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A strategic initiative of ServeMinnesota

Report to the Minnesota State Legislature Minnesota Math Corps May 2019

## National Service as a Solution to Addressing Critical Social Needs

The AmeriCorps programs in the state of Minnesota illustrate the power of aligning human capital with a clear and focused plan for addressing areas of critical need. Without AmeriCorps, our communities would be drastically and negatively affected. In 2016, over 2,100 AmeriCorps members devoted a year of service with one of 13 programs in the state. The existing AmeriCorps programs are diverse. Members might deliver academic interventions, help keep at-risk students on track to obtain a high school diploma, assist low-income adults in developing key employment skills, build or repair homes, or improve our state's ability to adapt to environmental change. Those targets are both meaningful and an excellent fit for service programs.

Although the nature of the work that members engage in is vastly different, there are common threads that tie successful programs together. As is the case across many disciplines and geographic areas, it is increasingly clear that effective programs are (1) designed with an explicit connection to existing evidence, (2) intentional about the collection *and use* of data to guide implementation and program decisions, and (3) monitored in real-time to ensure the program is implemented as designed. Those features facilitate continuous improvement and lay the foundation for summative evidence of program impact.

Minnesota Math Corps (MMC) is an AmeriCorps program in Minnesota serving students at risk for math problems. MMC is a strategic initiative of ServeMinnesota, which is the state commission for AmeriCorps state programs in Minnesota. ServeMinnesota partners with MMC to ensure the program is an effective and efficient application of national service to solve a critical social issue. This focus is inherent in ServeMinnesota's mission to promote innovation as well as the organization's investment strategy. That is, ServeMinnesota seeks to support and hold programs accountable to key questions from stakeholders. Those questions are directly aligned with the four characteristics outlined in the preceding paragraph and are outlined in Table 1.

Key Program Questions	Required Evidence
Why do you focus on that problem?	Compelling empirical data to illustrate the problem <i>and</i> the need (e.g., lack of capacity to adequately address the problem without the program).
Why do members do what they do?	A clear operational definition of member activities and research-based rationale for those activities.
How do you know activities are occurring?	Clear and efficient systems (e.g., program oversight, documentation) to monitor members during the program year and procedures in place to address situations when members deviate from the outlined activities.
How do you know if it's working?	Technically sound instruments that (1) are directly aligned with the program activities, (2) produce formative data that can be used in real-time to improve activities and (3) can be aggregated to inform annual programmatic decisions annually.
What are you doing to get better?	Operating under the assumption that there is no perfect program, what activities are you currently engaged in to improve the status quo?
What is the evidence for your program?	Designing an evidence-based program and being a program with evidence are two different things. What defensible data do you have to demonstrate program impact on key outcomes?

Table 1. Key Program Questions and Required Evidence for Math Corps

The evaluation activities and results outlined in this report explicitly address MMC's goal to demonstrate an impact on the trajectory of students' math development (i.e., question 6 in Table 1). More specifically, the primary purpose of this impact evaluation was to determine the short-term impact of the program on students' broad achievement in math from fall 2016 to winter 2017. This evaluation represents a critical first step in building the evidence-base for MMC.

# **About Minnesota Math Corps**

The following subsections provide detail on the extent to which Math Corps answers the key questions outlined in Table 1. The major components of Math Corps are illustrated in the program's logic model (Figure 1).

## **Historical Context**

MMC was started in 2007 in the St. Cloud School District in partnership with St. Cloud State University. Since its inception, MMC has expanded into new sites each year, with more than 116 tutors currently serving more than 104 schools statewide. With its expansion in recent years, MMC has seen several changes to program implementation. Most notably, the program distanced itself from an "off the shelf" intervention curricula and moved toward an internally created intervention curriculum in 2013. There were three primary reasons for this shift: (1) content, (2) delivery, and (3) scalability.

<u>In regard to *content*</u>, the publisher produced curriculum focused on concepts spanning across all grade-level math domains. For example, students received targeted support on Geometry concepts as well as those related to Operations and Data Analysis. While these concepts are all important for grade-level math proficiency, research is increasingly clear that students who struggle with math tend to need explicit and ongoing support with skills in working with whole and rational numbers. This is largely because those skills serve as the foundation for increasingly complex material. Thus, MMC sought to develop an intervention curriculum that focused explicitly on an understanding of whole and rational numbers.

<u>In regard to *delivery*</u>, the methods for instruction adopted by the publisher produced curriculum were not fully aligned with the existing evidence-base for supplemental intervention. Thus, MMC sought to develop an intervention curriculum that included scripts for delivery that generally corresponded to strategies with existing evidence for improving students' skills in the area of whole and rational number understanding. In addition, the use of data to guide decision-making was not present in the previous curriculum. MMC currently uses student performance data to select students and ensure students are ready to progress to the next skill in the curricular sequence.

<u>In regard to *scalability*</u>, the publisher-produced curriculum was associated with a per student cost that would have been prohibitive of ongoing expansion efforts. In addition to the expansion occurring in the state of Minnesota, ServeMinnesota held long-term plans for expanding the program to other states in the country (similar to Minnesota Reading Corps). The use of internally created intervention materials allowed more flexibility for MMC to expand the program to new students and schools at a relatively low cost.

#### Figure 1: Minnesota Math Corps logic model



## **Program Rationale**

Math Corps aims to improve the core math skills of at-risk students because this endeavor holds immense value for the individuals served as well as the society at large. Students with strong fundamental math skills are better prepared to succeed in advanced math courses and thus more likely to graduate from high school, attend college, and experience success in their careers relative to students who need to take remedial math courses (Adelmann, 2006; Long, Conger, & Latarola, 2012; Spielhagen, 2006). Those benefits extend beyond individual students insofar as there are significant monetary benefits to society when students stay on track to graduate for high school, attend college, and successfully enter the workforce (Levin & Belfield, 2007).

Given the strong relationship between academic skills and future success, it stands to reason that improving the math skills of at risk students is a critical issue for a variety of stakeholders. Yet, schools across the nation struggle to meet the needs of those students. In the most recent National Assessment of Educational Progress test, no more than 40% of students at any grade level demonstrated proficient skills in math (NAEP, 2016). In an effort to prevent ongoing academic deficits, many schools have adopted a tiered model of support in which additional school-based resources are provided on a continuum of student need (e.g., Response to Intervention [RtI]).

Nevertheless, the promise of that approach to school-based support is hindered by critical implementation obstacles. In most conceptualizations of prevention models, approximately 15% to 20% of students will require early intervention supports (Fuchs & Vaughn, 2012). In a typical school with approximately 400 students, even the best case scenario in which only 60-80 students require additional support would result in substantial logistical strain on the school system. Moreover, many schools are located in communities where considerably more than 15% to 20% of the students will need supplemental intervention. For example, providing 60-80 students with 90 min of intervention per week—as per the existing evidence-base for elementary literacy interventions (Gersten et al., 2009; Slavin et al., 2011)—translates to 30 to 54 hours of weekly support if those students are in groups of three. The demand on resources increases substantially if supplemental support is delivered in a 1:1 format (see Figure 1). It follows that most schools simply do not have the resources to meet the needs of students at risk for math problems. As a consequence, these students are often left behind. As outlined above, this has a substantial and negative impact on individual students and may result in financial burden for society. MMC was designed to directly address this critical need by merging the science of math intervention with the people power of AmeriCorps.



*Figure 2.* Representation of the assumed impact of student need on the demand for intervention resources.

## Activities

Prior to any service in the schools, all MMC interventionists receive training in the program during an intensive training in August. Once in the school, interventionists receive oversight and support from a professional within the school (Internal Coach) and a content expert associated with MMC (Master Coach; A in Figure 2).

MMC AmeriCorps members ("interventionists") provide math support for students in grades four through eight. Interventionists identify students for the program from the entire pool of fourth through eighth grade students using a tiered screening process (B in Figure 2). Specifically, the first tier of students consists of all students who were not proficient on the state test from the previous school year. Those students are then tested using a broad-based measure of math achievement (STAR Math). If students score below the grade-level benchmark on STAR Math, they qualify for MMC.

The content focus of MMC is directly aligned with expert and research-based recommendations for math intervention. Specifically, MMC is built around research that suggests skills with whole and rational numbers in late elementary and middle school are foundational for future math development (Torbeyns, Schnieder, Xin, & Siegler, 2015; Wang & Goldschmidt, 2003). Thus, MMC interventions focus on skills in the broad area of whole and rational number understanding (C in Figure 2). In regard to intervention delivery, each instructional target within the MMC curriculum is addressed via scripted protocols for conceptual understanding, computational proficiency, and word problem solving. For example, students in fifth grade working on multi-digit multiplication (one curricular content area) receive intervention on the conceptual basis for multi-digit multiplication, practice to develop procedural proficiency in multi-digit computation, and direct support to better solve word problems that include multi-digit multiplication. Finally, in addition to the standard curricular sequence, all interventionists provide short (~ 5 min) practice sessions on basic math facts. In this case, basic math facts are defined as 1 or 2 digit addition and subtraction problems and single digit multiplication/division problems.

Within the MMC curricular sequence, students are required to demonstrate mastery on brief, formative assessments (e.g., students must demonstrate mastery on conceptual understanding before moving to procedural practice). After receiving intervention via all subskills within a given unit, students complete a mastery assessment covering each of the subskills. If any subskills are not mastered, a remedial lesson is provided to facilitate mastery.

### Outcomes

There are a variety of short- and long-term goals for MMC. The outcomes most aligned with the intervention are those related to basic math fact fluency, skills in the area of whole and rational number understanding, and students' sense of self-efficacy. That is, the most pronounced effects might be expected in those outcomes because they are closely aligned with the actual activities of the intervention. However, the logic underlying MMC holds that if changes are observed in whole and rational number understanding, those changes should be observable in broad-based assessments of math achievement (e.g. STAR Math). Those changes might be expected to increase the number of students who meet proficiency criteria on the state test, which in turn might increase the number of students enrolling in advanced math courses, graduating from high school, and enrolling in college. This logical progression is outlined in area D of Figure 1.

## **Impact Evaluation**

## **Research Question**

The present evaluation was primarily concerned with the impact of MMC on broad based math achievement. Although fact fluency data were examined in the evaluation, students' performance on STAR Math was the primary outcome variable. Thus, the following research question guided the study:

#### What is the impact of the Minnesota Math Corps program on a broad-based test of students' math achievement?

To answer this research question, the evaluation team analyzed Minnesota Math Corps as typically implemented. The only exception was that the initial pool of eligible students at participating schools was randomly assigned to either a treatment group that received Math Corps interventions for the first semester of the school year or to a control group that did not receive the program until after the winter posttest data collection period. Thus, the study examined the impact of the program after students had participated in the program for one semester (see Figure 3).



Figure 3. Overview of evaluation design.

## **Outcome Measures**

Student fact fluency scores were obtained using tests that included basic addition, subtraction, multiplication, and division problems. Previous research with the fact fluency tests provided sufficient evidence for technical quality (e.g., Foegen et al., 2007). The impact on student math outcomes was measured using STAR Math (Renaissance Learning, 2015), a broad computer-adaptive assessment of math performance that can be used with students in grades one through twelve. Scaled scores on STAR Math range from 0-1400. Depending on the age and skill level of a student, a single administration typically requires 20-30 min and may include items related to numeration, computation, word problems, geometry, measurement, algebra, estimation, and data analysis and statistics. Reliability estimates across grades range from .94 to .95. The median concurrent validity estimate with the Minnesota Comprehensive Assessment (MCA), Minnesota's state math accountability assessment, across grades is reported to be .74 and the median predictive validity from fall STAR Math to spring state test scores is reported to be .71 across three state samples.

## **School and Student Selection**

Twelve schools serving students in grades four through eight participated in the study. To be eligible for participation, schools were required to serve a student population in which at least 50% of the students were eligible for free or reduced price lunch. Each school was provided a small compensatory stipend for their participation. Across the twelve participating schools, a total of 17 Math Corps tutors delivered interventions. The average age of Math Corps tutors was 35 (SD = 16), and approximately 83% were White, 5% were multi-racial, 6% were Black, and 6% were Asian. All tutors had graduated high school, and 67% had completed a college degree. On average, 61% of the students at participating schools were eligible for free or reduced-price lunch.

Students were selected for the study according to typical Math Corps selection criteria (described on page 7). According to those criteria, students with a state math assessment score below proficiency standards from the previous year were screened using STAR Math during the first few weeks of the fall semester; no students with proficient (or higher) scores from the previous year were screened with STAR Math. Students who were screened with STAR Math and had scores below the STAR Math fall benchmark were eligible for the program and thus eligible for randomization. In total, 550 eligible students were randomly assigned into treatment or control group conditions, using an approximately 60:40 probability for treatment assignment. Students assigned to the treatment group were put into pairs to receive Math Corps interventions according to typical procedures in the program.

Students assigned to the control group were not allowed to receive Math Corps interventions until after winter post-test, but were allowed to receive other school-based services. Surveys sent to school staff to determine the frequency and type of other math supports indicated that both treatment and control group students received supports other than Math Corps, although control group students received other supports more often. Approximately 42% of control group students and 25% of treatment students received 60 min of other weekly support for at least one month of the study duration. Other support typically consisted of semi-structured math activities provided by a school staff member; no evidence-based math interventions were reported.

The final analytic sample consisted of 490 students, including 311 treatment and 179 control students. Demographic characteristics for each group are shown in Table 2. The study had approximately 11% attrition, due primarily to students not having posttest scores. Missing data was not associated with assignment to treatment, and with the exception of ethnicity (Asian and Hispanic), there was no relationship between missing data and demographic or pre-test data.

Demographics	Control ( $n = 179$ )	Treatment $(n = 311)$		
Gender				
Male	49.3%	52.0%		
Female	50.2%	48.0%		
Ethnicity				
White	32.0%	33.6%		
Black	31.5%	31.0%		
Asian	17.7%	20.7%		
Hispanic	11.3%	7.5%		
American Indian/Alaskan Native	5.9%	6.0%		
Native Hawaiian or Other Pacific Islander	0.0%	0.3%		
Multi-Racial	1.5%	0.0%		
Grade				
Four	20.2%	19.8%		
Five	10.8%	14.4%		
Six	26.1%	24.4%		
Seven	20.2%	18.4%		
Eight	22.7%	23.0%		

#### Table 2: Demographic Distribution across Groups

### **Analysis Plan**

To evaluate the extent to which students assigned to the math intervention program demonstrated higher STAR Math scores than those assigned to the control group, the evaluation team fit two models to the data: an intent-to-treat (ITT) model and an Optimal Dosage (OD) model. The ITT model included all students assigned to receive intervention whereas the OD model only included students who received the intervention at an optimal dosage level as defined by MMC. More specifically, students were included in the OD group if they had at least 12 weeks of intervention, at least 60 minutes of support per week, and an interventionist with an average level of fidelity at or above 90%. In both models, students' posttest STAR Math scores were regressed on treatment assignment. Prior to selecting the final model, we evaluated the extent to which the treatment effect differed by grade, ethnicity, and school. In the ITT model, no substantive impact on the treatment effect was found for more complex models that incorporated demographic and school factors. Thus, in the

final ITT model, only pre-test score was included as a covariate. Slopes from the student level covariates were treated as fixed across schools.

The ITT analysis was used to obtain an estimate of the intervention program's effectiveness in typical conditions at schools that reflect the characteristics of those sampled. Nevertheless, the evaluation team was interested in understanding whether students with an optimal level of exposure to the program would demonstrate additional growth. The model for the OD analysis differed somewhat from the ITT model. After applying the inclusion criteria for the OD group, the treatment effect estimate differed as a function of whether the model controlled for school (with the treatment effect increasing when school was excluded). The evaluation team hypothesized that this bias in treatment effect estimation was related to differences across schools in terms of tendency to provide optimal dosage. To address this potential confound, a propensity score for students in the OD model was obtained by regressing OD assignment on demographic variables, the pre-test score, and school. Results from the propensity scoring suggested that school was in fact a significant predictor of treatment assignment. Thus, in the final OD model, students in the OD group were matched with a control student using nearest neighbor matching on the estimated propensity scores. The resulting matched sample was then used to estimate the treatment effect for the OD group.

## Results

## **STAR Math Scores**

Pre- and post-test descriptive results are displayed across grades and groups in Table 3. Average STAR Math scores tended to increase across grades, which is generally consistent with the scaling of the assessment. The one exception to this occurred among seventh and eighth grade students in the control group, with eighth grade students scoring slightly lower on average relative to seventh grade students. Across groups, students tended to score within the same range on the pre-test. With the exception of seventh grade students, the average pre-test scores were within nine points. Average scores in both grades also tended to reflect growth from pre- to post-test. This is generally expected as all students received typical instruction in math from their regular teachers. The average difference between pre- and post-test STAR Math scores was approximately 31 scaled score points for students assigned to the control group and 48 scaled score points for students assigned to MMC. Thus, the average score for students in the treatment group was approximately 17 scaled score points higher than the average score for control students.

	Control							Experimental					
	Pre-Test STAR Math			Post-Test STAR Math		Pre	Pre-Test STAR Math			Post-Test STAR Math			
Grade	Ν	М	SD	Ν	М	SD	Ν	М	SD	Ν	М	SD	
4	41	532.37	48.31	41	575.44	54.62	69	527.80	66.03	68	599.21	70.67	
5	22	602.14	65.73	21	666.76	68.29	50	611.94	67.01	48	670.85	87.84	
6	53	665.00	56.41	40	695.93	88.41	85	661.05	53.78	71	702.94	74.59	
7	41	708.73	68.35	36	741.08	83.92	64	690.28	68.30	61	739.57	71.14	
8	46	698.87	81.55	42	717.19	81.39	80	706.79	88.20	73	757.42	75.07	

#### Table 3. STAR Math Performance across Groups and Occasions

To evaluate the impact of group assignment on students' post-test scores inferentially, two regression models were fit to the data (described above). Results from the ITT model indicated that assignment to MMC was associated with a

statistically significant and positive effect on students' post-test STAR Math scores, controlling for pre-test scores ( $R^2$  = .44, F(2,487) = 2.23, p < .01). More specifically, assignment to the experimental group in the ITT model was associated with a STAR Math post-test score that was approximately 15.5 scaled score points larger than the control group. The standardized effect size (Cohen's d) for group assignment was equal to 0.15. When restricting the sample to include only students who received optimal intervention dosage, the effect of treatment remained significant ( $R^2 = .58$ , F(2, 307) = 3.14, p < .01). In the OD model, assignment to the experimental group was associated with a post-test score that was approximately 21 scaled score points larger than the control group; however, the Cohen's *d* effect size estimate increased only slightly (d = .18).

#### **Fact Fluency**

Similar methods were adopted to evaluate the impact of MMC on students' fact fluency scores; however, to be included in the analysis, students must have had a pre-test fact fluency score and a post-test fact fluency score. This restriction resulted in a sizeable loss in data as two fact fluency data points were not available for many students. More specifically, the number of students in the control group was equal to 85 (down from 179) and the number of students in the experimental group was equal to 239 (down from 311). Nevertheless, the fact fluency analysis is reported here as it provides preliminary insight into the impact of MMC on students' fact fluency skills. As noted, the fact fluency analytic models mirrored those adopted for STAR Math insofar as post-test scores were regressed on group assignment, controlling for pre-test scores.

Results from the ITT model indicated that assignment to MMC was associated with a statistically significant and positive effect on students' post-test fact fluency scores, controlling for pre-test scores ( $R^2 = .55$ ). Assignment to the experimental group in the ITT model was associated with a fact fluency post-test score that was approximately 2.75 problems greater than the control group. The standardized effect size (Cohen's d) for group assignment was equal to 0.13. When restricting the sample to include only students who received optimal intervention dosage, the effect of treatment increased. Assignment to the experimental group was associated with a post-test score that was approximately 3.6 problems greater than the control group and the Cohen's *d* effect size estimate increased only slightly (d = .19). Thus, similar to the observed impact of MMC on overall math achievement, students who received the intervention also outperformed their peers assigned to the control group on a measure of math fact fluency.

#### Contextualizing the Impact of MMC on Math Achievement

The previous subsections provide rigorous empirical evidence for the impact of the program—students assigned to MMC clearly outperformed their peers who did not have access to the intervention. Nevertheless, it is also useful to further contextualize the results.

To help illustrate the impact of MMC on students' math achievement, it is helpful to visually compare the performance of students in the control and experimental group on metrics of interest. For example, the difference in weekly growth (i.e., the change in students' STAR Math scores smoothed across weeks of service) is a helpful reference for interpreting impact. In Figure 4, students' weekly growth scores are displayed across groups. From that figure, the magnitude of differences between groups is clearer. For example the average weekly growth for students in the ITT group was about 1.5 times as fast as students in the control group. When comparing the OD group to the control group, only students in the schools with tutors who met OD criteria were included. This was done in an effort to control for school-related effects on student achievement (e.g., it is possible that students in schools where tutors had low fidelity were all generally low performers). After making that adjustment, the impact of Math Corps was similar to that observed for the ITT group.



\* Control group in Panel B was restricted to include students at schools who had tutors meeting OD criteria. *Figure 4.* Weekly growth for typical students and students assigned to the control group compared to students in the ITT Math Corps group (A) and students in the Math Corps group who received an optimal amount of dosage (OD).

The consideration of students' weekly growth rate is particularly useful as it allows for a comparison of student growth to a rate typically expected of students (STAR Math produces normative rates by students' initial level of performance). In effect, a comparison of the growth rates for students assigned to receive Math Corps with the rates of growth observed for typical students allows for the estimation of the added benefit in terms of instructional time. For example, the expected rate of growth for students in the sample (based on STAR Math norms) can be multiplied by the number of weeks students were served to get an estimate of an expected post-test score. The average magnitude of the difference between the expected post-test scores and the observed post-test scores for individual students can then be divided by the typical rate of growth to estimate the added benefit of the intervention in terms of time. This concept is illustrated below and the corresponding results are presented in Figure 5.



*Figure 5.* The added value of MMC expressed as instructional time, based on typical student growth and the average magnitude of the difference between expected post-test scores and observed post-test scores.

As might be inferred from Figure 4, the rate of weekly growth observed for students in the control group was roughly equivalent to the average expected rate of improvement for students included in the study sample. This is also reflected in Figure 5 insofar as the number of weeks associated with student growth in the control group was essentially equal to the number of weeks of support. That is, student growth was equivalent to about 17 weeks of typical instruction. However, as evident in Figure 4, students assigned to MMC demonstrated accelerated growth rates. In Figure 5, the impact of those growth rates is estimated in terms of added instructional time. On average, students assigned to MMC ended the study with a STAR Math post-test score equal to approximately 8 weeks of *additional* growth (based on STAR Math normative growth rates). That is, students assigned to receive Math Corps grew the equivalent of 26 weeks after 18 weeks of support. The impact of MMC was more pronounced among students who met criteria for the optimal dosage group (OD). More specifically, the average post-test score among students in the OD group was equal to approximately 17 weeks of additional growth (growth equivalent to 35 weeks after 18 weeks of support).

### **Implications and Discussion of Effects**

These findings extend existing research regarding the potential for community-based volunteers to substantively contribute to schools' support of at risk students. Previously, such research was limited exclusively to reading (Slavin et al., 2011), but the current study suggests community-based resources such as AmeriCorps can support schools' efforts in math. Further, the nature of the intervention program, which included full-time interventionists trained as AmeriCorps members, suggests promise with respect to more integrated school-community partnerships.

Schools dedicated a staff member to be trained in the program, assist in determining eligibility (by accessing and interpreting student state proficiency data), and allocate time for coaching sessions. Although substantive, these activities were relatively modest in comparison to the contribution of time and effort of the full-time interventionist. Further, other human and intellectual resources (e.g., coaches, data-driven decision-making support) were provided by the intervention program. The result was an integrated partnership that aligned community resources and expertise with school needs and structures (Gutkin, 2012). Although similar partnerships have documented success at the individual level (e.g., Sheridan, Bovaird, Glover, Garbacz, & Witte, 2012), efforts to support *systems* level needs like implementing comprehensive intervention programs are rare in general (e.g., Jacob et al., 2016) and nonexistent in math.

If tiered prevention frameworks like response to intervention—which presume comprehensive intervention programs are in place for academic and behavioral needs—are to be successful, an ecological perspective to integrate community-supported efforts is likely necessary (Burns, 2013). To illustrate from a strictly logistical perspective, the fourth grade math proficiency rate in Minnesota was 69% the year of the study, which means the average need in any given school was 31% instead of the 15%-20% assumed in tiered prevention framework literature (Tilly, 2008). Providing each of those students 80-120 minutes of weekly intervention, even in pairs, is a herculean challenge for schools, and adding the time and resources to develop capacity and systems for data-driven decision-making and implementation (e.g., coaching) protocols further exacerbates the problem. As demonstrated in this study, there is promise for schools to augment their internal capacity with both personnel and knowledge resources from AmeriCorps programs such as MMC. Much of the work involved in implementing prevention frameworks lends itself to structured protocols for implementation (Noell & Gansle, 2016), and well-organized community organizations such as MMC might be able to support schools in establishing and executing those protocols, which could potentially free schools to focus more intently on core instructional practices that offer even greater potential to reduce proportions of at-risk students (Jitendra & Dupuis, 2016).

Findings from the present study also have implications for math intervention in general. The current results suggest that comprehensive math intervention programs can produce meaningful outcomes for struggling students on distal math measures. This is important because a more comprehensive and replicable approach for supporting struggling students is consistent with the goal of prevention models to improve the overall academic health of school systems. As discussed, the evidence-base is well-established for specific interventions targeting conceptual understanding (Witzel et al., 2003), computational proficiency (Woodward, 2006), and word problem solving interventions (Montague et al., 1993). To date,

however, no study has examined the combined use of those approaches within a single intervention program spanning across multiple instructional targets. By using a broad construct measure, the present research captured distal program impact, whereas previous research focusing on the effects of a single intervention approach had used relatively proximal measures more likely to observe an effect (Montague, Krawec, Enders, & Dietz, 2014).

The use of randomization and a relatively large participant sample also advances methodological limitations of existing studies of math interventions for skills related to whole and rational number understanding. For instance, existing studies that support the use of explicit modeling with concrete and semi-concrete representations had small sample sizes (Butler et al., 2003; Flores, 2010; Witzel et al., 2003), and other notable limitations such as randomizing class sections of the same teacher and analyzing outcomes at the student level. Studies in support of interventions to build computational proficiency have relied heavily on single-case designs (e.g., Flores, 2010; Poncy, Skinner, & Jaspers, 2007; Woodward, 2006), which support internal validity but require systematic replications to establish external validity (Horner et al., 2005). The current findings do not isolate the direct benefit of subcomponents of MMC, but they do suggest the inclusion of these interventions contributes to effectiveness as part of a comprehensive intervention program, and the ultimate goal of math intervention programs should be to increase broad-based mathematical competence (NMAP, 2008).

## Limitations

Although this study used a rigorous design and a large sample to produce evidence that MMC improves student math outcomes, there are several limitations to the findings. Characteristics of the school sample limit the degree to which conclusions are applicable to other settings. The study occurred in schools with a relatively high proportion of students eligible for free or reduced price lunch, and thus findings cannot be extended to schools with relatively low socioeconomic need even though those schools are not devoid of students requiring supplemental support. Likewise, results from the present study do not represent the full impact of MMC—which is typically implemented for a whole year. Future research is underway to evaluate the impact of MMC on end-of-year benchmarks.

A separate limitation is that the comprehensive nature of the intervention program—inclusive of multiple evidence-based interventions, data-driven decision-making, and implementation support—prevents understanding of the degree to which any single component, or subcomponent, contributed to student outcomes. It is unlikely that one component could be omitted from the program and still produce positive effects, but that possibility cannot be ruled out with the current methodology. Better understanding of the unique value of each approach could inform optimal allocation of time during instruction and intervention. Thus, future research adopting novel methodologies designed to evaluate the value of modular interventions (e.g., Baker et al., 2016) may prove useful in the area of math. A final set of limitations pertains to methodological characteristics of the study. There was a relatively high level of missing data (11%), which is known to potentially bias outcomes. Differential attrition within the conditions was minimal and few demographic characteristics were related to missingness. Under such conditions, even relatively high overall attrition minimally biases estimates (What Works Clearinghouse, 2017), but biased estimates remain possible. It is also relevant to note that a large proportion (40%) of the missing data were the result of one school missing all study data—that particular school was unable to begin the study because no interventionist was placed at the school.

## Conclusion

In education, conventionally small effect sizes can have meaningful implications when interpreted in a broader context of student age, study rigor, and outcome measure (Hill, Bloom, Black, & Lipsey, 2008). Such effects were found in the current study, suggesting that community-supported comprehensive math intervention programs hold promise in late elementary and middle school. Given the challenges schools face in implementing intervention programs (Vujnovic et al., 2014), combined with the need of their students (NAEP, 2015), effective support from communities may be a valuable asset to reverse longstanding trends in student performance. Ongoing research that strengthens the understanding and impact of such an approach appears warranted.

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