

The Long-Term Impact of Systemic Student Support in Elementary School: Reducing High School Dropout

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Dropping out of high school has adverse consequences, including negative effects on employment, lifetime earnings, and physical health. Students often fail to complete high school for complex reasons that often manifest long before they reach high school. This study examines the link between participation in a comprehensive elementary school student support intervention and high school dropout. In this study, students who attended intervention elementary schools in a large, urban, high-poverty district during 2001–2014 (N=894) were compared to students who did not attend intervention schools (N=10,200). Likelihood of dropping out in grades 9–12 was estimated using propensity score-weighted Discrete Event History Analysis. Intervention students had approximately half the odds of dropout ($p < .001$); the probability of dropout for intervention was 9.2%, compared to 16.6% for non-intervention students. Individually tailored student support interventions during elementary school can lead to lasting and meaningful effects.

Keywords: *integrated student support, school dropout, elementary schools*

Introduction

AFTER stagnating for several decades, public high school graduation rates in the United States have increased over the past 15 years, peaking at 83% in 2014–2015 (Murnane, 2013; National Center for Education Statistics (NCES), 2016). Still, dropping out of high school has clear and measurable adverse consequences for both individuals and society (De Witte & Rogge, 2013; Hanushek & Wobmann, 2007; McNeal, 1995; Strom & Boster, 2007). These include negative effects on employment, lifetime earnings, and physical health; an increased risk of incarceration; and social costs associated with these outcomes (Belfield & Levin, 2007; Chapman, Laird, Ifill, & Kewal Ramani, 2011; Lleras-Muney, 2005). Therefore, despite generally positive trends in the national graduation rate, the loss of human potential associated with dropout necessitates research to identify interventions that may further reduce the rate of school dropout.

A recent review of the literature on interventions designed to prevent school dropout concluded that few have been designed to address multiple risk factors and to be implemented early in life rather than in high school (Freeman & Simonsen, 2015). The authors of this review conclude that “evidence does support the use of multicomponent interventions, early intervention, and strategies that address the school organizational structure,” further noting that “researchers...need to tackle the complexity of the dropout problem and conduct research that either confirms or denies current best practice recommendations with particular attention to the integration of practices...that address student needs proactively and effectively” (p. 242). Accordingly, the current study examines the link between high-quality, comprehensive, individualized elementary school student support and high school dropout. We examine whether students participating in an evidence-based, theory-guided student support intervention during elementary school drop out of high school at lower rates than comparable students who



were not exposed to comprehensive student support during elementary school.

Pathways Leading to Dropout

Sociological and psychological theories view dropout as the end result of a long-term process of academic disengagement that is influenced by both in- and out-of-school factors and that generally begins early in a students' academic career (Alexander, Entwisle, & Horsey, 1997; Freeman & Simonsen, 2015; Henry, Knight, & Thornberry, 2012; Hickman, Bartholomew, Mathwig, & Heinrich, 2008; Jimerson, Egeland, Sroufe, & Carlson, 2000; Rumberger & Rotermund, 2012). Economists add to theories of dropout an emphasis on the cost-benefit analysis that teenagers use in deciding whether or not to stay in school; as noted by Murnane (2013), the expected benefits and costs of staying in school vary depending on a student's particular skills and attributes as well as family circumstances. Thus, students who received early investment in the development of their core cognitive and social-emotional skills—whether by their parents or by a program—may perceive (and actually experience) greater benefit from staying in school than peers who enter high school with weak skills subsequent to poor investment early in life (Cunha & Heckman, 2007). Importantly, both the economic and psychological/sociological perspectives suggest that early intervention—to redirect students beginning on a trajectory of academic disengagement and to invest resources in young students for whom early skill development may otherwise be impeded due to a lack of resources in their family/community environments—will be more efficient than intervention in the high school years in reducing dropout.

Consistent with these theoretical frameworks, risk factors for dropout manifest early in life as well as during time frames closer to dropout (Alexander et al., 1997; Heers, Van Klaveren, Groot, & Maassen van den Brink, 2011; Murnane, 2013; Rumberger, 2011; Thyssen, De Witte, Groot, & Maassen van den Brink, 2010). Studies of high-quality, comprehensive preschool programs such as Head Start and the Perry Preschool program have shown that participation in these early childhood programs is associated with a decreased risk of high school dropout (Berrueta-Clement, 1984; Garces, Thomas, & Currie, 2002). Student academic indicators such as poor grades, low achievement test scores, and grade retention during elementary, middle, and high school are linked to an increased likelihood of high school dropout (Balfanz, Herzog, & Mac Iver, 2007; Battin-Pearson et al., 2000; Cairns, Cairns, & Neckerman, 1989; Heppen & Theriault, 2008; Neild & Balfanz, 2006; Rumberger, 1995; Wells, Bechard, & Hamby, 1989). Additionally, indicators of school engagement such as attendance, classroom behavior, perceptions of school belongingness, and extracurricular involvement also are linked to dropout (Archambault,

Janosz, Fallu, & Pagani, 2009; Azzam, 2007; Fall & Roberts, 2012; Janosz, Archambault, Morizot, & Pagani, 2008; Mahoney & Cairns, 1997; Reschly & Christenson, 2006).

With respect to sociodemographic and out-of-school risk factors, graduation rates are significantly lower for Black and Hispanic youth (Murnane, 2013; NCES, 2016; Pursley, Munsch, & Wampler, 1998) as well as for male—as compared to female—students (Chapman et al., 2011; Ekstrom, Goertz, Pollack, & Rock, 1986; Ensminger & Slusarcick, 1992; Murnane, 2013). Students who drop out of high school are more likely to come from low-income families and/or single-parent households, and parental education level is a strong predictor of high school completion (Ekstrom et al., 1986; Ensminger & Slusarcick, 1992; Goldschmidt & Wang, 1999; Janosz, LeBlanc, Boulerice, & Tremblay, 1997; Rumberger, 1983). English language learners are also at increased risk of dropout (NCES, 2016). Student mobility—that is, changes in home address or school attended—is associated with leaving high school before completion (Astone & McLanahan, 1994; Rumberger & Larson, 1998; Swanson & Schneider, 1999).

It has been hypothesized that engagement mechanisms at least partially explain the strong empirical link between student mobility/school transfers and increased risk of dropout (Rumberger & Larson, 1998; Swanson & Schneider, 1999). The association between socioeconomic indicators and dropout is consistent with the theory that disinvestment from education in adolescence can be linked to insufficient resource investment in skills development in childhood (Murnane, 2013); this association is also consistent with the idea that children from stressful socioeconomic backgrounds are likely to have lower school engagement due to their increased daily life stress as well as their increased likelihood of attending schools which have a high teacher turnover, unsafe conditions, poor instruction, and negative student-teacher relationships (Dearing, 2008).

Most importantly, studies of dropout risk indicate that the accumulation of multiple risk factors (e.g., living in a single-parent household and having failing grades) is more highly predictive of dropout than any single risk factor present in isolation (Bowers, Sprott, & Taff, 2013). In addition, in support of models that view dropout as the outcome of a long-term developmental process, analysis of the dropout literature shows that models accounting for growth over time—particularly in academic skills—are more effective at predicting dropout than cross-sectional models (Bowers et al., 2013). Thus, a multifaceted, comprehensive approach to meeting student needs early on may best address potential dropout trajectories.

Interventions to Prevent Dropout

The fact that risk of dropout is predicted by both in- and out-of-school factors suggests that effective dropout intervention

should address risks both in the school and in the larger family and community context. As noted by Freeman and Simonsen (2015, p. 240):

Intervention research must go beyond the typical school boundaries to mediate these [dropout risk] factors. This type of outreach cannot be accomplished by schools alone and will require significant, meaningful, and effective partnerships with community agencies, community mental health supports, and other public health initiatives (Bryan, 2005; Schorr, 1997).

Unfortunately, the research on preventing dropout shows little emphasis on this sort of comprehensive, systemic intervention. Further, though theory and empirical research suggests that students at high risk of dropout are already well along a path toward leaving school by the time they reach high school, few interventions have been implemented and tested at the elementary level with the goal of preventing dropout. *What Works Clearinghouse* has developed recommendations for prevention of dropout (Rumberger et al., 2017) and identifies 18 interventions designed to prevent dropout as having clear evidence of effectiveness, most of which are implemented during high school and focus on academic and attendance support (What Works Clearinghouse, 2018). Among the barriers to research in this area is the fact that many interventions that can be rigorously evaluated are narrow in focus and modest in scope; complex interventions that address multifaceted needs of students at risk of dropout can be difficult to study (Murnane, 2013).

Student Support Effects on Dropout

Beyond a specific focus on dropout, the child development literature has identified ways in which risk and protective factors—internal to the child as well as within the family, school, and neighborhood—can complement, contaminate, and/or compensate for one another (Bronfenbrenner & Morris, 1998). Empirical work from several disciplines has also highlighted that for children living in poverty, agents of harm operating in nearly every domain of children's experiences (e.g., day-to-day life at home, in the neighborhood, or in school) can prove chaotic, dangerous, and stressful (for reviews, see Dearing, 2008; Evans, 2004). Compounding the problem, students who arrive at school overstressed and under-resourced may be less likely than more advantaged students to experience recognition of their strengths and enrichment activities to foster them.

This complex reality has long been recognized by educators. Consequently, schools historically have attempted to address the diverse needs of students through channels complementary to the traditional work of teachers. The broad term “student support” has been used to refer to the combined work of nurses, counselors, social workers, psychologists, and others who directly address non-academic needs

and factors that affect students' success in school. Unfortunately, student support systems have varied widely across schools, resulting in a lack of standardized practice (Lean & Colucci, 2010). Additionally, student support work within schools has tended to operate in unsystematic and uncoordinated ways, and is often directed only to the most challenged students (Bridgeland & Bruce, 2011; Walsh & DePaul, 2008; Walsh et al., 2014).

There are now, however, recommendations for improving student support practice in a systematic manner (Adelman & Taylor, 2011; Walsh & DePaul, 2008). Theories of the impact of systematic student support suggest that when students' needs are met and strengths are enhanced across domains (including social-emotional, health, family, and academic needs and strengths), they will be better able to engage positively in their relationships at school, and that this will lead to increased effort, social-emotional skill, academic skills, and achievement (Deci & Ryan, 2000; Dweck, 1999; Eccles et al., 1993; Kellaghan, Madaus, & Raczek, 1996). Crucially, because it is expected that the attitudes and non-cognitive skills underlying achievement will be strengthened, high-quality student support systems should lead to academic benefits that persist in students over the long term.

These theoretically grounded recommendations for systematic student support have now been operationalized by different organizations (see Moore et al., 2014, 2017). Many include a process for assessing a school's and/or student's needs, a designated staff person to work with students in a school, a way of connecting schools and students to community agency services and resources, and a way of tracking service referrals and delivery. While these interventions and programs differ in various features of implementation, they share the goal of addressing in a systematic way individual student needs in areas that affect achievement in school.

Few studies have empirically tested the hypothesized relation between comprehensive student support and reduced dropout rates. Among these are studies of the Communities in Schools (CIS) model of student support. CIS is a national network with affiliates in 25 U.S. states. Affiliates work with local school districts to understand the non-academic needs their students face, and they also seek to understand community resources that might meet a variety of needs. The affiliate then develops partnerships with businesses, foundations, and districts to fund a CIS staff person in each school—a coordinator who connects the school as a whole as well as individual students to community resources. One study examining the impact of CIS on student outcomes showed that CIS schools had significantly lower rates of dropout and higher rates of graduation than comparison schools (Porowski & Passa, 2011). A limitation of this research was the fact that dropout was measured by comparing the number of 12th grade students to the number of 9th grade students in the same school three years earlier. As noted by Murnane (2013),

the grade-level enrollment approach to measuring dropout has been criticized, as it fails to account for students who leave for a different school, enter from a different school, or are retained and thus do not enter 12th grade three years after entering 9th grade. More recent analyses did not replicate the 2011 findings (Somers & Haider, 2017). The lack of clear effect of the CIS model on dropout may be related to implementation during secondary education, contrary to theory suggesting that implementation of student support in elementary school can set students on trajectories of positive school engagement and facilitate the development of core skills for learning and positive relationships.

In this study, we examined the impact of a systemic student support model implemented in elementary school—City Connects—on dropout. Past empirical research has found that comprehensive student support during elementary school leads to lasting benefits in middle school. Students enrolled in City Connects elementary schools demonstrate higher middle school report card and statewide standardized test scores (both in English language arts and math) relative to comparable students never enrolled in intervention elementary schools (Walsh et al., 2014). Positive academic effects during elementary school have been observed for first-generation immigrant students (Dearing et al., 2016). Because academic measures during earlier school grades are strongly associated with later high school dropout (Bowers et al., 2013), these positive findings suggest a possible link between high school dropout and systematic student support systems during elementary school.

Hypothesis

Sociological and psychological theory suggests that dropout is the end result of a long-term process of academic disengagement (Alexander et al., 1997; Freeman & Simonsen, 2015; Henry et al., 2012; Jimerson et al., 2000; Rumberger & Rotermund, 2012). Complementary economic theory suggests that the likelihood of dropout is influenced by a student's perception of the risk–reward profile of continued school attendance, which in turn is influenced by the student's core academic and non-cognitive skills, developed early in life (Cunha & Heckman, 2007; Murnane, 2013). Theories of comprehensive student support suggest that the implementation of evidence-based models in elementary school should intervene on pathways to dropout through addressing academic, health, social/emotional/behavioral, and family challenges; enhancing student strengths; and facilitating positive school engagement, all of which, in turn, allow for the development of higher levels of academic and social-emotional skill. Thus, we hypothesized that students who attended an elementary school implementing the City Connects model of student support would have a lower risk of dropping out of school in high school.

Method

Participants

This analysis draws on anonymized individual student data from Boston Public Schools (BPS) spanning school years 2001–2002 through 2013–2014. BPS is a high-poverty, urban school district. Across all BPS schools serving students in grades K–5 during this time period, over 90% of students were eligible for free or reduced-price lunch, and approximately 90% were students of color.

During the years of this study, schools in the district were grouped into one of five subdistricts, or “clusters,” based primarily on geography. The City Connects program was first implemented in one cluster composed of schools in two large neighborhoods, at the request of the district; all six elementary and K–8 schools in the cluster were required to participate. Two schools from a different cluster were added after one year, and two years after that, the district requested an expansion to all seven elementary schools in that geographic cluster.

Figure 1 displays the structure of available student data. School year is shown along the vertical axis. Cohort year is shown along the horizontal axis, and is named using the school year when the cohort was enrolled in kindergarten. Each cell displays the grade level of data available for the cohort at the top during the school year to the left. The analytic sample is restricted to students from kindergarten cohorts 2000–2001 through 2004–2005 because only students from these cohorts could potentially have been enrolled in schools by 1st grade and also have at least one year of high school outcome data by school year 2013–14.

Student assignment to schools in kindergarten was based on family choice of schools in their cluster, unless applicants outnumbered available spots in a school. In that case, an assignment mechanism taking into account family preference, school proximity, sibling attendance, and a random component was used for school assignment. For this analysis, treatment students are defined as those who attended any of six intervention elementary schools during grades K and/or 1. To estimate intent-to-treat effects, all students who attended these schools in grades K and/or 1 are included in the treatment sample even if they transferred out prior to the end of 5th grade. Comparison students are defined as those who were enrolled in the school district during the same time period as City Connects students, but never attended an intervention school. To ensure that a potential outcome under the treatment condition is conceivable for comparison students in the analytic sample (a condition necessary for counterfactual causal inference), the comparison sample is also restricted to students who were enrolled in BPS by K and/or grade 1; students who transferred into the district after grade 1 are excluded from the comparison group.

	Cohort Year				
	2000–2001	2001–2002	2002–2003	2003–2004	2004–2005
School Year					
2001–2002	1	K			
2002–2003	2	1	K		
2003–2004	3	2	1	K	
2004–2005	4	3	2	1	K
2005–2006	5	4	3	2	1
2006–2007	6	5	4	3	2
2007–2008	7	6	5	4	3
2008–2009	8	7	6	5	4
2009–2010	9	8	7	6	5
2010–2011	10	9	8	7	6
2011–2012	11	10	9	8	7
2012–2013	12	11	10	9	8
2013–2014		12	11	10	9

FIGURE 1. *Year of kindergarten entry (“cohort”) and grade by school year, analysis sample.*

For both City Connects and comparison groups, students are excluded from the analysis if they received high school instruction in a substantially separate special education placement. These students often do not fulfill high school graduation requirements due to their unique needs (though many remain enrolled until the district is no longer required to provide services) and thus are not included when estimating dropout rates meant to reflect the experience of students in typical educational settings. Students who received a substantially separate special education placement during elementary or middle school are not excluded from the analytic sample unless this placement also occurred during high school.

Students are lost from the analytic sample only when dropout status during high school is missing. Such missing outcome data only occur when students permanently discontinued enrollment in BPS prior to reaching 9th grade or students did not matriculate to 9th grade by school year 2013–2014 due to being held back in grade during elementary or middle school. The final analytic sample consists of all City Connects ($N=894$) and comparison ($N=10,200$) students whose records meet the described data requirements.

The City Connects Intervention

Developed through a Boston College collaboration with BPS and community agencies, City Connects was designed based on theoretical and empirical understandings from

developmental science for how a comprehensive student support intervention can be expected to impact student outcomes. City Connects works to make student support operations—the systems through which schools address students’ academic and non-cognitive barriers to learning—more comprehensive and efficient. The City Connects system takes advantage of resources and structures already present in schools and communities to connect every child in a school to the right supports and services at the right time. A full-time Coordinator meets with each classroom teacher and other school staff to review every student every year. They discuss each child’s strengths and needs in the areas of academics, social/emotional/behavioral development, health, and family. Using a proprietary database, each student is then linked to a tailored set of services and enrichment opportunities in the school and/or community that address his or her unique strengths and needs; Coordinators follow up throughout the year. City Connects offers a systematic practice, with supporting resources and technology, for a school to do this work efficiently.

Several features of the model make the work feasible. First, at the center of the practice is the Coordinator, a Masters-level licensed school counselor or social worker who receives induction and ongoing professional development. Second, processes are codified; for example, reviews are carried out as a shared conversation with a series of guiding questions that elicit teacher insights on student strengths and needs across developmental domains. Third, the model

offers protocols, embedded in practice software, for categorizing and organizing community- or school-based resources and supports so that they can be chosen to match each student's individual strengths, interests, and needs. For example, one student might benefit from a mentor and an enrichment program in art; another might be referred to a health service, an afterschool program that provides dinner, and an attendance support program. Coordinators also find programs and resources for delivery at the school and classroom levels to address wider needs. They offer crisis intervention for individual or small groups of children, family outreach, and general support for school-wide initiatives and priorities. Fourth, the secure, proprietary student support database includes features such as reminders, prompts, and automated reports that make the Coordinator's work more efficient and allow reporting to principals and others in the school on students' strengths, needs, goals set, progress toward goals, community partners by category, and services delivered to students.

Throughout the year, the Coordinator develops and maintains partnerships with community agencies and serves as the primary point of contact for families. A documented, standardized set of practices, oversight mechanisms, and fidelity monitoring tools guide implementation across school sites. This system was first implemented in six BPS elementary schools during the 2001–2002 school year; it now serves more than 90 schools across five states.

Data Analysis

Treatment and Comparison Group Equivalence on Factors Correlated with Dropout. Given the gradual growth of the model within the district in response to need and because serving all students in a school is a critical feature of the intervention, a study based on random assignment to treatment or control conditions was not possible. Thus, to examine the likelihood that selection effects may bias treatment estimates, treatment and comparison samples were compared across a number of observed student-level variables correlated with dropout: baseline (grade 1) attendance and demographic variables (i.e., gender, race, eligibility for free/reduced-price lunch, English language learner status, etc.). Variables were selected for baseline group equivalence assessment in accordance with the *What Works Clearinghouse* guidelines for evaluations of dropout prevention programs (What Works Clearinghouse, 2014).

We utilized student-level propensity score weights (Cook & Steiner, 2010; Guo & Fraser, 2010; Rosenbaum & Rubin, 1983) to reduce selection bias due to these variables. We estimated a propensity score for every student in the analytic sample via a main effects logistic regression that incorporated each baseline variable included in Table 2. The resulting coefficients table is provided in Appendix A. After examining propensity score distributions of the two groups

for adequate overlap, we then calculated student-level Average Treatment Effect on the Treated (ATT) propensity weights in the manner discussed by Hirano and Imbens (2001), applied them to the analytic sample, and recalculated covariate balance. ATT weights adjust the composition of the comparison sample so that its group means and proportions approach those of the treatment sample.

Outcome Variable: A Direct Measure of Dropout Timing. We utilized an outcome measure that is aligned with the commonly understood definition of dropout: permanent disenrollment from school prior to completion of high school graduation requirements. For each student's time series, we coded a dichotomous dropout indicator, D_{it} , at the repeated-measures level for each available time point beginning at grade 9 and concluding when the student discontinues enrollment in the school district. D_{it} reflects the dropout status of student i at the end of grade t (dropout = 1, non-dropout = 0). This variable was measured annually; only one time point per student per grade is coded. Time-series data span up to four grades (9–12). If a student repeated a grade during high school, D_{it} was calculated based on the final school year associated with the repeated grade. The exact number of time points in a given student's time series depended on the cohort of the student, as well as the specifics of his/her longitudinal record. Time-series were censored (i.e. did not extend to grade 12) if a student dropped out of school prior to grade 12, transferred out of the district prior to grade 12, or simply did not reach grade 12 by the 2013–2014 school year.

The school district assigns *withdrawal codes* to each student record when a student discontinues enrollment in a given school or in the school district entirely, including by graduation. For this study, dropout status was determined using the withdrawal code corresponding to the final time point of a student's time series. Dropout was coded as occurring for final withdrawal codes that indicated dropout consistent with the district's definition (Boston Public School District, 2006), as well as generally consistent with the literature. Codes associated with leaving the district for another reason, such as transferring to another school district, were not considered to indicate school dropout. The frequency of specific withdrawal codes used to indicate dropout status in this analysis is provided in Table 1. Table 1 presents withdrawal code distributions by treatment status for students identified as dropouts.

Although students were identified as having dropped out of school for a variety of reasons, there were no notable differences in withdrawal code distribution by treatment status. This suggests that D_{it} captures comparable types of dropout across study groups.

Here D_{it} is a direct measure of dropout status and timing for each student, comparable to the adjusted cohort graduation rate (ACGR) based on individual student trajectories

TABLE 1
Withdrawal Code Distributions for Cases Assigned Dropout Status

Withdrawal Code	Treatment Sample Dropouts With Withdrawal Code (%)	Comparison Sample Dropouts With Withdrawal Code (%)
Enrolled in non-diploma adult education	6.3	7.3
Entered job corps	4.5	4.1
Entered military service	0.0	0.1
Incarcerated	1.6	1.0
Left school due to employment	1.6	2.0
Completed the GED	12.5	11.6
Expulsion	0.1	0.3
Married, pregnant, or parenting	0.0	0.6
Confirmed dropout over age 16 / no plans known	10.9	11.1
Did not report to school (did not transfer)	62.5	61.9

(NCES, 2016). This is in contrast to group-level proxies of dropout, such as cohort enrollment differences across grades, which have been used to report official dropout statistics and in educational research/program evaluations (Hammond, Linton, Smink, & Drew, 2007; ICF International, 2010; Rumberger, 1987). This distinction is worth noting—group-based proxies neither contain information about specific students, nor the timing of dropout. Additionally, as Rumberger (1987) has pointed out, group-based dropout proxies are defined in ways that often need clarification because they do not always align with the common understanding of dropout, and can reflect a number of extraneous factors such as late, but eventual, graduation from high school. An additional advantage of our approach is that, following others, we do not count GED as high school graduation (Heckman & LaFontaine, 2006; Murnane, 2013). This approach avoids inflating the graduation rate/deflating the dropout rate by including a degree that has been shown to lack equivalence—in terms of the economic advantages it affords—to the high school diploma.

It is important to recognize that withdrawal code data contain errors that can result in the misclassification of students' dropout status. For instance, a false positive dropout classification can occur if a student transfers to a school outside of the district, but the student is assigned a dropout-related withdrawal code instead of an out-of-district transfer code. Similarly, false negative errors can occur if true dropouts are simply missing final withdrawal codes altogether. These types of errors cannot be readily identified using district data alone, and may bias group-level dropout rate estimates when aggregating D_{it} .

There are other instances, however, where the coding strategy used to create D_{it} is robust to withdrawal code errors. For example, even though an early withdrawal code may indicate dropout, if the student later reenrolls in BPS, the early withdrawal code is incorrect. The D_{it} coding strategy described above corrects for these types of errors

automatically except in instances where students who previously dropped out return to BPS after school year 2013–2014. For example, a student with the withdrawal code “did not report to school” who returned to school the following year would not be included in dropout rates based on D_{it} . Because group-based proxies for dropout do not track individual students, on the other hand, they offer no protection against these types of false positives.

Overall, given that both false positive and negative errors likely occur, it is possible that dropout rates based on D_{it} are biased, and the direction of the bias is unknown. Nevertheless, because there is no reason to believe that such bias differs across treatment and comparison groups, the threat of bias in treatment-effect estimates due to these errors is low.

Statistical Analysis. Given the school-level sample of six intervention schools, any analysis estimating school-level treatment effects will be underpowered. Consequently, treatment effects are estimated at the student level. Although City Connects is assigned at the school level, the intervention is carried out in an individualized way for each student. Thus, the overall intervention can be conceptualized as consisting of a range of student-level treatments, clustered within schools.

We leverage students' time-series records to examine dropout longitudinally using Discrete Event History Analysis (Allison, 1982; Singer & Willett, 1993) to compare the likelihood of dropping out over time for treatment students and comparable students who never experienced City Connects. Similar to a more commonly utilized technique, Survival Analysis (Breslow, 1975; Cox, 1972), Discrete Event History Analysis can be used to model the odds of an event occurring, when the occurrence of the event necessarily censors time-series data. After a simple transformation, both methodologies produce *hazard functions*—functions that describe the probability of the event occurring over time for subjects who have yet to experience the event. The hazard function associated

with Discrete Event History Analysis is defined at discrete time points, while the Survival Analysis function is defined along a continuous time range. In this analysis, time cannot be considered continuous, as it is measured in grade-level units. Thus, we proceed in the discrete time context.

Discrete Event History Analysis models *time-to-event* via hierarchical logistic regression—time points (level 1) are nested within subjects (level 2), and the outcome variable is dichotomous. To capture time, we specified a level 1 model that consists of a series of time-varying dummy variables indicating the high school grade of student i at time t . Grade 9 serves as the intercept. In our time-coding scheme, grade dummies turn on (equal 1) and remain on when time t is greater than or equal to the associated grade dummy. For example, for time points that occur at grade 10, the grade 10 dummy variable equals 1, while the grade 11 and 12 dummies equal 0. At grade 11, both the grade 10 and 11 dummy variables equal 1, and only the grade 12 dummy equals 0. Overall, this *base time specification* produces a non-parametric time function that yields grade-specific estimates of the log-odds of dropout. Grade dummy coefficients describe the magnitude of the “shifts” in the log-odds of dropout that occur across sequential grades.

In addition to this base time specification at level 1, we also modeled the effect of transferring schools during high school to reduce possible selection bias due to differential high school mobility across groups. This is achieved by including a time-varying dummy variable, *Transferred HS_{ti}*. For student i , this variable takes a value of 1 for all time points after the first high school transfer occurs and otherwise equals 0. Unlike baseline control covariates, *Transferred HS_{ti}* is time-varying during high school, and therefore cannot be incorporated in the level 2 propensity weights, which capture baseline characteristics only. Formally, the full level 1 model is as follows.

$$\log \left[\frac{P_{ti}}{1 - P_{ti}} \right] = \pi_{0i} + \pi_{1i} (\text{Grade10}_{ti}) + \pi_{2i} (\text{Grade11}_{ti}) + \pi_{3i} (\text{Grade12}_{ti}) + \pi_{4i} (\text{Transferred HS}_{ti}) \quad (1)$$

where P_{ti} is the probability of student i dropping out at time t .

Moving to the student level, every level 1 time coefficient was initially allowed to vary randomly at level 2 and as a function of the treatment *CityConnects_i* (i.e., City Connects = 1, comparison = 0). Models included student-level covariates gender, race, eligibility for free- or reduced-price lunch, special education status, English language learner status, immigrant student status, number of school days present, and interactions of treatment with all demographic covariates. The coefficient capturing high school transfer was fixed. Student-level selection bias was reduced by applying ATT propensity weights at level 2. Although a high degree of group equivalence was demonstrated after ATT

weighting, level 2 covariate adjustments were included in the outcomes analysis following the standards for propensity score-weighted models as outlined by What Works Clearinghouse (2017). The full level 2 model is as follows.

$$\begin{aligned} \pi_{0i} &= \beta_{00} + \beta_{01} (\text{CConnects}_i) + \sum_{k=2}^{11} \beta_{0k} (\text{Covariates}_i) \\ &\quad + \sum_{k=12}^{20} \beta_{0k} (\text{CConnects}_i * \text{Demographics}_i) + r_{0i} \\ \pi_{1i} &= \beta_{10} + \beta_{11} (\text{CConnects}_i) + \sum_{k=2}^{11} \beta_{1k} (\text{Covariates}_i) \\ &\quad + \sum_{k=12}^{20} \beta_{1k} (\text{CConnects}_i * \text{Demographics}_i) + r_{1i} \\ \pi_{2i} &= \beta_{20} + \beta_{21} (\text{CConnects}_i) + \sum_{k=2}^{11} \beta_{2k} (\text{Covariates}_i) \\ &\quad + \sum_{k=12}^{20} \beta_{2k} (\text{CConnects}_i * \text{Demographics}_i) + r_{2i} \\ \pi_{3i} &= \beta_{30} + \beta_{31} (\text{CConnects}_i) + \sum_{k=2}^{11} \beta_{3k} (\text{Covariates}_i) \\ &\quad + \sum_{k=12}^{20} \beta_{3k} (\text{CConnects}_i * \text{Demographics}_i) + r_{3i} \\ \pi_{4i} &= \beta_{40}. \end{aligned} \quad (2)$$

During the model building process, non-significant fixed effects associated with *CityConnects_i* and non-significant random effects were removed from the level 1 slope equations (some may recommend other approaches to model building, for example, Gelman & Loken, 2013). Non-significant fixed effects associated with the covariates and interactions of demographic covariates with treatment were maintained in the intercept equation because the fixed affect associated with *CityConnects_i* in this equation was significant, resulting in the final covariate-adjusted model.

$$\begin{aligned} \pi_{0i} &= \beta_{00} + \beta_{01} (\text{CConnects}_i) + \sum_{k=2}^{11} \beta_{0k} (\text{Covariates}_i) \\ &\quad + \sum_{k=12}^{20} \beta_{0k} (\text{CConnects}_i * \text{Demographics}_i) + r_{0i} \\ \pi_{1i} &= \beta_{10} \\ \pi_{2i} &= \beta_{20} \\ \pi_{3i} &= \beta_{30} \\ \pi_{4i} &= \beta_{40}. \end{aligned} \quad (3)$$

In (3), the student-level treatment variable affects the log-odds of dropout proportionally across the non-parametric

TABLE 2

Baseline (Grade 1) Group Equivalence before and after ATT Weighting

		Comparison					
		City Connects		Unadj.		Weighted	
		%/Mean	Std. Dev.	%/Mean	%/Mean	Unadj. Std. Bias	Weighted Std. Bias
Male		49.7%	25.0%	49.2%	49.5%	0.019	0.008
Race	Black	35.9%	23.0%	40.0%	35.9%	-0.178	-0.002
	White	10.7%	9.6%	10.9%	10.9%	-0.020	-0.013
	Asian	15.5%	13.1%	7.8%	15.3%	0.592	0.016
	Hispanic	36.6%	23.2%	40.1%	36.6%	-0.151	-0.002
	Multiracial/other	1.2%	1.2%	1.2%	1.2%	0.012	0.004
Free/reduced-price lunch		93.8%	5.8%	93.7%	93.8%	0.025	0.017
Special education		27.1%	19.7%	18.6%	27.2%	0.430	-0.009
English language learner		15.2%	12.9%	21.9%	15.3%	-0.522	-0.005
Foreign born		14.0%	12.0%	15.5%	14.1%	-0.126	-0.006
Days present in school		155.3	33.1	159.5	155.1	-0.126	0.006

time function (π_{0i} thru π_{3i}). Though we did not assume this relationship form initially, and only arrived at (3) after empirical examination of (2), we note that the form of (3) is similar to the Cox Proportional Hazard Model (Cox, 1972), a commonly utilized and widely accepted Survival Analysis specification.

Results

Table 2 presents the sample's composition in terms of group means or proportions on baseline variables. Standardized bias statistics are also provided. Aligned with our goal of estimating the ATT, we calculate standardized bias statistics as the group difference in means or proportions divided by the standard deviation of the treatment group (Harder, Stuart, & Anthony, 2010). Cells with standardized bias magnitudes larger than 0.250 are shaded—this level of bias indicates a degree of covariate imbalance across groups that does not meet WWC group equivalence standards (What Works Clearinghouse, 2017). By examining the unadjusted standardized bias column in Table 2, we find that prior to statistical adjustment, substantial covariate imbalance existed across treatment and comparison groups for three indicators.

The result of ATT weighting on comparison group composition and standardized bias statistics can be found in Table 2 in the “Weighted” columns. Here we see that the ATT weights substantially reduced bias across all cells, with post-weighting standardized bias statistics all smaller in magnitude than 0.05 standard deviations.

Outcome model fixed and random effects results are presented in Tables 3 and 4 respectively. Positive and negative fixed-effect coefficients reflect increased and decreased odds of dropout respectively. Exponentiated coefficients describe the odds ratio effect size, OR. Here β_{00} describes

the comparison student odds of dropout in grade 9 (OR = .062). Comparison student odds of dropout at subsequent grades are calculated by exponentiating the sum of the appropriate coefficients. For example, comparison group odds of dropout at grade 10 and grade 12 are given by $e^{\beta_{00}+\beta_{10}}$ and $e^{\beta_{00}+\beta_{10}+\beta_{20}+\beta_{30}}$ respectively. The effects of a high school transfer are found by examining π_4 . Generally, we find that the odds of dropout vary over the course of high school, and are highest at grade 9. Additionally, school transfers that occur after the start of the 9th grade are associated with large increases in the odds of dropout (β_{40} OR = 3.114, $p < .001$).

The fixed effect associated with β_{01} describes the proportional difference in the hazards functions for treatment and comparison groups. Our models show that, relative to comparison students, City Connects students have approximately half the odds of dropping out of school during any given grade (β_{01} OR = .528, $p < .001$). Stated inversely, relative to treatment students, comparison students have about twice the odds of dropping out at any given grade.

Transformation of the log-odds simplifies interpretation by allowing us to directly examine the probability of dropout occurring over time. Transformation from log-odds to probability is given by:

$$P_{it} = \frac{1}{1 + \exp\left(-\log\left[\frac{P_{it}}{1 - P_{it}}\right]\right)} \quad (4)$$

and is used to calculate grade-specific dropout probabilities for treatment and comparison students. Graphing these probabilities by grade produces the hazard function (see Table 5 and Figure 2).

Once grade-specific probabilities are calculated, the cumulative 9th grade cohort dropout probability is found by:

TABLE 3
Outcome Model Fixed Effects

		Coef.	S.E.	T	Df	OR	p
π_0 , Grade 9							
Intercept	β_{00}	-2.782	0.064	-43.532	11073	0.062	<.001
City Connects	β_{01}	-0.638	0.140	-4.556	11073	0.528	<.001
Male	β_{06}	0.255	0.058	4.379	11073	1.290	<.001
Black	β_{08}	-0.182	0.100	-1.817	11073	0.834	0.069
Asian	β_{09}	-0.833	0.170	-4.912	11073	0.435	<.001
Hispanic	β_{010}	0.034	0.101	0.337	11073	1.035	0.736
Multiracial/other	β_{011}	0.258	0.223	1.159	11073	1.294	0.247
Free/reduced lunch	β_{05}	1.079	0.181	5.966	11073	2.941	<.001
Special education	β_{03}	0.193	0.068	2.827	11073	1.213	0.005
English language learner	β_{04}	-0.222	0.084	-2.635	11073	0.801	0.009
Foreign born	β_{07}	-0.122	0.099	-1.227	11073	0.885	0.22
Days present	β_{02}	-0.002	0.001	-2.391	11073	0.998	0.017
City Connects*male	β_{015}	-0.133	0.266	-0.501	11073	0.875	0.616
City Connects*Black	β_{017}	0.320	0.455	0.703	11073	1.377	0.482
City Connects*Asian	β_{018}	-0.874	0.848	-1.030	11073	0.417	0.304
City Connects*Hispanic	β_{019}	0.020	0.468	0.043	11073	1.020	0.966
City Connects*multiracial	β_{020}	-0.002	1.180	-0.002	11073	0.998	0.999
City Connects*free/red. lunch	β_{014}	0.405	0.417	0.971	11073	1.500	0.332
City Connects*special education	β_{012}	-0.002	0.003	-0.629	11073	0.998	0.529
City Connects*English language learner	β_{013}	-0.332	0.291	-1.140	11073	0.718	0.255
City Connects*foreign	β_{016}	-0.109	0.467	-0.235	11073	0.896	0.815
π_1 , Grade 10 shift							
Intercept	β_{10}	-0.434	0.131	-3.327	31389	0.648	0.001
π_2 , Grade 11 shift							
Intercept	β_{20}	-0.187	0.132	-1.418	31389	0.830	0.156
π_3 , Grade 12 shift							
Intercept	β_{30}	0.418	0.129	3.246	31389	1.519	0.002
π_4 , Transferred high school 1+ Time							
Intercept	β_{40}	1.136	0.105	10.847	31389	3.114	<.001

TABLE 4
Outcome Model Random Effects

	SD	Var	df	p
r_0	0.041	0.002	11073	<.001

$$C_c = 1 - (1 - P_{9c}) * (1 - P_{10c}) * (1 - P_{11c}) * (1 - P_{12c}) \quad (5)$$

where C_c = cumulative probability of dropout for group c , P_{9c} = the probability of dropout at grade 9 for group c , P_{10c} = the probability of dropout at grade 10 for group c , P_{11c} = the probability of dropout at grade 11 for group c , and P_{12c} = the probability of dropout at grade 12 for group c . Given this formulation, we find that across grades 9 to 12 the probability of dropout for City Connects students is approximately 9.2%, while comparison students have a probability of dropout of about 16.6%, a difference of 7.4%

TABLE 5
Dropout Probabilities Using ATT Specification

	Grade				Cumulative
	9	10	11	12	
Comparison	5.8%	3.9%	3.2%	4.8%	16.6%
City Connects	3.2%	2.1%	1.7%	2.6%	9.2%

ATT: Average Treatment Effect on the Treated

points (see Figure 3). This finding corresponds to an effect size of -0.369, implying a moderate effect for the treatment group.

Discussion

Reducing dropout is challenging from a policy perspective because students often fail to complete high school for

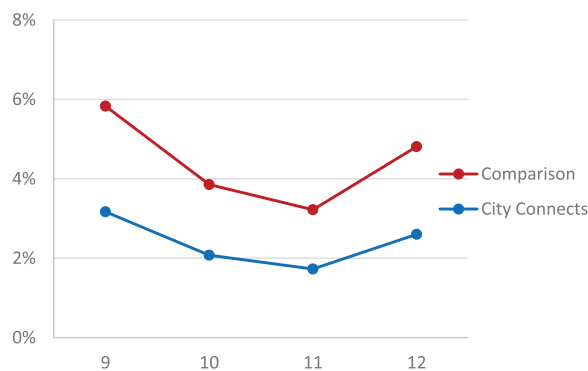


FIGURE 2. *Dropout hazard function: probability of dropout by grade in school.*

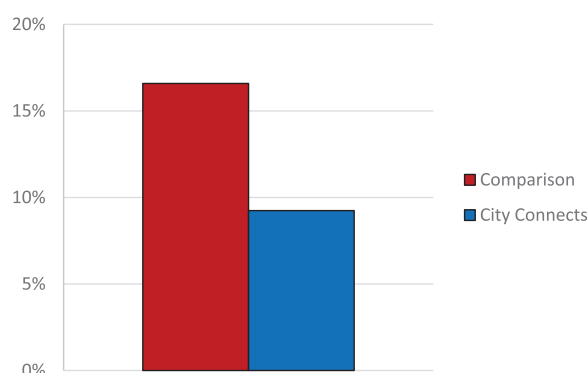


FIGURE 3. *Cumulative dropout hazard: cumulative probability of dropout across grades 9–12.*

complex reasons that involve factors both inside and outside of schools. Moreover, these factors often manifest and influence student achievement trajectories long before they reach high school. To limit the negative impact of these factors, theory and research suggest that it is possible to intervene early in ways that bolster protective factors in students while also addressing risk factors, though any such intervention must take into account the multidimensionality and cross-domain interdependency of development.

Previous studies have examined dropout employing discrete time hazards models (Bowers, 2010; Lamote et al., 2013). This analytic approach extends earlier work by using a large sample in which an intervention was implemented in a “real world” setting, applying propensity score weights, and taking into account school attendance, as recommended by standards.

An emerging area of research has focused on identifying different “types” of students who drop out of school (Fortin, Marcotte, Potvin, Royer, & Joly, 2006; Janosz, LeBlanc, Boulerice, & Tremblay, 2000; Kronick & Hargis, 1998; Lessard et al., 2008). Bowers and Sprott (2012a, 2012b) identified three subgroups of students who drop out of high school: (a) *jaded* students, who are characterized by disengagement from school, the lowest grades of the three groups, high

absences, and high behavior problems; (b) *quiet* students, who have the second lowest grades, second highest absences, and fewest behavior problems; and (c) *involved* students, who have the highest grades, highest test scores, and highest extra-curricular involvement of the three groups.

While the literature on dropout subgroups has not yet extended its focus to the elementary school years, it does emphasize a distinction between students who exhibit early indicators for risk of school failure (such as low grades, high rates of problem behavior, and low school engagement (Balfanz et al., 2007)) and students who may be less likely to be identified as at risk. We suggest that the elementary school intervention studied here may be effective in reducing dropout rates for students who would have ended up in the Bowers and Sprott (2012b) “*jaded*” group (who, because of the intervention, might receive early attendance support, academic enrichment and remediation services, and behavioral support) and students who would have ended up in the “*quiet*” group (who, similarly, might be identified for early academic support—and who, because of the whole school review approach used in the intervention, might be identified as at risk in other domains more readily than they otherwise would have been).

The results from this study provide direct empirical evidence that a systematic and individually tailored student support intervention during elementary school years can lead to lasting and meaningful effects. With an estimated reduction in odds of approximately one half, for a district-wide 9th grade cohort of typical size in BPS (~5000 students), the estimated treatment effect in this study translates into approximately 375 fewer dropouts over the course of high school. Given that each new high school graduate has been estimated to yield social benefits of \$260,300 over a dropout (Bowden et al., 2015), the significance of staying in high school rather than dropping out is highly meaningful. In terms of social benefit: one approach, estimating the benefit–cost of the City Connects model based on reported effects of the model on dropout and academic attainment, and including a portion of the costs associated with services students are referred to through the practice and the costs associated with implementation of the model itself, showed that the model provides a return on investment of \$3 for every \$1 spent (Bowden et al., 2015).

Despite the promise of this type of comprehensive approach to intervention, efforts targeting dropout often are highly focused, directing attention to one or two specific needs instead of a wide range of both strengths and needs (e.g., Darney, Reinke, Herman, Stormont, & Ialongo, 2013; Prevatt & Kelly, 2003; Somers & Piliawsky, 2004). Additionally, such efforts tend to be aimed solely at high school students (e.g., Fries, Carney, Blackman-Urteaga, & Savas, 2012; Hartmann, Good, & Edmunds, 2011; Lever et al., 2004; Vaughn and Roberts, 2014), overlooking theory and research suggesting that elementary school and early childhood years are critical periods of development during which relatively modest increases in resource investment can have substantial impacts on later outcomes. As noted by

Cunha and Heckman (2007), investment in middle childhood and adolescence also carries potential benefits, but in general the amount of investment required in these later years must be greater to reach the same effects on achievement and non-cognitive skill trajectories as early childhood investment.

The City Connects intervention, in contrast, leverages these insights from the evidence to intervene comprehensively, systematically, and early in life in order to reduce barriers to achievement both proximally and in the long term. The findings of this study suggest that this intervention is effective for preventing dropout when implemented in elementary school. An important follow-up step will be to examine intervening mechanisms for this effect. We suggest that comprehensive, systematic student support in grades K–5 may positively affect later high school dropout because such support bridges resource gaps experienced by low-income students, removing barriers and enhancing facilitators of early skill development and thereby setting students up to (a) enter trajectories of school engagement characterized by the strong connections to school that are facilitated by experiences of academic and social success at school, and (b), because of their increased skills, receive greater benefit from staying in school during the middle and high school years than they otherwise would have. Future research to evaluate these mechanistic hypotheses is needed.

Limitations

We note limitations of the present study. A randomized design was not employed because the implementation was carried out in successive waves in this school district and all students in a school are served. Thus, one limitation is the presence of possible selection threats to internal validity due to unobserved variables. Treatment and comparison groups were well-balanced in observed pre-intervention characteristics once propensity score weights were applied. However, a weakness of propensity score methods is the inability to take unmeasured characteristics into account. There may be unmeasured differences between treated and untreated students or schools that influenced both selection into City Connects and the likelihood of school dropout.

Regarding school-level selection, the district chose participating geographic clusters based on concerns about student support and academic performance and required all schools within the cluster to participate. City Connects schools started at a disadvantage in terms of report card and test scores relative to comparison schools; treatment schools had significantly lower academic achievement than comparison schools before implementation (Walsh et al., 2014), suggesting that selection effects would potentially be in the direction of less positive school completion outcomes for treatment schools.

Conceivably, a plausible unmeasured selection mechanism could be that families of students choosing to attend

intervention schools are characterized in some way also related to eventual lower rates of dropout. It is of note that during the time students in this study attended elementary school, the implementation of City Connects was not marketed as a feature to attract family interest in enrollment. As a pilot implementation, the program had not been long-implemented and was not well known, so it is unlikely families selected schools because of the intervention. To further explore this possibility, we studied available school application and enrollment data to compare the proportions of City Connects and non-City Connects schools that were over-demanded at the time of kindergarten enrollment; that is, more student families requested placement than seats were available. These data were not available to us for kindergarten enrollment years 2001–2002 to 2004–2005, but for the eight subsequent years (2006–2007 to 2013–2014) there was no difference between treatment and comparison schools in terms of being over-demanded. It is likely that some omitted variables do operate in this context. However, in other research (An, Braun, & Walsh, 2017), observed achievement differences between students who did and did not participate in City Connects were subject only to a mild sensitivity to hidden bias.

Although systematic student support is necessarily customized at the student level and may perhaps be considered an individual treatment, assignment to City Connects occurs at the school level. Thus, another limitation of this study is that we estimate student-level effects instead of school-level effects. However, the choice to estimate student-level treatment effects was made due to practical concerns about statistical power—a treatment group sample size consisting of only six schools is underpowered regardless of the student-level sample size.

Given the flexible nature of a systematic student support intervention, it is also plausible that the treatment has differential effects across subgroups or groups of students with different constellations of strengths and needs. Thus, average treatment-effect estimates, like the one presented in this article, may not precisely quantify the effect of the treatment for different subgroups or types of students. Future research examining the effects of integrated student supports in subgroups of students with differing dropout rates and differing patterns of risk factors for dropout is warranted.

Finally, we note that because we estimated treatment effects using ATT propensity score weights, valid generalization of results can only be made to the population who received the treatment (i.e., the population of students who attended kindergarten or 1st grade in BPS and have a demographic composition similar to the City Connects sample). Average Treatment Effects (ATEs)—those that more broadly generalize to the population represented by the joint treatment and comparison samples—also were estimated. We found that the magnitude of the ATT and ATE results were similar. This provides some evidence that our findings are robust across treatment-effect specifications, and suggests that more broad generalization may be appropriate.

Appendix A: Propensity Score Estimation

Logistic Regression Coefficients

	Coef.	S.E.	Wald	df	OR	p
Intercept	−2.598	.254	105.048	1		<.001
Male	−.049	.071	.482	1	.952	.488
Race						
Black	−.220	.127	2.977	1	.803	.084
Asian	.931	.146	40.473	1	2.537	<.001
Hispanic	−.054	.128	.179	1	.947	.672
Multiracial/other	−.022	.335	.004	1	.979	.949
Free/reduced-price lunch	.073	.155	.225	1	1.076	.635
Special education	.493	.083	35.543	1	1.637	<.001
English language learner	−.579	.110	27.819	1	.560	<.001
Foreign born	−.015	.113	.017	1	.985	.897
Days present in school	−.003	.001	7.174	1	.997	.007

Outcome variable = City Connects (1 = treatment, 0 = comparison)

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