(0.021)			(0.0035)	(0.012)			(0.0022)	(0.0022)
3-4 month lag			0.010	-0.017			-0.0085	-0.020***			-0.0030	-0.0079*
			(0.010)	(0.017)			(0.0044)	(0.0059)			(0.0039)	(0.0037)
5-6 month lag			-0.0058	-0.028			-0.0054	-0.021***			-0.0052	-0.0095**
			(0.0099)	(0.019)			(0.0059)	(0.0063)			(0.0039)	(0.0036)
7-11 month lag			0.012	0.0077			-0.0064	-0.0027			-0.0056*	0.0015
			(0.011)	(0.020)			(0.0039)	(0.0089)			(0.0026)	(0.0072)
12-18 month lag			0.015	-0.021			-0.0087*	-0.0064			-0.0071**	-0.0020
			(0.011)	(0.013)			(0.0039)	(0.0070)			(0.0024)	(0.0053)
18+ month lag			0.0065	-0.0018			-0.0047	-0.0055			-0.0053*	-0.0040
			(0.013)	(0.014)			(0.0046)	(0.0047)			(0.0025)	(0.0025)
p-value: (H_0:β_1=β_2)	0.264				0.907				0.504			
p-value: (H_0:β_1=β_2=0)	0.450				0.023				0.005			
Panel B: By new home location												
	1 or more referrals				2 or more referrals				3 or more referrals			
	(1) Non-City	(2) City	(3) Non-City	(4) City	(1) Non-City	(2) City	(3) Non-City	(4) City	(7) Non-City	(8) City	(9) Non-City	(10) City
Post application/referral	0.011	-0.00082			-0.0081*	-0.0054			-0.0073*	-0.0035		
	(0.0098)	(0.0070)			(0.0040)	(0.0029)			(0.0029)	(0.0019)		
Month of app/referral			-0.0050	0.029			-0.0019	0.00047			-0.0057**	-0.0064***
			(0.018)	(0.018)			(0.0097)	(0.0099)			(0.0018)	(0.0019)
1-2 month lag			0.012	-0.0016			-0.013*	-0.0027			-0.0039*	-0.0046**
			(0.017)	(0.012)			(0.0056)	(0.0060)			(0.0018)	(0.0014)
3-4 month lag			0.021	-0.012			-0.011	-0.013***			-0.0046*	-0.0053*
			(0.016)	(0.010)			(0.0074)	(0.0034)			(0.0018)	(0.0021)
5-6 month lag			-0.0061	-0.018			-0.0038	-0.015***			-0.0064***	-0.0070**
			(0.014)	(0.012)			(0.0090)	(0.0038)			(0.0018)	(0.0021)
7-11 month lag			0.011	0.0098			-0.0086	-0.0031			0.00056	-0.000098
			(0.015)	(0.013)			(0.0060)	(0.0051)			(0.0043)	(0.0041)
12-18 month lag			0.011	-0.0026			-0.013*	-0.0047			-0.0012	-0.0019
			(0.016)	(0.0096)			(0.0057)	(0.0044)			(0.0033)	(0.0032)
18+ month lag			0.016	-0.0049			-0.0051	-0.0047			-0.0045*	-0.0052**
			(0.015)	(0.014)			(0.0064)	(0.0042)			(0.0022)	(0.0019)
p-value: (H_0:β_1=β_2)	0.337				0.571				0.268			
p-value: (H_0:β_1=β_2=0)	0.547				0.023				0.008			

Standard errors clustered at student level. Columns 1 and 2, 3 and 4, 5 and 6, etc. each come from the same model. All models contain student, month, and grade fixed effects. Dataset covers five school years (2013-14 through 2017-18) of data on 24,099 unique student ID numbers. 301 students received homelessness prevention services and were stably enrolled in USD prior to application/referral (i.e. have >=6 months prior data). 221 of these students were rehoused, 80 received some form of eviction prevention only. 143 of these students were rehoused outside of the City, 158 remained living in the City. P-values shown are for F-tests of the null hypotheses that the coefficients for rehoused and non-rehoused students are equivalent, and that they are both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001

APPENDIX B: Additional Sample Restrictions

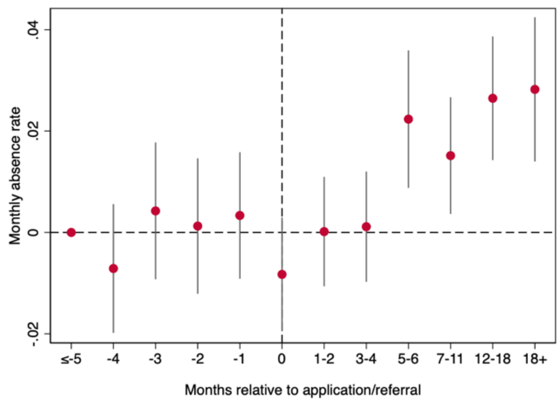
It is possible that students whose families are rehoused in cities outside the City but continue to have attendance records in USD schools are technically enrolled in the City's school system, even if they effectively no longer attend school there. If this were the case, and if this were more likely to be true for households who move further away from the city proper, it would threaten the internal validity of this study. To ensure that my findings—particularly with regard to attendance— are robust to this possibility, I estimate supplemental models where I implement increasingly strict sample restrictions that would exclude any observations for students who are technically enrolled in USD but no longer actually coming to class.

For Sample Restriction #1, I drop all students from the analytic sample who have more than one month with an absence rate of 100 percent. Using the primary analytic sample as the basis for these restrictions, this results in dropping 390 students from the sample, 12 of whom are treated students. I additionally drop all student-month observations where the absence rate is greater than or equal to 75 percent. Sample Restriction #2 again drops all students who have more than one month with a 100 percent absence rate, and drops all student-month observations where the absence rate is greater than or equal to 50 percent. Sample Restriction #3 is the same as #2, but additionally drops any treated students who have *any* months with 100 percent absence rates post intake to the HPRP (n=13).

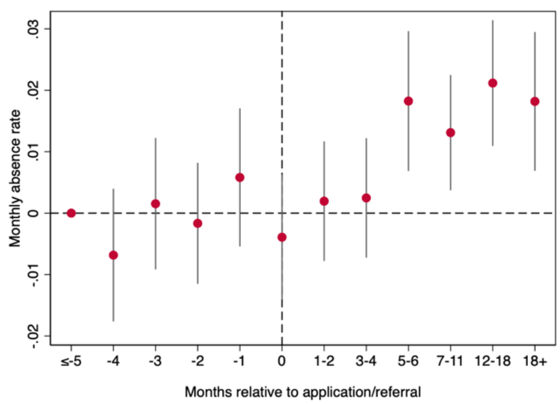
The results for these supplemental models where the outcomes are absence rates are shown in Figure B1; regression results are shown in Table B1. The results for heterogeneous models that estimate separate treatment effects for students based on the location of their new housing are shown in Figure B2 and Table B2. Across all three restricted samples, the general patterns of increased student absence hold and are consistent with findings using the primary analytic sample. It is worth noting that with the sample restrictions, particularly # 2 and #3, the dynamic point estimates for students who are rehoused more than 30 miles from the City have lower magnitude and less statistical significance. However, there remains suggestive evidence that absence rates grow more for students moving further away and strong evidence that, overall, the reduction in attendance is seen primarily among students rehoused outside the City.

Figure B1 – Estimated dynamic effects of HPRP services on student attendance: Additional sample restrictions

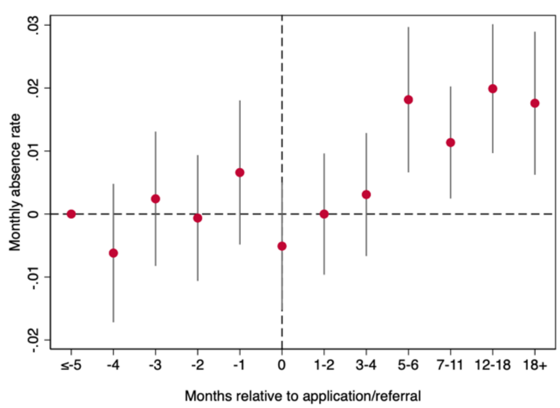
A. Sample restriction #1: Drops students having more than one monthly absence rate equaling 1.0 and drops student-month observations if absence rate≥ 0.75



B. Sample restriction #2: Drops students having more than one monthly absence rate equaling 1.0 and drops student-month observations if absence rate≥ 0.50



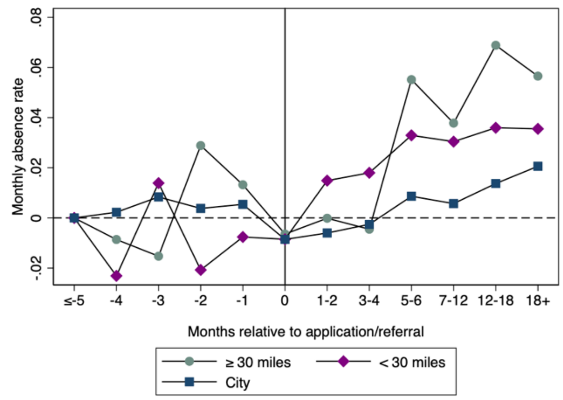
C. Sample restriction #3: Same as restriction #2, additionally drops all treated students with any monthly absence rates equaling 1.0 post-intake



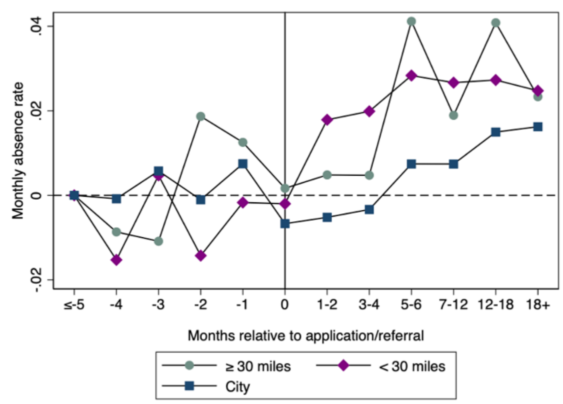
Notes: Sample restrictions made relative to primary analytic sample. All models include student, month-year, and grade fixed effects.

Figure B2 – Estimated dynamic effects of HPRP services on student attendance by location of new housing: Additional sample restrictions

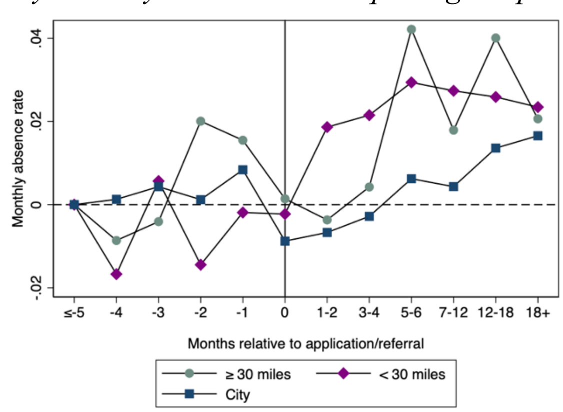
A. Sample restriction #1: Drops students having more than one monthly absence rate equaling 1.0 and drops student-month observations if absence rate≥ 0.75



B. Sample restriction #2: Drops students having more than one monthly absence rate equaling 1.0 and drops student-month observations if absence rate≥ 0.50



C. Sample restriction #3: Same as restriction #2, additionally drops all treated students with any monthly absence rates equaling 1.0 post-intake



Notes: Sample restrictions made relative to primary analytic sample. All models include student, month-year, and grade fixed effects.

Table B1 - Effect of HPRP services on monthly absence rates: Additional sample restrictions

	Monthly absence rate: Sample restriction #1		Monthly absence rate: Sample restriction #2		Monthly absence rate: Sample restriction #3	
	(1)	(2)	(3)	(4)	(5)	(6)
Post application/referral	0.018***		0.014***		0.013***	
	(0.0042)		(0.0035)		(0.0034)	
Month of app/referral		-0.0090		-0.0043		-0.0057
		(0.0052)		(0.0048)		(0.0047)
1-2 month lag		0.00075		0.0027		0.00061
		(0.0052)		(0.0048)		(0.0047)
3-4 month lag		0.0015		0.0032		0.0036
		(0.0055)		(0.0049)		(0.0049)
5-6 month lag		0.023***		0.018**		0.018**
		(0.0067)		(0.0057)		(0.0058)
7-11 month lag		0.015**		0.013**		0.011**
		(0.0056)		(0.0046)		(0.0043)
12-18 month lag		0.026***		0.021***		0.020***
		(0.0060)		(0.0051)		(0.0051)
18+ month lag		0.030***		0.019***		0.018**
		(0.0070)		(0.0057)		(0.0057)
N	948,590	948,590	941,742	941,742	941,411	941,411
R^2	0.31	0.31	0.31	0.31	0.31	0.31

Standard errors clustered at student level. Absence rates are calculated as the number of days per month a student is marked absent divided by the number of days per month for which a student has an attendance record. Sample restriction #1 drops all students who have more than one month where absence rate is 1.0 and drops all student-month observations where the absence rate ≥0.75. Sample restriction #2 drops all students who have more than one month where absence rate is 1.0 and drops all student-month observations where the absence rate ≥0.50. Sample restriction #3 is the same as #2, but additionally drops all treated students who have 1 or more months post-intake with an absence rate of 1.0.

* p<0.05 ** p<0.01 *** p<0.001

Table B2 - Effect of HPRP services on monthly absence rates by location of new home: Additional sample restrictions

	Monthly absence rate: Sample restriction #1						Monthly absence rate: Sample restriction #2						Monthly absence rate: Sample restriction #3					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(7)	(8)	(9)	(10)	(11)	(12)
	SF	< 30 miles	≥ 30 miles	SF	< 30 miles	≥ 30 miles	SF	< 30 miles	≥ 30 miles	SF	< 30 miles	≥ 30 miles	SF	< 30 miles	≥ 30 miles	SF	< 30 miles	≥ 30 miles
Post application/referral	0.0086	0.031***	0.037*				0.0084	0.025***	0.020				0.0071	0.025***	0.017			
	(0.0049)	(0.0077)	(0.015)				(0.0043)	(0.0066)	(0.011)				(0.0042)	(0.0066)	(0.011)			
Month of app/referral				-0.0094	-0.0062	-0.0081				-0.0071	-0.00029	0.00053				-0.0094	-0.00050	-0.00054
				(0.0070)	(0.0089)	(0.014)				(0.0063)	(0.0086)	(0.013)				(0.0060)	(0.0087)	(0.013)
1-2 month lag				-0.0069	0.017	-0.0019				-0.0056	0.020	0.0036				-0.0073	0.020*	-0.0057
				(0.0055)	(0.010)	(0.018)				(0.0050)	(0.010)	(0.016)				(0.0048)	(0.010)	(0.016)
3-4 month lag				-0.0034	0.020	-0.0061				-0.0038	0.022	0.0037				-0.0034	0.023*	0.0023
				(0.0065)	(0.013)	(0.014)				(0.0055)	(0.011)	(0.014)				(0.0054)	(0.011)	(0.014)
5-6 month lag				0.0078	0.035**	0.054*				0.0070	0.030**	0.040*				0.0056	0.031**	0.040*
				(0.0076)	(0.013)	(0.022)				(0.0070)	(0.011)	(0.016)				(0.0070)	(0.012)	(0.016)
7-11 month lag				0.0049	0.033**	0.037				0.0070	0.028**	0.018				0.0037	0.029**	0.016
				(0.0062)	(0.011)	(0.023)				(0.0053)	(0.010)	(0.015)				(0.0045)	(0.010)	(0.016)
12-18 month lag				0.013*	0.038**	0.068**				0.015*	0.029**	0.040*				0.013*	0.028**	0.039
				(0.0064)	(0.013)	(0.023)				(0.0058)	(0.010)	(0.020)				(0.0058)	(0.010)	(0.020)
18+ month lag				0.020*	0.038**	0.056*				0.016*	0.027*	0.023				0.016*	0.025*	0.019
				(0.0086)	(0.012)	(0.024)				(0.0073)	(0.010)	(0.017)				(0.0074)	(0.010)	(0.017)
p-value: (H_0:β_1=β_2=β_3)		0.019						0.088						0.071				
p-value: (H_0:β_1=β_2=β_3=0)		0.000						0.000						0.000				

Standard errors clustered at student level. Columns 1, 2, and 3; 4, 5 and 6; 7, 8, and 9, etc. each come from the same model. All models contain student, month, and grade fixed effects. Sample restriction #1 drops all students who have more than one month where absence rate is 1.0 and drops all student-month observations where the absence rate ≥0.75. Sample restriction #2 drops all students who have more than one month where absence rate is 1.0 and drops all student-month observations where the absence rate ≥0.50. Sample restriction #3 is the same as #2, but additionally drops all treated students who have 1 or more months post-intake with an absence rate of 1.0. P-values shown are for F-tests of the null hypotheses that the coefficients for all three categories of students (SF, <30 miles, ≥30 miles) are equivalent, and that they are all both equal to each other and to zero.

* p<0.05 ** p<0.01 *** p<0.001