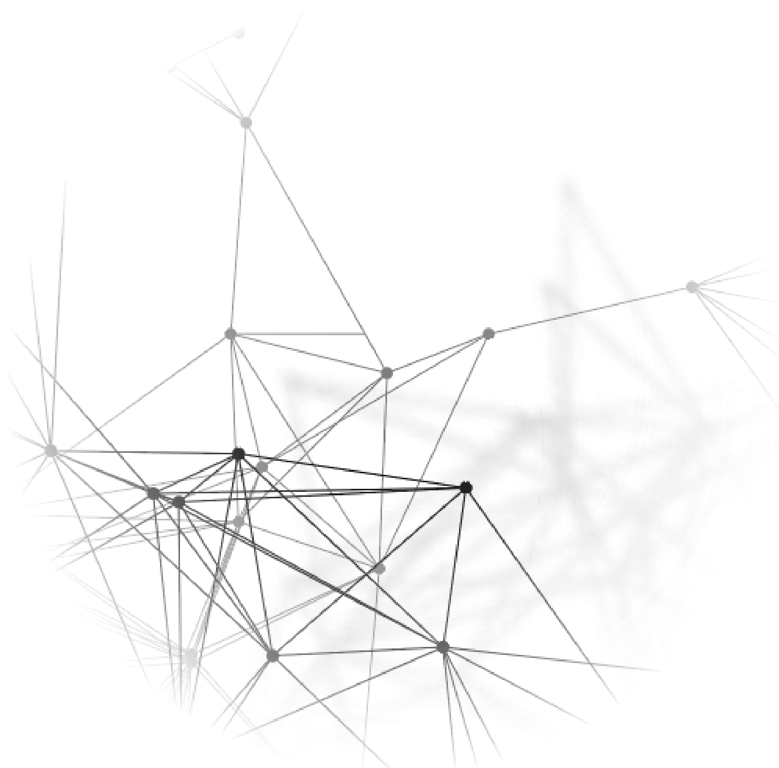
JULY 2023

HOMELESS PREVENTION: AT-RISK STUDENTS IN NEW YORK CITY SCHOOLS

The City of New York
Mayor Eric Adams

Center for Innovation through Data Intelligence



THE CENTER FOR INNOVATION THROUGH DATA INTELLIGENCE (CIDI)

MAKING DATA COME ALIVE TO INSPIRE CHANGE

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Acknowledgments

CIDI would like to thank Mayor Eric Adams, First Deputy Mayor Sheena Wright, Deputy Mayor for Health and Human Services Anne Williams Isom, and Deputy Mayor for Strategic Initiatives Ana Almanzar for their support of CIDI and this project. We would also like to thank the New York City agencies that provided data and insight for this project: NYC Schools, NYC Department of Youth and Community Development, NYC City Department of Social Services (Department of Homeless Services and Human Resources Administration). We would also like to thank our partners at the University of Pennsylvania, Dennis Culhane and Antoine Lovell. We would like to acknowledge key CIDI and city staff including Jessica Sell, Oliver Ponce, Nebahat Noyan, Eileen Johns, Michelle Paladino, Ben Cosman, Ellen Levine, Kinsey Dinan, Karl Snyder, Jessica Raithel, Dana Laventure and Sara Workman.

Finally, we would like to thank the generous funding from the Trinity Foundation for this project and for their commitment to preventing homelessness among students, youth, and families.

With gratitude,

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1 SUMMARY

In the 2021-2022 school year, more than 104,000, or 1 out of 10 students resided in temporary housing (New York City Department of Education, 2022). Most of these students' families lived doubled up with another family, while nearly one third resided in shelter. Students in such circumstances face enormous challenges to learning, contributing to a vicious cycle of poverty, homelessness, and educational underattainment which can be devastating to students and their families.

New York City has implemented a multifaceted response to support those at risk of homelessness. Specifically, the Department of the Human Resources Administration and Social Services (HRA/DSS) operates homeless prevention programs that provide services to households identified as at-risk and who, without an intervention, might experience homelessness. Despite providing services to many families at risk of homelessness and preventing homelessness, the risk pool is often so large that most families with risk factors for homelessness never enter shelter or ever experience homelessness. This situation makes identifying families who will become homeless in the absence of an intervention critically important.

This report presents findings from research designed to identify risk factors and produce a new predictive model to help school staff identify students at the highest risk of imminent homelessness. The report starts by summarizing prior efforts to target homelessness prevention programs. Then, the report describes factors that are known to be associated with student homelessness. After this background, the report describes the methods, key findings, and implications of the analysis. The Center for Innovation through Data Intelligence (CIDI) conducted the study in collaboration with partners at the University of Pennsylvania.

TARGETING HOMELESSNESS PREVENTION RESOURCES

Numerous programs aim to keep New York City's residents stably housed. These include the nation's largest public housing authority, tax subsidies that promote affordable housing, rent vouchers, childcare subsidies and other community based and financial assistance programs. The City's flagship program aimed at preventing homelessness is called Homebase, which provides a suite of services tailored to address the specific circumstances of program participants. A partial list of these services includes legal assistance to prevent eviction, help obtaining public benefits, emergency rental assistance, financial counseling, and other short-term financial assistance.

Rigorous studies support the Homebase approach. In the first four years of Homebase (2004-2008), family shelter entries decreased markedly in neighborhoods in which Homebase operated, preventing an estimated 1,700 shelter entries (Goodman, Messeri, & O'Flaherty, 2016). Other experimental and quasi-experimental evaluations support the efficacy of providing customized services to families at imminent risk of homelessness (Shinn, Greer, Bainbridge, Kwon, & Zuiderveen, 2013). Like many homelessness prevention programs, however, there are more families at risk than Homebase can serve.

To provide services to those most likely to become homeless in the absence of an intervention, the NYC Department of Social Services developed a predictive model to generate risk scores for Homebase applicants based on assessment data. This Risk Assessment Questionnaire (RAQ) provides a score that is associated with the risk of entering shelter (Shinn, Greer, Bainbridge, Kwon, & Zuiderveen, 2013). Recent analyses by the NYC Department of Homeless Services confirmed the value of using the predictive model and recommended further analysis to improve the model's accuracy (Mullen et. al, 2022). Though the model's "hit rate" —the percentage of families identified as at ‘elevated risk of homelessness’ that become homeless—is very low, even marginal improvements in targeting services improves the efficacy and efficiency of the intervention.

Further analysis of the Risk Assessment Questionnaire (RAQ) implemented by Homebase resulted in identifying predominant risk factors associated with different combinations of risk. The groups with the highest rate of shelter entry included the combination of risk factors associated with moving residences frequently, having a high rate of childhood trauma, and experiences with other institutions and shelter. Nevertheless, even among these highest risk groups there are many who do not enter shelter (Farrell, et.al.,2023).

CIDI developed the present study to develop a model to identify York City students at risk of homelessness. While the individual and structural risk factors of homelessness are well known, there is little research that identifies the warning signs that predict homelessness for school-age children (Rog, D.J. & Buckner, J.C., 2007). The aims of preventing student homelessness overlap with those of preventing family homelessness but have some distinct characteristics. While Homebase focuses on families at imminent risk of homelessness, an intervention for students is most effective if it starts further upstream to prevent the instability that inhibits learning and educational success.

Developing a model focused on student homelessness has many advantages. School staff spend more time with students than most other adults, providing many opportunities to develop supportive relationships. School staff are already tasked with supporting students’ physical and emotional well-being. Moreover, seeking help from school staff bears less stigma than seeking assistance from social services agencies. Critically, providing school staff with the tools to connect students at risk of homelessness with prevention services advances the New York City Department of Education’s educational mission, as students in the shelter system face overwhelming obstacles to learning.

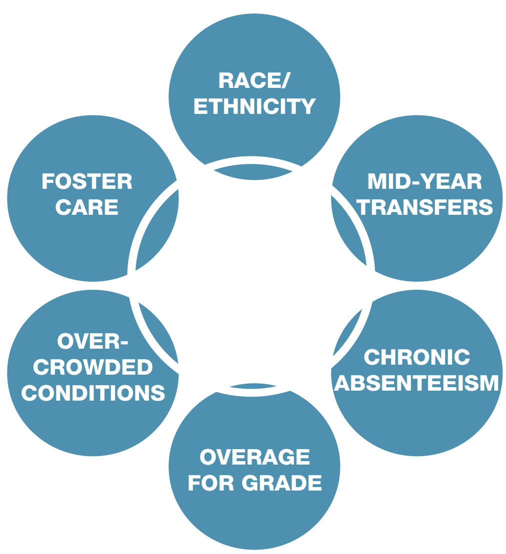
THE INTERSECTION OF SCHOOLS AND HOMELESS

Homelessness is usually preceded by a long period during which families teeter on the brink of losing housing, employment, education, and the support of family and friends. Previous studies have identified several risk factors associated with homelessness among students. These include:

- Non-Hispanic Black Race/Ethnicity
- Mid-year Transfers
- Chronic Absenteeism
- Being overage for a grade
- Living in overcrowded conditions
- Experiencing foster care

These risk factors are discussed individually below, but readers should understand the pervasive intersectionality in their association with homelessness. Students entering foster care, for example, are more likely to experience a mid-year school transfer than other students, more likely to be chronically absent from school, and are disproportionately Black/African American.

INTERSECTIONALITY OF RISK FACTORS



RACE/ETHNICITY

While Black people make up approximately 13% of the U.S. population, they make up over 40% of people experiencing homelessness (Jones, 2016; Lee, Shinn, & Culhane, 2021; Olivet, et al., 2021). The legacy of slavery, defined by its brutality, cruelty and hatred, has resulted in ongoing discrimination and sytemic racism which drive racial disparities in the homeless population (Fowle, 2022). Inequitable access to employment, education, healthcare, and quality housing make Black Americans more susceptible to housing instability and homelessness (Aitken, 2022; Willse, 2010; Fowle, 2022). Furthermore, daily exposure to racism impacts a person's mental and physical health, compounding the negative effect that homelessness has on a person's health (Williams, 2019; Bourabain & Verhaeghe, 2021). The intersectionality of race and other risk factors for homelessness places Black families at an ever-greater risk of homelessness.

MID-YEAR TRANSFERS

Shah, et.al (2017) found that youth who had experienced four or more school moves within two years prior to exiting school were more likely to become homeless post-exit than their counterparts who had fewer than two school moves. Students who transfer schools mid-year due to housing instability have poor academic performance (Alexander, Entwisle, & Olson, 2001). Diminished learning may occur due to difficulty in adjustment to a new curriculum, a new social environment, or underlying family challenges that led to the mid-year transfer (Julianelle & Foscarinis, 2003). Mid-year transfers are particularly detrimental to elementary-school-aged children as they are in a critical period of personal development (Alexander, Entwisle, & Olson, 2001).

CHRONIC ABSENTEEISM

Chronic absenteeism is associated with experiences of future homelessness, as it is often associated with housing instability. Though there are many causes, in some cases absenteeism occurs due to landlord-tenant issues, pending evictions, and poor health either by the head-of-household or the child (Allison, et al., 2019; Todres & Meeler, 2021). Absenteeism also disrupts educational progress, impeding a homeless student's pathway out of poverty. Homeless students experience higher rates of absenteeism than stably housed students (Bassuk & Rubin, 1987; Allison, et al., 2019).

OVERAGE FOR GRADE

Grade retention occurs when children are required to repeat a grade level because they failed to meet required benchmarks. Grade retention is the primary cause of students being overage for their grade. Students who are overage for their grade are at an increased risk of dropping out of school (Roderick, 1994; Garcia, et al., 2017) and therefore have poorer economic outcomes as adults due to limited options in the labor market. The relationship between homelessness and being overage is bidirectional: students that experience grade retention often live in families that have multiple stresses that undermine educational performance and housing stability. Should students become homeless, they face the additional obstacle that attitudes regarding the cognitive capabilities of homeless students can lead to grade retention (Masten & Coatsworth, 1998). Black students are more likely to overstay their grade while also being more likely to experience homelessness (Gamoran, 2001).

STUDENTS LIVING IN OVERCROWDED CONDITIONS

Students whose families are in overcrowded conditions with another family have particularly fragile living situations. Many families move in with relatives or friends, when possible, to avoid becoming homeless or to stretch their incomes to cover other needs. It is no surprise, then, that crowded housing is most common among low-income families (Lopoo & London, 2016). Children living in overcrowded households are also less likely to graduate from high school and tend to have lower educational attainment at age 25 (Lopoo & London, 2016), which facilitates pathways to future homelessness.

EXPERIENCING FOSTER CARE

Child-welfare involvement and foster-care placement correlate strongly with poverty, a lack of material supports, and social isolation, and are associated with future homelessness (Ehrle & Geen, 2002; Walsh, 2004; Font, Berger, Slepicka, & Cancan, 2021). Foster care itself is an adverse childhood experience and can lead to more school moves, behavioral difficulties, and poor educational outcomes, which all are associated with future homelessness (Shah, et al., 2017). Placement in congregate care (as opposed to family-based care) exacerbates these effects. Black youth are more likely to experience foster care, more likely to be placed into congregate care, and have longer stays in care. This prolonged trauma increases the odds of future homeless, as groups that are exposed to prolonged trauma often face housing insecurity and homelessness (Panter-Brick, Grimon, Kalin, & Eggerman, 2015; Riebschleger, Day, & Damashek, 2015).

STUDY OBJECTIVES AND METHOD

This study describes student homelessness in New York City, identifies risk factors for students who might experience homelessness in the subsequent academic year, and explores the development of a model to predict student homelessness in the following academic year. The study uses a unique dataset compiled for this project, which for the first time integrates administrative data from the Department of Education (DOE), the Administration for Children's Services (ACS), the Department of Youth and Community Development (DYCD) and the Department of Homeless Services (DHS). The dataset includes students who had not previously experienced homelessness and who had been enrolled in a DOE school between the 2011-12 and 2020-21 academic years.

METHOD

Researchers produced a myriad of descriptive analyses to understand association with the onset of student homelessness in the following academic year. The descriptive analyses examined student homelessness by age, race/ethnicity, and other characteristics. The research team built and evaluated a multivariate logistic regression model aimed at identifying the factors associated with the onset of initial homelessness in the following school year.

FINDINGS

The analysis produced several important findings. Critically, the analysis found that only 0.3% of students became homeless for the first time in any given academic year. The data indicates that once students become homeless, they stay in the shelter system for extended periods and are at high risk of re-entry. This finding amplifies the importance of developing a predictive model, as delivering prevention services to all students in the elevated risk group is neither affordable nor necessary and the benefits of reducing housing instability and homelessness are enormous.

As expected, each of the risk factors described above were associated with a greater risk of the onset of student homelessness. The study also produced additional risk factors, including attending high school in districts 75 (special education) or 79 (alternative schools), being a high school student with an individualized education plan (IEP), having ever participated in any ACS prevention services, and attending a school in the Bronx, regardless of race/ethnicity. Readers should note that these factors are associated with but not the cause of future homelessness.

The predictive model is robust statistically and can be used to estimate the relative likelihood of students becoming homeless for the first time in a succeeding school year. However, the model identifies such a large pool of at-risk students that targeted intervention among this group would be costly and inefficient. Several findings from this analysis stand out and are listed below:

RACE/ETHNICITY

Compared to white students, Black students with no prior experience of homelessness were 7.7 times as likely to become homeless in the following academic year, although their absolute risk level remains low at less than 1 percent. The risk for Hispanic students was four times that of White students, while Asian students were slightly less likely than White students to become homeless in the following school year.

ACS PREVENTION SERVICES

Students from families that had received ACS prevention services had a 50 percent greater chance of entering shelter than those that had not received such services. ACS prevention services are designed to support families, many of them in or near a crisis, with case management, counseling, family thera-py, access to critical services such as drug treatment and mental health care; concrete benefits, and other services that can help prevent deeper involvement in the child welfare and juvenile justice sys-tems. They are not specifically designed to address housing instability.

SCHOOL BOROUGH

Students attending school in Staten Island were the least likely to become homeless in the following year. Compared to students in Staten Island, those in the Bronx were more than twice as likely to become homeless in the following year. The risk is also higher among students in Manhattan and Brooklyn than in Queens. Students attending schools in the Bronx were at an increased risk of experiencing homelessness, regardless of their race or ethnicity.

TEMPORARY HOUSING

Students who experience doubled-up living arrangements are more than twice as likely to become homeless in the following year compared to those that were stably housed, although fewer than 1% of doubled-up students became homeless the following year.

IMPLICATIONS

Preventing student homelessness advances the well-being of students and their families, the educational mission of the NYC DOE, and saves countless dollars. Findings from this study can be used to target services more efficiently and divert students and their families from entering the shelter system. Further research may improve the model's hit rate, providing more benefits to New York City's residents and to the city coffers.

2 STUDY OBJECTIVES AND DEFINITIONS

KEY OBJECTIVES

The three key objectives of this study were to:

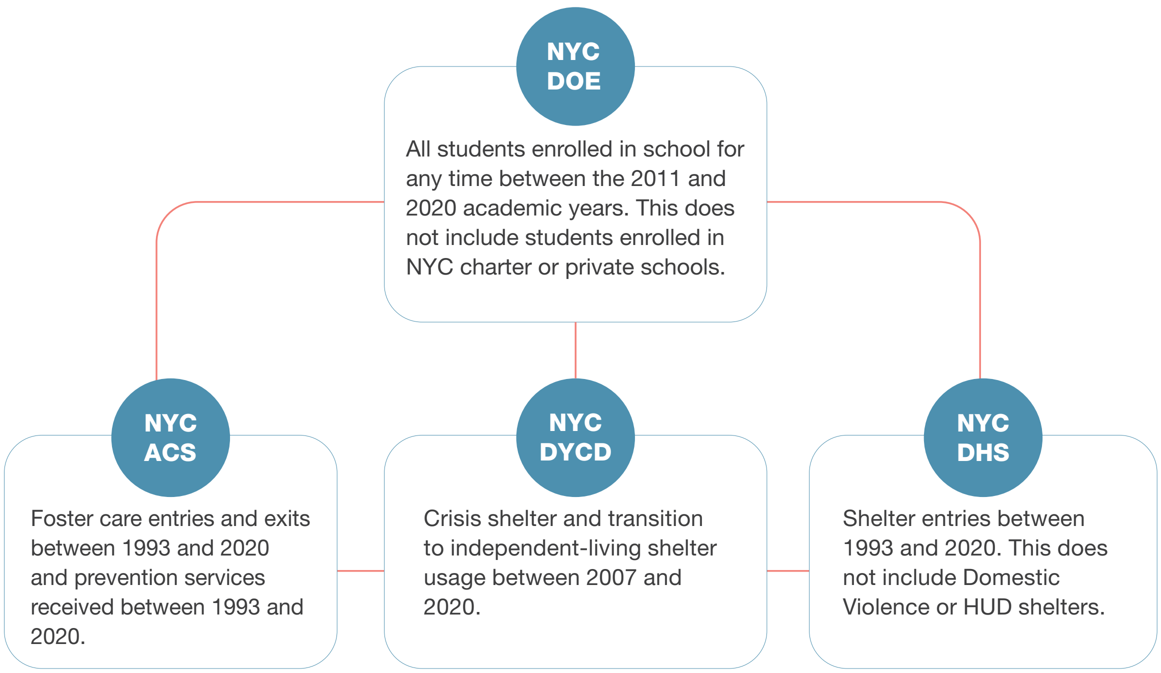
Describe student homelessness in New York City

Identify risk factors for students who might experience homelessness in the following academic year

Predict student homelessness in the following academic year

POPULATION

This study integrates data from four New York City (NYC) sources, NYC Department of Education (NYC DOE), NYC Administration of Child Services (NYC ACS), New York City Department of Youth and Community Development (NYC DYCD), New York City Department of Homeless Services (NYC DHS).



The universe of DOE students was matched to all ACS, DYCD, and DHS records to obtain a full picture of each student's history of homelessness, educational involvement, foster care, and prevention service usage.

We limited the analysis to students enrolled in DOE no earlier than the 2011-2012 academic year, which is the year that the Students in Temporary Housing indicator became consistently available in DOE data. The final dataset for analysis included one observation per student per academic year.

KEY DEFINITIONS

We used the definitions that the four NYC agencies supplied to classify students included in this study.

DOE

Age: Student's age at the start of the academic year.

Sex: Binary sex of student.

Race/Ethnicity: The race and/or ethnicity of the student. Categories are White, Black, Hispanic, or Asian/Other and are mutually exclusive of one another.

School Borough: NYC borough of the school attended for the most days that school year. This is not always the same borough as the student's residence, especially in middle and high school when students often attend schools outside their district and borough.

District Type: If the school was in a geographic district or in districts 75 or 79, which are meant for special education and alternatives school students, respectively.

School Level: Elementary (grades Pre-K-5th), Middle (grades 6th-8th), and High (grades 9th-12th).

Overage: This calculated measure indicates whether a student is two or more years older than the typical age at the beginning of a school year. For example, a student entering 3rd grade is 8, or turning 8 before December 31st. A student would be considered overage if the student was 10 years old at the start of the school year.

Chronic Absenteeism: Students who missed 10% or more of the days in the academic year. Due to the COVID-19 pandemic, attendance in the 2019-2020 school year is captured through March 13, 2020, the last full day of in-person school that year. Students returned to a mixture of in-person, hybrid, and remote school in the 2020-2021 school year.

English Language Learner Status: A DOE indicator that classifies students as English language learners (ELL).

DOE
(Cont'd)

Individualized Education Plan: The presence/absence of a written statement that describes efforts to address a disability that may interfere with an individual's learning.

Student in Temporary Housing (STH) Indicator: TThe NYC Department of Education captures student housing status using housing questionnaires completed by families and data exchange with Department of Homeless Services. A student who lives in any of the following situations is considered in temporary housing: overcrowded conditions, shelter, hotel or motel, car, bus, train, park, public space, or abandoned building. Any unaccompanied youth, without a regular adequate nighttime residence is also considered in temporary housing (New York City Department of Education, 2022). The STH flag describes a student's housing status at the beginning of the school year. This information is self-reported by the student's family and updated yearly or when a student's living situation changes.

School Transfers: They occur when a student formally changes enrollment in a school. Transfer types include:

- Non-promotional end-of-year transfers include school moves at the end of the school year that are not at the end of 5th or 8th grade.
- Mid-Year transfers occur before the end of a school year.
- Other transfers and discharges.

ACS

Foster Care Experience: If a student is or was in any of three foster care placements: residential care, family foster care, or kinship foster care. The categories are not mutually exclusive.

Prevention Services: If a student currently or previously participated in any of the following types of prevention services offered by ACS:

- Family Treatment and Rehabilitation. Supports families whose children are at risk of foster care placement by addressing safety and well-being challenges arising out of mental health and/or substance abuse by children and/or caregivers.
- Family Therapies. Various types of therapy to address the needs of children and families.
- Generalized Prevention Services. Programs with both supportive and concrete services in communities.
- Juvenile Programs. Programs designed to prevent youth from getting involved in the juvenile justice system.

DYCD

Shelter Utilization: If a student has resided in a DYCD-run shelter in the past, present, or in the following academic year. These include Transition to Independent Living (TIL) shelters and Crisis shelters.

DHS

Shelter Utilization: If a student has resided in a DHS shelter in the past, present, or in the following academic year. This includes Family with Children, Single Adult, and Adult Family shelters.

3 METHODS

DESCRIPTIVE ANALYSIS

A descriptive analysis was undertaken to better understand the characteristics of the students in this study. The following characteristics are all examined.

- Student Demographics
- Educational Factors
- Foster Care Experiences
- Participation in ACS Prevention Programs
- History of DHS Homelessness
- History of DYCD Homelessness

Homelessness disproportionately affects Black people. We therefore stratified all analyses by race/ethnicity to better understand other factors within each race/ethnicity that may contribute to student homelessness,

Similarly, homelessness may present differently depending on the student's age or grade; therefore, all analyses are stratified by school level (elementary, middle, and high school).

STUDENT RISK FACTORS OF HOMELESSNESS

SAMPLE

All NYC students enrolled between 2011 and 2019, who had not previously experienced homelessness.
There is one observation per student per academic year.

MODEL

We used logistic regression, clustered by student, to identify risk factors for student homelessness in the following academic year. Logistic regression produces an odds ratio for an outcome while controlling for multiple other variables. Our fully adjusted model provides the impact of each variable on the odds ratio of experiencing homelessness in the following academic year. The value of the odds ratio determines how much a variable is a risk factor for homelessness.

OUTCOMES

All models predicted whether the student would experience the following types of homelessness in the following academic year (2012 – 2020):

- Any Department of Homeless Services (DHS) or Department of Youth and Community Development (DYCD).
- DYCD Crisis or Transition to Independent Living (TIL) shelter. *Restricted to students currently aged 16 years or older.*

PREDICTORS

DOE variables included in the model were age, sex, race/ethnicity, school borough, district type, school level, over-age for grade, absenteeism, English Language Learner status, IEP status, student in temporary housing flag, and school transfers. ACS variables included in the model were type of foster care experience, prevention services received, juvenile program participation, and participation in other programs. *All variables are defined in the Key Definitions section.*

MODEL STRATIFICATIONS

Because homelessness disproportionately affects Black people and because homelessness may present differently depending on grade level, separate models were created for each race/ethnicity and school level.

PREDICTING STUDENT HOMELESSNESS

USING THE PREVIOUSLY DESCRIBED MODEL

1. We calculated the probability that each student would experience homelessness in the following academic year.

2. We evaluated how well the model predicted student homelessness by calculating the area under the receiver-operator curve, which shows the performance of the model at all possible probability thresholds.

3. We determined the threshold at which someone would qualify for an intervention using Youden's method. This probability cutoff maximizes the number of students included in an intervention that will become homeless next year while minimizing the size of the intervention group.

4. This threshold was then applied to students at a school using data from the 2018 and 2019 school years.

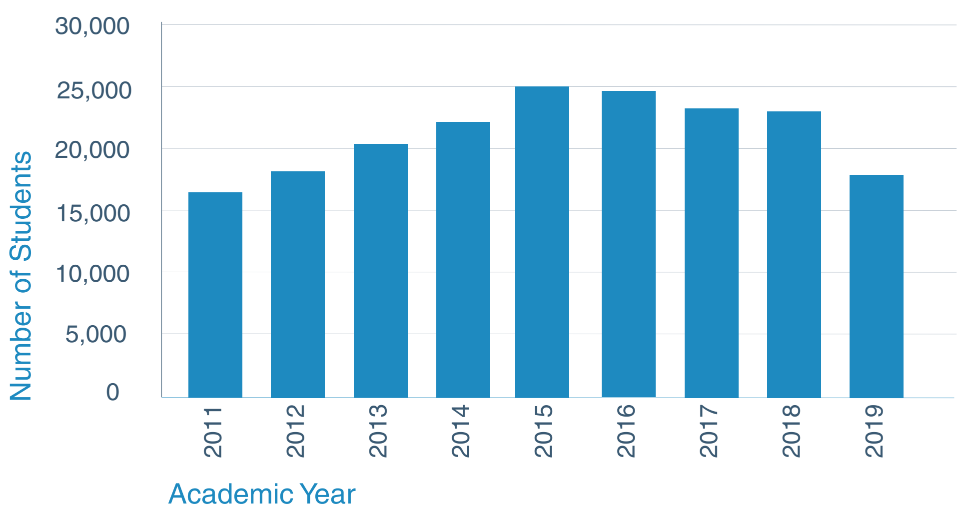
4 RESULTS FROM DESCRIPTIVE ANALYSIS

The students included in this study were born between 1993 and 2014 and enrolled in DOE schools between the 2011 and 2020 academic years. While the study team has student histories of homelessness, foster care, and prevention services participation dating to 1993, this analysis begins in the 2011-2012 school year and follows each student for one year after exit from a DOE school.

The study includes one observation per student per academic year, which amounts to about 1 million students per year. The next set of graphs refer to all spells of homelessness—not the initial experience of homelessness that is the focus of the multivariate analysis.

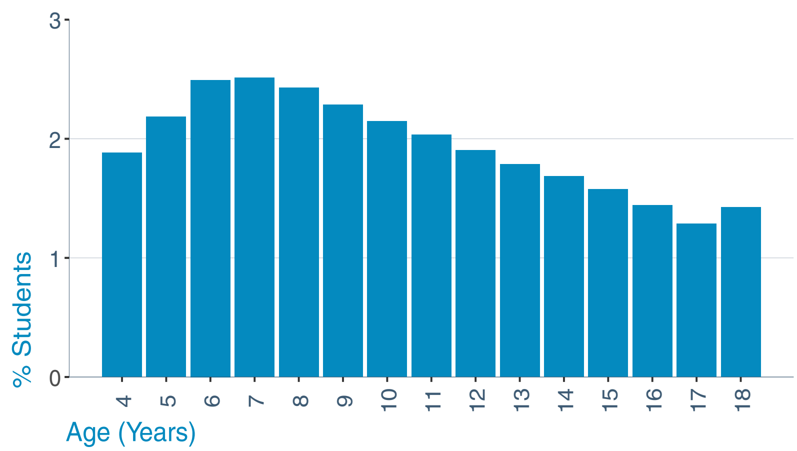
Each academic year, between 1.5% and 2.5% of students (which is 15,000 to 25,000 students) experienced homelessness (Figure 1).

FIGURE 1. Students Experiencing Homelessness by Academic Year



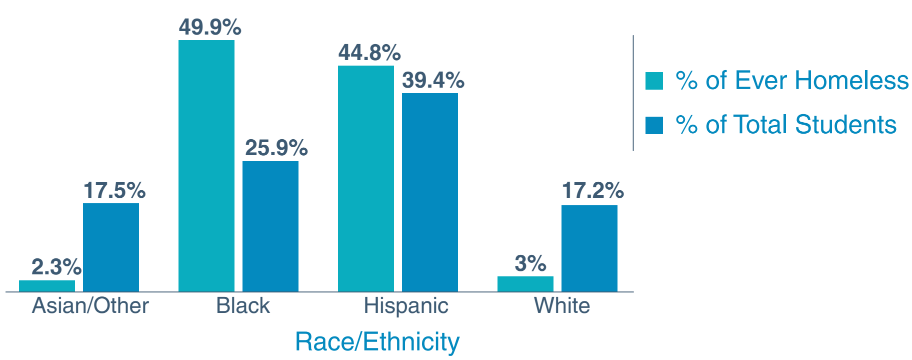
Younger students experience higher rates of homelessness. Two and one-half percent of 6- and 7-year-olds experienced homelessness during any given academic year (Figure 2). The percentage of students experiencing homelessness steadily decreases through age 17, with only 1.3% of 17-year-olds experiencing homelessness during any given academic year.

FIGURE 2: Percent of Students Experiencing Homelessness by Age



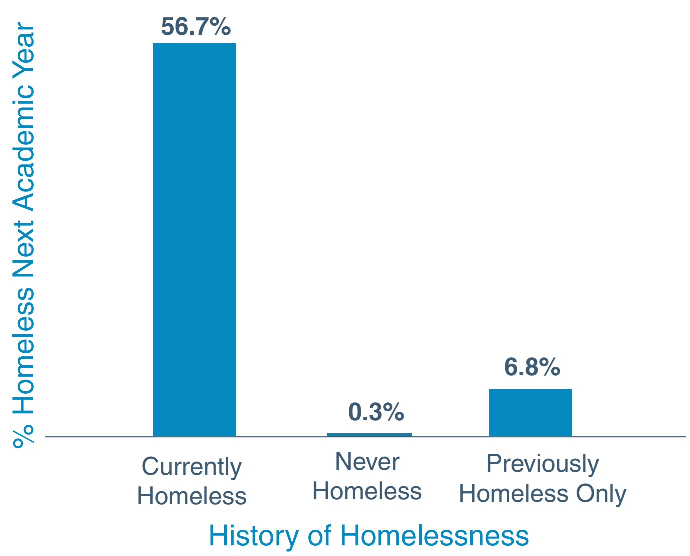
Homelessness disproportionately affects Black students. While Black students only make up 25.5% of the student population, they constituted 50% of the students who had ever experienced homelessness (Figure 3). Three and a half percent of Black students in our study ever experienced homelessness. However, this rate is far higher than White students, of whom only 0.3% were ever homeless. For this reason, we examined risk factors for student homelessness within each race/ethnicity category.

FIGURE 3. Disproportionality of Student Homelessness by Race/Ethnicity



Of the students who were currently homeless, 57% remained homeless in the following academic year (Figure 4). Approximately 7% of students with a history of past homelessness, but who were not currently homeless, became homeless in the next academic year. Student homelessness was much rarer among students who had never experienced homelessness, with only 0.3% of students who had never experienced homelessness previously becoming homeless in the next academic year.

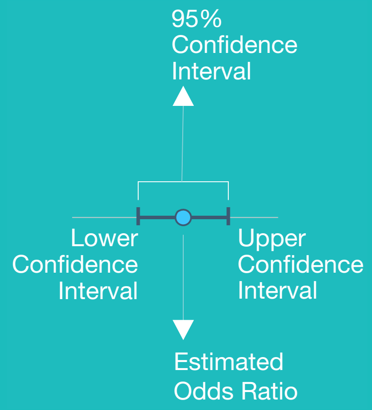
FIGURE 4: Percent of Students Becoming Homeless by Their History of Homelessness



5 RESULTS: RISK FACTORS OF STUDENT HOMELESSNESS

HOW TO READ THE CHARTS

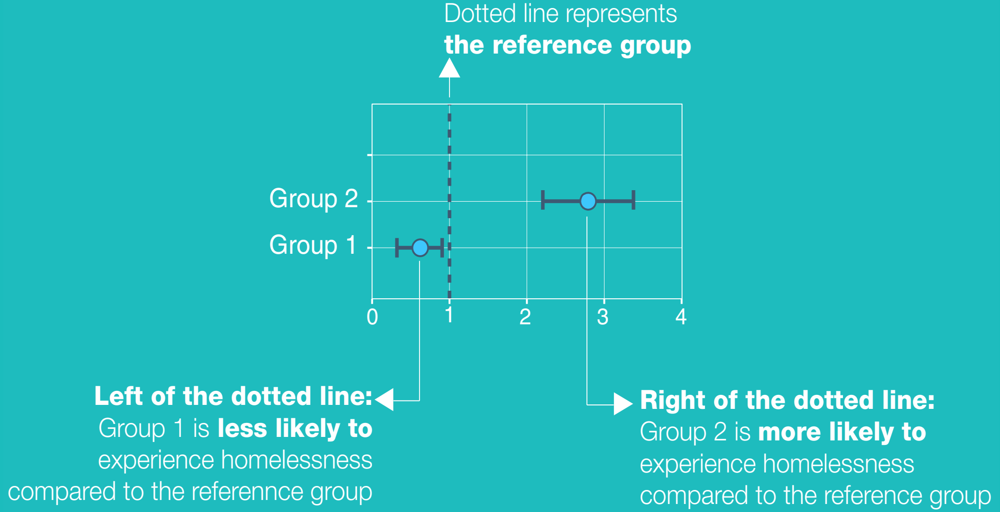
This section presents the results using odds ratio plots. In these plots, bars represent the 95% confidence intervals. The confidence interval demonstrates the range of values for the odds ratios. The mid-points are the estimated odds ratios.



Each estimated odds ratio is in comparison to the reference group, represented with the dotted line. If an estimate and confidence interval lie entirely to the left of the dotted line, that group is less likely to experience homelessness than the reference group. If an estimate and confidence interval are entirely to the right of the dotted line, that group is more likely to experience homelessness than the reference group.

If the estimate and confidence interval do not overlap with 1 (the dotted line), the difference between this group and the reference group is statistically significant.

We'll use the next figure, Figure 5, as an example to go over these descriptions in detail. We'll then highlight the most significant findings for later figures.



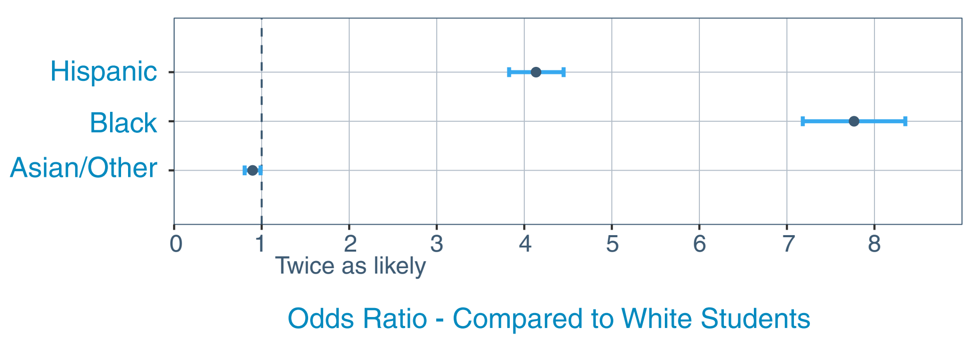
RACE/ETHNICITY

In figure 5, the reference group is White Students represented by the dotted line. Hispanic and black student groups' estimated odd ratios lie right to the dotted line. This signifies that these groups are more likely to experience homelessness compared to White students. Specifically, hispanic students were estimated to be 4.13 times as likely to become homeless in the next school year. The real value lies between 3.83 and 4.45, as represented by the bar.

Black students with no prior experience of homelessness were 7.7 times as likely to be homeless in the following year. The real value lies between 7.18 and 8.35, as represented by the bar. Since the estimates and confidence intervals of the Hispanic and Black students do not overlap with 1 (the dotted line), the difference between the reference group and them is statistically significant.

Asian/Other student group's estimated odd ratio lies left to the dotted line. This signifies that this group is less likely to experience homelessness compared to White students. Specifically, Asian/Other student group is estimated to be 0.89 times as likely to become homeless in the next school year. The real value lies between 0.80 and 0.99, as represented by the bar.

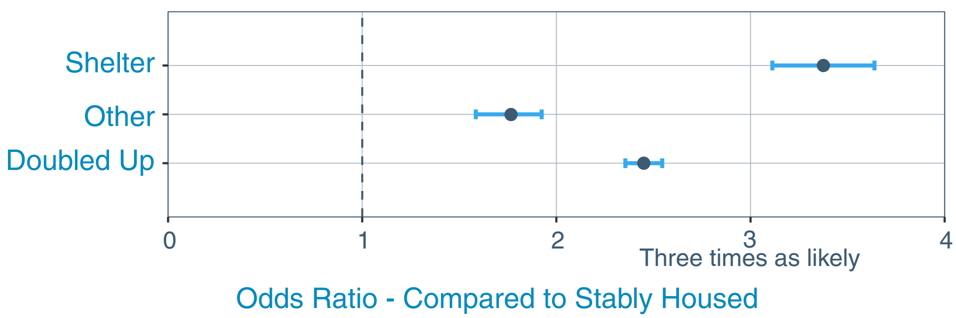
FIGURE 5: Odds Ratios of Students Becoming Homeless in the Following Year by Race/Ethnicity



STUDENTS IN TEMPORARY HOUSING INDICATOR

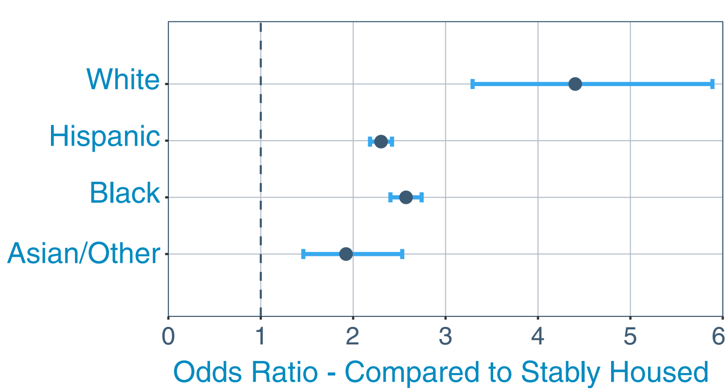
Students in temporary housing, but not in a DHS or DYCD shelter, were at an increased risk of becoming homeless the following year. Students whose family shared living space with another family ("doubled up") were more than twice as likely to become homeless than those not living in temporary housing. The risk of homelessness tripled for those who were indicated as living in a shelter. These students likely resided in a non-DHS or DYCD shelter such as those operated by Housing Preservation and Development (HPD) or those that serve domestic violence survivors.

FIGURE 6: Odds Ratios of Becoming Homeless in the Following Year by Temporary Housing Indicator



White students with the doubled-up STH indicator were more than four times likely to become homeless compared to stably housed white students. The strength of the effect of being doubled-up decreases across other race/ethnic groups, with doubled-up Asian students being twice as likely to experience homelessness the following year compared to stably housed Asian students.

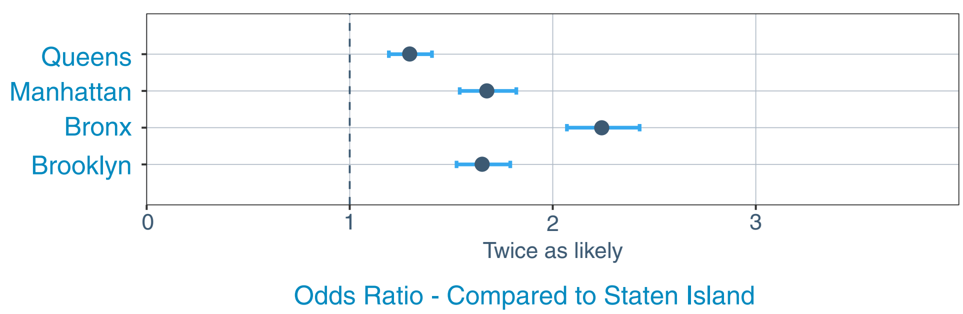
FIGURE 7: Odds Ratios of Students Becoming Homeless in the Following Year by Race and "Doubled Up" Temporary Housing Value



BOROUGH OF SCHOOL

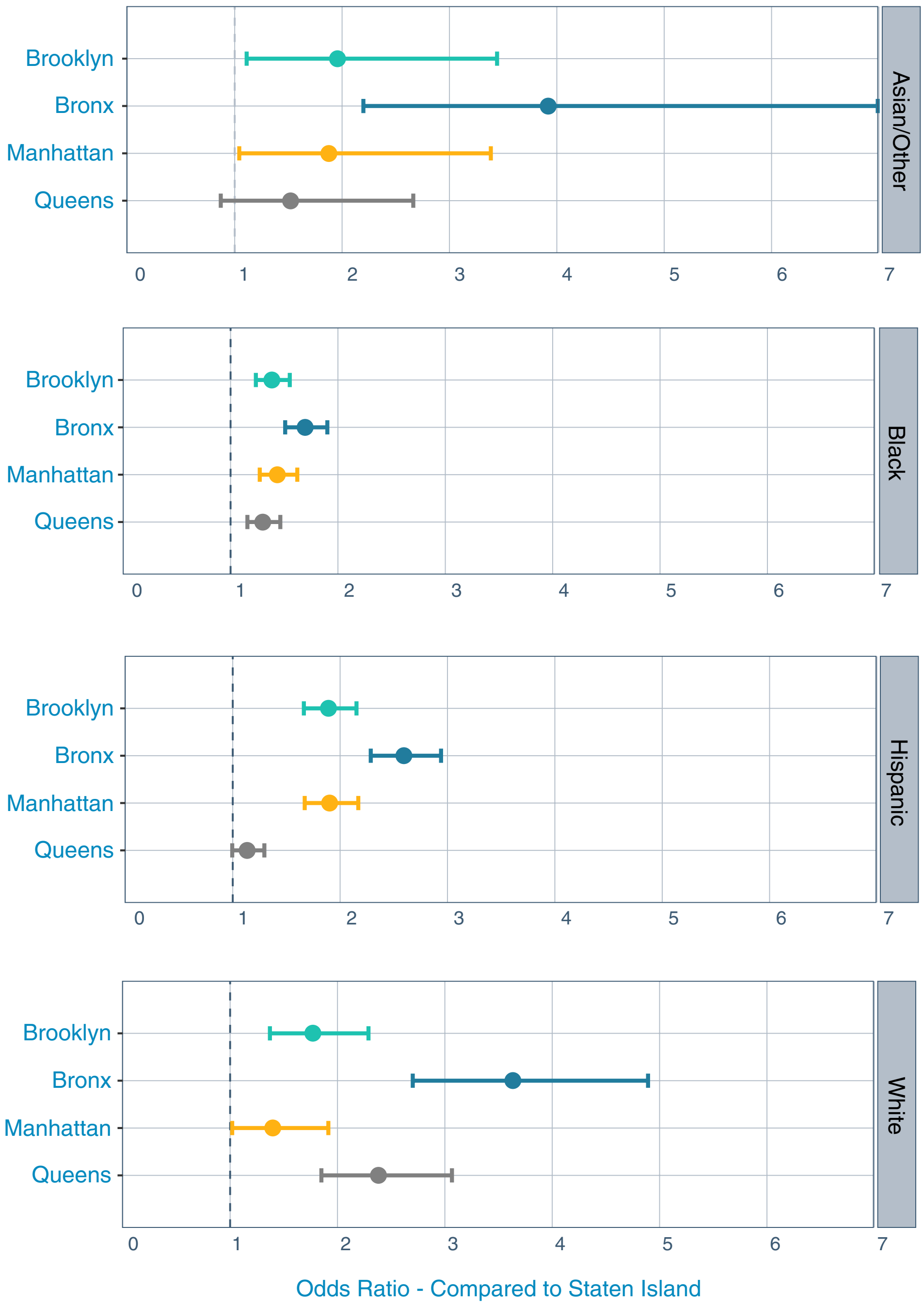
Students attending school in Staten Island were the least likely to become homeless in the following year. Compared to students in Staten Island, those in the Bronx were more than twice as likely to become homeless in the following year. The risk was also higher among students in Manhattan and Brooklyn (1.7 times as likely), and in Queens (1.3 times as likely).

FIGURE 8: Odds Ratios of Students Becoming Homeless in the Following Year by School Borough



Regardless of race/ethnicity, students who attended a school in the Bronx were at an increased risk of becoming homeless in the following year compared to those in Staten Island.

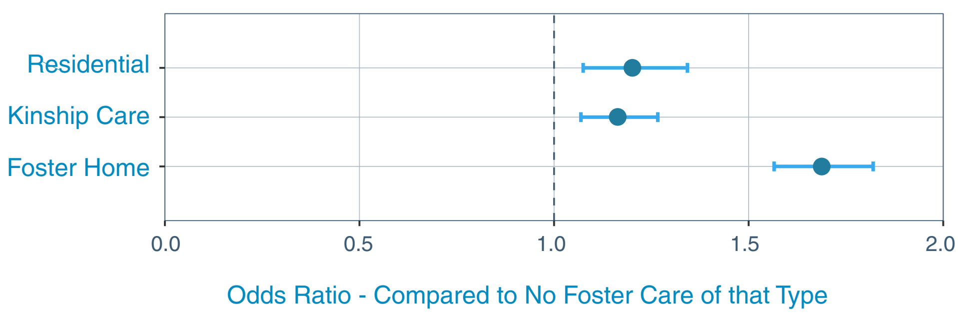
Figure 9: Odds Ratios of Students Becoming Homeless in the Following Year by School Borough and Race/Ethnicity



ACS FOSTER CARE

All types of prior and current foster care were associated with an increased risk of homelessness, compared to students with no foster care experience. Students with foster home experience were at the highest risk.

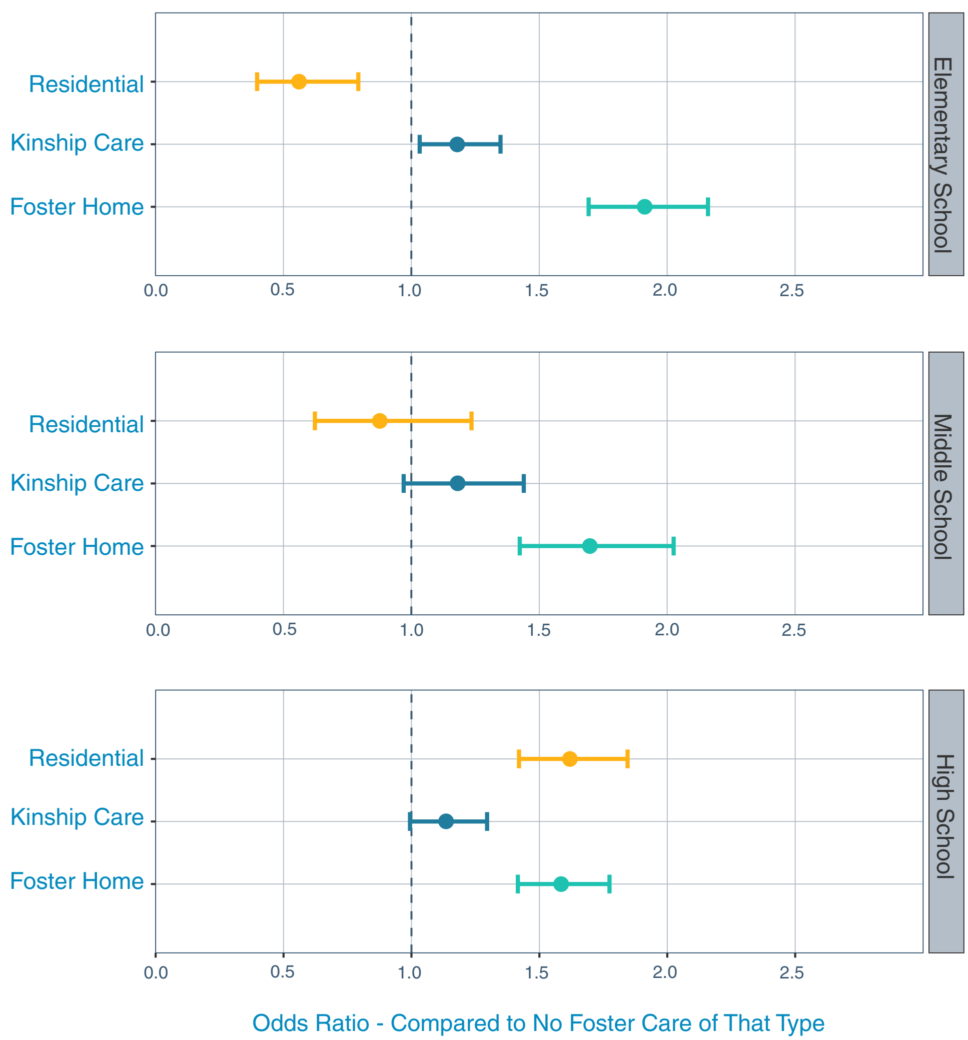
Figure 10: Odds Ratios of Students Becoming Homeless in the Following Year by Foster Care Experience



Older students with foster home experience are at the highest risk of homelessness.

High school students who had ever experienced residential foster care were 60% more likely to become homeless the following school year compared to high school students who had not experienced residential foster care.

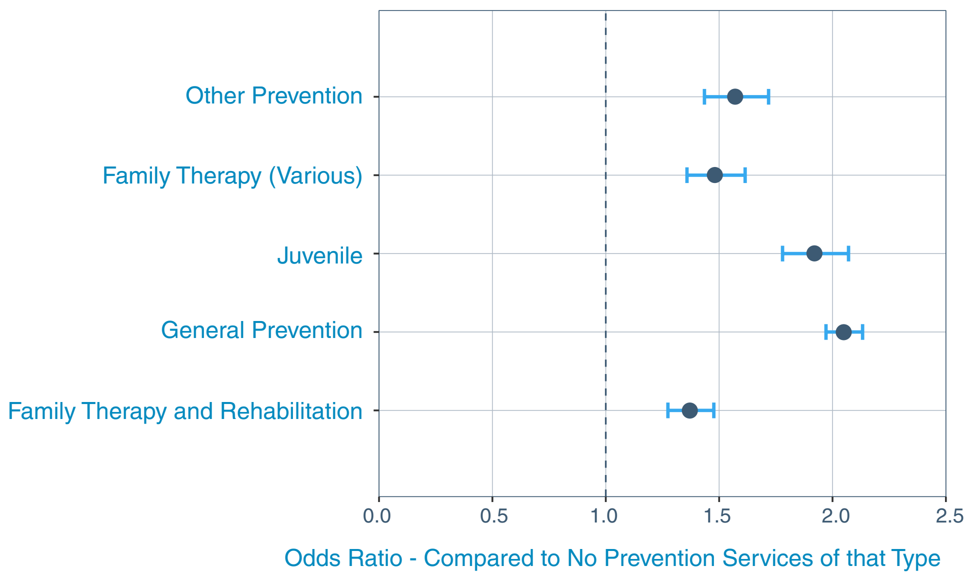
Figure 11: Odds Ratios of Students Becoming Homeless in the Following Year by Foster Care Type and Grade Level



ACS PREVENTION SERVICE

Any prior or current participation in ACS prevention services was associated with an increased risk of student homelessness. Students participating in general or juvenile prevention services were approximately twice as likely to become homeless. All other services were associated with an approximate 50% increase in the likelihood of homelessness in the following year.

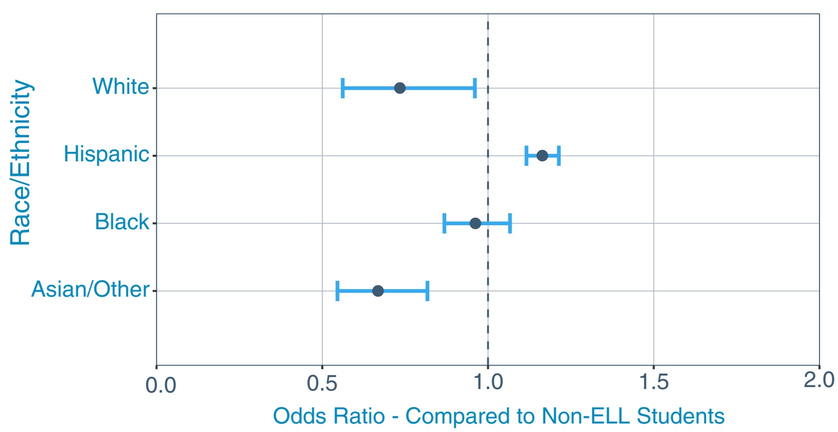
Figure 12: Odds Ratios of Students Becoming Homeless in the Following Year by ACS Prevention Services Received



ENGLISH LANGUAGE LEARNERS

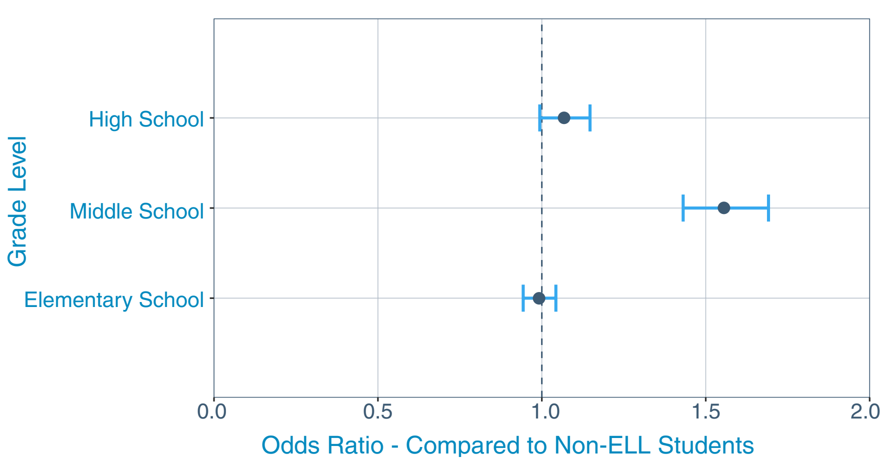
Overall, English Language Learner (ELL) students did not have a higher risk of homelessness in the following year compared to non-ELL students. The analysis shows comparatively small differences by race/ethnicity. Asian and White ELL students were less likely to become homeless compared to non-ELL Asian and white students, respectively. Hispanic ELL students were at a slightly increased risk of experiencing homelessness compared to Hispanic non-ELL students. Hispanic ELL students were at increased risk of homelessness compared to non-ELL Hispanic students.

Figure 13: Odds Ratios of ELL Students Becoming Homeless in the Following Year by Race/Ethnicity



Middle school ELL students were 50% more likely to be homeless in the following year compared to non-ELL middle school students. There was no association between ELL status and homelessness in the following year among elementary or high school students.

Figure 14: Odds Ratios of ELL Students Becoming Homeless in the Following Year by Grade Level

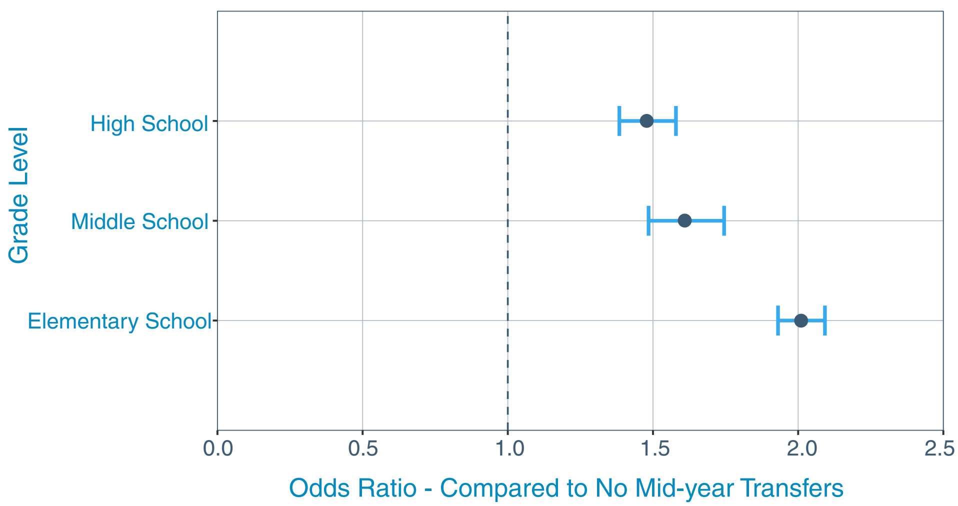


MID-YEAR TRANSFERS

Transferring schools during the school year increased a student's risk of homelessness the following year by approximately 75%.

Elementary school students with mid-year transfers were more than twice as likely to experience homelessness the following year compared to elementary school students without a mid-year transfer. The strength of the effect of mid-year transfers on homelessness diminishes as the student moves to middle school and then high school.

Figure 15: Odds Ratios of Students with Mid-Year Transfers Becoming Homeless in the Following Year by Grade Level



CHRONIC ABSENTEEISM

Students with attendance of 90% or lower were more than twice as likely to become homeless compared to students who consistently attended school . This varied slightly by race, with White and Asian/Other students who were chronically absent more than three times as likely to experience homelessness in the following year compared to their counterparts with consistent school attendance.

OVERAGE FOR GRADE

Compared to students who are typically aged for their grade, students overaged for their grade had double the risk of homelessness in the following year. This did not vary by race.

DISTRICT TYPE

High school students in districts 75 and 79 were at an increased risk of becoming homeless in the following year compared to those attending high schools in geographic school districts.

White students in district 75 were 70% more likely to experience homelessness than white students in geographic districts. Asian/Other and White students attending schools in district 79 are twice as likely to experience homelessness compared to their counterparts in geographic districts.

Individualized Education Plan (IEP)

High school students with an IEP were slightly more likely to become homeless in the following year compared to high school students without an IEP. White and Asian/Other students with an IEP were 50% more likely to experience homelessness compared to White and Asian/Other students who did not have an IEP.

6 RESULTS: RISK FACTORS OF DYCD HOMELESSNESS

DYCD provides shelter for youth and young people, provides a focus on this age group 16- 24 years. Students entering DYCD shelter are included in the previously described analysis. This analysis identifies risk factors that are specific to the population of students utilizing DYCD shelters.

Risk factors for DYCD homelessness are similar to those for any type of homelessness. However, there was a stronger association between age, sex, and school district type and DYCD homelessness than any type of homelessness.

The risk of DYCD homelessness nearly doubles for the following factors:

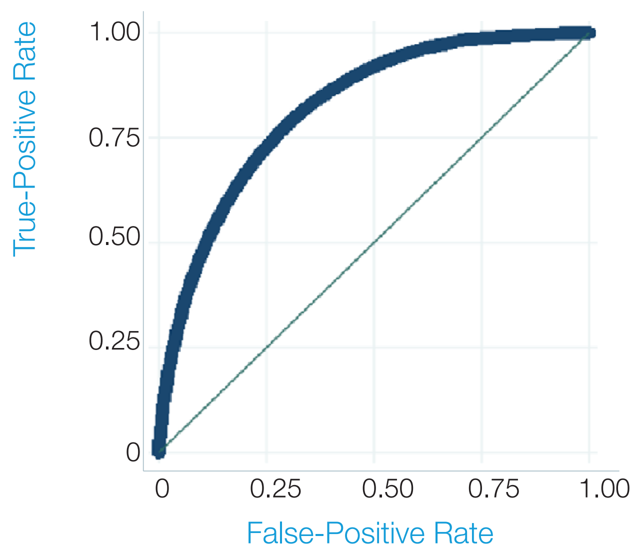
- Every one-year increase in age
- Female students, compared to male students
- Students attending school in district 79, compared to those attending schools in geographically defined districts

7 RESULTS: A MODEL TO PREDICT INITIAL STUDENT HOMELESSNESS

MODEL PERFORMANCE

The predictive model calculates a student's probability of becoming homeless in the following year. When choosing a probability cut-off that would qualify a student for an intervention, it is important to balance statistical sensitivity; the probability that a true positive will qualify for an intervention; and specificity, or the probability that a true negative will not qualify for an intervention. A receiver-operator curve (ROC) plots true-positive rates against false-positive rates for all possible probability thresholds. The area under the ROC curve tells how well the model performed, with an area closer to 1 meaning that the model predicted the outcome nearly perfectly. The closer the area under the curve is to 0.5, the closer the model performs just as good as chance. Figure 16 shows the ROC curve for the model predicting any homelessness in the following year. The area under the curve is 0.82, meaning that the model reliably predicts homelessness in the next academic year.

Figure 16: Receiver-Operator Curve for Model Predicting Student Homelessness in the Following Year



Youden's J statistic was used to find the optimal cutoff value between sensitivity and specificity, which calculated a probability threshold of 0.33% and maximizes sensitivity at 73%, and specificity at 72%. This means that all students whose predicted probability of homelessness the following year was higher than 0.33% would qualify for an intervention.

A sensitivity of 73% means that if there were 100 students who became homeless next year, 73 would have qualified for the intervention. However, the intervention would not include 27 students who would also become homeless in the following year.

A specificity of 72% means that if there were 100 students who did not become homeless the following year, 72 would not qualify for the intervention. The intervention would include 28 students who would not become homeless in the following year.

EXAMPLE INTERVENTION GROUP

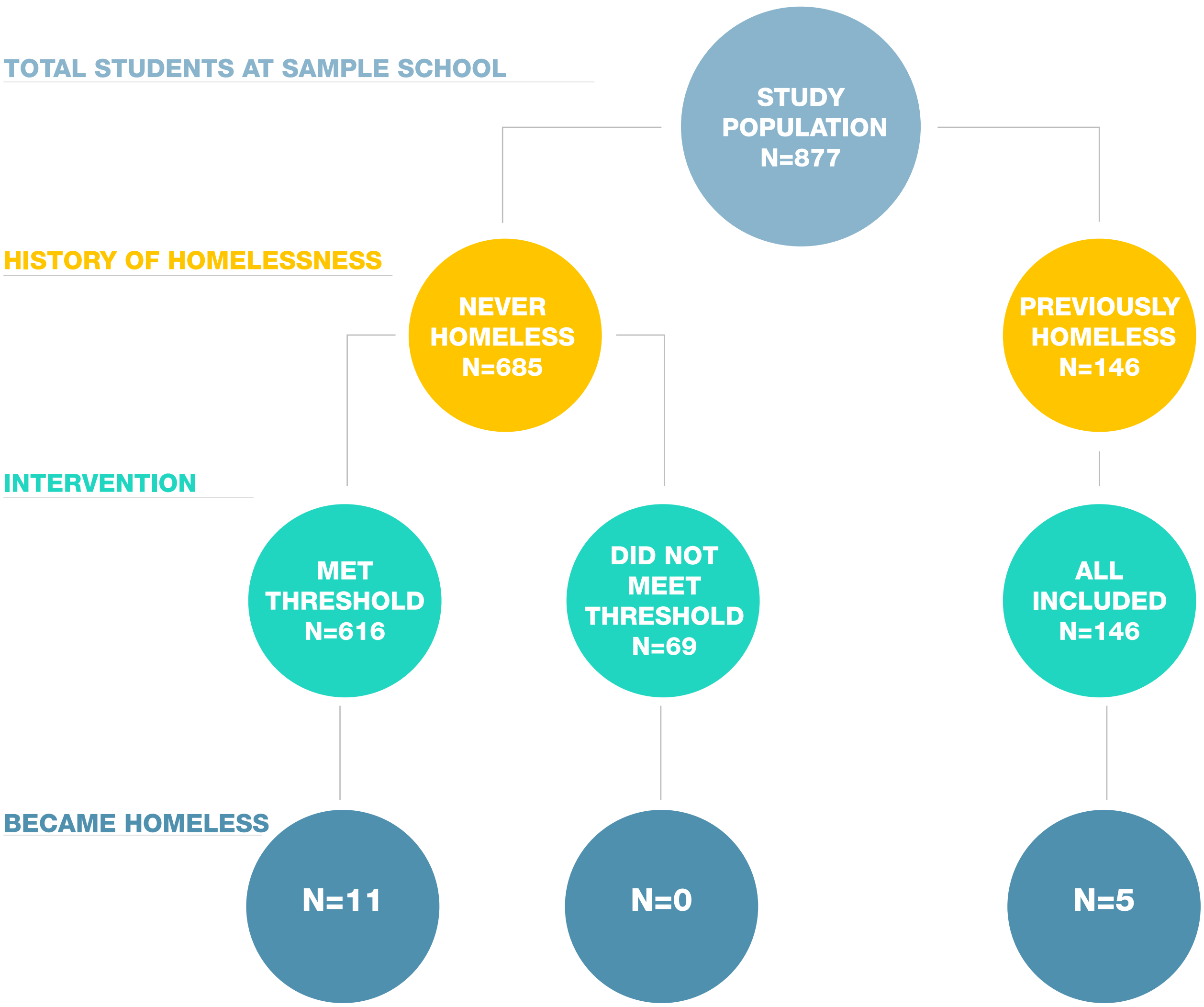
We applied the previously described threshold of 0.33% to an elementary school, using 2018-19 data with the outcome being any homelessness in the 2019-2020 school year.

Figure 17 shows a flowchart for intervention of students at an example school.

In this example, 877 students were enrolled in 2018-2019 school year. Of these, 685 had never previously experienced homelessness. The intervention included 616 students whose probability of homelessness the following year was higher than 0.33%. Of the 616, only 11, or approximately 1.8%, of students did in fact become homeless the following year. Every student who became homeless the following year was included in the intervention.

If we had expanded the intervention to include students who were previously but not currently homeless, we would have intervened with an additional 146 students, five of whom would become homeless the next year. This would have increased the rate of intervention to 2.1%.

Figure 17: Flowchart for Intervention of Students at an Example School



8 CONCLUSIONS

THIS STUDY

IDENTIFIED RISK FACTORS that were strongly associated with the likelihood of students experiencing their first episode of homelessness in the following academic year.

These risk factors include:

- One or more mid-year transfers
- Low rate of school attendance
- Over-age for their grade
- Doubled-up/overcrowded living situation
- Attending high school in districts 75 and 79
- High school students with an Individualized Education Plan (IEP)
- Previous or current foster care experience
- Participation in ACS prevention services
- Attending a school in the Bronx
- Identifying as either Black or Hispanic

WILL HELP INFORM ONGOING CITY INITIATIVES including:

- The NYC Children's Cabinet
- Fair Futures
- Interagency Homeless Accountability Counsel (IHAC)
- The Youth Homelessness Task Force
- Opportunity Starts with a Home (OSH)

SUPPORTS THE GOALS of preventing and ending youth homelessness and ensuring New York City is a place where all people can prosper and thrive regardless of their demographics or life experience.

POLICY IMPLICATIONS

NYC Schools and Health and Human Service agencies will use these findings to focus efforts to prevent students from becoming homeless. These findings also inform the expansion of Fair Futures, a model that provides academic support to foster care and other students, including students at risk of homelessness. Below, we describe an approach to using the findings to improve outcomes for students and their families.

PROMISING INTERVENTION: JUST IN TIME

While the predictive model is robust statistically, the size of the group the model indicates as ‘at elevated risk’ of experiencing homelessness is much larger than a prevention program focused on this population could serve. This is the case with most models focused on predicting a rare event: only a small percentage of students—even those identified as at-risk—become homeless for the first time in any given academic year. Delivering prevention services to all students in the elevated risk group is not an affordable or necessary intervention.

This is a common situation and program designers have developed interventions to address it. Just-in-time interventions are one such approach (Hardeman, Houghton, Lane, Jones, & Naughton, 2019). Rather than providing a prevention program to all people in a high-risk category, many of whom will never actually need such a program, just-in-time interventions involve training those who have relationships with high-risk groups to check in regularly to identify when a more proactive approach is needed. Many military veterans, for example, are at risk of developing post-traumatic stress disorder (PTSD), but only a small percentage experience symptoms of PTSD requiring an intervention. An approach called “watchful waiting” helps identify those veterans who need a PTSD treatment intervention as opposed to those who experience common, short-term reactions to trauma (Greenberg, Brooks, & Dunn, 2015).

Centering existing homelessness prevention strategies to focus on low-touch and wide-reaching efforts among at-risk students until a family passes a certain threshold at which point a more assertive homelessness prevention action may be taken. Students attending school in New York City often access many city services, including after-school programs, ACS prevention services, summer youth programs and community-based programs. A low-touch intervention based on connection and relationship-building, could allow service providers to identify red flags for high-risk students so that situations can be addressed before resulting in shelter entries.

Such a prevention strategy would rely heavily on well-coordinated, cross-agency collaboration among social service agencies. Improved administrative data-matching and sharing techniques would need to be implemented to establish a composite threshold that could be used to initiate a more proactive prevention response.

Engaging community members as well as government staff could serve as a compliment or alternative to this approach. Participation by community members in problem-solving solutions to issues that affect them is one of the most effective ways to create successful public policies. One method for stimulating such engagement, human-centered design, engages people who play a range of social roles to create interventions, making communities themselves the authors of the solutions that impact them most (Nandan, Jastkye, & Mandayam, 2020).

Utilizing human-centered design and a just-in-time intervention approach combined with coordinated cross-agency collaboration is a holistic prevention approach that offers a potentially affordable upstream solution to preventing homelessness. While some number of households may be prevented from entering shelter by low-cost services, many require actual housing resources at the point of a just-in-time intervention. Any intervention based on this approach will need to cost both sets of tools into the cost-benefit analysis, and the very small number of at-risk students who actually enter shelter means that ensuring even a relatively low-cost prevention effort is cost-effective will be challenging.

LIMITATIONS

The study uses administrative data sets from three different city agencies enabling robust data findings. However, relying solely on administrative data limits the variables used in the prediction models. For example, variables such as gender, sexual orientation and type of living arrangement are either limited or not asked, precluding us from using specific variables in the study. In addition, administrative data precludes the benefits of other factors that may be important in predicting homelessness, such as the resiliency, strengths and resources of the students and their families.

FUTURE RESEARCH

The study highlights the risk factors among students who are at risk of homelessness. As noted, the risk groups are large and raise concerns about the efficiency of using administrative data solely for identifying students at risk of homelessness. However, these risk factors help to underscore and steer overall policy initiatives already underway, such as Fair Futures, which aims to improve attendance, Math and English scores for every student enrolled. However, these risk factors are limited in their ability to assist in identifying the actual students who would become homeless in the following year. This may reflect the lack of collection measures relevant to students and their families. A future study could utilize a mixed-methods approach and incorporate focus groups with students and parents, which may elucidate how these risk factors are experienced and provide more feedback on interventions and resources that are needed to improve outcomes.

Because this study aims to predict imminent homelessness among all students, it may not capture risk factors that are present long before an episode of homelessness. Additionally, preventing homelessness among young students may look very different than among young adults. A future study would examine risk factors of high school aged children for entering shelter as young adults. The aim would be to have a comprehensive and in-depth understanding of the risk factors impacting high school students to inform policy, practice, and future research to prevent young adult homelessness.

APPX

TABLES

TABLE 1. PREDICTORS OF STUDENT HOMELESSNESS

PREDICTORS	NOT HOMELESS NEXT YEAR	HOMELESS NEXT YEAR	ODDS RATIO (95% CI)	P>Z
AGE, MEDIAN (IQR)	11 (8-15)	10 (7-14)	0.96 (0.95-0.97)	<0.001
FEMALE, N (%)	4,226,154 (48.40%)	13,581 (51.90%)	1.21 (1.18-1.24)	<0.001
RACE/ETHNICITY, N (%)				
ASIAN/OTHER	1,636,593 (18.97%)	757 (2.91%)	0.89 (0.80-0.99)	0.027
HISPANIC	3,503,034 (40.61%)	11,958 (46.02%)	4.13 (3.83-4.45)	<0.001
BLACK	2,037,055 (23.61%)	12,509 (48.14%)	7.74 (7.18-8.35)	<0.001
WHITE (REFERENCE)	1,449,783 (16.81%)	760 (2.92%)	-	-
SCHOOL BOROUGH, N (%)				
MANHATTAN	1,290,014 (14.77%)	3,733 (14.27%)	1.68 (1.54-1.82)	<0.001
BRONX	1,694,327 (19.40%)	8,931 (34.13%)	2.24 (2.07-2.43)	<0.001
BROOKLYN	2,554,698 (29.26%)	7,838 (29.95%)	1.65 (1.53-1.79)	<0.001
QUEENS	2,633,745 (30.16%)	4,974 (19.01%)	1.29 (1.19-1.41)	<0.001
STATEN ISLAND (REFERENCE)	558,977 (6.40%)	691 (2.64%)	-	-
GRADE GROUPING				
ELEMENTARY (REFERENCE)	4,271,052 (48.91%)	14,191 (54.23%)		
MIDDLE	1,801,980 (20.64%)	4,291 (16.40%)	0.79 (0.75-0.83)	<0.001
HIGH	2,658,729 (30.45%)	7,685 (29.37%)	0.83 (0.78-0.89)	<0.001
OVERAGE	291,387 (3.34%)	2.537 (9.70%)	2.01 (1.91-2.12)	<0.001
DISTRICT TYPE				
GEOGRAPHIC	8,476,032 (97.07%)	24,377 (93.16%)		
75	194,515 (2.23%)	1,103 (4.22%)	1.10 (1.03-1.18)	0.004
79	61,214 (0.70%)	687 (2.63%)	2.00 (1.83-2.19)	<0.001
ELL	1,294,912 (14.83%)	3,894 (14.88%)	1.09 (1.05-1.13)	<0.001
IEP	1,563,477 (17.91%)	6,761 (25.84%)	1.07 (1.04-1.11)	<0.001
CHRONIC ABSENTEEISM	1,896,033 (21.71%)	12,882 (49.23%)	2.23 (2.16-2.29)	<0.001
STUDENT IN TEMPORARY HOUSING				
NONE	8,253,459 (94.52%)	21,564 (82.41%)		
DOUBLED UP	402,498 (4.61%)	3,279 (12.53%)	2.45 (2.36-2.55)	<0.001
SHELTER	33,126 (0.38%)	794 (3.03%)	3.37 (3.11-3.64)	<0.001
OTHER	42,678 (0.49%)	530 (2.03%)	1.75 (1.58-1.92)	<0.001
SCHOOL TRANSFERS				
NON-PROMOTIONAL END-OF-YEAR TRANSFER	383,982 (4.40%)	907 (3.47%)	0.83 (0.77-0.89)	<0.001
MID-YEAR TRANSFER	805,486 (9.22%)	5,778 (22.08%)	1.75 (1.70-1.81)	<0.001
OTHER TRANSFER	181,947 (2.08%)	1,899 (7.26%)	1.48 (1.39-1.57)	<0.001
ACS FOSTER CARE				
EVER IN FOSTER HOME	95,452 (1.09%)	1,507 (5.76%)	1.69 (1.57-1.82)	<0.001
EVER IN KINSHIP FOSTER CARE	76,967 (0.88%)	975 (3.73%)	1.16 (1.07-1.27)	<0.001
EVER IN RESIDENTIAL FOSTER CARE	21,046 (0.24%)	467 (1.78%)	1.20 (1.07-1.34)	<0.001
ACS PREVENTION SERVICE				
EVER PPRS FAMILY TREATMENT & REHABILITATION	90,378 (1.04%)	848 (3.24%)	1.37 (1.27-1.48)	<0.001
EVER PPRS VARIOUS FAMILY THERAPY	53,079 (0.61%)	641 (2.45%)	1.48 (1.36-1.61)	<0.001
EVER PPRS GENERAL	370,149 (4.24%)	3,904 (14.92%)	2.05 (1.97-2.13)	<0.001
EVER PPRS JUVENILE	59,981 (0.69%)	881 (3.37%)	1.92 (1.78-2.07)	<0.001
PPRS OTHER	42,446 (0.49%)	578 (2.21%)	1.57 (1.44-1.72)	<0.001

TABLE 2. PREDICTORS OF STUDENT HOMELESSNESS BY RACE/ETHNICITY

	ASIAN/OTHER		HISPANIC		BLACK		WHITE	
	OR (CI)	P	OR (CI)	P	OR (CI)	P	OR (CI)	P
AGE	0.98 (0.94-1.03)	0.42	0.96 (0.95-0.97)	<0.001	0.95 (0.94-0.96)	<0.001	1.00 (0.96-1.05)	0.88
FEMALE	1.25 (1.08-1.45)	<0.001	1.20 (1.15-1.24)	<0.001	1.22 (1.17-1.26)	<0.001	1.20 (1.04-1.39)	0.002
BOROUGH								
MANHATTAN	1.88 (1.04-3.39)	0.004	1.90 (1.67-2.17)	<0.001	1.44 (1.27-1.62)	<0.001	1.40 (1.02-1.91)	0.04
BRONX	3.92 (2.20-6.99)	<0.001	2.59 (2.29-2.94)	<0.001	1.69 (1.51-1.90)	<0.001	3.64 (2.70-4.89)	<0.001
BROOKLYN	1.96 (1.11-3.44)	0.02	1.89 (1.66-2.15)	<0.001	1.38 (1.24-1.55)	<0.001	1.77 (1.37-2.29)	<0.001
QUEENS	1.52 (0.87-2.66)	0.14	1.14 (1.00-1.29)	0.06	1.30 (1.16-1.46)	<0.001	2.38 (1.85-3.07)	<0.001
GRADE LEVEL								
MIDDLE	0.77 (0.57-1.04)	0.09	0.83 (0.77-0.89)	<0.001	0.76 (0.70-0.81)	<0.001	0.74 (0.55-0.99)	0.04
HIGH	0.66 (0.43-0.99)	0.05	0.80 (0.72-0.88)	<0.001	0.88 (0.80-0.96)	0.01	0.71 (0.48-1.05)	0.09
OVERAGE	2.33 (1.62-3.36)	<0.001	2.06 (1.90-2.23)	<0.001	1.97 (1.82-2.12)	<0.001	1.88 (1.32-2.70)	<0.001
DISTRICT TYPE								
75	0.79 (0.49-1.30)	0.36	1.10(0.99-1.23)	0.07	1.04 (0.95-1.14)	0.41	1.68 (1.26-2.25)	<0.001
79	2.33 (1.23-4.43)	0.01	2.60 (2.26-2.98)	<0.001	1.63 (1.43-1.84)	<0.001	2.17 (1.31-3.58)	<0.001
ELL	0.67 (0.55-0.82)	<0.001	1.16 (1.12-1.21)	<0.001	0.96 (0.87-1.07)	0.46	0.73 (0.56-0.96)	0.02
IEP	1.58 (1.27-1.97)	<0.001	1.01 (0.96-1.06)	0.72	1.10 (1.05-1.15)	<0.001	1.49 (1.25-1.78)	<0.001
CHRONIC ABSENTEEISM	3.86 (3.24-4.61)	<0.001	2.30 (2.21-2.39)	<0.001	2.01 (1.94-2.09)	<0.001	3.12 (2.63-3.71)	<0.001
STUDENT IN TEMPORARY HOUSING								
DOUBLED-UP	1.92 (1.46-2.53)	<0.001	2.30 (2.18-2.42)	<0.001	2.56 (2.41-2.72)	<0.001	4.40 (3.29-5.89)	<0.001
SHELTER	17.22 (11.49-25.82)	<0.001	3.89 (3.47-4.36)	<0.001	2.65 (2.37-2.97)	<0.001	10.25 (6.10-17.23)	<0.001
OTHER	2.40 (1.16-4.95)	<0.001	1.60 (1.37-1.86)	<0.001	1.70 (1.49-1.93)	<0.001	4.13 (2.49-6.85)	<0.001
SCHOOL TRANSFERS								
NON-PROMOTIONAL END-OF-YEAR TRANSFER	0.67 (0.43-1.07)	0.09	0.91 (0.82-1.01)	0.07	0.77 (0.69-0.85)	<0.001	1.06 (0.69-1.64)	0.78
MID-YEAR TRANSFER	2.58 (2.16-3.08)	<0.001	1.92 (1.84-2.01)	<0.001	1.53 (1.47-1.61)	<0.001	2.19 (1.83-2.63)	<0.001
OTHER TRANSFER	1.28 (0.83-1.98)	0.26	1.44 (1.32-1.58)	<0.001	1.52 (1.40-1.66)	<0.001	1.96 (1.39-2.77)	<0.001
ACS FOSTER CARE								
EVER IN FOSTER HOME	2.95 (1.62-5.37)	<0.001	2.05 (1.82-2.31)	<0.001	1.50 (1.35-1.65)	<0.001	2.66 (1.68-4.20)	<0.001
EVER IN KINSHIP FOSTER CARE	1.13 (0.56-2.29)	0.73	1.35 (1.17-1.54)	<0.001	1.09 (0.97-1.21)	0.15	1.68 (1.01-2.80)	0.05
EVER IN RESIDENTIAL FOSTER CARE	2.95 (1.62-5.37)	<0.001	2.05 (1.92-2.31)	<0.001	1.50 (1.35-1.65)	<0.001	2.66 (1.68-4.20)	<0.001
ACS PREVENTION SERVICE								
EVER PPRS FAMILY TREATMENT & REHABILITATION	1.62 (0.83-3.19)	0.16	1.24 (1.11-1.39)	<0.001	1.50 (1.36-1.66)	<0.001	1.92 (1.13-3.24)	0.02
EVER PPRS VARIOUS FAMILY THERAPY	1.75 (0.90-3.42)	0.1	1.49 (1.31-1.69)	<0.001	1.43 (1.27-1.62)	<0.001	2.02 (1.27-3.21)	<0.001
EVER PPRS GENERAL	3.49 (2.72-4.48)	<0.001	2.11 (1.99-2.23)	<0.001	1.86 (1.76-1.97)	<0.001	3.97 (3.04 -5.18)	<0.001
EVER PPRS JUVENILE	2.26 (1.16-4.39)	0.02	1.89 (1.68-2.12)	<0.001	1.92 (1.73-2.13)	<0.001	2.36 (1.60-3.50)	<0.001
PPRS OTHER	4.73 (2.68-8.35)	<0.001	1.60 (1.40-1.82)	<0.001	1.39 (1.23-1.58)	<0.001	2.73 (1.77-4.21)	<0.001

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