Increased Math Achievement in Elementary Students Participating in JUMP Math's 2014-15 National Book Fund Program.

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Executive Summary

JUMP Math characterizes its approach to math instruction as *guided discovery*, a combination of direct instruction, discovery learning, and varied practice.[2] Complex math problems are taught by decomposing them into incremental steps and advocating mastery of simpler concepts before advancement to more complex concepts. Scaffolding of math problems is widely used to assist with independent learning. The program also promotes the importance of building student confidence and the notion that all students are capable of learning mathematics with appropriate supports.[3] Components of the program include professional development; *Teacher Resources* composed of lesson plans, quizzes/tests, and answer keys; *SMART Lesson Materials* for use with interactive white boards; and student *Assessment & Practice* books.

To evaluate the growth of students using the JUMP Math program, math achievement was assessed in both the fall and spring for students in grade 3 to 9 who participated in JUMP Math's 2014-15 National Book Fund (NBF) program. A total of 248 students in fifteen classrooms completed the math computation subtest of the *Wide Range Achievement Test, Fourth Edition* (WRAT-4) in October 2014 and May 2015. Average student growth in math achievement was 2.9 times that of the WRAT-4 standardization sample, and mean standard scores in the spring ($M = 92.3$, $SD = 12.4$) were significantly higher than mean standard scores in the fall ($M = 86.9$, $SD = 10.4$), paired $t(247) = 10.1$, $p < 0.001$. The corresponding percentile rank of students increased from the 19th percentile in the fall to the 30th percentile in the spring. The number of students scoring 'above average' or higher increased 3-fold in the spring (21 students) compared to the fall (7 students). The number of students scoring 'below average' decreased by 28% in the spring (111 students) compared to the fall (155 students). We cannot know for certain whether the increased growth in math achievement relative to the WRAT-4 was due solely to the JUMP Math program because this study did not employ randomized control and treatment groups. By using a standardized test with alternate forms, however, we reduced the potential impact of several confounding variables. In addition, we found a significant positive correlation between a teacher's reported fidelity to the JUMP Math program and the percent change in their classroom mean standard score. These findings are consistent with the notion that increased use of the JUMP Math program produced increased student growth in math achievement.

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[2] http://www.jumpmath.org/

[3] Mighton, J. (2004). The myth of ability: nurturing mathematical talent in every child. Toronto: House of Anansi Press.

Background

Every year, JUMP Math's National Book Fund Program awards free JUMP Math resources to classrooms across Canada. This program is funded primarily through a grant from TD Bank Group, with additional support from SAP and internally generated funding from JUMP Math. To be considered for the award, school principals and teachers must submit an application in which they describe their community and the needs of their students. Priority for awards is given to schools serving high-need communities where student achievement in mathematics is below national standards. In the 2014-15 school year, JUMP Math's National Book Fund Program awarded resources to over 3,000 students in 131 classrooms across 7 Canadian provinces (AB, BC, MB, NS, ON, QC, and SK).

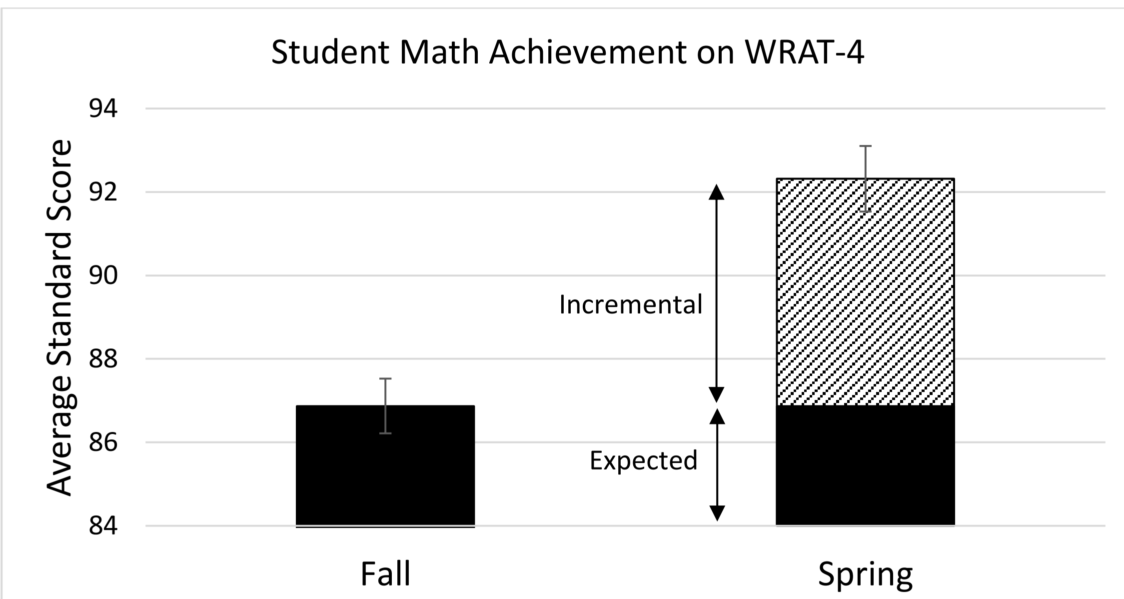
In order to assess the growth in math achievement for students participating in the NBF program, non-blended grade 3 to 9 classrooms were selected for testing. Teachers were asked to administer the math computation subtest of the *Wide Range Achievement Test, Fourth Edition* (WRAT-4)[4] to their students in October 2014 and again in May 2015. Teachers were sent two alternate forms of the WRAT-4, designated the green form and the blue form, consisting of different questions but considered equally difficult. Detailed instructions on how to administer the test and return envelopes were provided to each teacher. In the fall, teachers were asked to administer the blue form to half of their students and the green form to the remaining half. For the spring testing, tests forms were pre-labelled with students' names to ensure that they received the alternate coloured form. Completed tests were sent back to JUMP Math and scored by a qualified teacher and the researcher. Standard scores were determined for each student in the spring and fall by looking up their raw test score in a conversion table that corresponds to the student's grade, test form (blue versus green), and time of testing (fall versus spring).

[4] Wilkinson G. & Robertson G. (2006). *Wide range achievement test (4th ed.).* Lutz, FL: Psychological Assessment Resources, Inc.

Results

Teachers from all of the 15 classrooms selected for testing administered the WRAT-4 in both the fall and spring of the 2014-15 school year. Standard scores were determined for the 248 students who completed the tests in both the fall and spring of the 2014-15 school year. The mean standard score in the spring spring (M[5] = 92.3, SD[6] = 12.4) was significantly higher than the mean standard score in the fall (M = 86.9 SD = 10.4), paired t (247) = 10.1, $p < 0.001$ (see Figure 1). We would expect the students in the 2014-15 NBF to have the same standard score in the fall and spring if their math achievement had increased at the same rate as the WRAT-4 standardization sample. The fact that their mean standard score was significantly higher in the spring indicates that their math achievement grew at a higher rate than the WRAT-4 standardization sample. The corresponding percentile rank of students (relative to the WRAT-4 standardization sample) increased from the 19th percentile in the fall to the 30th percentile in the spring. Using the published standard deviation for the WRAT-4 (SD = 15), this increase in standard score corresponds to an effect size of 0.36 ((92.3 – 86.9)/15).

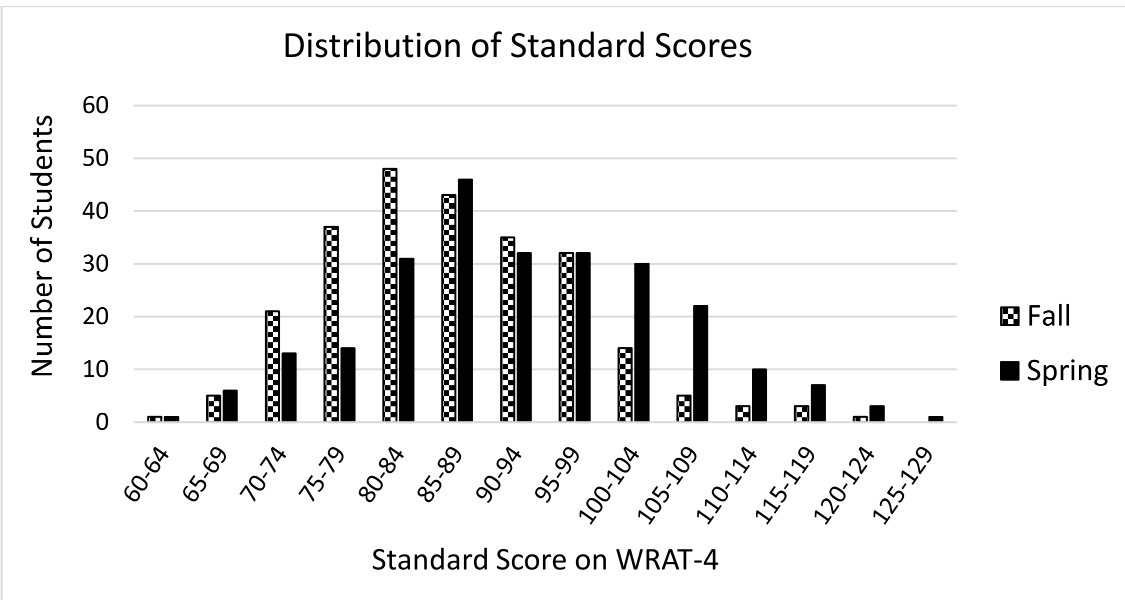
Figure 1:



[5] M= mean
[6] SD = standard deviation

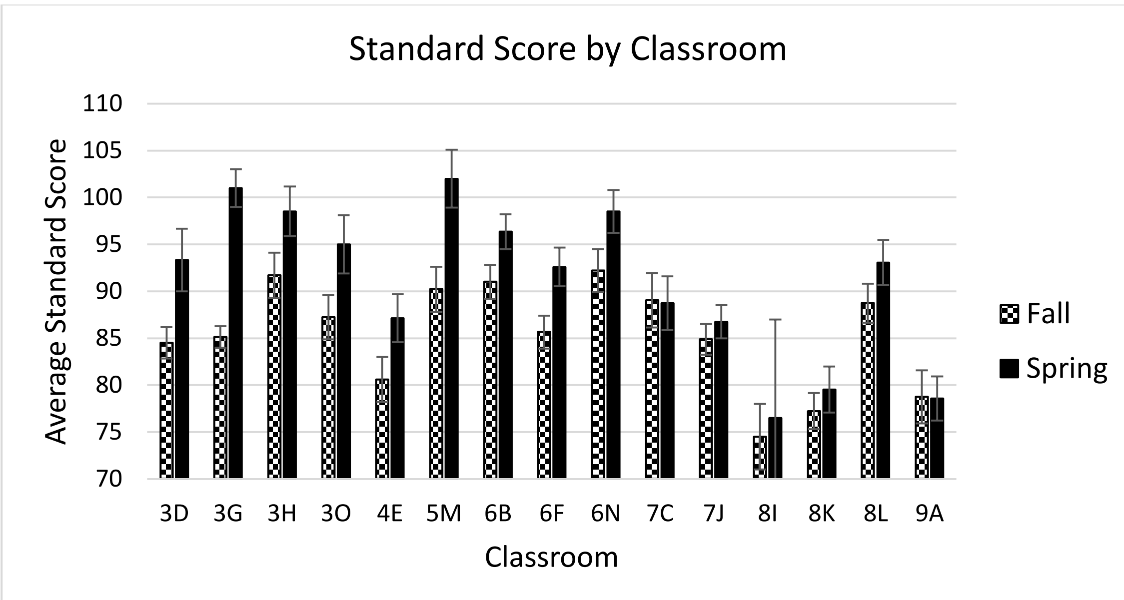
The frequency distributions of standard scores obtained in the fall and spring are shown below in Figure 2. The distributions include only those students (N=248) who completed either a blue or green test in the fall and then completed the alternate coloured test in the spring (students who completed the same test in both the fall and spring were excluded from the analysis). The graph illustrates that the distribution of scores obtained in the spring is shifted to the right (towards higher scores) compared to the distribution obtained in the fall. The median score increased from 87 in the fall to 92 in the spring. The number of students scoring 'above average' or higher (110 or higher) increased 3-fold in the spring (21 students) compared to the fall (7 students). The number of students scoring 'below average' (89 or lower) decreased by 28% in the spring (111 students) compared to the fall (155 students).

Figure 2:



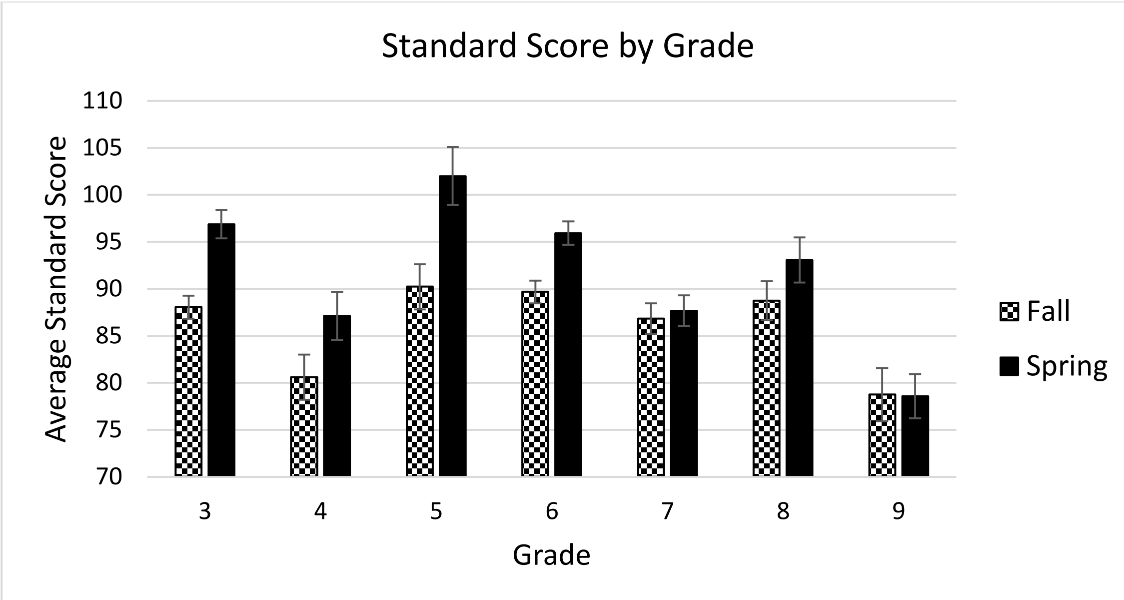
Mean standard scores in the fall and spring for each of the fifteen classrooms are shown in Figure 3 (error bars for all graphs denote the standard error of the mean (SEM)). Mean standard scores in the fall ranged from 74.5 (classroom 8I) to 92.2 (classroom 6N) whereas mean standard scores in the spring ranged from 76.5 (classroom 8I) to 102 (classroom 5M). Percent increases in standard score ranged from 2.2% (classroom 7J) to 18.6% (classroom 3G); two classrooms had slight decreases in mean standard score (classroom 7C & 9A).

Figure 3:



Mean standard scores in the fall and spring for each grade are shown in Figure 4. Mean standard scores in the fall ranged from 78.8 (grade 9) to 90.2 (grade 5) whereas mean standard scores in the spring ranged from 78.6 (grade 9) to 102 (grade 5). Percent increases in standard score ranged from 1% (grade 7) to 13% (grade 5); the single grade 9 classroom had a slight decrease in standard score.

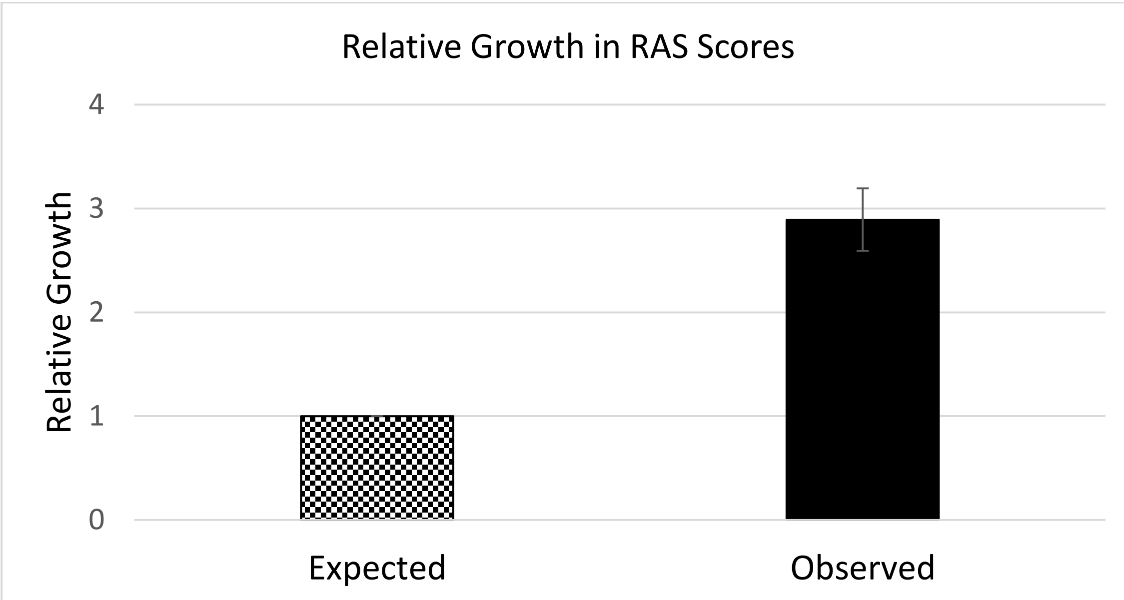
Figure 4:



Each student's raw score on the WRAT-4 math test was also converted to a Rasch Ability Scaled (RAS) score using conversion tables for the blue and green forms of the WRAT-4. A student's RAS score will increase over time as their math achievement (raw score) increases; the RAS score is therefore well suited to measuring growth in student achievement from one time to another. In contrast, standard scores will remain constant over time if the student grows at the same rate as the standardization sample.

We defined *observed growth* as the difference between a student's RAS score in the spring and their RAS score in the fall (observed growth = RAS score in spring – RAS score in fall). *Expected growth* was also calculated for each student by subtracting their RAS score in the fall from their expected RAS score in the spring (expected growth = expected RAS score in spring – RAS score in fall). The expected RAS score in the spring was determined for each student by calculating the raw score in the spring that would result in the same standard score the student had obtained in the fall. We defined each student's *relative growth* in math achievement (relative to the WRAT-4 standardization sample) as the ratio of observed growth to expected growth (relative growth = observed growth/expected growth). Thus, a student with a relative growth score of 1 grew at the same rate as students from the WRAT-4 standardization sample with the same fall standard score. On average, math achievement of students in the 2014-15 NBF grew at 2.9 times the rate of the WRAT-4 standardization sample (Figure 4).

Figure 5:



A regression analysis was performed to determine which variables were significant predictors of student growth in math achievement. We started with a simple linear model in which student growth was regressed against centred standard score in the fall (c.ss.fall), grade[7], gender, and a classroom-level variable (average classroom standard score in the fall (avg.ss.fall). Standard scores in the fall were 'centred' by subtracting the overall average standard score in the fall, thus making the value of the intercept more meaningful. A step-wise linear regression was performed on the data using the lm (linear model) function in R, an open-source statistical package[8]. A student's initial math achievement (c.ss.fall), grade, and their classroom's average standard score in the fall (avg.ss.fall) were significant predictors of student growth whereas gender was not a significant predictor of student growth (see Appendix I.A). A hierarchical linear mixed model was subsequently fit to the data using the lme (linear mixed effects) function in R; initial math achievement (c.ss.fall), grade, and classroom average standard score in the fall (avg.ss.fall) were included as fixed variables and classroom was included as a random variable (see Appendix I.B). Mixed models that include both fixed and random effects are able to account for the effect of clustering of students in classrooms. Students from the same classroom tend to be more alike than students from different classrooms as reflected by the intraclass correlation (ICC). The ICC of 0.29 for these data was calculated by dividing the component of the variance due to the random variable 'classroom' by the total variance (see Appendix I.C). Coefficients for the linear mixed model are shown in Table I.

[7] To simplify the analysis, 'grade' was treated as an interval variable.
[8] R Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Table I: Linear Mixed Effects Model

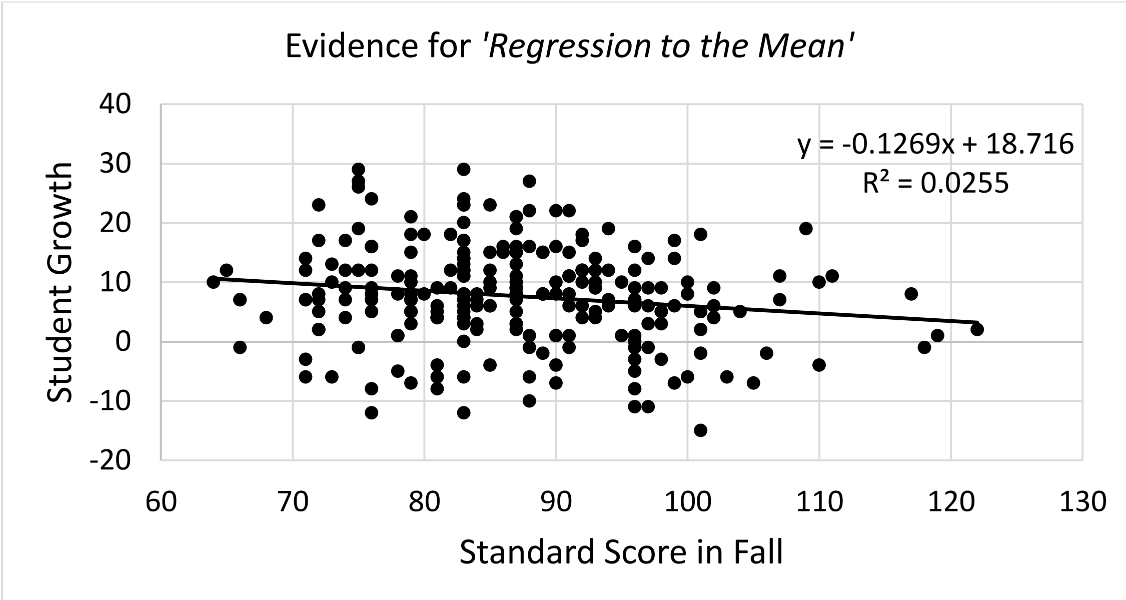
Predictor	Coefficient	Standard Error	Degrees of Freedom	t-value	p-value
Intercept	1.15	14.01	232	0.08	0.93
c.ss.fall (centred standard score in fall)	-0.21	0.05	232	-4.52	0.0000*
grade	-2.08	0.35	12	-5.89	0.0001*
avg.ss.fall (classroom average standard score in fall)	0.22	0.15	12	1.40	0.19

*statistically significant

The linear mixed model found that student growth was predicted by a student's achievement in the fall (ss.fall) and their grade (note that the classroom-level variable, avg.ss.fall, is no longer statistically significant once we add classroom as a random variable to the regression model). Both coefficients for c.ss.fall and grade are negative; this shows that students who started the school year with lower standard scores tended to show more growth than students who started the school year with higher standard scores and students in lower grades tended to show more growth than students in higher grades.

A scatter plot of each student's standard score in the fall versus their growth on the WRAT-4 is shown in Figure 6. The regression line through these points has a negative slope (-0.13) and a correlation coefficient (R^2) of 0.03. This weak but statistically significant correlation (see Appendix I.D) is evidence of regression-to-the-mean (RTM) and is unlikely to reflect any selective effect of the JUMP program on low-achieving students. The implications of RTM are discussed below (see page 12).

Figure 6:



<u>Discussion</u>

Standard scores are a useful measure for comparing student achievement on a standardized test; a student with a standard score of 100 has achieved a score equal to the mean score of the sample of students used to standardize the test. The corresponding percentile rank is 50%; half of the students in the standardization sample scored above 100 and half scored below 100. Students who composed the WRAT-4 standardization sample were tested in both the fall and spring of the school year. Thus, a student who demonstrates the same growth rate as the standardization sample will achieve the same standard score in the fall and spring of the school year. Students participating in JUMP Math's 2014-15 National Book Fund Program showed significant increases in mean standard score in the spring (M = 92.3, SD = 12.4) compared to the fall (M = 86.9 SD = 10.4). The corresponding percentile rank of NBF students increased from the 19th percentile in the fall to the 30th percentile in the spring. The number of students scoring 'above average' or higher (110 or higher) increased 3-fold in the spring (21 students) compared to the fall (7 students). The number of students scoring 'below average' (89 or lower) decreased by 28% in the spring (111 students) compared to the fall (155 students). On average, students participating in the 2014-15 National Book Fund grew at 2.9 times the rate of the WRAT-4 standardization sample.

Whereas the distribution of standard scores for the WRAT-4 standardization sample has a normal distribution (i.e. a symmetric, bell-shaped curve) centred on a standard score of 100, the distribution of standard scores obtained in the present study is positively skewed, particularly in the fall, and centred on a lower standard score (median standard score in the fall was 87). A positive skew occurs when the right tail of the distribution is longer than the left tail. Our skewed distribution could be due to the selection process for the National Book Fund Program. Classrooms that were selected for the program were (mostly) from high-need communities where math achievement was below national standards. In the spring the distribution of scores shifted towards higher standard scores and was less skewed.

JUMP Math has used the WRAT-4 to assess student math achievement since 2011-12[9]. A comparison of the test results for the past 4 years is shown in Table II. We observed a step increase in student growth between the 2011-12 and 2012-13 NBF (1.8 vs 2.8, respectively) that remained high in 2013-14 (2.5) and 2014-15 (2.9). The step increase could be due to policy changes that were implemented in 2012-13, the most significant of which was requiring all participating teachers to complete a JUMP Math professional development session prior to the start of the school year. In contrast, less than half of the teachers selected for classroom testing in the 2011-12 NBF had completed JUMP Math professional development by mid-October 2011 (only 8 of 18 teachers). In addition, changes were made in the process for assessing NBF applications which may have improved our ability to identify high-needs classrooms. This may account for the increase in the percentage of low-scoring students participating in the 2012-13 NBF. Either or both of these policy changes could have impacted growth in student math achievement.

[9] Murray, B. (2013, September 18). *Increased math achievement in grade 3 and 6 students participating in JUMP Math's 2011-12 National Book Fund Program.* Retrieved from http://www.jumpmath.org/cms/sites/default/files/Student%20Achievement%20From%202011-12%20JUMP%20Math%20Book%20Fund%20%282013%29.pdf

Table II: NBF Student Test Results

	2014-15 NBF	2013-14 NBF	2012-13 NBF	2011-12 NBF
# of students tested in both fall & spring	248	241	286	326
Grades tested	3 to 9	4	4 to 7	3 and 6
SS fall vs SS spring	86.9 vs 92.3	89.6 vs 95.3	90.8 vs 94.6	96.8 vs 100.9
Percentile rank fall vs spring	19th vs 30th	25th vs 37th	27th vs 37th	42nd vs 53rd
Average student growth relative to WRAT-4	2.9	2.5	2.8	1.8
% of students scoring 'above average' in fall vs spring	3% vs 9%	5% vs 10%	7% vs 12%	10% vs 22%
% of students scoring 'below average' in fall vs spring	63% vs 45%	54% vs 35%	47% vs 36%	26% vs 20%

This study is an example of a single-group, pre- and post-test research design. This design is also referred to as "pre-experimental" because subjects have not been randomly assigned to treatment and control groups as in a true experimental design. The lack of randomized control and treatment groups in this study limits our ability to make causal inferences due to possible confounding factors. There are four well-recognized confounding factors unique to pre-experimental research studies: history, maturation, test effects, and regression-to-the-mean[10]. We have reviewed the potential impact of each of these factors and conclude that it is unlikely they can account for the statistically significant gains in math achievement obtained for all of the 3 years of the NBF in which student testing has been completed and analyzed. In particular, our use of a standardized test with two alternate forms eliminates any possible practice effect that may occur when students complete the same test in the fall and spring of the same school year.

[10] Emma Marsden & Carole J. Torgerson (2012): Single group, pre- and post-test research designs: Some methodological concerns, Oxford Review of Education, 38:5, 583-616.

One potential confounding factor that requires careful consideration in studies employing a pre-experimental design is regression-to-the-mean (RTM). RTM is a statistical phenomenon whereby a distribution of measurements (e.g. test scores) narrows with repeated observations[11]. The effect is due to the greater measurement error in the tails of the distribution. Students with very low test scores will be more likely to have higher scores on a subsequent test. Similarly, students with very high test scores will be more likely to have lower scores on a subsequent test. The effects of RTM can lead education researchers to erroneously conclude that their treatment had a greater effect for low-achieving students. In order to determine whether RTM was evident in this data set, the observed growth for each student (RAS score in spring – RAS score in fall) was plotted against their standard score in the fall (Figure 6). If RTM was present, students with a low standard score in the fall would tend to have a higher score in the spring (and therefore greater growth) whereas students with a high standard score in the fall would tend to have a lower score in the spring (and therefore lower growth). We would therefore expect growth to be negatively correlated with standard score in the fall (i.e. a regression line through the points would have a negative slope). The scatter plot and regression line in Figure 6 indicate a negative correlation for these data (slope = -0.13). The correlation is statistically significant but weak, accounting for only 3% of the variance in student growth (R^2 = 0.03).

If RTM was entirely responsible for the increases in standard score, we would expect that the shifts in standard score would be observed in the tails of the distribution, i.e. for students with the lowest and highest test scores. The impact of RTM can be summarized as an overestimation of gains for low-scoring students and an underestimation of gains for high-scoring students. Given that we observed an overall change in the mean standard score, we can conclude that other factors must have contributed to the increases in standard score and that any potential effect of RTM was most likely greatest at the tails of the distribution.

We hypothesized that variability in teachers' fidelity to the JUMP Math program could be one factor accounting for the variability in student growth across classrooms. As part of a feedback survey administered in the spring of 2015, teachers were asked to report on a scale of 1 (never) to 7 (every class) how frequently they used the JUMP Math lesson plans (lesson plan fidelity) and, in a separate question, how frequently they used the student assessment and practice books (student AP book fidelity). Responses to each fidelity question were added in order to obtain a combined measure of fidelity to the JUMP Math program. Thirteen of the 15 teachers who participated in the student assessments also completed the end-of-year feedback survey. We compared the relationship between a teacher's combined fidelity measure and the percent increase in their classroom's mean standard score. Data for one of the 13 teachers was identified as an "extreme" outlier using a

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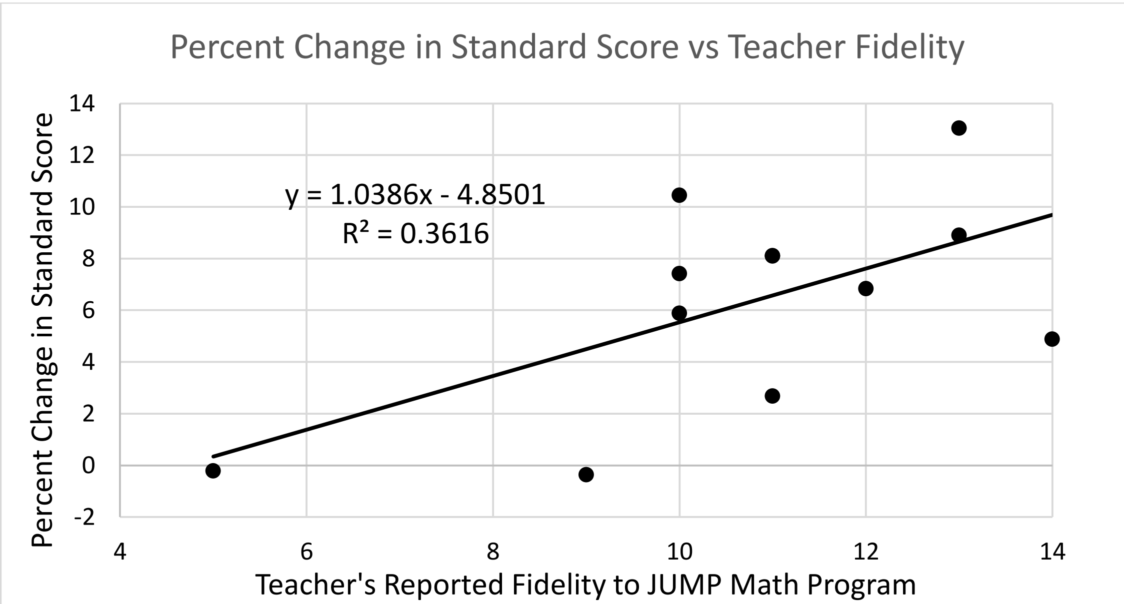
[11] Adrian G Barnett, Jolieke C van der Pols & Annette J Dobson (2005): Regression to the mean: what it is and how to deal with it, International Journal of Epidemiology, 34:215–220 .

standard statistical procedure (higher than the third quartile plus 3 times the interquartile range (Q3 + 3 x IQR)) and removed from the remaining analysis.[12] The scatter plot and regression line for the remaining 12 teachers is shown in Figure 7 (note: two data points (11, 8.1) are overlapping).

Figure 7:



There is a statistically significant positive correlation between a teacher's reported fidelity to the JUMP Math Program and the percent change in their classroom mean standard score (see Appendix I.E; $t = 2.38$, $df = 10$, $p < 0.05$). The square of the correlation coefficient indicates that reported fidelity to the JUMP Math program accounts for 36% of the variance in the percent change in classroom mean standard score ($R^2 = 0.36$). Although correlation does not prove causation, these data demonstrate that increases in use of the JUMP Math program are associated with increases in student math achievement. This is further support for the notion that the JUMP Math program is responsible for the increased growth in student math achievement.

[12] *NIST/SEMATECH e-Handbook of Statistical Methods*, http://www.itl.nist.gov/div898/handbook/prc/section1/prc16.htm, retrieved on August 30, 2015.

Appendix: Statistical Analysis in R[13]

I.A. A Simple Linear Model

```
> model1 <- lm(growth ~ c.ss.fall + grade.int + gender + class.avg.fall, data = Da
ta.for.R.2014.15)
> step <- stepAIC(model1, direction="both")
Start:  AIC=977.98
growth ~ c.ss.fall + grade.int + gender + class.avg.fall

                 Df Sum of Sq   RSS     AIC
- gender          2     27.15 12219  974.53
<none>                        12192  977.98
- class.avg.fall  1    181.46 12373  979.64
- c.ss.fall       1    985.12 13177  995.25
- grade.int       1   3006.14 15198 1030.64

Step:  AIC=974.53
growth ~ c.ss.fall + grade.int + class.avg.fall

                 Df Sum of Sq   RSS     AIC
<none>                        12219  974.53
- class.avg.fall  1     195.9 12415  976.47
+ gender          2      27.2 12192  977.98
- c.ss.fall       1     965.9 13185  991.40
- grade.int       1    3302.4 15521 1031.86
> step$anova
Stepwise Model Path
Analysis of Deviance Table

Initial Model:
growth ~ c.ss.fall + grade.int + gender + class.avg.fall

Final Model:
growth ~ c.ss.fall + grade.int + class.avg.fall


      Step Df Deviance Resid. Df Resid. Dev      AIC
1                            242   12191.66 977.9795
2 - gender  2 27.15216       244   12218.81 974.5312

> model2 <- lm(growth ~ c.ss.fall + grade.int + class.avg.fall, data = Data.for.R.
2014.15)
> summary(model2)

Call:
lm(formula = growth ~ c.ss.fall + grade.int + class.avg.fall,
    data = Data.for.R.2014.15)

Residuals:
     Min       1Q   Median       3Q      Max
-22.5272  -4.9108   0.3521   4.5410  16.7759

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    -0.32571   10.43272  -0.031   0.9751
c.ss.fall      -0.21157    0.04817  -4.392 1.68e-05 ***
grade.int      -2.01068    0.24760  -8.121 2.30e-14 ***
class.avg.fall  0.22717    0.11487   1.978   0.0491 *
---
```

[13] R Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.077 on 244 degrees of freedom
Multiple R-squared:  0.2717,	Adjusted R-squared:  0.2627 
F-statistic: 30.34 on 3 and 244 DF,  p-value: < 2.2e-16
```

I.B. Linear Mixed Effects Model

```
> model3 <- lme(growth ~ c.ss.fall + grade.int + class.avg.fall, data = Data.for.R
.2014.15, random = ~ 1|classroom)     #add random variable classroom
> summary(model3)
Linear mixed-effects model fit by REML
 Data: Data.for.R.2014.15 
       AIC      BIC    logLik
  1684.993 1705.976 -836.4966

Random effects:
 Formula: ~1 | classroom
        (Intercept) Residual
StdDev:    1.828517 6.876552

Fixed effects: growth ~ c.ss.fall + grade.int + class.avg.fall 
                    Value Std.Error  DF   t-value p-value
(Intercept)     1.1525988 14.008684 232  0.082277  0.9345
c.ss.fall      -0.2115727  0.046813 232 -4.519489  0.0000
grade.int      -2.0789277  0.353050  12 -5.888472  0.0001
class.avg.fall  0.2155195  0.153636  12  1.402795  0.1860
 Correlation: 
               (Intr) c.ss.f grd.nt
c.ss.fall       0.290              
grade.int      -0.416  0.000       
class.avg.fall -0.989 -0.305  0.287

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max 
-3.20984836 -0.63952396  0.02325706  0.61560307  2.80018760 

Number of Observations: 248
Number of Groups: 15 

> anova(model3,model2)
       Model df      AIC      BIC    logLik   Test  L.Ratio
model3     1  6 1684.993 1705.976 -836.4966                
model2     2  5 1688.059 1705.544 -839.0293 1 vs 2 5.065568
       p-value
model3        
model2  0.0244

> #model 3 significantly better than model 2
```

I.C. Calculation of Intraclass Correlation (ICC)

```
> mod1 <- lme(growth ~ 1, data = Data.for.R.2014.15, random = ~ 1|classroom)
> summary(mod1)
Linear mixed-effects model fit by REML
 Data: Data.for.R.2014.15 
       AIC      BIC    logLik
  1712.874 1723.402 -853.4372

Random effects:
 Formula: ~1 | classroom
        (Intercept) Residual
StdDev:    4.534135 7.172155

Fixed effects: growth ~ 1 
               Value Std.Error  DF  t-value p-value
```

```
(Intercept) 8.099046  1.279833 233 6.328205       0

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max 
-3.13704554 -0.55959061  0.02911864  0.64355571  2.92650703 

Number of Observations: 248
Number of Groups: 15 
> 4.534135^2/(4.534135^2 + 7.172155^2)  # ICC
[1] 0.2855402
```

I.D. Analysis of Regression-to-the-Mean

```
> fit0 <- lm(RASS.Diff ~ SS.Fall, data = RTM)
> fit0

Call:
lm(formula = RASS.Diff ~ SS.Fall, data = RTM)

Coefficients:
(Intercept)      SS.Fall  
    18.7155      -0.1269  

> cor.test(RASS.Diff,SS.Fall,method = "pearson")

        Pearson's product-moment correlation

data:  RASS.Diff and SS.Fall
t = -2.5352, df = 246, p-value = 0.01186
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.27859827 -0.03571154
sample estimates:
       cor 
-0.1595688 
```

I.E. Correlation between Percent Change in Classroom Standard Score and Teacher Fidelity to JUMP Math Program.

```
> cor.test(Teacher.Fidelity$percent.change,Teacher.Fidelity$Fidelity,method = "pea
rson")

        Pearson's product-moment correlation

data:  Teacher.Fidelity$percent.change and Teacher.Fidelity$Fidelity
t = 2.3798, df = 10, p-value = 0.03863
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.04184721 0.87370217
sample estimates:
      cor 
0.6013077 
```