Final Performance Report for R342A110270

A Randomized Trial of a Tutor-Based Mathematics and Attention Intervention for Low Performing Preschoolers at Risk for Mathematical Difficulties in School

The principal objectives of this proposal were: to test the efficacy of an intensive math intervention, *Pre-K Mathematics Tutorial* (PKMT) for especially low performing pre-k children; and to compare the efficacy of PKMT alone vs. when used with an attention intervention. Secondary objectives were to identify mediators and moderators of hypothesized impacts on mathematics outcomes; the effects of interventions on attention, working memory, and literacy; and what characterizes children who show different levels of responsiveness to intervention. This project is the first of its kind, as far as we know, to have: 1) conducted an RCT of a tutor-based Tier II mathematics intervention for very low-performing pre-kindergarten children; and 2) tested whether an accompanying attention intervention provides any additional benefit to math for these very low-performing children given the strong empirical and theoretical connections between difficulties in attention and later learning disabilities (Tannock, 2013).

We first present information on the sample, including Consort Flow Diagrams as well as demographic information. We then present findings based on the aims and hypotheses from the original proposal. For aims and hypotheses that have been discussed in detail in previous reports, we provide summaries and implications of the findings. For analytic work conducted between 09/01/2016 to 02/28/2017 (the time from the last annual report to the end of the second no cost extension period) findings are presented in greater detail (see Aims 4 & 5 below). Finally, broader implications of the findings are presented under the Additional Questions in Section C.

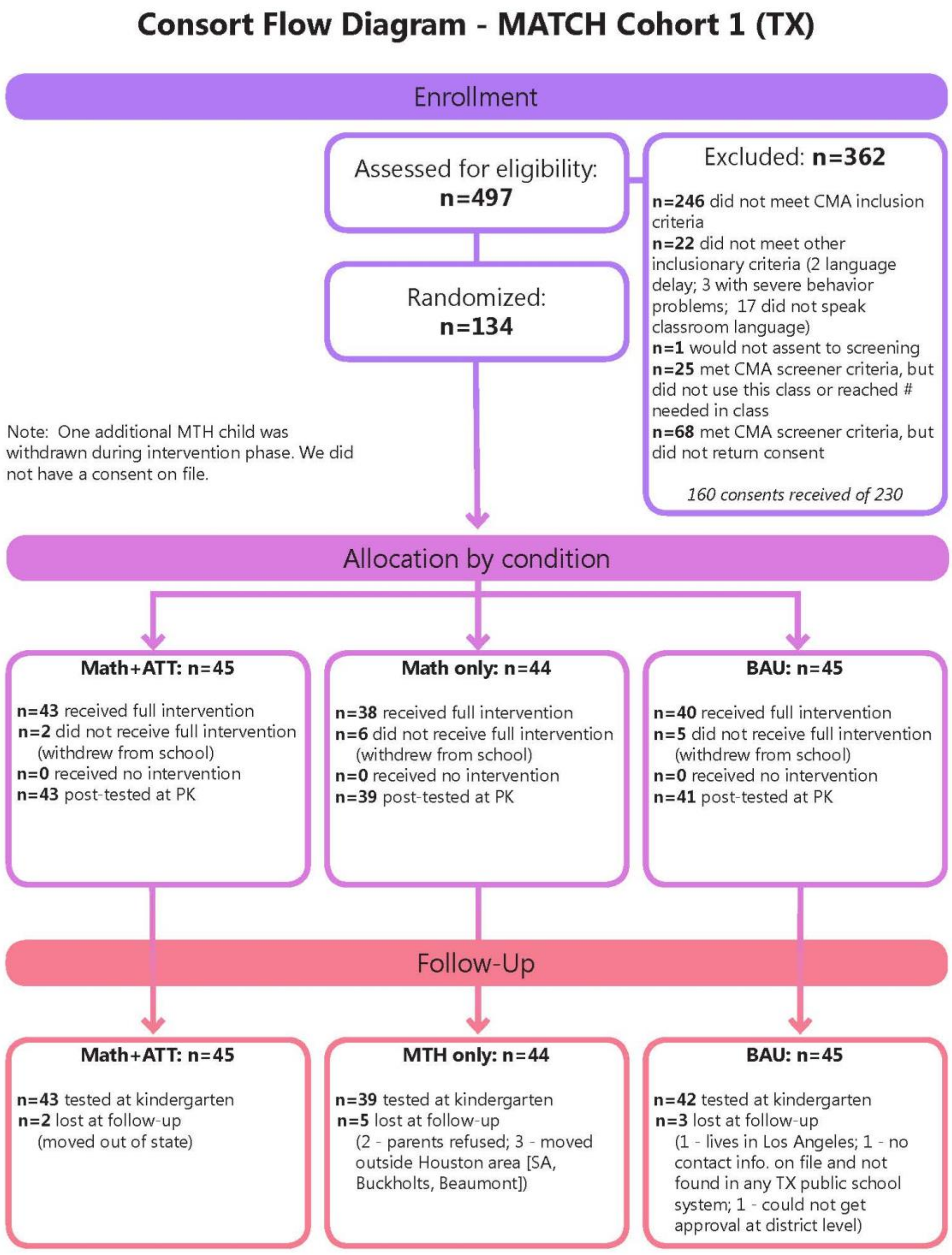
Section A: FINAL PERFORMANCE REPORT

Sample, Attrition, and Consort Flow Diagrams

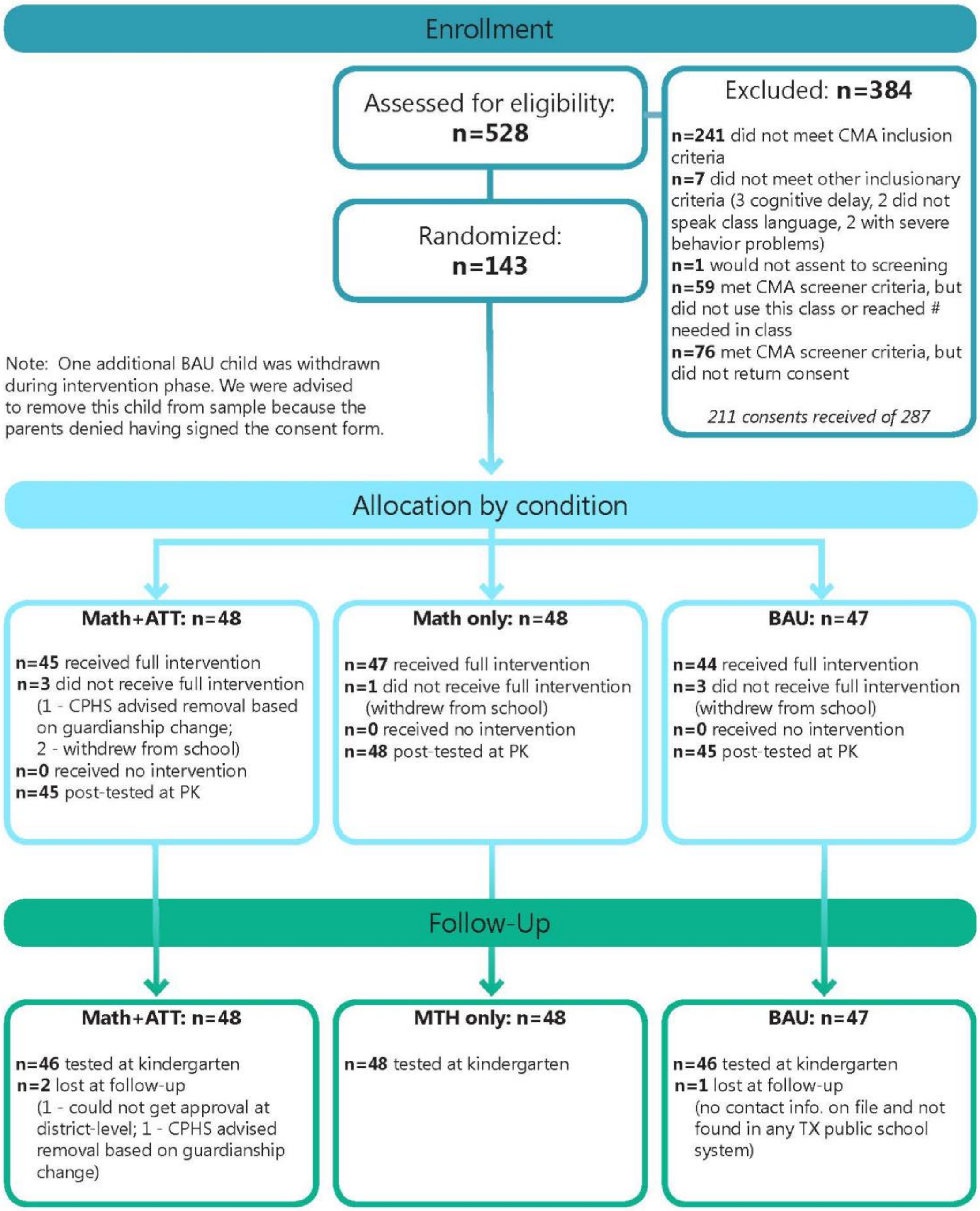
The main goals of this project were to test the effectiveness of an intensive math intervention for the lowest performing children entering pre-kindergarten and to see whether additional intervention in attention has any benefit for improving math outcomes in this group. Our approach was driven by two considerations: 1) findings from studies by the Co-PIs that a significant proportion of very low performing children make relatively little progress in math across the pre-k year (Starkey & Klein, 2012) even when provided with classroom-level math instruction that produces significant, large gains for many children; and 2) findings that attention problems often accompany difficulties in learning and, when present, are associated with more severe learning disabilities in math and reading (reviewed in Barnes et al., 2017). Because epidemiological data showing that a child entering and exiting kindergarten with low math skills has a high probability of having a math disability at 5th grade (Morgan, Farkas, & Wu, 2009), it is necessary to find new ways to intervene for preschool children who are considered to be at high risk for later math difficulties. We identified a group of high risk very low performing pre-k children using a math screening measure based on three subtests from the Child Math Assessment (CMA Screener; Klein & Starkey, 2012). Consented children were randomized to a math only intervention (Math Only), math + attention (Math + ATT) intervention, or BaU.

The Consort Flow Diagrams are presented below for each site and each cohort. Our target was to randomly assign 528 children to the three conditions; in total, 541 children were randomized to condition. Attrition was lower than expected across the pre-k year (predicted 10% vs. actual 4%

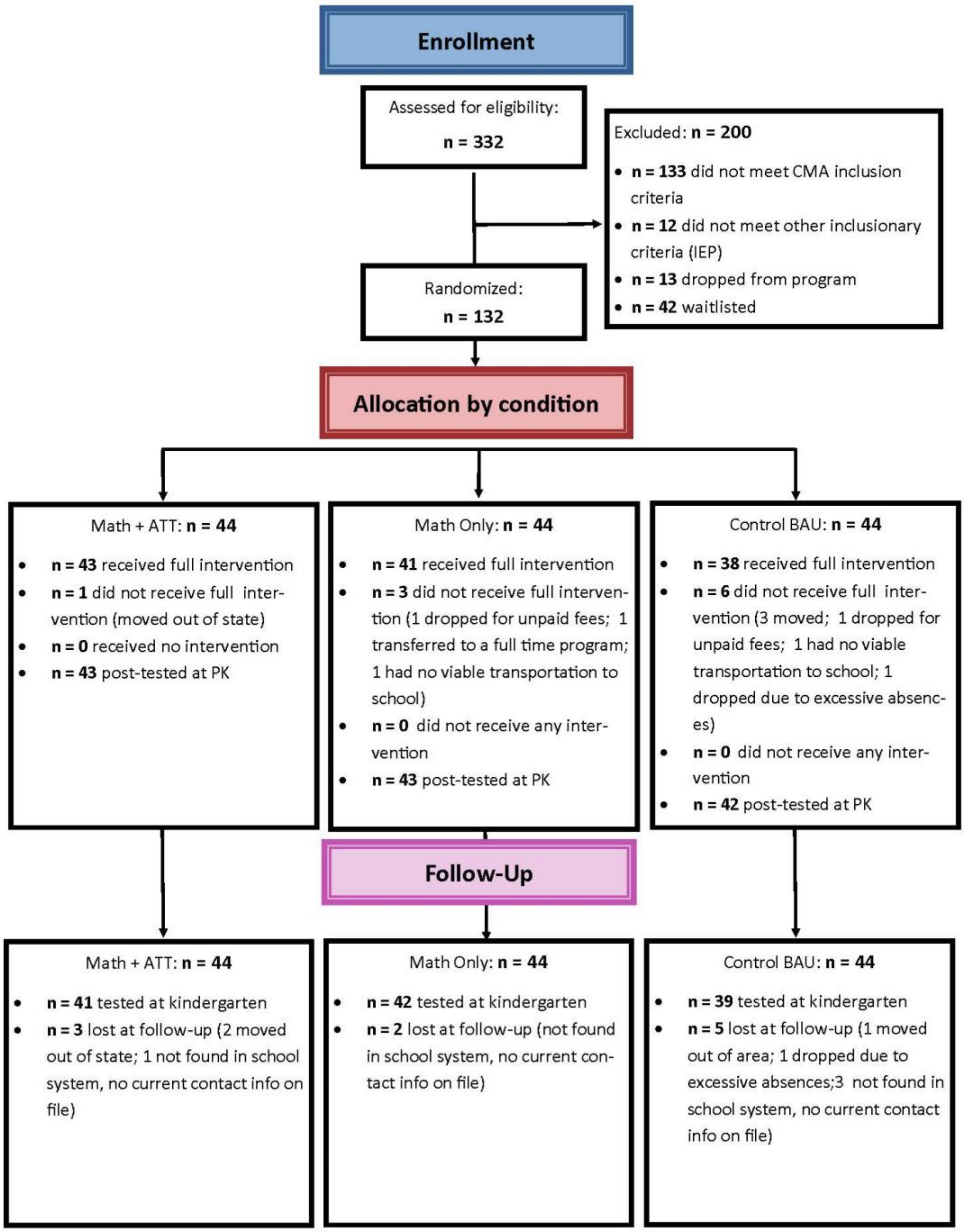
attrition) as well as into kindergarten follow-up (predicted follow-up sample of 428 vs. actual sample of 510). The demographics of the sample are in Table 1 at the end of this report.



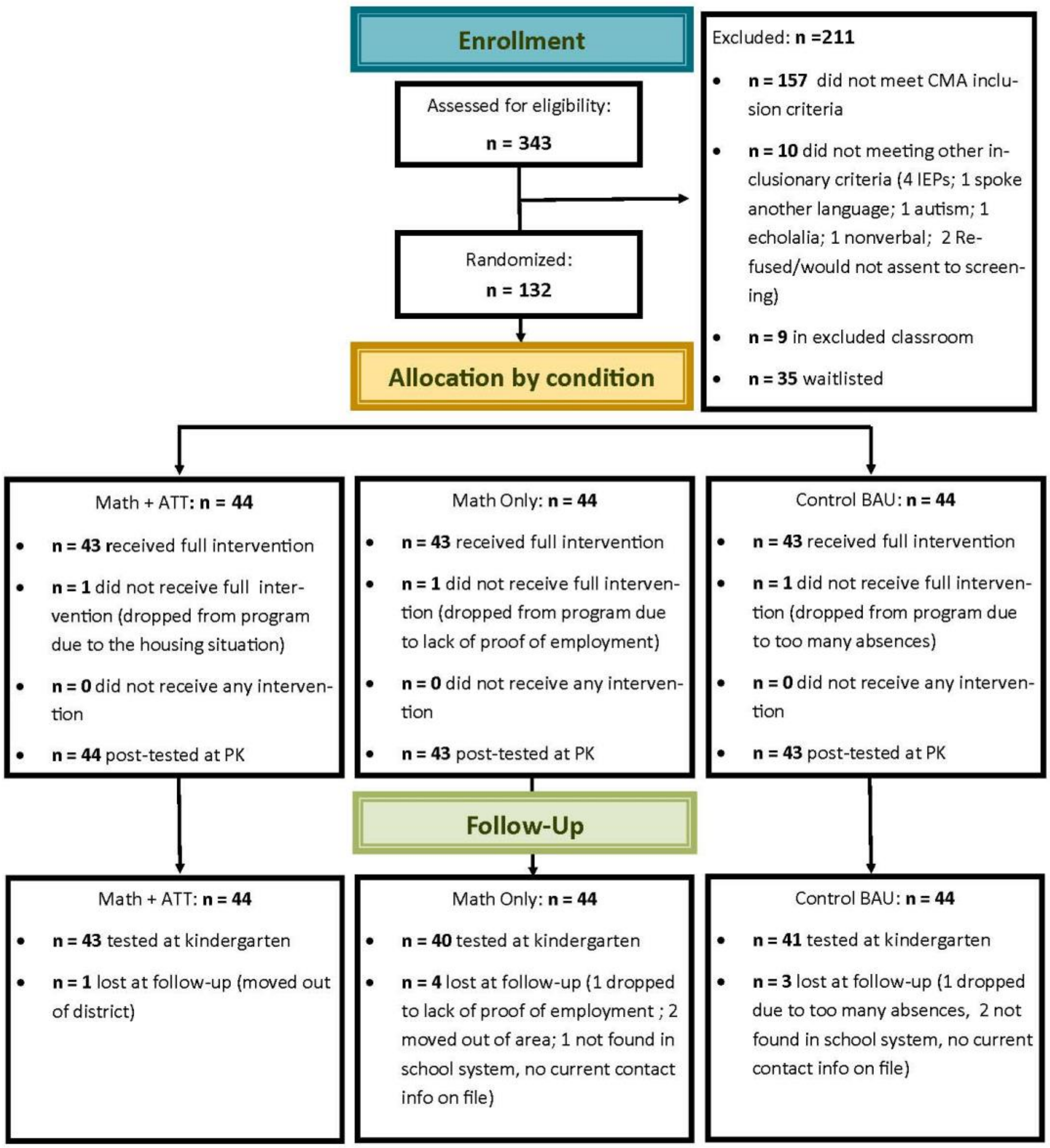
Consort Flow Diagram - MATCH Cohort 2 (TX)



Consort Flow Diagram—California Cohort 1 MATCH



Consort Flow Diagram—California Cohort 2 MATCH



FINDINGS BASED ON PROJECT AIMS

Aim 1. Effects of the math intervention on math outcomes

To test whether the math intervention has an impact on math outcomes for pre-k children who score especially low in math at beginning of pre-k: Math scores will be better at pre-k post-test and at kindergarten follow-up for Math Only and Math + ATT children than for Control children.

Pre-Kindergarten:

As reported previously and documented in Barnes, Klein, et al., (2016), the *PKMT* had significant effects on two math outcomes, the Child Math Assessment or CMA (Klein & Starkey, 2011), which assesses informal mathematical knowledge in several of the math domains instructed in the *PKMT*, but which is not overly aligned with the intervention, and on the TEMA-3 (Ginsburg & Baroody, 2003), which assesses informal and formal mathematical knowledge in number and operations. Compared to the BaU group, the effect sizes for the CMA were Hedges' g = .60 for the Math Only group and g = .43 for the Math + ATT group, which differed from each other. For the TEMA-3, the effect size was Hedges' g = .18 comparing the combined math intervention groups to BaU. Data are in Table 2 below.

An additional finding of interest was that the math scores of children from Texas were significantly higher than those from California across all of the conditions, and this was related to a stronger Tier 1 mathematics program in Texas. The importance of this finding is further discussed in the special questions category at the end of this report.

Kindergarten:

Follow up testing was conducted in the spring of the kindergarten year. Although there were no effects on mathematics of the intervention discernable at kindergarten, the Texas children continued to have higher math scores than those in California on both the CMA and the TEMA-3. These data are in Table 3. It is unclear whether the continued higher performance of the Texas cohort into kindergarten reflects a strong foundation in Tier 1 mathematics instruction from pre-kindergarten, a continued focus on mathematics in kindergarten, or both. Classroom observations of mathematics were not conducted in kindergarten; however, we are exploring this issue using data from a teacher questionnaire on math instruction adapted from the ECLS-K that we gave to the kindergarten teachers of the children in the study.

Aim 2. Effects of Attention Training on Attention

To test whether the attention intervention has an impact on attention outcomes for children who score especially low in math at beginning of pre-k: Attention scores will be better at pre-k post-test for Math + ATT children than for Math Only and Control children.

As reported in Barnes, Klein et al. (2016), attention training yielded significant, small effects on measures of attention. Children in the *M +ATT* condition outperformed students in the combined *Math only* and *BaU* group on all of the measures of attention, including cued trials (where the child is cued that a stimulus will appear on the computer screen (β =0.03, SE =0.01, p = .01; g = .19); uncued trials where the child must remain vigilant to respond to the target without a cue (β =0.03, SE =0.01, p = .04; g = 0.19); on congruent trials where the target and distractors are compatible (β =0.02, SE =0.01, p = .03, g = .21); and on incongruent trials where the target and distractors are incompatible or "in conflict" (β =0.05, SE =0.02, p = .03, g = 0.18). In short, children who received attention training showed effects on measures of both vigilance and executive attention. However, as noted above, these improvements in attention were not associated with additional benefits for mathematics. These data are in Table 2 below.

Aim 3. Effect of attention training on math outcomes

To address questions about possible impacts of attention training on math outcomes for children who score especially low in math at the beginning of pre-k: Will math scores be better at pre-k post-test and kindergarten follow-up for Math + ATT children than for Math Only children? If so, does attention partially mediate math outcomes at post-test?

Note that the findings on the CMA reported above are in the opposite direction to what would have been expected had a combined math and attention intervention been facilitative in terms of math learning. Follow-up analyses have not thus far provided data on why the math intervention groups differed on the CMA. The difference is not due to factors such a general cognitive ability. Because of these findings, attention was not tested as a mediator of math outcomes.

Aim 4. Effects of math and attention interventions on other domains

To address questions about possible impacts of math and attention interventions on working memory literacy, and approximate number system (ANS) acuity.

Research Question 1: Will working memory or literacy or ANS acuity be better at pre-k post-test and kindergarten follow-up for Math Only and Math + ATT children than for Control children? This question is based on the possibility that an intensive intervention in mathematics may affect growth in domain-general and domain-specific abilities not specifically targeted by the interventions. An implicit assumption from some *correlational* studies is that the direction of the relation is *from* a cognitive ability such as working memory or a domains-specific ability such as ANS acuity *to* mathematics achievement. Here, we test, using an *experimental method*, whether the direction of the relation might be *from* the academic intervention *to* other cognitive skills.

Research Question 2: Will working memory, literacy, or ANS acuity scores be better at pre-k post-test for Math + ATT children than for Math Only and Control children? This question is based on the strong relation of attention and academic skills (math and reading) as well as theoretical views that higher-level cognitive systems such as working memory develop from the attention system. To the extent that the attention intervention was associated with an effect on attention, we ask whether the Math + ATT group would also have an advantage compared to the Math Only group on other skills (working memory, early literacy) associated with attention.

To test whether the interventions affect working memory, literacy, and approximate number system outcomes we fit a series of three-level regression models. Students were nested within classrooms and classrooms were nested in schools. For all models except WJ Letter-word identification (the post-test literacy measure), we included group-mean centered pretest scores at level 1. State (Texas or California) was included as a fixed effect in the level-3 models. We estimated its moderating effect on the relationships of treatments and outcomes by including the appropriate cross-level interaction terms. We used an iterative model fitting process, fitting fully specified models (i.e., intercept, covariates, treatment effects, and interaction terms), removing non-treatment related terms that were statistically non-significant, and then estimating final models to include statistically significant covariates along with the associated treatment effects for each outcome. For skewness and kurtosis, all variables were within an acceptable range. The inspection of plots and histograms indicated that the statistical assumptions underlying our models were reasonable.

To answer our first research question, the Math only and M + ATT groups were combined and compared to the control group. The groups did not differ on visual spatial working memory (β = -.03, *SE*= .17, *p* = .84), ANS acuity (β = .60, *SE*= .52, *p* = .25), or phonological awareness (β = -.08, *SE*= .12, *p* = .52). The difference between groups was statistically significant on WJ Letter-word identification (β = -4.18, *SE*= 1.61, *p* = .01), with students in M + ATT and M only group scoring 4 points lower than students in the BAU condition.

To answer the second research question, we compared the M + ATT group to the combined Math only and control groups. The difference between groups was not statistically significant on any of the measures, including visual spatial working memory (β = -0.14, *SE* = 0.15, *p* = 0.38), approximate number system acuity (β = -0.01, *SE* = 0.51, *p* = 0.98), phonological awareness (β = -0.14, SE = 0.16, *p* = 0.39), or WJ letter-word identification (β = -1.25, *SE* = 1.85, *p* = 0.50).

To summarize, the effects of attention training were specific and narrow: although attention training resulted in improvements in vigilance and executive attention, these treatment effects did not confer benefits for early mathematics (discussed under Aim 3 above) or for early literacy. In addition, the effects of attention training did not generalize to performance on a related cognitive construct – working memory, nor did they affect performance on a measure thought to assess early number sense.

Aim 5. **What are the relations among attention, working memory, ANS acuity and math including whether any of these math-related correlates distinguish different levels of response to intervention?**

Because knowledge in the field has grown considerably since we first wrote this particular aim, we asked a different series of questions than those in the original proposal. These questions are as follows: a) what domain-specific and domain-general correlates of math are associated with math performance and growth in math when all are included in the same model; b) Are there ability profiles that distinguish intervention children with different levels of response to intervention at pre-k post-test?

Research Question 5a. Do working memory, phonological awareness, and ANS acuity account for significant variance in mathematics in the presence of attention? Many studies that look at the domain-specific (e.g., ANS acuity) and domain general (e.g., working memory, phonological awareness) correlates of mathematics do not include direct assessment of child attention abilities. Attention is importantly related to both academic competence (Tannock, 2013) and working memory (Posner & Rothbart, 2001), suggesting that predictive models of mathematics ability ought to include attention in addition to these other cognitive correlates. Executive attention (i.e., inhibitory control) and visual-spatial working memory have been related to performance on ANS tasks (Bugden & Ansari, 2016; Fuhs & McNeil, 2013). Thus it is also important to understand whether ANS acuity contributes to the prediction of mathematics in the presence of visual-spatial working memory and executive attention.

To examine the unique contributions of attention, ANS acuity, visual spatial working memory and phonemic awareness in predicting CMA and TEMA scores at both pre and posttest hierarchical regression analysis using Cholesky decomposition (de Jong, 1999) in structural equation modeling (SEM) was used. Such an analysis can be used when the extra amount of variance accounted for in a dependent variable by a specific independent variable is the main focus of interest, and the independent variables are highly correlated (deJong, 1999). Four hierarchical regression analyses were conducted for both TEMA and CMA in which the latent factors were entered in a prespecified order. The parameters were estimated using the full information maximum likelihood method (MLR estimation in Mplus). Model fit was evaluated with the root mean square error of approximation and the comparative fit index (Kline, 2011). First, we present results for CMA and then results for TEMA, first for pretest and then at posttest. Posttest analyses controlled for pretest mathematics performance. In this analysis, we used a latent attention score.

CMA. The models for CMA fit the data well, $\chi 2$ (26) = 120.83, p =.00, CFI = .95, TLI = .90, RMSEA = .08, SRMR = .06. Attention (β = .48, *p* =<.01), ANS acuity (β = .16, *p* =<.01), visual spatial working memory (β = .17, *p* =<.01), and phonemic awareness (β = .22, *p* =<.01) were significant unique predictors of CMA scores at pretest. Together they explained 34% of the variance in CMA pretest scores. While a significant predictor of time 1 CMA performance, ANS acuity accounted for a small amount of variance in all models (~1%).

At posttest, the model with pretest CMA, condition and the cognitive predictors accounted for about 50% of the variance (30% for CMA pretest; 8% for condition; 12% for other predictors). Attention (β = .27, *p* =<.01), ANS acuity (β = .12, *p* =<.01), visual spatial working memory (β = .18, *p* =<.01), and phonemic awareness (β = .09, *p* =<.01) were significant predictors. In order 1, in which attention was entered first, attention accounted for 7% of the additional variance in CMA at posttest, ANS acuity contributed an 1% additional effect, visual spatial working memory added another 3% of variance to CMA posttest scores and phonemic awareness had an 1% additional effect on posttest scores after attention, ANS acuity, and visual spatial working memory had been incorporated. Reversing the order of inclusion (Orders 2,3, or 4) revealed similar findings: attention and visual spatial working memory explain the majority of the variance in CMA posttest scores while ANS acuity and phonemic awareness explain minimal or no variance in CMA posttest scores.

TEMA. The models for TEMA fitted the data well, $\chi 2$ (17) = 45.40, p =.00, CFI = .98, TLI = .96, RMSEA = .056, SRMR = .034. Attention (β = .36, *p* =<.01), visual spatial working memory (β = .12, *p* =<.01), and phonemic awareness (β = .15, *p* =<.01) were significant predictors of TEMA scores at pretest. Together they explained 38% of the variance in TEMA pretest scores.

At posttest, pretest TEMA scores accounted for 30% of the variance, and the cognitive variables added about an additional 9% (condition added < 1%). When entered first, attention accounted for 8% of the additional variance in TEMA posttest scores. ANS acuity had no significant additional effect on TEMA posttest scores after attention had been incorporated. Subsequent inclusion of visual spatial working memory added 1% of variance while phonemic awareness had no significant additional effect on posttest scores when added after attention, ANS acuity, and visual spatial working memory. Reversing the order of inclusion (Orders 2, 3, or 4) revealed that attention continued to show the largest effects regardless of order of entry, followed by visual-spatial working memory and phonemic awareness. ANS acuity remained non-significant in all models.

To summarize, attention accounted for additional variance in posttest CMA and TEMA performance, regardless of its order of entry in the predictive models, underlining the importance of attention for mathematics. Visual-spatial working memory was also implicated, but more so for the CMA. Phonological ability accounted for additional variance in some models, but only for the TEMA, and, interestingly, not when attention was added first. ANS acuity accounted for very small effects (often not significant), regardless of the math measure.

These findings are similar to those conducted using a different analysis, initially reported on in the Year 5 annual report in which we used separate scores for the individual attention variables. In those analyses, we found that even after accounting for several other cognitive (working memory), intellectual (nonverbal IQ), linguistic (phonological awareness), and math (ANS acuity) variables, attention was positively related to the TEMA-3 at posttest and associated with greater gains on the TEMA over and above other measures. Furthermore, visual-spatial working memory at pretest was related to *growth* on the CMA and pretest phonological awareness and visual-spatial working memory were related to *growth* on the TEMA.

Research Question 5b. Are there demographic and cognitive profiles that distinguish children with lower and higher response to intervention?

We have looked at this question in a variety of ways. In one analysis using the CMA as the math outcome, Flynn, Klein, Huang, & Barnes (2017) used gain scores of children from the two intervention groups (n = 347) to classify them into three groups. The low responder group (n = 88) was composed of children whose gains on the CMA from pretest to posttest were at or below the 25th percentile in terms of gain scores. The moderate responder group (n = 171) was composed of children whose gains on the CMA from pretest to posttest were between the 26th and 75th percentiles in terms of gain scores. The high responder group (n = 88) was composed of children whose gains on the CMA from pretest to posttest were above the 75th percentile in terms of gain scores. The three groups differed at pretest on visual-spatial working memory and the low and high response groups differed on visual spatial working memory at posttest after controlling for pretest scores. At kindergarten follow-up, the low response group (from prekindergarten) was significantly lower on the CMA-Kindergarten test than the moderate and high response groups. This latter finding adds to other findings presented above; children at the end of prekindergarten who make less progress in math over the prekindergarten year are at high risk for continued low performance in mathematics in kindergarten. We discuss the importance of these findings of stability in math performance from prekindergarten to kindergarten under responses to the additional questions at the end of this report.

The main findings are that the groups did not differ in terms of gender, language dominance (whether the children were primarily English or Spanish speakers at pretest), or on a measure of nonverbal cognitive ability (K-Bit Matrices). Higher pretest visual spatial working memory was associated with higher levels of response to the math intervention as was posttest visual spatial working memory even controlling for pretest memory.

In the next set of analyses, we included the entire set of domain-specific and cognitive variables used in the previous analyses discussed under Aim 5. For these analyses we included all of the study participants, even those in the BaU group as we were interested in the broader question of whether there is a set of predictors that distinguishes children who grow more versus less in mathematics as a function of whatever math instruction they received (Tier 1 only or Tier 1 plus PKMT). Because the effects of the intervention on the TEMA-3 were relatively small, this analysis also allowed us to model responsiveness based on performance on this standardized math assessment.

We used Multivariate Analysis of Variance (MANOVA) to evaluate profiles across six cognitive attributes, including 3 attention measures, ANS acuity, visual spatial working memory, and phonemic awareness. The analysis involved four steps. First, we identified three groups of students (low and moderate responders and high responders) based on the change from pretest to posttest on the two measures of math – the CMA and the TEMA. Students were identified as low responders (LR) if they performed below the 25th percentile on the change from pretest to posttest. Based on the CMA measure we identified 129 students as LR. The number of LR using the TEMA measure was 141. We selected the 25th percentile as the growth cut score because a cut-point at the 25th percentile has been used to identify low responders in previous studies (Fletcher et al., 2011; Vellutino, Scanlon, Small, & Fanuele, 2006). Students were identified as moderate responders (MR) if their change from pretest to posttest was above the 25th percentile and below the 75th percentile. Based on the CMA measure we identified 259 students as MR. The number of MR using the TEMA was 241. Students were identified as high responders (HR) if their change score was at or above the 75th percentile. 130 students were identified as HR using the CMA and 136 students were identified as HR using the TEMA.

Second, we transformed the scores to z-scores so that the measures were on a comparable metric across the six attributes. Third, we conducted profile analyses and found statistically significant differences in cognitive attributes across the groups, F (6, 365) = 3.58, $p < .001$, Wilk's Λ = 0.9444. Post-hoc comparisons for the groups created based on TEMA revealed that LRs scored lower on all cognitive attributes compared to the group of MRs and also compared to the group of HRs (ps < .05). On the TEMA, MR and HR groups differed only on attention (p <.05). Post-hoc comparisons for the groups based on CMA revealed that LRs scored lower on all cognitive attributes compared to the group of MRs (ps < .05). LRs and HRs differed on all of the cognitive measures except for phonemic awareness. For the CMA, the MR and HR groups did not differ on any of the cognitive variables. These findings are in Table 4.

In the final analytic step, we used discriminant function analyses for each contrast to estimate the relative contribution of each cognitive attribute in *discriminating* the groups. Standardized discriminant coefficients determine the relative contribution of a particular measure controlling for others. For the TEMA, the LR and MR groups were best discriminated by phonemic awareness followed by visual spatial working memory and then ANS acuity. The LR and HR groups were best discriminated by phonemic awareness and attention. Attention discriminated the MR and HR groups. Looking at the groups created based on CMA change score we found that for the LR and MR contrast, attention measures and visual spatial working memory were the strongest predictors. For the LR and HR contrast, attention contributed to the identification of groups. For the MR and HR contrast, one of the attention measures was a discriminant predictor.

<u>Summary.</u> What discriminates young children with various levels of responsiveness to math instruction? The first analysis showed that responsiveness amongst children who received the intensive math intervention did not differ on demographic variables including gender and dominant language status (children were instructed in our interventions in their stronger language), which is important for knowing for whom such interventions are likely to be effective. That responsiveness was not related to nonverbal cognitive ability is consistent with many reading studies showing that response to intervention is not associated with IQ (reviewed in Fletcher et al., 2007; in press), and adds to a growing body of research suggesting that intensive, well-designed interventions are similarly effective for children across a range of broadly average intellectual function. The discriminant function analyses suggest that: 1) low

responders differ from both moderate and high responders on many cognitive factors. This is a common finding in other math and reading studies; 2) cognitive factors do not consistently discriminate moderate from high responders; 3) looking across different measures of math, attention and visual spatial working memory are factors that strongly discriminate children with lower response from their better responding peers. This finding is consistent with those for the other analyses under Aim 5; 4) phonemic awareness is additionally a strong discriminator of children with low response versus better response on the TEMA, consistent with the idea that several items on the TEMA-3 draw on verbal expressions of number knowledge, including counting, number naming and number recognition, and the like.

Aim 6. Child moderators of intervention effects

Will pre-intervention literacy scores, attention scores, working memory scores, or ANS acuity scores moderate the impact of the math intervention at pre-k post-test follow-up for Math Only or Math + ATT children?

This Aim was reported on extensively in the Year 5 Annual Report and is summarized here. For the TEMA-3, there were no moderating effects of pretest cognitive abilities or ANS acuity. For the CMA, the two math intervention groups gained more from the intervention when children began the intervention with visual spatial memory that was average or above average *for the sample* (working memory for the sample as a whole was lower than that found in samples of typically developing preschoolers who are not selected for very low math knowledge). The findings for ANS acuity and attention showed a different pattern of results. Children in the two intervention groups who scored below the mean for the sample on ANS acuity and attention gained relatively more from the math intervention.

SECTION C

Final Questions

1. Utilizing your evaluation results, draw conclusions about the success of the project and its impact. Describe any unanticipated outcomes or benefits from your project and any barriers that you may have encountered.

This project is the first randomized controlled trial of a Tier 2 mathematics intervention at prekindergarten and also the first to combine an academic intervention with a cognitive attention intervention for these very low performing preschool children. The project was successful in terms of what we learned from findings both consistent as well as inconsistent with our hypotheses. The fact that there were significant effects of the Tier 2 math instruction on math outcomes for these very low performing children is a positive finding that provides evidence for the value of higher tiers of math instruction even in very young children.

Some of our findings also inform the field about what *does not* work in terms of early interventions for children at high risk for math disabilities. The effect of the attention intervention on attention, although significant, was small and not associated with additional beneficial effects on math. Although recent systematic reviews (e.g., Jacob & Parkinson, 2015; Melby-Lervag & Hulme, 2016) have failed to find transfer effects from cognitive training to academic outcomes, our study differed from previous studies because we *combined* academic and cognitive interventions to see whether there would be any synergistic effect of such a combined approach. In light of the small effects of attention training on attention outcomes, Barnes et al. (2016) noted that cognitive interventions for preschoolers like the attention intervention used in the present study, are often much less intensive than domain-specific academic interventions. Thus we ask whether it might be worthwhile in future studies to combine academic and cognitive interventions that are more balanced in terms of their intensity. Our findings also prompt questions about whether the timing of intensive cognitive interventions might be important (e.g., prior to versus concurrent with academic instruction) and also whether cognitive interventions may need to be integrated with academic interventions, using content-specific materials. It is possible that none of these alternate approaches to cognitive training will produce benefits for mathematical learning in children at high risk for learning disabilities; however, issues of low response of a significant subgroup of children despite the use of generally effective high quality academic interventions is recognized as a major problem in special education for which innovative solutions are needed (Fuchs & Fuchs, 2015). Addressing the cognitive weaknesses of children with learning disabilities may be one strategy among many that is tested in this endeavor to improve learning outcomes in these most at risk children.

Despite the null findings for attention in this study, several of the analyses point to the importance of attention in mathematical learning and performance: 1) attention often contributed the largest amount of unique variance to the prediction of growth in mathematics across the pre-kindergarten year in models that included several cognitive correlates known to be strongly related to mathematics; 2) attention often served to discriminate low responders from moderate and high responders; and 3) attention was found to moderate the effects of the intervention such that the math intervention most supported those children who were low in attention abilities at pretest. These are interesting findings given recent intervention studies with older children in which different components of a fractions intervention were differentially effective for children with lower versus higher levels of working memory (Fuchs et al., 2014). We think that another fruitful avenue for future research would be to use such treatment by ability findings to engineer interventions that compensate for the cognitive weaknesses that children with or at risk for learning disabilities bring into the intervention context.

Unanticipated Findings and Barriers:

An unanticipated finding of interest for the field of Early Special Education was that the math scores of children from Texas were significantly higher than those from California across all of the conditions at posttest (they did not differ at pretest), and this was related to a stronger Tier 1 mathematics program in Texas. This was due to a change in preschool program leadership in the Texas preschool program before the start of the intervention year. The new leadership mandated a “daily numeracy block” along with extensive professional development in early math. Differences in mathematics instruction was assessed using the Early Mathematics Classroom Observation tool or EMCO, which assesses the amount and type of focal math activities in the classroom, including whole- and small-group instruction, as well as activities in which math is embedded but not the primary focus. The main difference in Tier 1 classroom instruction between states was the average number of minutes of daily whole group instruction in mathematics - 22.3 minutes in Texas pre-kindergarten classrooms compared to 6.5 minutes in California classrooms. At the end of the pre-k year, 18% of children in the Texas sample were below the 10th percentile on the TEMA-3 compared to 30% of the California sample. We cite statistics for the 10th percentile here because studies based on large longitudinal datasets show that children entering and exiting kindergarten below the 10th percentile have a high probability of having a math disability by 5th grade (Morgan et al., 2009). Thus, the current findings suggest that a strong Tier 1 mathematics program combined with an intensive Tier 2 intervention delivered during preschool may reduce the number of children who later develop mathematical disabilities (Fletcher, Lyon, Fuchs, & Barnes, 2007; in press). In Barnes, Klein et al. (2016), we suggested that strong Tier 1 mathematics instruction combined with higher tiers of instruction beginning in preschool for the lowest performing children might provide a productive avenue for preventing or attenuating learning difficulties in mathematics. In our report on predictors of intervention response, Flynn et al. (2017) found that children who were classified as low responders at the end of pre-kindergarten were also significantly lower than their better responding peers on a math assessment in kindergarten. These findings point to the importance of early and ongoing assessment for children who are low in math in prekindergarten and into kindergarten. They also point to the importance of linking these early assessments of mathematics to timely implementation of higher tiers of instruction for these most at risk children at an earlier point in schooling than is the case in typical practice (Barnes, Martinez-Lincoln, & Raghubar, 2017).

Another unanticipated finding has to do with how rapid changes in learning at this age (i.e., maturational changes and/or changes due to uptake of classroom math instruction) can affect assessment of mathematical knowledge. We found that in the BaU group, children who were post-tested a few weeks later in the year had significantly higher math scores than those assessed a few weeks earlier. Although this effect was relatively small and it was controlled for in our impact analyses (see Barnes, Klein et al., 2016), such findings underline the importance of strict time windows in the assessment of young children in experimental studies.

One barrier that we encountered early in the study was the difficulty that some children had with the attention intervention when it was being conducted on a more frequent schedule and we began to experience problems with children who did not want to participate in either the math or attention intervention. We quickly scaled back the delivery of the attention intervention to one day a week in order to make the attention intervention standard for all children in the Math + ATT condition and to retain children in the study. Although this change to the protocol was necessary at the time given our design, researchers in future studies might think about ways to incorporate and test flexible adaptive cognitive interventions where, for example, the intervention is more individualized for the child's level of ability and tolerance.

In closing, although the mathematics intervention was effective for many children, there were some children at the end of pre-kindergarten and into kindergarten who remained at a low level in terms of their mathematics knowledge and performance. Furthermore, some of the children who responded to the intervention may be at continued risk for low math achievement because the intervention, while effective in the context of this RCT, likely did not close the achievement gap with average performing peers in mathematics. As described above, we think that modifications to interventions that explicitly take cognitive weaknesses of children into account may be a valuable next step in the design of novel intervention studies for young children at high risk for learning disabilities in mathematics.

2. What would you recommend as advice to other educators that are interested in your project? How did your original ideas change as a result of conducting the project?

Based on the findings we have the following suggestions for educators and other professionals who work with preschool children: 1) early and ongoing assessment of mathematics is important over the prekindergarten year; 2) children who are not responding adequately to mathematics instruction should receive higher tiers of intervention in mathematics beginning in the prekindergarten year given the stability of math difficulties from prekindergarten to kindergarten and the high association of kindergarten math difficulties with math disability by 5th grade; and 3) assessment of attention and working memory in prekindergarten does not help with the identification of a learning difficulty, but may add valuable information about the potential severity of the learning difficulty in math and how to structure intensive math interventions to support or compensate for cognitive difficulties that can interfere with learning.

These points are reviewed in an online International Dyslexia Association paper written for parents, educators and practitioners at https://dyslexiaida.org/perspectives/ (Barnes et al., 2017; *Winter edition – Taking on Math Difficulties*).

As noted in the answers to Question 1, our findings suggest that researchers might test the promise of different types of approaches for combining academic and cognitive interventions for young children at very high risk for learning disabilities in mathematics. We provided some suggestions about what some of these options might look like. Although there is considerable skepticism in the field of education around cognitive interventions, and we too are skeptical as a result of our experiences in this study, we think there is more basic empirical work that needs to be done to be able to determine whether interventions with a cognitive component hold any promise for improving mathematical learning, and if so, for whom and under what conditions. Furthermore, the explicit engineering of academic interventions to compensate for or provide support for cognitive weaknesses may hold considerable promise based on a few studies (see work by L. Fuchs and colleagues, and L. Swanson and colleagues), including our own findings above, but the knowledge base in this area is still relatively thin.

3. If applicable, describe your plans for continuing the project (sustainability; capacity building) and/or disseminating the project results.

A replication study of the math tutorial intervention (PKMT) along with a strong Tier 1 math program in a different preschool context from the one used in the current study would be an important next step. This type of replication study would serve to further test hypotheses about the benefits of early high quality Tier 1 mathematics instruction combined with higher tiers of intervention for very low performing preschoolers. We are also interested in pursuing exploratory research on the instructional conditions that may best support children with low levels of cognitive abilities that impact their response to early math interventions. We plan to continue to disseminate the findings from the current study in peer-reviewed papers, specifically findings related to the moderation analyses and those from the responder analyses.

Publications & Presentations

Publications:

Barnes, M.A., Klein, A., Swank, P., Starkey, P., McCandliss, B., Flynn, K., Zucker, T., Huang, K., Fall, A-M, & Roberts, G. (2016). Effects of tutorial interventions in mathematics and attention for low-performing preschool children. *Journal of Research in Educational Effectiveness, 9,* 577-606.

Presentations:

Barnes, M.A., Klein, A., Starkey, P., Flynn, K., Swank, P., Zucker, T., & McCandliss, B. (2014). The effects of intensive early interventions in mathematics and attention for low-performing preschool children. In the symposium *Improving Early Math Outcomes for Students with Disabilities through Intensive Intervention.* Paper presented at the Society for Research on Educational Effectiveness meeting, Washington, D.C. September 5. (Barnes & Klein co-presenters)

Barnes, M.A. (2014). Organizer and speaker in the session, Neurocognitive aspects of learning disabilities: Implications for identification and intervention. Council for Learning Disabilities Conference, Philadelphia. October 3.

Barnes, M.A., & Klein, A. (2015). The effects of intensive early interventions in mathematics and attention for low-performing preschool children. In the panel *Training Cognitive Processes and Academic Skills Together: Clever Synthesis or Fool's Errand?* Paper presented at the Pacific Coast Research Conference, Coronado Bay, CA. February 5-7. (presented by Klein)

Flynn, K., Barnes, M.A., & Klein, A. (2015). Characteristics of low responders: Secondary analyses from a tier 2 math and attention intervention. Poster presentation at the Pacific Coast Research Conference, Coronado Bay, CA. February 5-7.

Barnes, M.A. & Klein, A. (2015). Intensive interventions in mathematics and attention for low-performing preschool children. Invited IES panel presentation at the Council for Exceptional Children Annual Conference, San Diego, April 10. (Barnes & Klein co-presenters).

Flynn, K., Klein, A., Huang, K., & Barnes, M. (2017). What factors influence responsiveness to a pre-kindergarten tier 2 math intervention? Poster presentation at the Pacific Coast Research Conference, Coronado Bay, CA. February.

Klein, A., Starkey, P., & DeFlorio, L. (2017). Enhancing mathematical development and learning in preschool children: Two approaches to early math intervention. Paper presented at the fifth annual Math Cognition Conference, Nashville, TN, May 15-16. Book chapter manuscript, in preparation.

Other Publications and Dissemination Supported by the Grant:

Peng, P., Namkung, J., Barnes, M., & Sun. C. Y. (2016). A Meta-Analysis of mathematics and working memory: Moderating effects of working memory domain, type of mathematics skill, and sample characteristics. *Journal of Educational Psychology. 108(4),* 455-473.

Raghubar, K.P., & Barnes, M.A. (2017). Early numeracy skills in preschool-aged children: A review of neurocognitive findings and implications for assessment and intervention. *The Clinical Neuropsychologist. 31*(2), 329-351.

Barnes, M.A., Martinez-Lincoln, A., & Raghubar, K. (2017). Mathematical learning disabilities: What does the science tell us about assessment and diagnosis? In *Perspectives on Language and Literacy (Winter)* (Edited by M. Toplak & L. Siegel), International Dyslexia Association. (publication for parents, educators, and practitioners of children with learning disabilities)

Table 1: Demographic Characteristics of Pre-test Sample (from Barnes, Klein et al., 2016)

		Overall	M+ATT	Math only	BAU
Sample *N*					
	Total	541	181	180	180
	TX	277	93	92	92
	CA	264	88	88	88
Gender (% female)					
	Total	46.7	44.8	0.50	47.8
	TX	45.5	45.2	43.5	48.9
	CA	48.5	44.3	56.8	46.6
Race/ethnicity (%)					
Hispanic	Total	71.7	75.7	70.6	68.9
	TX	54.2	57.0	53.3	52.2
	CA	90.2	95.5	88.6	86.4
African American	Total	17.9	17.1	17.2	19.4
	TX	31.8	31.2	30.4	33.7
	CA	3.4	2.3	3.4	4.5
Asian American	Total	1.7	0.6	2.2	2.2
	TX	0.7	1.2	0.0	1.2
	CA	2.7	0.0	4.5	3.4
Caucasian	Total	2.2	1.7	3.3	1.7
	TX	3.2	2.2	4.3	3.3
	CA	1.1	1.0	2.3	0
Mixed/other	Total	3.7	2.2	3.3	5.0
	TX	4.7	3.2	5.4	5.4
	CA	2.7	1.1	1.1	5.7
Unknown	Total	2.8	2.8	3.3	2.2
	TX	5.4	5.4	6.5	4.3
	CA	n/a	n/a	n/a	n/a
Child age in years, *M* (*SD*)					
	Total	4.50 (0.27)	4.50 (0.27)	4.53 (0.27)	4.46 (0.26)
	TX	4.57 (0.28)	4.56 (0.28)	4.63 (0.27)	4.53 (0.28)
	CA	4.42 (0.23)	4.43 (0.23)	4.42 (0.23)	4.40 (0.23)
KBIT pretest, *M* (*SD*)					
	Total	91.25 (14.29)	92.14 (13.96)	92.00 (13.60)	89.61 (15.22)
	TX	90.78 (14.46)	92.10 (14.01)	92.19 (13.34)	88.04 (15.82)
	CA	91.51 (14.22)	92.16 (14.01)	91.90 (13.82)	90.47 (14.91)

Note. M+ATT = math + attention condition; Math only = math only condition; BAU = business as usual condition; CA = California; TX = Texas; KBIT = KBIT Matrices subtest administered only at pretest.

Table 2 (from Barnes, Klein et al., 2016)
Pretest and Posttest Means, Standard Deviations for Math and Attention Outcomes

	Pretest			*Posttest*		
Measures	*M*	*SD*	*N*	*M*	*SD*	*N*
Math outcomes						
Child Math Assessment						
Full sample						
M + ATT	0.29	0.11	181	0.61	0.13	175
M only	0.28	0.11	180	0.64	0.15	172
BaU	0.26	0.12	180	0.52	0.15	171
Texas sample						
M + ATT	0.29	0.12	93	0.61	0.13	88
M only	0.30	0.10	92	0.67	0.14	87
BaU	0.26	0.12	92	0.55	0.15	86
California sample						
M + ATT	0.28	0.10	88	0.61	0.14	87
M only	0.26	0.12	88	0.60	0.14	85
BaU	0.26	0.12	88	0.49	0.15	85
Test of Early Mathematics Ability (TEMA-3)						
Full sample						
M + ATT	3.38	2.96	181	13.51	6.00	175
M only	3.17	2.49	180	14.09	6.08	172
BaU	3.28	2.79	180	12.82	6.86	171
Texas sample						
M + ATT	3.57	3.13	93	14.83	6.25	88
M only	3.62	2.54	92	16.59	6.48	87
BaU	3.38	2.72	92	15.43	7.19	86
California sample						
M + ATT	3.17	2.78	88	12.18	5.45	87
M only	2.70	2.36	88	11.53	4.37	85
BaU	3.17	2.87	88	10.18	5.37	85
Attention outcomes						
Cued Trial Accuracy						
Full sample						
M + ATT	0.69	0.17	179	0.87	0.14	174
M only	0.68	0.18	180	0.83	0.16	171
BaU	0.67	0.18	180	0.83	0.18	171
Texas sample						
M + ATT	0.69	0.17	92	0.87	0.14	88
M only	0.70	0.17	92	0.87	0.14	86

BaU	0.67	0.18	92	0.83	0.18	86
California sample						
M + ATT	0.68	0.17	87	0.87	0.13	86
M only	0.66	0.18	88	0.80	0.18	85
BaU	0.66	0.17	88	0.82	0.17	85
Un-cued Trial Accuracy						
Full sample						
M + ATT	0.67	0.17	179	0.85	0.14	174
M only	0.66	0.18	180	0.82	0.17	171
BaU	0.65	0.18	180	0.82	0.17	171
Texas sample						
M + ATT	0.68	0.18	92	0.85	0.15	88
M only	0.68	0.17	92	0.84	0.16	86
BaU	0.65	0.17	92	0.83	0.17	86
California sample						
M + ATT	0.65	0.17	87	0.86	0.14	86
M only	0.64	0.18	88	0.79	0.17	85
BaU	0.65	0.18	88	0.81	0.16	85
Congruent Trial Accuracy						
Full sample						
M + ATT	0.84	0.17	179	0.96	0.06	174
M only	0.83	0.18	180	0.94	0.10	171
BaU	0.79	0.19	180	0.93	0.12	171
Texas sample						
M + ATT	0.83	0.18	92	0.95	0.07	88
M only	0.85	0.16	92	0.94	0.08	86
BaU	0.78	0.20	92	0.92	0.14	86
California sample						
M + ATT	0.84	0.17	87	0.96	0.05	86
M only	0.82	0.21	88	0.93	0.11	85
BaU	0.81	0.18	88	0.94	0.10	85
Incongruent Trial Accuracy						
Full sample						
M + ATT	0.51	0.26	179	0.77	0.26	174
M only	0.50	0.27	180	0.71	0.30	171
BaU	0.52	0.24	180	0.72	0.28	171
Texas sample						
M + ATT	0.53	0.26	92	0.77	0.27	88
M only	0.53	0.26	92	0.76	0.27	86
BaU	0.54	0.24	92	0.75	0.27	86
California sample						

M + ATT	0.48	0.26	87	0.77	0.25	86
M only	0.47	0.27	88	0.66	0.31	85
BaU	0.50	0.23	88	0.69	0.29	85

Table 3

Follow-up (Kindergarten) means, standard deviations for math outcomes

			Follow-up		
			n	*M*	*SD*
CMA					
	Full sample	M + ATT	173	0.67	0.16
		M only	169	0.70	0.16
		BaU	168	0.67	0.17
	CA only	M + ATT	84	0.64	0.16
		M only	82	0.64	0.16
		BaU	80	0.63	0.17
	TX only	M + ATT	89	0.71	0.15
		M only	87	0.75	0.14
		BaU	88	0.70	0.16
TEMA					
	Full sample	M + ATT	173	24.04	7.81
		M only	169	24.37	7.57
		BaU	168	24.93	8.24
	CA only	M + ATT	84	22.13	8.23
		M only	82	22.43	7.65
		BaU	80	22.78	8.62
	TX only	M + ATT	89	25.84	6.98
		M only	87	26.21	7.05
		BaU	88	26.90	7.39

Table 4

Pairwise Comparisons of Responder Groups

	TEMA based			
	LR vs MR		LR vs HR	
	Estimate	p-value	Estimate	p-value
Cued Attention Accuracy	-0.32	0.00	-0.77	0.00
Uncued Attention Accuracy	-0.26	0.01	-0.69	0.00
Congruent Trial Accuracy	-0.46	0.00	-0.72	0.00
Visual Spatial Working Memory	-0.41	0.00	-0.42	0.00
ANS Acuity	-0.26	0.01	-0.29	0.02
Phonemic awareness	-0.31	0.00	-0.48	0.00
	CMA based			
Cued Attention Accuracy	-0.31	0.01	-0.29	0.02
Uncued Attention Accuracy	-0.29	0.01	-0.23	0.06
Congruent Trial Accuracy	-0.27	0.01	-0.39	0.00
Visual Spatial Working Memory	-0.34	0.00	-0.50	0.00
ANS Acuity	-0.29	0.01	-0.25	0.04
Phonemic awareness	-0.36	0.00	-0.19	0.13

Note. LR = low responders; MR = moderate responders; HR = high responders