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Integrated Student Support and Student Achievement: A Replication Study*

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Abstract

Growing up in poverty presents numerous nonacademic barriers that impede academic progress for economically disadvantaged students (Duncan and Murnane, 2016). Because schools alone have limited capacity to address the systemic nature of economic inequalities that directly affects student outcomes, policymakers and researchers in recent years have increased calls for the use of comprehensive, integrated support models and wraparound services (Wasser Gish, 2019). Although research on the effects of such interventions has been mixed, evaluations of one model – City Connects – have found significant achievement gains for students who received the intervention in elementary school (Walsh et al., 2014). Given the need to understand the replicability of interventions beyond initial sites of implementation, we assessed the degree to which the intervention effect on math and English Language Arts (ELA) achievement in elementary and middle school replicates in a new site with important geographical variation. Results from two-way fixed effects and event-study models suggest positive treatment effects of nearly half a standard deviation in both subjects following five years of implementation, supporting the replicability of City Connects.

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INTRODUCTION

The impact of growing up poor on academic and long-term economic outcomes is well-established (Duncan & Murnane, 2011); in fact, Berliner (2013) has identified poverty as the single most critical factor to address in educational reform. Yet, collectively, prior research on the effect of poverty on academic attainment points to a straightforward conclusion: schools cannot close the achievement gap without a systemic approach to addressing out-of-school disadvantage (Henig & Reville, 2011; Bryk, 2010). Research spanning a half century confirms that children's lives outside of school are critical determinants of their achievement in school, accounting for up to two-thirds of the variance in academic achievement (Coleman, 1968; Rothstein, 2010). And, in high-poverty urban school districts across the United States, children face exceptional challenges outside of school that impede their success inside school and in life.

The impact of out-of-school factors on student achievement and thriving has only heightened in the past few years as a result of the COVID-19 pandemic. In 2022, most public school leaders report a negative impact of the pandemic on student socio-emotional development and behavior, seeking more support for student mental health and socio-emotional development (National Center for Education Statistics, 2022). Many states have used American Rescue Plan Elementary and Secondary School Emergency Relief funds to increase investment in non-academic supports and resources such as more social workers, mental health counselors, and nurses (U.S. Department of Education [DOE], 2021). Still, many schools lack a systematic and effective way to support the strengths and address the needs of every child.

The potential for schools to partner with community agencies has emerged as a promising approach to reducing in- and out-of-school barriers to learning in a more comprehensive manner. Intervention models that provide schools with a systemic way to meet students' out-of-school needs and support their strengths and interests by leveraging community resources are broadly described as “Integrated Student Support” (ISS) (e.g., Boston College Walsh Center for Thriving Children, 2022; Moore et al. 2014, 2017). As researchers, practitioners, and the federal government call for comprehensive strategies that leverage community resources to mitigate the impact of out-of-school risk factors on student academic achievement (García & Weiss, 2017; U.S. DOE, 2021), rigorous evidence on the impact of ISS models is needed. Positive effects on student academic outcomes have been demonstrated for several ISS models (Borman et al, 2021; Dearing et al., 2016; Figlio, 2015; Lee-St. John et al., 2018; Parise et al., 2017; Walsh et al., 2014) but the generalizability of program impacts is not well established.

The specific focus of this study is on an ISS program called City Connects, which began over 20 years ago in Boston but has since expanded, currently implemented in more than 200 schools in five states (Walsh et al., 2014). Recent evaluations of City Connects at the elementary school level have found positive outcomes on elementary and middle school report card grades, standardized achievement tests, high school graduation, and college enrollment and completion (Lee-St. John et al., 2018; Pollack et al., 2020; Walsh et al., 2014). A limitation of prior research on the City Connects model is that much has focused on one school district. There may be distinct features in the first implementation site that contributed to the intervention’s success in ways that might not replicate elsewhere. Studying outcomes for students across other sites is imperative to understanding the degree to which findings about City Connects can be generalized, and contributes to information about contexts in which ISS can effectively be implemented. A second limitation concerns selection bias. Prior evidence has effectively compared the academic trajectories of otherwise similar students who attended schools implementing City Connects to those that did not. However, because the intervention was not randomly assigned to schools, it is difficult to disentangle whether observed effects were due to pre-existing differences in schools.

In this study, we sought to measure the replicability of the City Connects intervention's effect on academic achievement in a different site from prior studies using a method more suited for reducing selection bias at the school level. Specifically, we examined how academic achievement at the school level changed following the introduction of City Connects to schools in a new district in the same state, relative to similar schools that did not implement the intervention. We leveraged the staggered adoption of the intervention in this new site using difference-in-differences models, reducing concerns over the comparability of the treatment and comparison groups. Our findings have implications for the discussion of whether comprehensive and whole-child student support interventions can reduce existing and widening achievement gaps between students from low and high socio-economic backgrounds. In the following sections, we describe the ISS model of focus in the present study, the value of replication in educational research, and the context of implementation in the new site.

BACKGROUND

"Integrated Student Support" Interventions

Families living in the context of poverty exhibit many strengths (e.g., González et al., 2005; Moore et al., 2002), but the risks children may be exposed to as a result of poverty have been well-documented (e.g., Brooks-Gunn & Duncan, 1997; Conger & Donnellan, 2007; Evans, 2004; Leventhal & Brooks-Gunn, 2000; Magnuson & Votruba-Drzal, 2009). Such risks have been linked with problems in brain neural development, cognitive functioning, and self-regulation beginning in infancy and accumulating through childhood when exposure is chronic (Hanson et al., 2013; Johnson et al., 2016; Noble & Farah, 2013; Williams Shanks & Robinson, 2013).

ISS programs were developed with the idea that schools can address the dynamic and complex risks faced by children living in poverty by identifying them and then tailoring a plan of supports (Moore et al., 2014; Moore et al., 2017). ISS programs are often implemented by a core person in the school (such as a school counselor) and have been described as including five components: an assessment to identify children's needs, strengths, and interests; coordination of school and community-based supports for children and families; development of partnerships with community organizations; integration of supports and processes into the school setting; and data collection (Moore et al., 2017).

The City Connects Model of Student Support

City Connects is a school-based intervention based on theoretical and empirical understandings from developmental science for how comprehensive student support can be expected to impact student outcomes (Walsh et al., 2014). It emerged in response to the need for a systemic approach to addressing the out-of-school factors that can impede a student's ability to succeed and thrive in school (Walsh & Brabeck, 2006). Through a two-year planning process, university researchers and experienced practitioners in school counseling, social work, and educational leadership met with school principals, teachers, school staff, community agency representatives, civic organizational leaders, and families to collaborate on the development of City Connects.

At the core of the intervention is a full-time, master's-trained Coordinator (a licensed school counselor or social worker) in each school. In the fall of the school year, the Coordinator meets with each classroom teacher to discuss the strengths, interests, and needs of every student in the class. The conversation is guided by standardized questions across the developmental domains of academics, social-emotional/behavioral development, health, and family. Students with more intensive needs at any point during the school year receive a more in-depth individual review by a wider team of professionals (which may include school psychologists, teachers, principals, nurses, and community agency staff) to develop specific goals and strategies for that student.

Based on the identified strengths, interests, and needs, the Coordinator tailors unique support plans for each student with different combinations of quantity and type of services. Coordinators then leverage the resources available in the school and community, and in consultation with the family, work to carry out the plan. Examples of services include before- and after-school programs, sports, mentoring, tutoring, social skills interventions, health screenings, family counseling, and food or clothing donations. Services are sometimes available in the school (e.g., school-based after-school program or classroom health lessons), but are also provided by institutions in the community (e.g., community sports program). Throughout the year, Coordinators connect children and their families with service providers, monitor service quality and fit, cultivate and maintain partnerships with community providers, and coordinate activities of agencies working within the school.

Enabling the implementation of City Connects in schools is a secure web-based information system that centralizes information about student needs and community resources, allowing the Coordinator to record and track the individual support plan for each student. Features such as action steps and status indicators facilitate follow-up for each student, and dashboards and automated reports make it easy to monitor and communicate progress to teachers and principals.

Through the software system, information can automatically be compiled to show the degree to which City Connects is being delivered in any location and network-wide. Fidelity monitoring provides multi-item scores for each of seven core model components to provide data regarding evidence of standard implementation across school sites (City Connects, 2020).

Several program features are intended to ensure that delivery of the City Connects model is consistent across districts in different geographic areas. A set of program resources, including manuals, lists of key practice tasks and benchmarks, and practice checklists are available via an online learning management system and are used by all practitioners. A standard induction institute is provided for all new Coordinators in the network, and all Coordinators receive regular coaching and in-service professional development throughout the academic year. Program Managers (local leaders who supervise the practice) provide the coaching and deliver in-service trainings using a professional development library developed and maintained by City Connects. Program Managers themselves receive professional development via monthly virtual and an in-person meeting each summer. Program Managers and implementation leaders regularly review practice data in the information system to identify places where the practice is and is not being delivered as intended, and to provide supportive coaching as needed.

City Connects Theory of Change

Classic developmental systems theories (e.g., Bronfenbrenner & Morris, 1998) posit that development is the result of interactions between the various contexts in which the child lives, including school, home, and neighborhood. From this theoretical position, interventions designed to combat the potential harms of poverty and build on strengths must pay attention to the whole child and the various contexts which may contribute to his or her development. Developmental-contextual theory (Ford & Lerner, 1992; Lerner, 1995, 2012) builds on the bioecological model, considering development to occur across multiple levels of the individual, including physical, cognitive, affective, and social domains. The developmental-contextual theory also emphasizes that outcomes are a result of the interactions between risk factors, strengths, and protective factors. Because risks and strengths co-occur, the presence of a risk factor does not necessarily lead to a negative outcome. Appropriate interventions can make a substantial difference in child outcomes, despite the presence of risk factors. Theories of resilience emphasize the value of enhancing assets within the child or his or her context in addition to reducing risk factors (Masten, 2015; Masten, et al., 2008).

City Connects was designed based on these theoretical and empirical understandings from developmental science for how a comprehensive student support intervention can be expected to impact student outcomes. First, by leveraging individual, family, and community resources to both bolster student protective factors and address risk factors, positive student outcomes are promoted. When children receive the academic, behavioral, social, and health supports they need, they are more able to achieve and thrive. Second, City Connects supports teachers in high-poverty schools and provides opportunities for the teacher-student relationship to change as teachers learn more about students' out-of-school lives, strengths, and needs that may influence behavior and achievement. In fact, teachers in City Connects schools generally report that they gain a deeper understanding of the out-of-school lives of their students, develop effective classroom management strategies, and feel more supported in their work (Sibley et al., 2017). Third, the whole-school nature of the intervention can act to transform school climate. Research indicates that the climate and overall social conditions of schools have consequences for academic development (Benbenishty et al., 2016; Berkowitz et al., 2017; Thapa et al., 2013).

Prior Studies of the Intervention

Past research, including a study involving random student (but not school) assignment, has demonstrated positive effects of this ISS intervention on student achievement. In elementary school, students who attend schools implementing City Connects significantly outperform their peers on report card scores in reading, writing, and math (Walsh et al., 2014). A recent study showed that students randomly assigned to schools implementing City Connects via an enrollment lottery demonstrated significantly higher statewide test scores by grade 5 than peers who were not randomly assigned (Lawson et al., under review). First-generation immigrant students attending City Connects schools had higher standardized test scores in elementary school, compared to their counterparts in non-intervention schools (Dearing et al., 2016).

After leaving City Connects and moving on to middle school, students had higher grade point averages and scored higher on statewide math and English Language Arts (ELA) tests than comparison peers who were never enrolled in a school implementing City Connects (Walsh et al., 2014). Students previously enrolled in elementary schools with City Connects dropped out of high school at about half the rate of comparison students (Lee-St. John et al., 2018). After leaving high school, students previously enrolled in intervention schools significantly surpassed comparison peers in both enrollment and degree completion at two- and four-year colleges (Pollack et al., 2020).

Replication in Educational Research

To best identify what works for whom under what conditions, systematic replications of interventions that have evidence of impact can be used to test conditions that may affect the impact.

Varying implementation conditions such as student demographics, geographic locations, delivery method, or technology can illuminate when an intervention will likely show positive outcomes. By systematically varying aspects of prior impact studies, factors that may lead to and sustain successful implementation may be identified. It is common, however, in the social sciences for programs and interventions to not replicate findings of effectiveness when implemented in different sites (Cook, 2014).

"Efficacy Replications" are described as those providing more support than is typically provided under routine conditions while "Effectiveness Replications" evaluate the intervention under routine implementation conditions (Pentimonti, 2020). Here we study an Effectiveness Replication in which the geographic location has been varied from the implementation under which positive effects were first demonstrated.

Prior evaluations of City Connects have reflected outcomes from a single urban school district. A replication study of the effect of City Connects is important because there may be important characteristics of the original site of implementation that could have impacted the previously reported findings. For example, as shown in Table 1, there are clear demographic differences between the initial and new sites, which are both situated in the same state. Specifically, the past site is more racially diverse and includes a larger population of English Language Learners. While most students in both districts are economically disadvantaged, nearly 90 percent of students in the new site are from low-income backgrounds. Compared to the prior site, the new site is situated in a city three times smaller in population and half as large in terms of physical size. These demographic differences may reflect variation in needs and strengths across the communities. Therefore, assessing the degree to which City Connects may be responsive to such differences in strengths and needs is salient.

Additionally, while City Connects was designed to be flexible and responsive to different environmental contexts, the original site of implementation may have been especially conducive to the intervention's success. For instance, the original site is in the state capital, which is surrounded by a number of higher education institutions and community resources. Access to higher quality community resources that can effectively target student strengths and needs is an important feature of program success. The City Connects information database identifies more than 300 organizations in the original site available to support schools compared to about 200 in the new site. In sum, these differences provide an opportunity to assess whether this intervention leads to positive student outcomes in a smaller, more diverse and economically disadvantaged, and less well-resourced community compared to the original implementation site.

THE CURRENT STUDY

We sought to replicate prior evidence of the effectiveness of the City Connects intervention by estimating how academic achievement in math and ELA changed in schools following implementation of the intervention in a large urban school district that serves 30,000 students across over 60 schools, most of whom are economically disadvantaged.

Implementation of the Intervention

City Connects was implemented in the new district as one response to several schools being identified as needing reform. In 2010–2014, to comply with federal educational reform legislation, the state department of education designated "persistently low performing" or turnaround schools based on four-year trends in student achievement, growth, and improvement on statewide standardized assessments. Once designated, turnaround schools were provided additional supports designed to improve student achievement; these strategies typically included replacing teaching and administrative staff, expanding learning opportunities, implementing data-driven strategies to improve instruction, and providing non-academic student support.

City Connects was first implemented by five turnaround elementary schools in the district during the 2011/12 academic year as part of their turnaround strategy. Over the next two years, seven additional district schools were identified for turnaround by the state and adopted City Connects. Most other turnaround schools in the state implemented similar reform strategies, including some wraparound support models distinct from City Connects (LiCalsi et al., 2015). In subsequent years, other non-turnaround schools in the district began implementing the intervention; as of 2022, 43 schools in this district operate the intervention in at least one grade level.

Given this implementation history, we sought to address two research questions in this study:

1.) To what extent did student math and ELA achievement change in schools that implemented City Connects following its adoption relative to other schools in the *district*?

2.) After controlling for turnaround status, to what extent did student math and ELA achievement change in schools that implemented City Connects following its adoption relative to other schools in the *state*?

Through these research questions, we aimed to understand the extent to which prior evidence on the academic effects of City Connects replicates in one other school district.

Implementation of the model in the new district was designed to be identical to that in the original site, with the exception that Coordinators were employed by the district rather than the

City Connects organization. The City Connects fidelity of implementation system documented consistently strong fidelity to the practice in the site during the years of this study.

METHODS

Data

We leveraged school-level publicly available data produced by the state department of elementary and secondary education to conduct our analyses. The state makes available a range of longitudinal school-level data dating back to the 1990s, including school-level demographic information such as student race/ethnicity, student economic disadvantage, English Learner (EL), and special education status. Grade-level average scores on the statewide standardized assessment in mathematics and ELA also were available. For the purposes of our analyses, we standardized scores within grade, subject, and year to have a mean of 0 and a standard deviation of 1. We determined school accountability status (turnaround or not) through a review of state documents for each year from 2010 onwards, when the school reform program was initiated.

Analytic Samples

To answer our first research question – the impact of schools implementing City Connects compared to other schools in the district – we restricted the sample to schools in the district that served at least one grade between grades 3 and 8, which is when students are assessed by state standardized tests. Furthermore, we restricted the study to between the 2006–07 and 2018–19 school years, before the COVID-19 pandemic, to avoid potential difficulties in interpreting assessment results. The total within-district sample included 51 schools, 30 of which implemented City Connects for at least one school year in at least one grade level as of 2018–19.

For our second research question – designed to isolate the effect of City Connects from turnaround-related effects – we constructed a separate dataset that includes *all schools in the state* that served students in at least one grade between grades 3 and 8. This resulted in a sample of 1,500 schools. Due to small sample sizes and our interest in specifically estimating the effect of City Connects for all treatment schools, we opted not to directly compare City Connects turnaround schools to non-treatment turnaround schools across the state.

Empirical Strategy

Within-district Impact

Given the non-random and staggered nature by which schools were assigned City Connects, we estimated how math and ELA achievement at the grade-school level changed, relative to expected change given trends in comparison schools, following the introduction of the intervention using a series of difference-in-differences models. Accordingly, our estimands reflect the average treatment effect on the treated (ATT). The level of observation was at the grade-level instead of school-level because not every grade in a treatment school received the intervention. At the grade-level, there were about 130 observations in any given year, half of which (n = 66) ever received the intervention.

We estimated difference-in-differences models using two-way fixed effects (TWFE), which estimate changes in academic achievement for City Connects schools following the first few years of implementation, relative to the pretreatment period, while also accounting for average change in comparison schools. The TWFE model allows for variation in the time at which units started receiving the intervention by the inclusion of school and year fixed-effects (Wooldridge, 2021). Such an analysis is robust to pre-existing differences in schools and only requires that the treatment and comparison schools demonstrated parallel trends in the outcome measure in the pretreatment period. Parallel trends support the notion that comparison schools offer an adequate counterfactual for what would have occurred to treatment schools in the posttreatment period had they not received treatment.

The TWFE model is presented in Equation 1 below:

$$Y_{gst} = \beta_0 + \beta_1(Post_t * CCNX_{gst}) + \theta_g + \delta_s + \lambda_t + \varepsilon_{gst} \quad (1)$$

Here, the outcome, Y_{gst}, is average academic achievement for grade *g*, in school *s*, in year *t*. The main coefficient of interest is β_1, which is the differential impact of being in a grade where City Connects is offered in the post-treatment period. School fixed-effects, δ_s, remove all time-invariant heterogeneity between schools. Similarly, year (λ_t) and grade fixed-effects (θ_g) remove heterogeneity between years and grades, thereby estimating the average change in achievement over time for non-City Connects observations. Robust standard errors are clustered at the school level in order to correct for correlations in the errors among repeated school observations.

To test the assumption of pre-treatment parallel trends, as well as to allow for treatment effects to vary dynamically by implementation year, we also estimated a non-parametric event-study model using the following equation:

$$Y_{gst} = \beta_0 + \sum_{r=-5}^{8} \beta_r I(t - t_t^{treat} = r) + \theta_g + \delta_s + \lambda_t + \varepsilon_{gst} \quad (2)$$

The main predictor of interest, β_r, is a vector of regression coefficients capturing within-grade-school change in achievement for each year before and after receiving treatment, relative to the immediate pre-treatment year (i.e., β_{-1}).

Across-district impact

To isolate the City Connects effect beyond that due to turnaround status or treatment, we replicated our TWFE and event-study analyses above using a sample of all schools in the state. Through the inclusion of non-treated turnaround schools from other districts in the analytic sample, we were able to include a time-varying indicator of turnaround status to Equation 2. The resulting estimand is thus the net change in achievement for treatment relative to comparison schools in the post-treatment period minus the general effects of turnaround.

Robustness Checks

Econometricians have recently uncovered a myriad of issues associated with TWFE estimators, particularly in contexts where treatment is staggered and most units adopt treatment by the last period in the panel, as is the case with Research Question 1 (Goodman-Bacon, 2021). We assessed the degree to which our analyses may be limited due to such bias and noted no serious concerns stemming from the negative weighting described in Goodman-Bacon (2021).

For robustness, we tested the replicability of our TWFE and event-study models using one of the recently developed estimators in the literature (see De Chaisemartin & D'haultfoeuille (2022) for a full survey of recently proposed estimators). We focused on the estimator developed by Callaway and Sant'Anna (2021) due to its ability to include not-yet-treated units as controls, which is important given that most units in the analysis for Research Question 1 eventually adopt treatment. Additionally, this estimator accommodates for conditional parallel trends and places fewer assumptions on the functional form of the outcome model.

For Research Question 2, we used the Callaway and Sant'Anna estimator to incorporate propensity score weights that control for basic school demographic information at baseline (proportion of economically disadvantaged, Black, Hispanic, White, special education, and EL students). We also included the time at which schools first received turnaround. Given baseline differences between ever- and never-treated schools, we consider this analysis our preferred model for Research Question 2 due to the ability of this estimator to control for these characteristics at baseline. Standard errors were clustered by school and presented alongside tests for statistical significance. Our analyses were conducted in Stata 16 using the user-written "csdid" command (Rios-Avila et al., 2021).

Our second set of robustness checks focused on testing for changes to student composition. Given that the unit of analysis is at the grade level, there is concern that student composition within schools may change over time in ways that are correlated with achievement. If, for example, students from traditionally higher achieving backgrounds entered City Connects schools around the same time as the intervention was implemented, this may artificially inflate achievement. As a robustness check, we therefore tested for changes to the racial, socioeconomic, and EL makeup of the student population following the implementation of City Connects by estimating the event-study models with demographic characteristics as the outcome variable. Special education composition was not included because such changes may be an outcome of the intervention. We also tested for changes to three school-level inputs – average class size, student-teacher ratio, and the percentage of teachers with licensure – to see if treatment schools made structural changes in other ways that are previously known to be correlated with achievement.

RESULTS

We begin by first presenting demographic characteristics of the district by treatment status. Next, we present estimates from the within-district TWFE and event-study models. Then, we proceed with the findings from our preferred model estimates using the Callaway and Sant'anna estimator that includes the full state sample, isolating turnaround effects. Finally, we conclude with findings from our sensitivity analyses and a discussion around the robustness of our results.

As shown in Table 1, at baseline (2010/11), schools in the district that eventually adopted treatment by the 2018/19 school year differed in important ways from comparison schools in the district that did not adopt the intervention. Ever-treated schools tended to have larger proportions of non-White, EL, and economically disadvantaged students compared to never-treated schools. Ever-treated schools also had higher enrollment and suspension counts, along with lower teacher retention, and math and ELA performance on state standardized tests. We note that this lack of comparability is partially mitigated through our analytic approach that uses not-yet-treated units as controls for earlier treated units. For Research Question 2, we further mitigated these concerns through the use of the full state sample and incorporation of inverse probability weighting with the Callaway and Sant'Anna estimator.

Findings From Within-district Analyses

The results of our TWFE models – depicted in Table 2 – show that, in the years following implementation, achievement in schools implementing City Connects in Springfield increased significantly relative to expected growth given trends in comparison schools across the district. We specifically observed ATT estimates of 0.32 SDs and 0.29 SDs in math and ELA, respectively, across the eight years following the intervention.

Our event-study estimates, presented in Table 3, demonstrate evidence of dynamic and accumulating treatment effects through the first eight years of implementation. More specifically, achievement in math and ELA increased, respectively, by about 0.11 SDs and 0.07 SDs in the first year of implementation to 0.65 SDs and 0.66 SDs by the eighth year, relative to expected change.

All treatment effects, with exception to the first-year ELA effect, were statistically significant at $p < 0.05$. We note similar findings when using the Callaway and Sant'Anna estimator (see Figures A1 and A2 in Appendix A).

Importantly, the coefficients on the lag indicators do not support compelling evidence of parallel trends. While not statistically significant, math achievement decreased in each year preceding treatment until the immediate pre-implementation year. A similar trend was observed with ELA achievement, although the decline was larger and statistically significant in the second year before treatment. In both subjects, by the year before implementation, achievement had returned to levels observed five years prior, suggesting at least some of this pre-treatment effect is due to regression to the mean.

Treatment anticipation may have stemmed from district-pressure to avoid becoming subject to turnaround reforms given repeated years of low performance. It is thus important to partial out from the treatment effect both this anticipation and the overall effect of turnaround.

Across-district Findings

In an effort to partial out the effects of turnaround from these estimates, our next set of analyses used the Callaway and Sant'Anna estimator with the full state sample. We also calculated the equivalent of the TWFE estimate for this model, which amounts to an average across all post-treatment year estimates relative to the pre-treatment years. As expected, when accounting for turnaround status and other baseline covariates, the effects of City Connects implementation were found to be lower than the within-district estimates, but we still observed an ATT estimate of 0.22 SDs in math ($p < 0.01$) and 0.17 SDs in ELA ($p < 0.01$).

Event-study estimates, depicted in Figures 1 (math) and 2 (ELA), demonstrate evidence of dynamic and accumulating treatment effects through the first five years of implementation, after which the estimates stabilize. Specifically, achievement in math and ELA, respectively, increased by about 0.08 and 0.04 SDs in the first year of implementation to 0.49 and 0.44 SDs by the fifth year, relative to expected change. These findings support the notion that the initial within-district estimates were upwardly biased due to the inclusion of effects from turnaround.

Despite the accounting of baseline covariates and turnaround status, we still observed treatment anticipation and inconclusive evidence of pre-treatment parallel trends. We argue below, however, that these assumption violations likely have limited consequences on the validity of the findings.

In math, shown in Figure 1, the pre-treatment trend was largely parallel until a 0.12 SD ($p < 0.05$) increase in achievement before City Connects implementation. This most likely reflects some regression to the mean following 0.07 SD decreases in the fourth and six years before treatment. Additionally, the treatment effect remained similar in the first two years of implementation before a large increase to 0.27 SDs in the third year and 0.49 SDs in the fifth year. There is thus a significant break from the trend starting in the third year that cannot be explained by either treatment anticipation or regression to the mean. In the year before implementation, math achievement had returned to levels observed five years prior, suggesting at least some of this pre-treatment effect is due to regression to the mean. This resonates with prior evidence of City Connects suggesting that it takes three years of exposure before meaningful increases in achievement begin to emerge (Walsh et al., 2014).

For ELA achievement, shown in Figure 2, we observed similar pre-treatment trends as observed in math that concluded with increases of about 0.14 SDs in the last year before City

Connects implementation. These gains followed modest declines in achievement across the preceding years, suggesting some evidence of regression to the mean. This is further strengthened by the fact that the 0.14 SD gain in the two years before treatment did not continue in the first post-treatment year, where a non-statistically significant effect of 0.04 SDs was observed. It was not until the third year of City Connects treatment that schools noticeably broke from the prior trend and experienced noticeable gains in ELA achievement. Accordingly, we argue that the increase in ELA achievement following City Connects implementation is not likely due to a continuation of pre-treatment trends.

Robustness Checks

As noted above, to test the robustness of our findings, we looked for differential changes in student composition, average class size, student-teacher ratio, and the percentage of teachers with licensure over time for treatment schools relative to comparison schools. In doing so, we assessed the plausibility that achievement was driven by students from traditionally higher achieving backgrounds entering treatment schools and/or structural school-level changes also correlated with increased achievement. These analyses were conducted using the Callaway and Sant'Anna estimator by replacing the outcome in our main models with each school characteristic. Covariates included baseline math and ELA achievement and turnaround status.

As our findings show in Table 4, overall, we found minor changes in these school-level characteristics over time, and hardly in ways that would substantially affect achievement as observed in our main findings. Compared to similar schools across the state, treatment schools became approximately three percentage points more White, three percentage points less EL, and one percentage points less Hispanic on average in the posttreatment period. Although these changes may suggest that our observed effects are slightly upwardly biased, we found changes to class size and student-teacher ratio to work in the opposite direction. Average class size *increased* in schools implementing City Connects by approximately 3.5 students in the post-treatment period, and accordingly, the student-teacher ratio slightly increased by 0.7 (i.e., more students per teacher). Increases in class size and student-teacher ratios have been found in prior research to be associated with decreased achievement (Angrist & Lavy, 1999). Nonetheless, we cannot completely rule out the presence of unobserved shocks that may have contributed to achievement, and therefore stop short of making causal inferences about the impact of City Connects on academic achievement.

DISCUSSION AND CONCLUSIONS

Given the limited internal and external validity of past evaluations of the City Connects model, in this study we sought to examine the extent to which prior findings exploring intervention impacts on student achievement replicated in a distinct geographical context while also using stronger methodologies to draw causal inferences. We focused on one particular high-poverty and low-performing district where the intervention was implemented in most elementary and middle schools over the past decade. Using school-level data from the state in which this district is situated in, we leveraged the staggered implementation of City Connects to understand how achievement in math and ELA changed after schools adopted the intervention relative to growth within the district using a difference-in-differences approach. To partial out the effects of turnaround reforms, we also examined growth in City Connects schools compared to similar schools across the state while specifically controlling for turnaround status.

The results of our within-district models suggest that achievement in math and ELA increased by over half of a standard deviation greater than expected following five years of implementation of City Connects. Adjusted for turnaround status, model estimates demonstrate that these effects were only partially driven through turnaround reforms, as we observed effects of 0.49 and 0.44 SDs in math and ELA, respectively. These findings were robust to sensitivity analyses testing for changes to modeling approaches as well as considerations to student demographic composition and classroom-level input changes following the intervention. Below, we conclude with a discussion of practical significance, policy implications, and study limitations.

Practical Significance

Over a period of about fifteen years, City Connects has been implemented in six different U.S. states and in Dublin, Ireland. This increase in program adoption has heightened the need to understand the degree to which City Connects is effective across different contexts. The current study adds to the existing evidence in a way that matters to districts and schools by demonstrating that the practice can indeed be adapted to communities in different geographies, leading to beneficial outcomes for students,

Further, the current study is significant in a practical way to City Connects' work with the Massachusetts Department of Elementary and Secondary Education (DESE) in efforts to support districts wishing to implement ISS in their schools. Through a partnership that also includes the Rennie Center for Education Research and Policy, City Connects and DESE have offered a Systemic Student Support Academy to assist districts wishing to move in the direction of effective student support. By demonstrating beneficial outcomes of City Connects in a new community, the current study offers districts considering the Academy additional evidence to support their decisions about how best to direct their efforts to support the whole child in their schools.

Finally, the current study assists schools, districts, municipalities, and state-level policymakers in considering ISS as an approach to address needs make clear in the context of COVID-19. At the national level, ISS is increasingly recognized as an effective way of addressing children's comprehensive out-of-school needs; for example, the U.S. DOE post-COVID-19 guidance for school reopening in April 2021 cited ISS as a strategy for addressing inequities exacerbated by the pandemic, and also cites City Connects specifically (U.S. DOE, 2021). The current study adds to the evidence base warranting the adoption of City Connects as a way schools can begin to address such inequities.

Policy Implications

With growing attention to replication and reproducibility studies and their role in building the evidence base, the Institute of Education Science continuously supports systematic replication studies of interventions that have produced beneficial effects on education outcomes, by offering research grants and releasing guidelines on replication and reproducibility in education research. Yet replication is rare, perhaps far too rare (Perry et al., 2022). This study responded to the call to address the replication "crisis" faced by the education field when educational stakeholders and decision-makers start questioning whether the field's impact is being unnecessarily limited (Wiliam, 2022). We believe the successful replication of positive achievement outcomes from this research provides policymakers with confidence to justify the investment of scarce public resources in implementing evidence-based interventions like City Connects.

A second important implication of this study stems from the wide range of activities across the nation to adopt a whole community, whole child approach. Over the past few decades, policymakers and other educational stakeholders have learned that intervening in a child's developmental trajectory can have profound positive consequences. This leads to a deepened appreciation of the importance of addressing students' complex and changing needs by implementing integrated student support strategies that must be customized, comprehensive, coordinated, and continuous.

This study builds on prior evidence to extend existing studies in a way that can further strengthen the causal warrant suggested by prior evidence (Walsh et al., 2014). Hence, it contributes to a better understanding of whether integrated student support improves education outcomes of students and the conditions under which they would likely work and for whom. The findings from this research support further identification of the factors needed for successfully implementing integrated student support and replicating the core components of the City Connects intervention in other sites. It can provide leaders at the municipal and state levels with policy recommendations and guidance to advance effective systems of integrated student support like City Connects that transform disjointed and siloed resources for students into a coherent and potent system of opportunities (Wasser Gish, 2019). It can also help determine which aspects of the previous studies are systematically varied. This offers school and community leaders promising practices and insights for progress, and provides local and state policymakers evidence and ideas for legislation advancing evidence-based student support like City Connects.

Limitations

Given that schools were not randomly assigned to implement City Connects, this study is inevitably limited in several ways in its capacity to make causal inferences about the impact of the intervention. To evaluate whether the findings may have been driven by selection bias, we tested the assumption of parallel trends in the outcome measures during the pre-treatment period. While we observed anticipation effects in the immediate year before treatment (see previous discussion), we argue that this violation of the parallel trends assumption does not attenuate the inference that schools experienced large academic gains following the implementation of City Connects. However, it does suggest that our observed effects are likely upwardly biased and at least partly driven by unobserved differences among schools.

Next, we acknowledge potential limitations stemming from the fact that most schools subject to City Connects also received turnaround. While we show that schools with City Connects experienced achievement gains beyond that of turnaround alone, these findings may plausibly be attributed to a more effective turnaround strategy in the district compared to other turnaround schools, as opposed to City Connects. We argue this is likely not the case for two reasons. Firstly, while turnaround strategies may certainly differ across school districts, based upon the information available, we found that most districts in the state undertook similar approaches (American Institutes for Research, 2016). We examined documentation in the state specifying turnaround strategies across different districts and noted no major apparent differences in particular practices, although the efficacy and fidelity of implementation by which they were carried out may have differed. Certainly, this information was limited and may conceal important nuances.

Secondly, even in the presence of differences and efficacy in turnaround strategy between City Connects and other turnaround schools, however, very few prior studies of school turnaround *alone* approach the achievement gains we observed in this study. A recent meta-analysis of over 60 studies estimating the impact of school turnaround, for example, revealed average effects of 0.08 SDs and 0.09 SDs on math and reading achievement, respectively, after three years of treatment (Schueler et al., 2021). In the district operating City Connects, however, turnaround schools tripled these effects upon three years of implementation, after which effects continued to grow. In fact, the treatment effects observed in this study in both subjects closely resemble those found in a prior study of City Connects in a separate school district (City Connects, 2020). We thus find it implausible that the effects observed in this study can be attributed to a more effective turnaround strategy. Our within-district analyses also rule out the possibility that non-turnaround related initiatives at the district-level drove the treatment effects.

Additionally, through our sensitivity analyses aimed at measuring changes in school characteristics over time, we discovered some differences between schools that adopted City Connects and those that did not. Although these changes were relatively minor and on their own do not likely account for treatment effects observed, there may be other unobserved differences also confounded with City Connects implementation.

Finally, we also acknowledge that our analyses were at the grade-school-level instead of at the individual student level, and this may downwardly bias our estimates of the treatment effect. Because the intervention is largely focused on individuals through the receipt of tailored services, we expect that the treatment effect would accumulate over time as students receive more treatment exposure. While the implementation of City Connects may theoretically impact school-based inputs – such as improved climate and culture, and increased teacher experience through more retention – which in return spills over to students regardless of their individual exposure to the intervention, much of the treatment effect stems from the receipt of services to students over time. The nature of our analyses does not allow us to distinguish between individuals who received the intervention for the first time as opposed to those with accumulating years of dosage. Since many students do in fact receive City Connects for multiple years, we still observed evidence of accumulating effects but found that effects stabilize after five years, which is the maximum years of exposure most students can potentially receive in our data. Were we to focus our analyses at the individual level, examining treatment effects by years of dosage instead of the number of years the school has had the intervention, we likely would discover larger effects. Due to the research design and data limitations, we were unable to examine our research question through this perspective.

Based upon these limitations, we stop short of interpreting our observed findings as evidence of definitive causal effects, and instead conclude that they are strongly suggestive of the notion that City Connects improves math and ELA achievement. Combined with prior evidence of the intervention, however, this replication study strengthens the connection between comprehensive student support and student academic achievement.

Future Research

Replication research that produces findings consistent with previous studies of an educational intervention can provide confidence in the likely impact of the program in future implementations. This study did find positive academic outcomes for students in schools implementing City Connects, as has been previously observed (Walsh et al., 2014). Additional replication studies would improve the evidence for impact of the intervention under various conditions. For example, City Connects has recently expanded to rural and suburban school districts across other states, including states in the Midwest. Studies of City Connects implementation and outcomes in these different contexts would shed light on whether effects observed for elementary school students in two large northeastern urban school districts generalize to other settings. Another variation in implementation to be studied is whether and to what extent experiencing the intervention during the middle school years (grades 6–8) has an impact on academic or non-cognitive outcomes.

Uncovering the mechanisms through which integrated student support leads to better academic achievement is also an important area of inquiry. We theorize various channels that are worthy of study. Improvements in students’ early academic skills, teacher retention, or school climate are promising candidates for study as mediators. Changes in other school practices such as fewer and more accurate referrals made to special education services may also be of interest. Given the many potential mechanisms by which ISS may produce academic benefits, conducting qualitative research on components of the model may provide an additional and deeper understanding of the specific features of this intervention that facilitate improvements in educational experiences.

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Tables and Figures

Table 1. Differences in student demographics between past and new site of City Connects implementation, December 2021.

Student characteristic	Past site (%)	New site (%)
Black	29%	18%
Hispanic	43%	68%
White	15%	9%
Asian	9%	2%
English Learner	30%	16%
First language not English	48%	30%
Economically disadvantaged*	71%	87%
Special education	22%	25%

Note. *student participates in one or more of these state-administered programs: SNAP, TAFDC, DCF foster care, and MassHealth

Table 2. Description of school characteristics in district at baseline (2010/11), by treatment status.

School characteristic	Treatment	Comparison
Black (%)	21%	21%
Hispanic (%)	60%	51%
White (%)	13%	22%
English Learner (%)	17%	7%
Economically disadvantaged* (%)	88%	81%
Special education (%)	20%	20%
Average enrollment size (n)	511	374
Average school suspension count (n)	66	32
Teacher retention	70%	82%
Math achievement (relative to state mean)	-0.74 SDs	-0.39 SDs
ELA achievement (relative to state mean)	-0.76 SDs	-0.38 SDs
Number of schools	28	12

Note. *student participates in one or more of these state-administered programs: SNAP, TAFDC, DCF foster care, and MassHealth

Table 3. Results of within-district two-way fixed effects models.

	Math	ELA
Treatment	0.32***	0.29***
	(0.10)	(0.08)
Constant	-0.69***	-0.64***
	(0.05)	(0.05)
Adjusted R^2	0.65	0.69
Observations	1687	1687

Robust standard errors clustered by school in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Results of within-district event-study model estimates.

Time since treatment	Math	ELA
Pre-5	0.01	-0.00
	(0.09)	(0.08)
Pre-4	-0.06	-0.09
	(0.09)	(0.08)
Pre-3	-0.05	-0.10
	(0.08)	(0.07)
Pre-2	-0.09	-0.15***
	(0.06)	(0.05)
Post-1	0.11**	0.07
	(0.04)	(0.05)
Post-2	0.20***	0.16**
	(0.07)	(0.06)
Post-3	0.41***	0.34***
	(0.09)	(0.09)
Post-4	0.54***	0.37***
	(0.12)	(0.13)
Post-5	0.61***	0.55***
	(0.10)	(0.10)
Post-6	0.53***	0.48***
	(0.12)	(0.12)
Post-7	0.69***	0.62***
	(0.12)	(0.12)
Post-8	0.65***	0.66***
	(0.10)	(0.10)
Constant	-0.74***	-0.66***
	(0.05)	(0.06)
Adjusted R^2	0.67	0.71
Observations	1687	1687

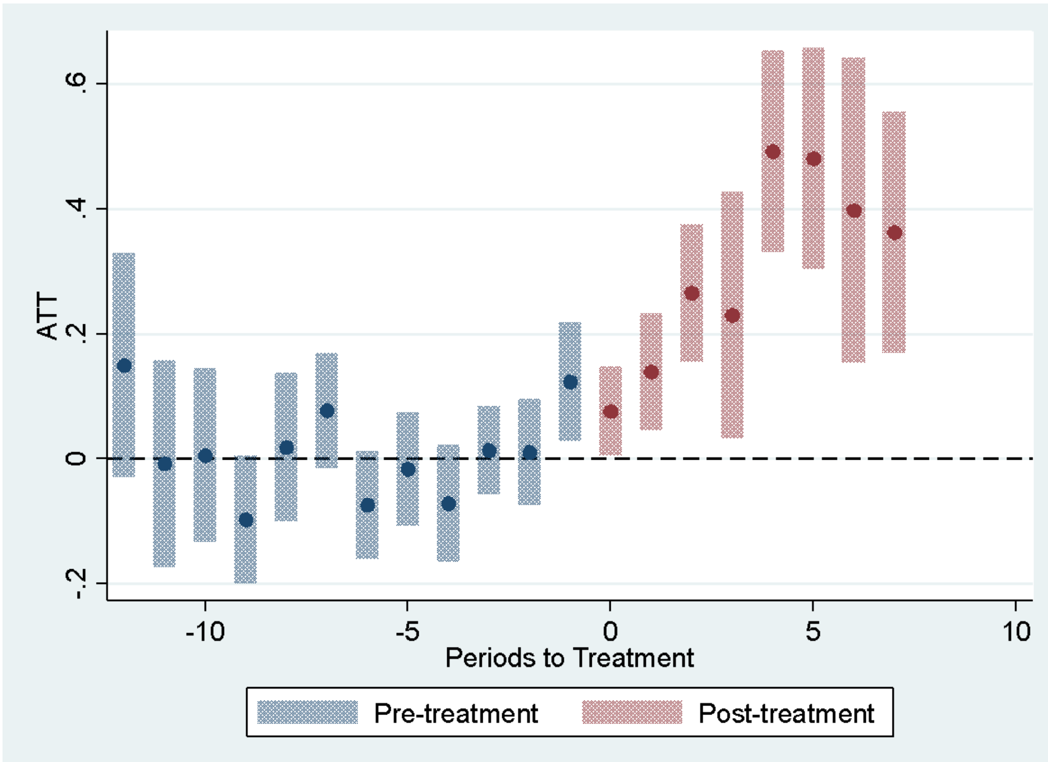
Robust standard errors clustered by school in parentheses.
Pre-# and Post-# indicate years before and after City Connects implementation, respectively.
Reference group is Pre-1, the year before City Connects was implemented.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Sensitivity analyses testing for changes to student demographic composition, teacher certification, and average class size following introduction of City Connects.

School characteristic	ATT estimate
Low-income	1.5%
Black	-0.7%
White	2.7%**
Hispanic	-1.2%**
English Learner	-3%***
% of Teachers licensed	1.5%
Average class size	3.5*
Student-teacher ratio	0.7**
Total observations	17,972
Number of schools	1,519

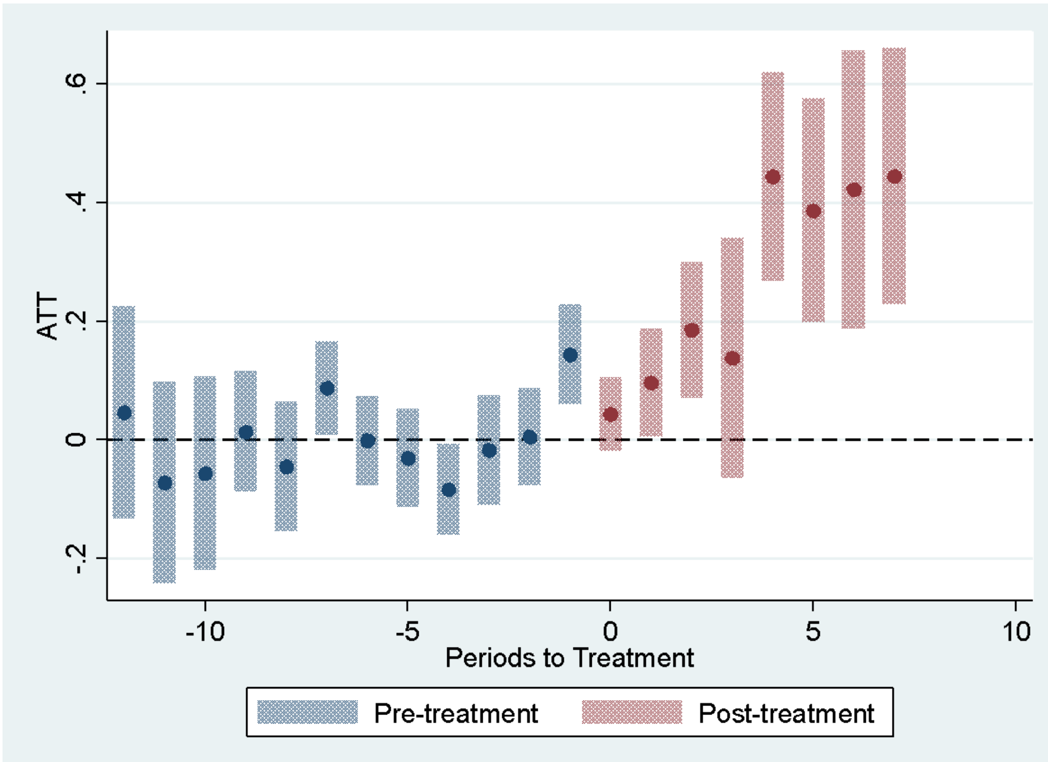
Note. ***p<0.01, **p<0.05, *p<0.10
The estimates in this table represent the average change in these school-level variables following the implementation of City Connects relative to other schools in the state. Model estimates are based upon the Callaway and Sant'Anna estimator. The average treatment effect on the treated (ATT) estimate is the average change in the characteristic of interest across all post-treatment periods. Estimates with a percentage sign indicate changes in percentage points. The average class size and student-teacher-ratio estimates represent changes in the number of students. Baseline covariates include math and ELA achievement and turnaround status. The reference category includes all years prior to City Connects implementation.

Figure 1. Estimates of City Connects Effect on Math Achievement Over Time using Callaway and Sant'Anna Estimator.



Note. Figure depicts point estimates and 95% confidence intervals using the Callaway and Sant'Anna Estimator (2021). Baseline covariates include racial composition of school (percent Black, White, and Hispanic), and proportion of low-income, EL, and special education students. The reference category in the pre-treatment period is the immediate prior year. For example, the reference category for T-2 is T-3, and for T-3 it is T-4. In the post-treatment period, the reference category is the year prior to City Connects implementation (T-1).

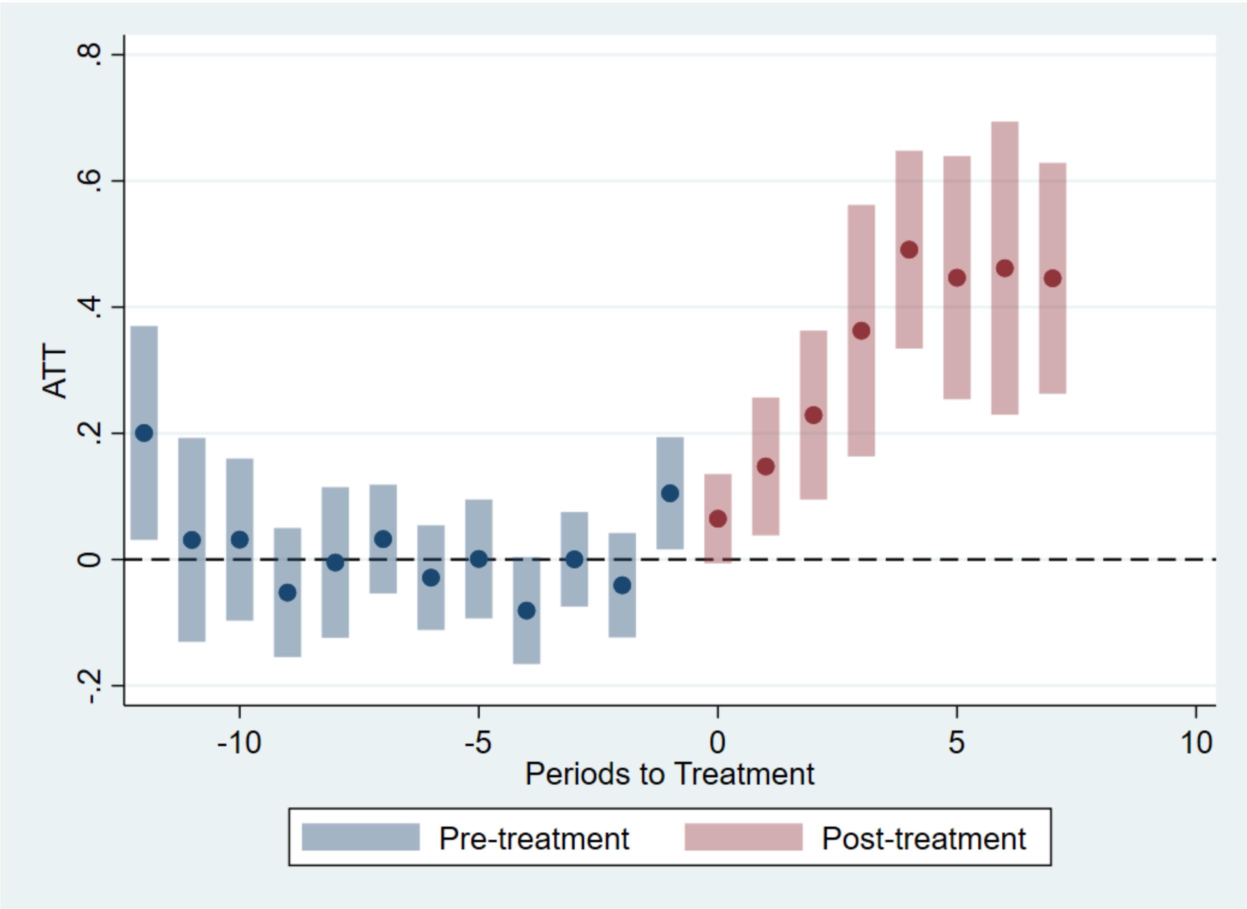
Figure 2. Estimates of City Connects Effect on ELA Achievement Over Time Using Callaway and Sant'Anna Estimator.



Note. Figure depicts point estimates and 95% confidence intervals using the Callaway and Sant'Anna Estimator (2021). Baseline covariates include racial composition of school (percent Black, White, and Hispanic), and proportion of low-income, EL, and special education students. The reference category in the pre-treatment period is the immediate prior year. For example, the reference category for T-2 is T-3, and for T-3 it is T-4. In the post-treatment period, the reference category is the year prior to City Connects implementation (T-1).

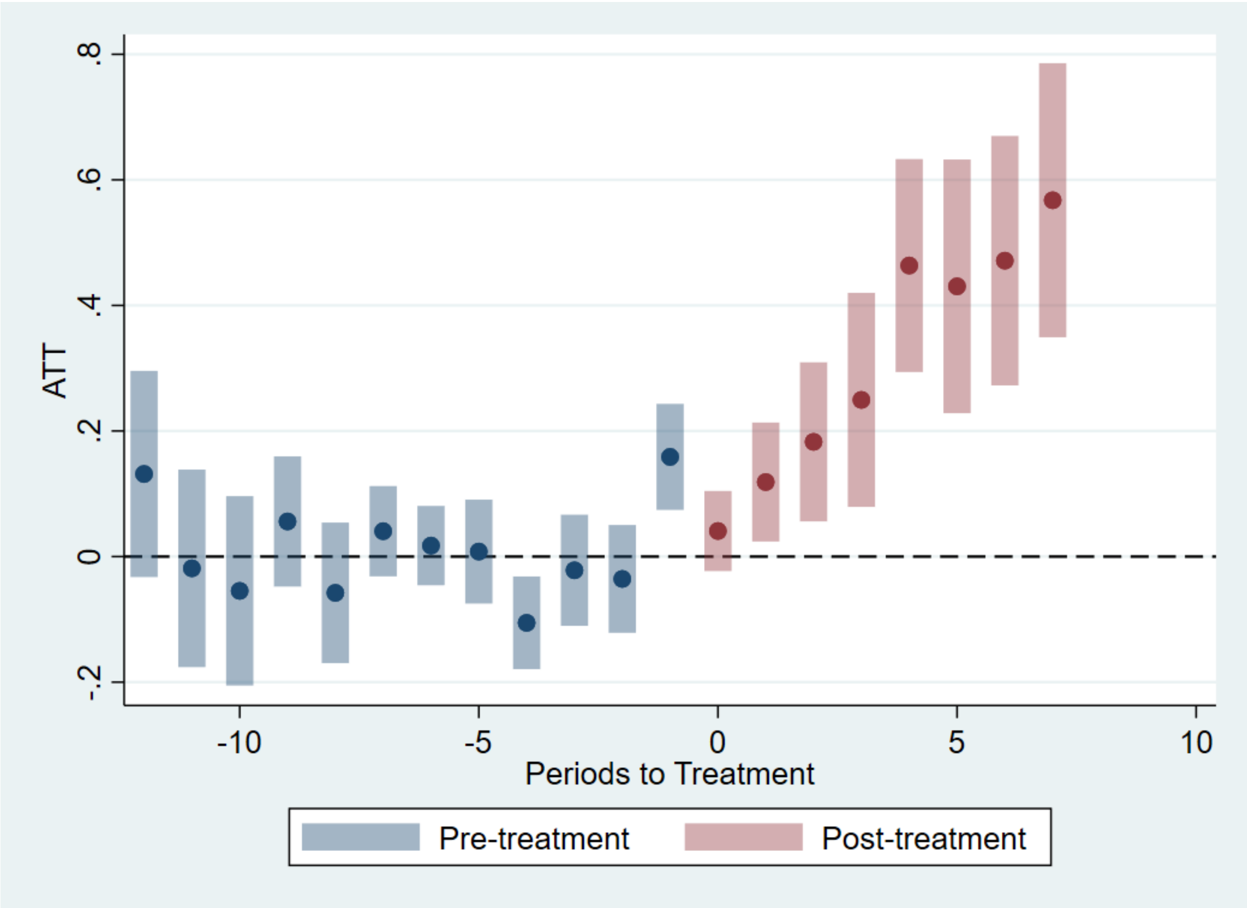
Appendix Figures

Figure A1. Within-district Effects of City Connects on Math Achievement Using Callaway & Sant'Anna (2021).



Note. Figure depicts point estimates and 95% confidence intervals using the Callaway and Sant'Anna Estimator (2021). The reference category in the pre-treatment period is the immediate prior year. For example, the reference category for T-2 is T-3, and for T-3 it is T-4. In the post-treatment period, the reference category is the year prior to City Connects implementation (T-1).

Figure A2. Within-district Effects of City Connects on ELA Achievement Using Callaway & Sant'Anna (2021).



Note. Figure depicts point estimates and 95% confidence intervals using the Callaway and Sant'Anna Estimator (2021). The reference category in the pre-treatment period is the immediate prior year. For example, the reference category for T-2 is T-3, and for T-3 it is T-4. In the post-treatment period, the reference category is the year prior to City Connects implementation (T-1).