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DEPARTMENT OF RESEARCH, EVALUATION, AND ANALYTICS

Evaluation of the Charlotte-Mecklenburg Schools Personalized Learning Initiative - Year 2

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In collaboration with the CMS

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Table of Contents

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Executive Summary

The Charlotte Mecklenburg Schools' Department of Research, Evaluation, and Analytics in the Office of Accountability conducted its second evaluation of the Personalized Learning (PL) Initiative.The PL initiative began in the 2014-15 academic year with a group of students in Cohort 1 and continued in 2015-16 with a group of students in Cohort 2. Specifically, this evaluation addressed the following two research questions:

1. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students?
    a. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students disaggregated by subgroup?
    b. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students disaggregated by race?
2. Do Personalized Learning teachers have greater attendance and retention rates than a similar group of teachers?

Evaluation Question 1: Student Math and Reading Outcomes

For purposes of comparing student math and reading outcomes, the treatment group sample consisted of students in Cohorts 1 and 2 who received Personalized Learning instruction in the subject measured (math or reading) during the 2015-16 school year. The comparison group consisted of students at the same schools who did not receive Personalized Learning instruction in the 2015-16 school year in the subject measured. The growth index scores for the PL Group and the Comparison Group were compared to one another. Larger differences in scores delineate larger differences in magnitude, with magnitudes larger than +/- 2 considered statistically significant. We also compared student subgroup growth index differences for the PL Group and Comparison Group in math and reading for Academically and Intellectually Gifted (AIG), Students with Disabilities (SWD), and Limited English Proficient (LEP) students, as well as by racial group.

For each cohort, on average, there was a statistically significant difference in math growth but no statistically significant difference in reading growth; therefore, the results in this evaluation often combine Cohorts 1 and 2 for ease of interpretation. Combined results indicated that, on average, students receiving PL instruction in math showed statistically significantly more growth than students in the Comparison Group in 2016. Students receiving PL instruction in reading often demonstrated a greater growth index score compared to the Comparison Group; however, these differences in growth were not statistically significant.

With regard to subgroups, students in PL Cohorts 1 and 2 who were *not* identified as AIG, LEP, or SWD showed statistically significantly more growth in math and reading during 2016 compared to a similar group of students in the Comparison Group. Figure 5 displays math growth by subgroup and Figure 6 displays reading growth by subgroup.

In math in 2015-16, Personalized Learning AIG students showed more growth than the Comparison Group. In reading in 2015-16, differences for AIG, LEP, and SWD subgroups in both PL Cohorts 1 and 2 were not statically significant when compared to the Comparison groups.

In only one area did the PL subgroup demonstrate outcomes that were statistically significantly lower than the Comparison Group. In 2015-16, math growth for students identified as SWD in PL Cohorts 1 and 2 was significantly less than those students identified as SWD in the Comparison Group.

With regard to race, African American PL students in Cohorts 1 and 2 showed significantly more growth in math and reading when compared to African American students in the Comparison Group in 2015-16. Hispanic PL students in Cohorts 1 and 2 also showed significantly more growth in math compared to Hispanic students in the Comparison Group in 2015-16. In all other racial subgroups, including White and Asian, the growth differences between those in the PL Group and the Comparison Group in Cohorts 1 and 2 were not statically significant.

Evaluation Question 2: Teacher Engagement: Absenteeism and Retention

Teachers who received professional development on PL standards and received coaching in at least one course in either school year 2014-15 or 2015-16 (PL Group; n=190) were compared to a similar group of teachers (Comparison Group; n=503). On average, PL teachers were absent 5.7% of yearly instructional hours and Comparison Group teachers were absent 6.2% of yearly instructional hours in 2014-15 and 2015-16. This means that the Comparison Group was absent from school, on average, ½ of a percentage point more than the PL Group, which equates to a 9% greater absence rate for the Comparison Group in relation to the PL Group. We found that a greater proportion (15.1%) of Comparison Group teachers are absent 10.1% or more of the school year compared to 10.5% of PL Group teachers. It is important to note that leaves of absence, jury duty, workshops/In-service time were excluded from the absence rate because these were days missed due to circumstances out of teachers' control or due to attending professional development.

The analysis for teacher retention focused on the percentage of PL teachers that were retained as employees of CMS compared to non-PL teachers from March of school year 2014-15 to March of school year 2015-16. The PL Group consisted of 51 teachers who could have been retained and the Comparison group consisted of 146 teachers who could have been retained. The retention rate for PL Cohort 1 teachers is 88.2% compared to 97.9% for the Comparison Group. The overall CMS District retention rate for 2015-16 was 86.1%, which the PL Group exceeded by 2.1 percentage points. While the retention rate for PL teachers is lower than the Comparison Group, it is worth noting that the net difference is only three teachers (6 teachers not retained for PL versus 3 teachers not retained for Comparison). While both the PL Group and the Comparison Group have retention rates that are slightly greater than the district average, they still fall short of the 2017-2018 target of a 95% retention rate in the CMS 2018 Strategic Plan.

In conclusion, the results of this evaluation indicate that, on average, Personalized Learning students demonstrated greater math growth than similar non-PL students. There seems to be a positive impact of PL in math in general, and for African American and Hispanic students in particular. Generally, there was no statistically significant difference in reading between the treatment group and the comparison group. For teachers, there appears to be a positive impact of personalized learning on teacher engagement, as demonstrated by greater attendance. It is important to note that the data should be interpreted with caution due to small sample sizes for the PL group, particularly for teachers.

Despite these promising results, findings should be interpreted with caution. Causality can only be inferred to the point that teacher assignment to be trained or not trained in PL is random, and that the standardized tests used in the estimation of the EVAAS growth scores are sensitive to differences in student subject knowledge. Small sample sizes, particularly for teachers in the PL Group, mean that caution should be used in generalizing the results outside of the study sample. For those areas where findings were found to be statically significant, it is recommend that further research be completed.

Personalized Learning Year 2 Evaluation

Introduction

When Helen Parkhurst created the Dalton Plan in the 1920s, she created one of the first methods of Personalized Learning for students. The goal was to create a learning environment that tailored to the student's interests, needs, and talents. The program created opportunities for a students to have choice in their learning, by exploring what interested them and choosing optional activities in which they would participate (Savio-Ramon, 2015).

Since then, learning has evolved from traditional teaching and learning of core subjects that typically has involved all or most students in a class being assigned the same tasks and all students progressing through the course at the same pace. In general, Personalized Learning optimizes learning by allowing students to interact and be more active with learning that is uniquely suited to their needs. Some generally-accepted ideas behind personalized learning (Sahabudin & Ali, 2013) include the following:

- Each individual is involved in the learning process,
- Teachers get to know the strengths and growth areas of each student,
- Creating an environment of student independence, and
- Students are able to set goals and measure their own learning.

However, Personalized Learning does not have to follow one set of rules or guidelines for implementation. The ways in which teachers, schools, or districts implement policies regarding pace, style, or use of technology can vary greatly (Netcoh, 2017).

Starting in 2014-15, Charlotte-Mecklenburg Schools (CMS) implemented the first cohort of the Personalized Learning (PL) Initiative in 15 schools across the district. In 2015-16, a second cohort of 18 schools was added, for a total of 33 schools. The Personalized Learning initiative was implemented in various course subjects, including but not limited to math, reading/language arts, science, physical education, health, and web design. Five teaching and learning strategies serve as the tenets of implementing personalized learning in CMS (Pane, Steiner, Baird & Hamilton, 2015):

1. **Whole Child —**Building positive relationships and creating a learning environment that enables personalized learning, student collaboration, and promotes creativity.
2. **Ownership** — Teachers work along with students to create unique personalized goals, using data from multiple sources to guide the process, and establish a voice in what they are doing and why.
3. **Mastery Progression** — Student mastery is assessed when the student is ready, allowing students to progress at their own pace and value feedback to achieve academic standards and pursue personal growth.
4. **Instructional Shift** — Tailored learning content, which allows students to be flexible in their content, pace, and direction of their learning.
5. **Emphasis on College and Career Readiness** — Curriculum that develops a student's skills beyond academic content.

Aligning to these tenets, CMS's vision for Personalized Leraning is grounded in the district's *four cornerstones*: 1) whole child, 2) student ownership, 3) mastery learning, and 4) paces, playlists, and pathways.

The Personalized Learning Evaluation in Year 1 took place from January 2016 to July 2016. The following research questions were addressed in the first year:

1. Do students taught by teachers with PL training in math demonstrate more growth in math than students taught by teachers not trained in PL?

2. To what extent do the students who participate in PL report engagement?

To answer Question 1, the mean Educational Value-Added Assessment System (EVAAS) growth scores for students who took a math course taught by a PL-trained teacher were compared to students at the same schools who did not have a PL-trained teacher. Students with two years of math growth data (i.e., 2013-14 and 2014-15 Normal Curve Equivalent [NCE]), attended the same school, and had at least one quarter of the academic year with PL exposure in a math course were included in the Comparison Group. Students who had a PL-trained teacher in 2014-15 showed significantly more growth on average (M = 2.32) than students who did not (M = 0.60). To answer Question 2, we measured engagement using seven items selected from the Personalized Learning Student Survey that measure the construct of *engagement* and used the Engagement Subscale of the Gallup Student Survey as a comparison. Personalized Learning schools demonstrated greater engagement than the entire district. In particular, findings indicated that 81% of students from the PL Cohort reported being engaged versus 47% of students on the district's Gallup Student Survey.

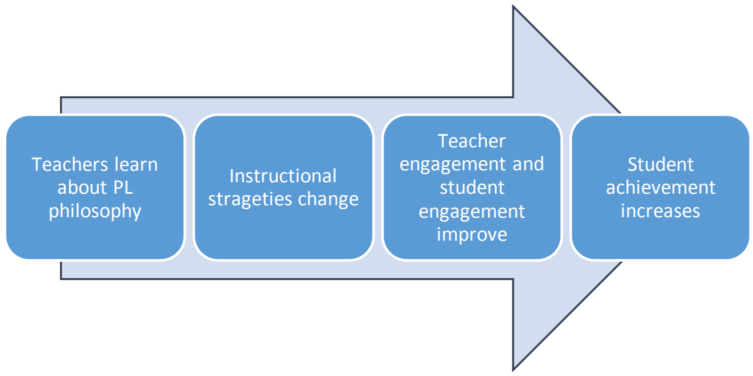
From January 2017 through June 2017, the Department of Research, Evaluation, and Analytics (REA), in conjunction withpartners from the CMS Personalized Learning Department in the Technology, Personalized Learning and Engagement Division, completed a continuation (Year 2) evaluation of the Personalized Learning initiative.

For the Year 2 Evaluation, the original cohort of both PL and non-PL students (Cohort 1) was not only compared in math, but also reading, across two years of growth (2014-15 to 2015-16). A second cohort (Cohort 2) of PL students was added to the Year 2 Evaluation and they were compared to students who took the same courses at the same schools with a teacher who was not trained in PL. Cohort 2 PL students had their first experience with a PL-trained teacher in either math or reading during the 2015-16 school year. Student growth was compared by computing mean growth scores for the various student groups and then transforming them into index scores in the same way that teacher index scores are computed by SAS (Rivers, Sanders, Wright, & White, 2010). The index scores for the PL Group and the Comparison Group were compared to one another. Larger differences in scores delineate larger differences in the magnitude of effect, with magnitudes larger than +/- 2 considered statistically significant. We also compared student subgroup growth index differences for the PL Group and Comparison Group in math and reading for Academically and Intellectually Gifted (AIG), Students with Disabilities (SWD), and Limited English Proficient (LEP) students, as well as by racial group. Finally, teacher engagement was examined in the Year 2 evaluation by comparing absenteeism and retention rates for PL teachers compared to a similar group of teachers not trained in PL.

Goals of Personalized Learning

There are three main goals of the CMS Personalized Learning Initiative. The first is to change teachers' instructional strageties to adapt to the needs of students in a digital age. Upgrading teaching practices to incorporate the many learning strageties and activities in a mobile age is crucial to maximize learning for students. The second goal is to improve teacher and student engagement. The third goal is to increase student achievement. These goals are represented in the theory of change in Figure 1.

Figure 1. Theory of Change of Personalized Learning.



Evaluation Questions

This evaluation is intended to provide stakeholders with a general understanding of the extent to which implementing PL leads to greater growth outcomes for students as well as to compare teacher engagement outcomes. Teacher engagement and student growth are the distal and proximal outcomes expected from implementing PL, respectively. Another intent of this evaluation, and the reason for the more granular subgroup analysis, is to allow stakeholders to identify groups of students for whom PL is having the most positive impact, and to assist with decision making about future PL initiatives.

The Year 2 Personalized Learning Initiative Evaluation addressed two main questions:

1. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students?
    a. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students disaggregated by subgroup?
    b. Do Personalized Learning students in Cohorts 1 and 2 in math and reading show more growth than a similar group of students disaggregated by race?
2. Do Personalized Learning teachers have greater attendance and retention rates than a similar group of teachers?

Evaluation Question 1: Student Math and Reading Outcomes

Method

<u>Sample</u>

The sample consists of students who are in PL Cohort 1 or Cohort 2, as well as students who comprise the respective Comparison Groups. Students who took a math or reading course form a PL-trained teacher during the 2014-15 and 2015-16 school years make up Cohort 1. Students who took a math or reading course from a PL-trained teacher for the first time during the 2015-16 school year make up Cohort 2. An independent comparison group was created for both cohorts in order to account for potential sample bias, and to account for grade-level or other differences between Cohort 1 and Cohort 2. The Comparison Group consists of students enrolled in a math and/or reading course at the same school and year as students from Cohort 1 or Cohort 2, but who did not receive Instruction from a PL-trained teacher in math or reading. Table 1 displays the total number of students included in the study overall (N), as well as sample sizes of each PL Cohort and its associated Comparison group.

Table 1: Number of Students in the Personalized Learning and Comparison Groups

Student Group	N	Cohort 1	Cohort 2
Personalized Learning Group	4,432	1,657	2,775
Comparison Group	6,092	3,012	3,080
Total	10,524	4,669	5,855

Measures

Demographics. Student characteristics were identified to create subgroups for analysis**.** Students received a flag in the data set for any group into which they fit: Academically and Intellectually Gifted (AIG), English Language Learners (or Limited English Proficient; LEP), Exceptional Children (designated here as Students with Disabilities; SWD), Not Identified (that is, Non-AIG, Non-LEP, and Non-SWD), and racial group (African American, Hispanic, Asian, or White).

Students who did not have a growth score recorded were removed from the sample.

Educational Value-Added Assessment System (EVAAS). The North Carolina State Board of Education selected SAS EVAAS as the statewide model for measuring student, teacher, and school growth. This model is used by the state to assess teacher effects above and beyond other influences. It is psychometrically sound to be used as a performance indicator, and research has shown that teacher indices are stable over time and good predictors of future performance. Beginning with the 2012-13 school year, the State began to report EVAAS data in the READY Accountability model.

EVAAS includes multiple indices to assess student progress. The indices are based on a value-added statistical methodology. The indices account for the influence of school, teacher, past test performance, grade level, and current-year test performance and are defined below. [1]

Actual Growth is a measure of student progress from one year to the next as measured by changes in class standing based on end-of-year standardized test performance.

Predicted Growth is a score based on a value-added analysis of the student's performance, after accounting for the influence of at least four standardized test scores and the influence of school, teacher, grade level, and state averages.

Gain represents the difference between the **Actual Growth** and the **Predicted Growth**. Differences reflect the influence of teacher and error (or unexplained variance).

Growth Index = Gain/Standard Error. The Growth Index is the same as a *t*-score. Index score values between -2 and +2 points are defined as "*Met Expected Growth*," index values less than -2 indicate "*Not Met Expected Growth*," and index values greater than +2 indicate "*Exceeded Expected Growth*."

Analysis

A value-added estimate (that is, the Gain) and standard error (SE) are calculated by SAS for each teacher for each tested subject and grade; then Gain and standard error are used to compute a growth index. For the purposes of this evaluation, the growth index was used to compare the PL Group mean Gain to the comparison mean Gain; statistical significance was determined by examining the differences in the growth index for each group (the "index difference"). Larger differences in scores delineate larger magnitude differences when comparing groups in the same analysis. Magnitudes larger than +/- 2 are statistically significant. SEs are dependent upon individual variability and the sample size of the group (SE=Standard Deviation/√N). Thus, to make group comparisons easier to interpret, and to avoid the introduction of bias due to unequal variances, pooled and weighted SEs were used to determine the growth index,

[1] For more information on EVAAS see http://www.dpi.state.nc.us/effectivenessmodel/evaas /selection/

which is why it is important to only compare magnitudes of difference within groups that share a common SE. Pooling is a technique used to calculate the average SD across groups, and weighting is used when the group sizes are unequal in order to adjust the influence that larger groups have on the average SD value. Note that the sample groups for both PL and non-PL were larger than a single classroom; thus when the SEs were computed ($SE=SD/\sqrt{N}$), they were smaller than would be found for any single teacher. Having a smaller SE means the Index value will be larger (Index=Gain/SE), thus the values in this report in both the negative and positive direction will be slightly inflated from the traditional teacher growth index.

Results: Math and Reading Outcomes

District: Cohort 1

On average, students from the PL group in Cohort 1 met or exceeded expected growth expectations in reading and math in 2014-15 and 2015-16. This is evident because the average growth index for the PL group is 1.9 in math in 2014-15 and 7.5 in math in 2015-16 and is 8.8 in reading in 2014-15 and 2.9 in reading in 2015-16. All of these values are greater than -2, indicating that the group, on average, met or exceeded growth.

In math, in both 2014-15 and 2015-16, students in PL Cohort 1 had, on average, statistically significantly more positive growth than the students in the Comparison Group. Specifically, in Math, differences in growth between the PL Group and Comparison Group were significant in 2015 (Index Difference [ID] = 5.9, $p < 0.001$) and in 2016 (ID = 3.9, $p < 0.001$).

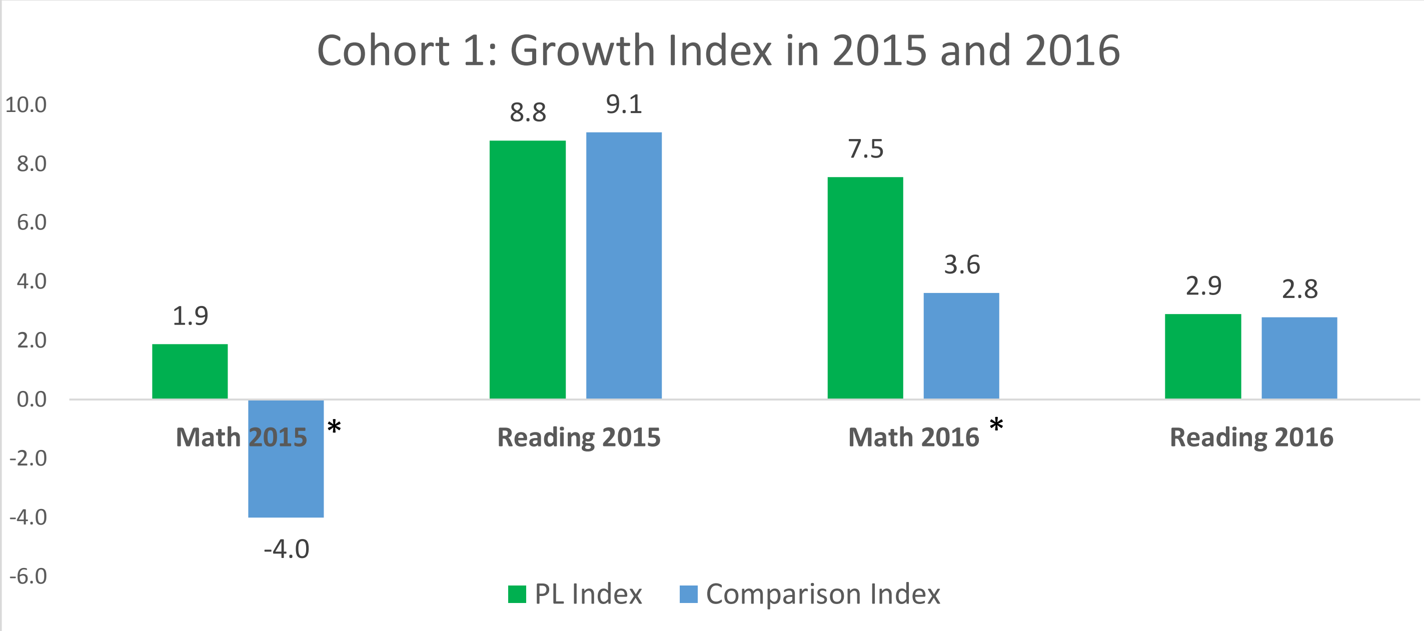
In reading, in 2014-15, the Comparison Group performed slightly better than PL Cohort 1; conversely, in 2016, PL Cohort 1 performed slightly better than the Comparison Group. However, differences in growth between the PL and Comparison Groups were not statistically significant in either 2014-15 or 2015-16 (see Figure 2).

District: Cohort 2

On average, students from the PL group in Cohort 1 exceeded expected growth expectations in reading and math in 2015-16 (math growth index = 2.3; reading growth index = 6.0).

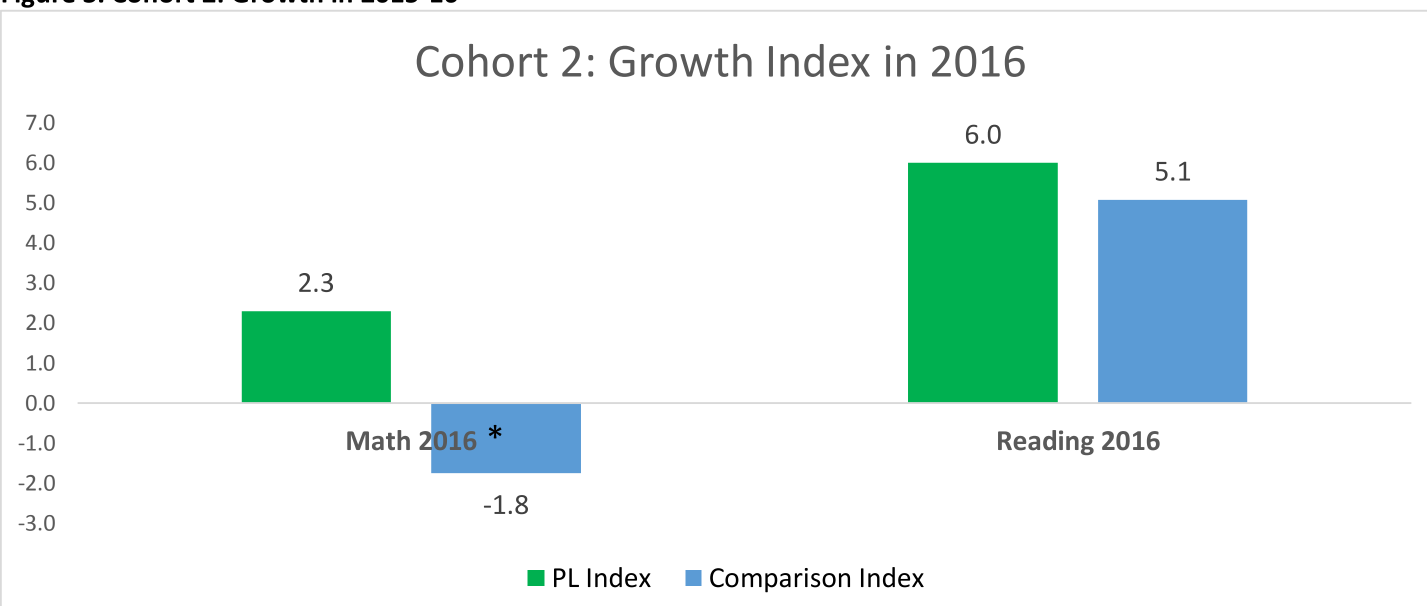
In math, students in PL Cohort 2 had, on average, statistically significantly more growth than the students in the Comparison Group in 2016 (ID = 4.1, $p < 0.001$; see Figure 2). In reading, while PL Cohort 2 demonstrated greater growth compared to the Comparison Group, the differences in growth between the PL and Comparison Groups were not statistically significant (see Figure 3).

Figure 2. Cohort 1: Growth Index in 2014-15 and 2015-16



*Indicates a statistically significant difference. Note: The *N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

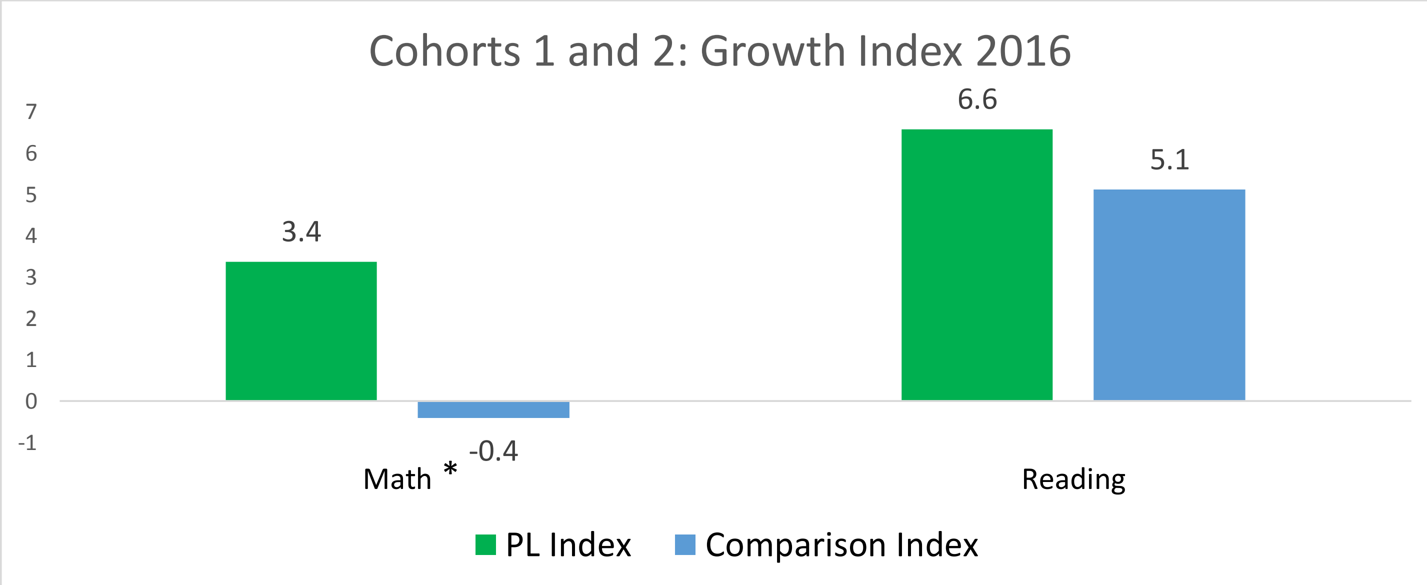
Figure 3. Cohort 2: Growth in 2015-16



*Indicates a statistically significant difference. Note: The *N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

Because the pattern of results was similar for both cohorts (a statistically significant difference in math growth but not a statistically significant difference in reading growth), we combined Cohorts 1 and 2 for ease of interpretation. When students from their respective cohort years were combined , we see that students receiving PL instruction, on average, show statistically significantly more growth in math than students in the Comparison Group in 2016 (ID = 3.8, $p < 0.001$), similar to the results for each Cohort individually. Also similar to the individual Cohorts, while students receiving PL instruction in reading demonstrate a greater growth index score compared to the Comparison Group, these differences in growth were not statistically significant (see Figure 4).

Figure 4. Cohorts 1 and 2: Growth in 2015-16



*Indicates a statistically significant difference. Note: The *N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

Student Subgroups

Academically and Intellectually Gifted, Exceptional Children, and Limited English Proficient Students

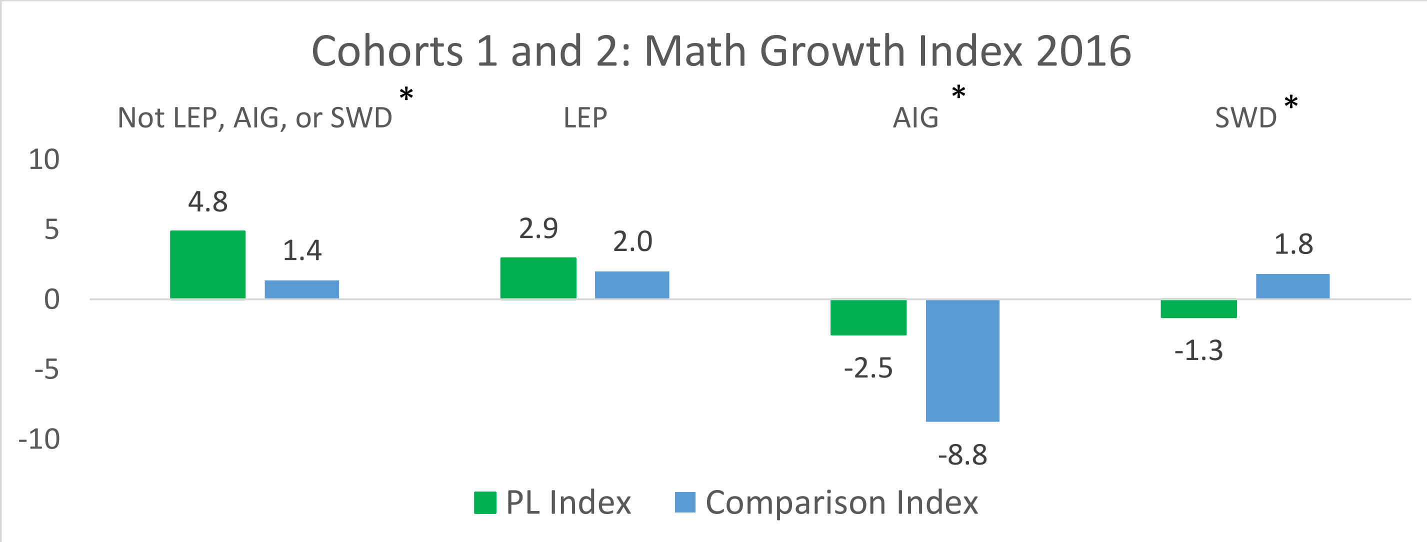
On average, PL Limited English Proficient (LEP) students and Exceptional Children (or Students with Disabilities; SWD) in Cohorts 1and 2 met growth expectations in math in 2016 (average growth index for LEP = 2.9; average growth index for SWD = -1.3). Students *not* identified as AIG, LEP, or SWD (henceforth referred to as "Not Identified") students in Cohorts 1and 2 exceeded growth expectations in math in 2015-16 (math growth index = 4.8). In reading, on average, PL students in *all* subgroups (AIG, LEP, SWD, and Not Identified) met or exceeded growth expectations in 2015-16.

Not Identified students in PL Cohorts 1 and 2 showed statistically significantly more growth in math and reading in 2015-16 compared to students in the Comparison Group (ID = 3.4, $p < 0.001$; Reading ID = 2.3, $p < 0.05$). Figure 5 displays math growth by subgroup and Figure 6 displays reading growth by subgroup.

AIG students in PL Cohorts 1 and 2 showed statistically significantly more growth in math in 2015-16, AIG students in the Comparison Group (ID = 6.3, $p < 0.001$). In reading in 2015-16, differences for LEP, AIG, and SWD subgroups in both PL Cohorts 1 and 2 were not statically significant when compared to the Comparison groups.

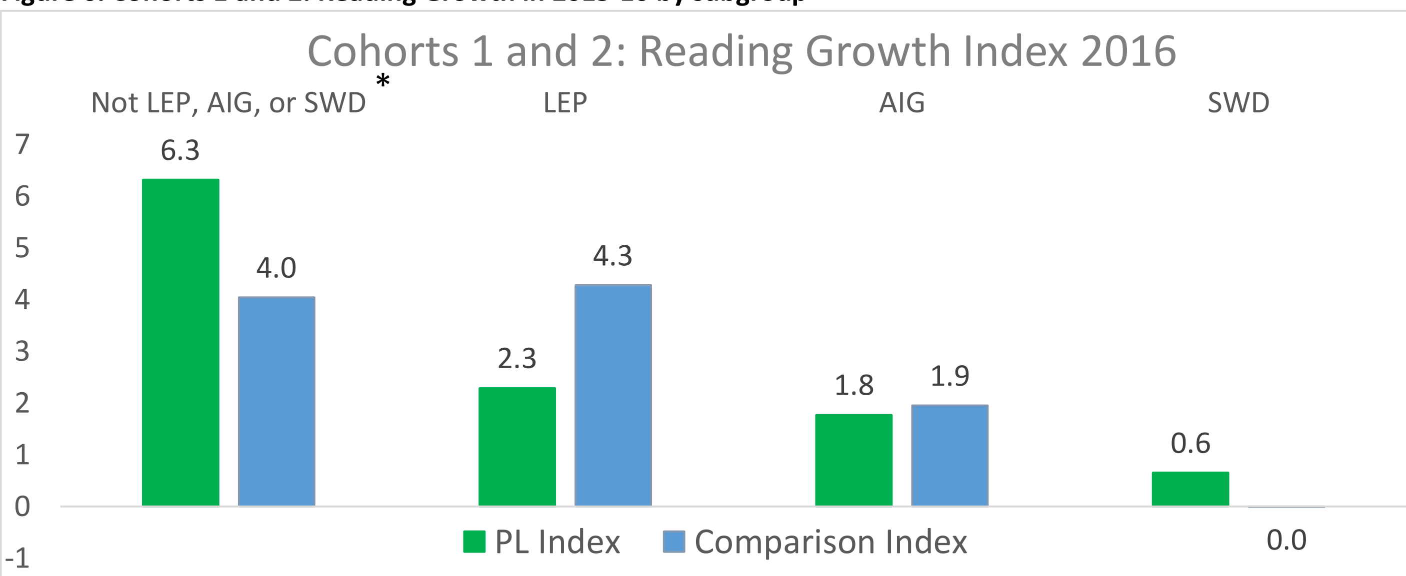
In only one area did the PL subgroup demonstrate outcomes that were statistically significantly lower than the Comparison Group. In 2015-16, math growth for students identified as SWD in PL Cohorts 1 and 2 was significantly less (ID = -3.1, $p < 0.01$) than those students identified as SWD in the Comparison Group (see Figure 5). A review of the literature suggests that personalized learning and teaching groups of students with particular learning needs, such as Students With Disabilities, go hand in hand. Research suggests PL as a way to effectively teach SWDs (Murphy, Redding, & Twyman , 2016). Indeed, special education places a focus on using multiple methods of instruction, individualized pacing, varied instruction, and creating special teacher-student relationships. Much of the core feature of PL is a focus on these same activities: individualized student learning based on needs and preferences. It is important to note that by defininition, an identified student with disabilities has an *Individualized* Educational Plan (IEP) in place. Thus, both the PL and Comparison groups of SWDs share many similarities in the educational environment, perhaps minimizing the distinction between the two groups.

Figure 5. Cohorts 1 and 2: Math Growth in 2015-16 by subgroup



*Indicates a statistically significant difference. Note: *The N* value for each subgroup, race, evaluation year, and cohort, is different thus comparisons of index values are only valid within analyses and charts by subgroup.

Figure 6. Cohorts 1 and 2: Reading Growth in 2015-16 by subgroup

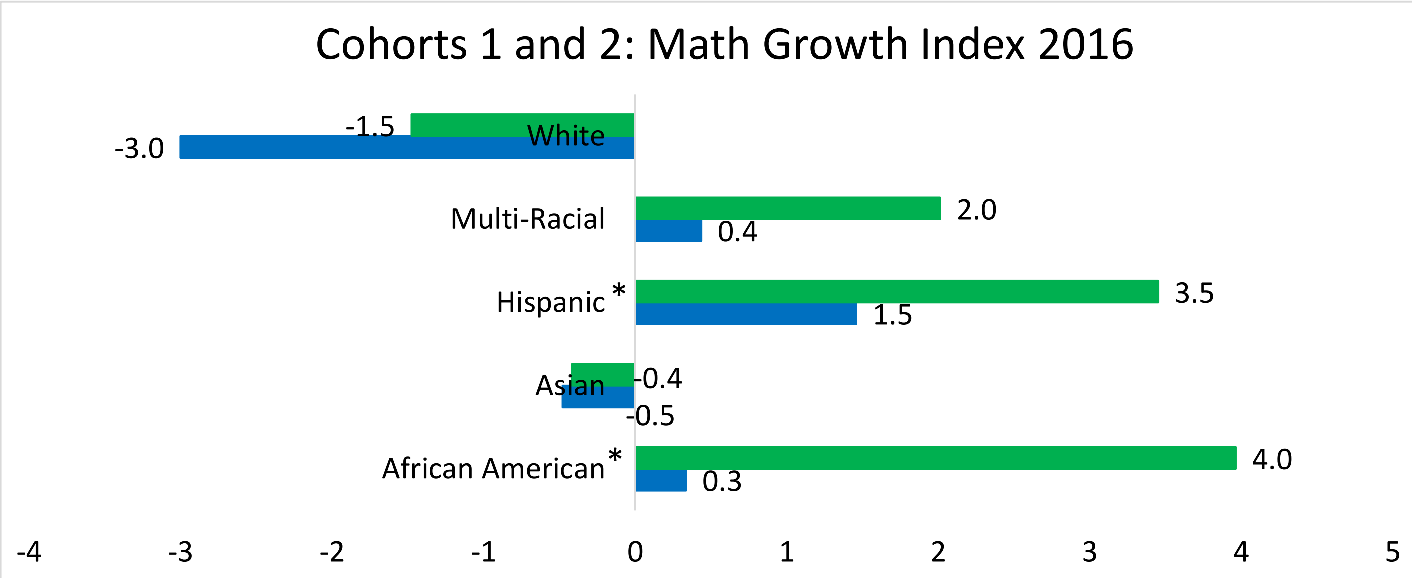


*Indicates a statistically significant difference. Note: *The N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

Racial Groups

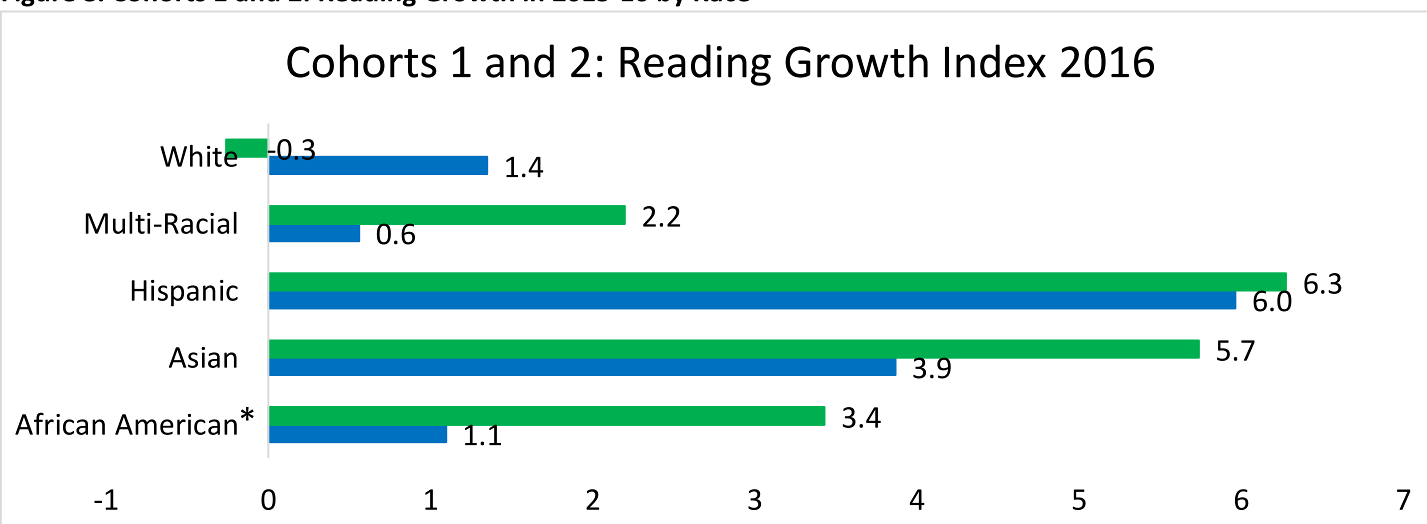
African American students in PL Cohorts 1 and 2, on average, showed significantly more growth in math (ID = 3.6, $p < 0.01$) and in reading (ID = 2.3, $p < 0.01$) when compared to African American students in the Comparison Group in 2015-16. Hispanic students in PL Cohorts 1 and 2 also showed significant more growth in math (ID = 2.0, $p < 0.05$) compared to Hispanic students in the Comparison Group in 2015-16. In all other racial subgroups the growth differences between those in the PL Group and the Comparison Group were not statically significant (see Figure 7 and Figure 8).

Figure 7. Cohorts 1 and 2: Math Growth in 2015-16 by Race



*Indicates a statistically significant difference. Note: The *N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

Figure 8. Cohorts 1 and 2: Reading Growth in 2015-16 by Race



*Indicates a statistically significant difference. Note: The *N* value for each subgroup, race, evaluation year, and cohort, is different; thus comparisons of index values are only valid within analyses and charts by subgroup.

In sum, while we cannot be completely confident that differences in teacher training in PL are responsible for differences in student performance, we can be certain that, to the extent the end-of-year standardized tests are sensitive to differences in student content knowledge, teacher index scores represent individual teacher effects with minimal error. To the extent that teacher assignment to be trained in PL or not was random, differences between index scores for PL and non-PL groups represent the isolated effects of PL on student growth, above and beyond unique teacher effects, school influence, student demographics, and measurement error.

Evaluation Question 2: Teacher Engagement: Absenteeism and Retention

Understanding teacher engagement is an important piece of the success of implementing Personalized Learning. Similar to how creating an environment of choice, independent learning, and self advocacy for students is important for PL, it is also important for teachers. The expectation is that by giving teachers first-handexperience with PL in their professional lives, they can better understand how students relate and react to PL in their classroom (Rickabaugh, 2016).

Additionally, research indicates that student achievement is related to teacher absenteeism. Indeed, there is a negative impact on student achievement when teachers are absent 10 or more days (Miller, Murnane, & Willett, 2007). Schools where teachers have a high rate of absenteeism also tend to have a high rate of student absenteeism. Substitutes have not been shown to be a direct replacement for lost time with the regular teacher as substitutes generally are not as familiar with the material, routines of the classroom, or first-hand knowledge of student behaviors (Miller, Murnane & Willett, 2007). A study of 40 largely metropolitan schools, found that, on average, teachers were absent 11 days a year (Joseph, Waymack, & Zielaski, 2014). Higher rates of absenteeism were found to occur in elementary schools, schools of high poverty, and schools with large proportions of minority students (Bruno, 2002; Clotfelter, Ladd, & Vigdor, 2009).

Method

Sample and Measures

For the purposes of measuring teacher engagement, teachers who received professional development on PL standards and implemented them in at least one course in either school year 2014-15 or 2015-16 were considered part of the PL group (n=190). All other teachers from the same schools make up the Comparison Group (n=503).

Teacher Absenteeism. We analyzed teacher attendance data from both 2014-15 and 2015-16. For the purposes of this analysis, the average number of instructional hours for the 2014-15 and 2015-16 school years was estimated at 1068 hours per year. The percentage of time absent for each group was calculated as the group's total hours absent divided by the number of teacher hours available (total hours absent/[number of teachers x 1068 hours]). That is, the absence rate is weighted by the total number of instructional hours available for each group.[2] Thus, we examined the total percentage of teacher absences as well as the absence rate for 10-percentage-point bands (e.g., 0-10%, 10.1-20%).

Teacher Retention. We focused on the percentage of PL teachers who were retained as employees of CMS compared to non-PL teachers from March of school year 2014-15 to March of school year 2015-16. Teachers who transferred to a non-teaching position but continued in a role in CMS from 2014-15 to 2015-16 were also considered retained[3]. Teachers who were no longer employed in CMS were considered not retained. Based on these criteria, the PL Group consistedof 51 teachers who could have been retained and the Comparison Group consisted of 146 teachers who could have been retained.

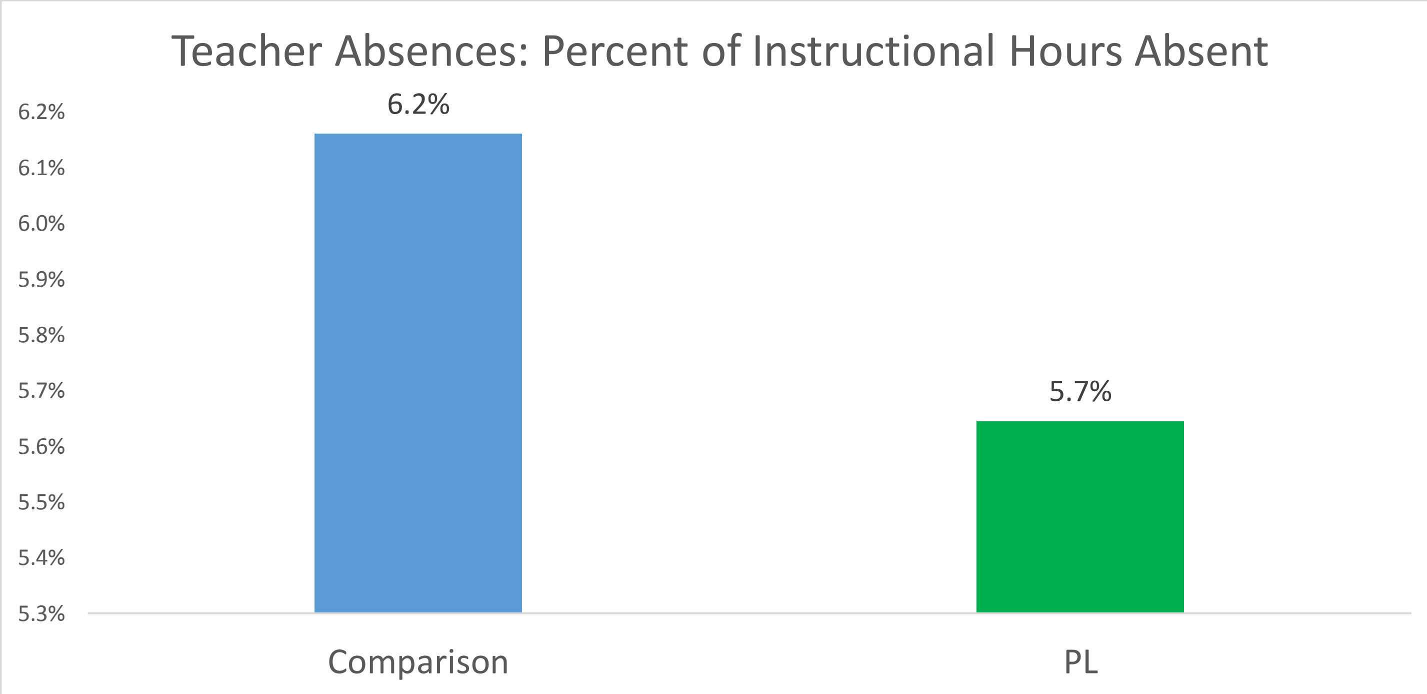
Results

Teacher Engagement: Absenteeism

On average, PL teachers were absent 5.7% of yearly instructional hours and Comparison group teachers were absent 6.2% of yearly instructional hours in 2014-15 and 2015-16 combined. This means that the Comparison Group was absent from school, on average, ½ of a percentage point more than the PL Group, which equates to a 9% greater absence rate for the Comparison Group in relation to the PL Group (see Figure 9).

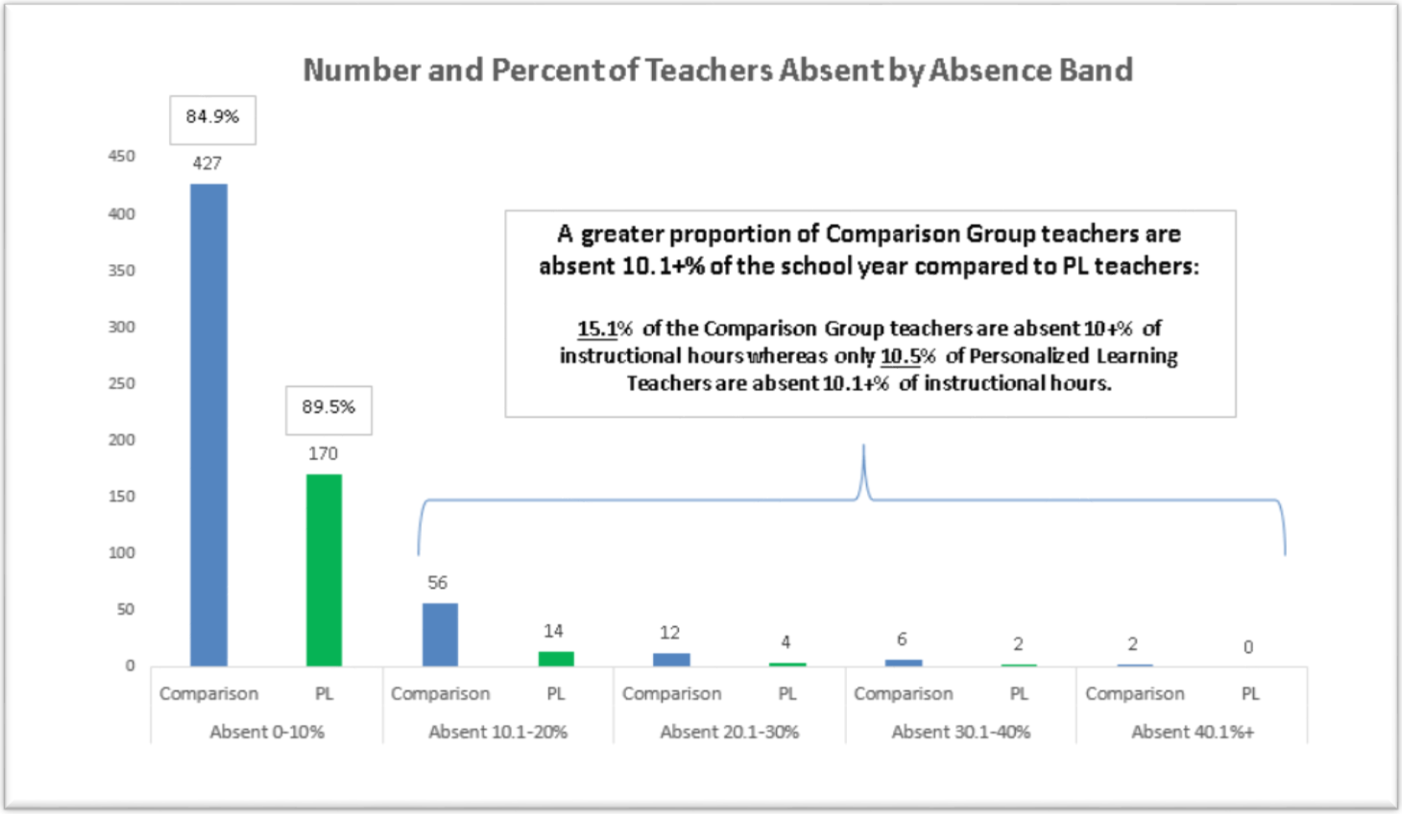
[2] Exclusions included leaves of absence, jury duty, workshops/In-service time because these are days missed due to circumstances out of teachers' control or due to attending professional development.
[3] However, they are no longer included in the PL cohort at time of position change.

Figure 9. Teacher Absences: Percent of Instructional Hours Absent in 2014-15 and 2015-16 Combined



We were interested in determining how absences are distributed along a continuum. Thus, we examined the total percentage of teacher absences for each 10-percentage-point band (i.e., 0-10%, 10.1-20%, 20.1-30%, 30.1-40%, and 40.1% or more). Figure 10 displays the number and percentage of teachers absent by absence band. On average, 84.9% of Comparison Group teachers were absent 0-10% of yearly instructional hours while 89.5% of PL Group teachers were absent 0-10% of hours. This means that a greater proportion of Comparison Group teachers were absent *10.1% or more* of the school year compared to PL Group teachers. That is, 15.1% of the Comparison Group teachers were absent 10.1% or more of instructional hours, whereas only 10.5% of Personalized Learning Teachers were absent 10.1% or more of instructional hours. Taken together, both of these results indicate that PL instruction may be positively related to teacher engagement. PL teachers appear to be more actively engaged in their classrooms, missing fewer hours of instructional time overall than their non-PL colleagues.

Figure 10. Teacher Absences: Teachers Absent by Absence Band 2014-15 and 2015-16



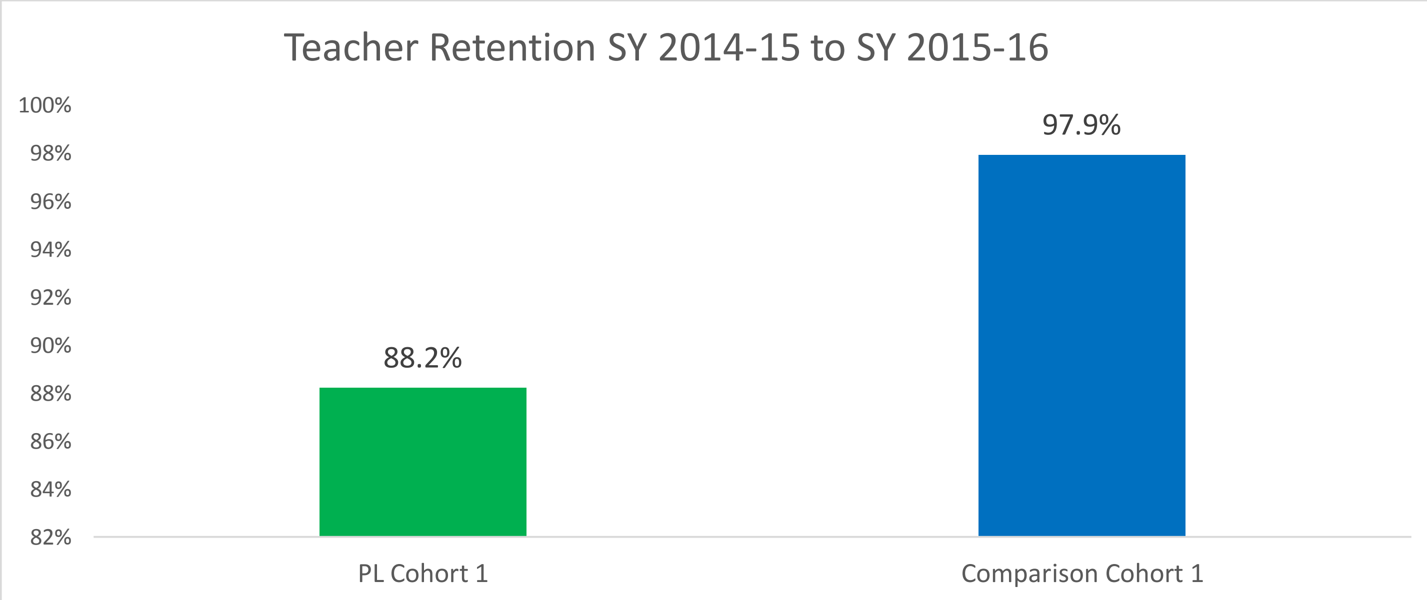
Teacher Engagement: Retention

While retention is important for any organization, it is particularly important for a school district. In fact, the topic of teacher retention is specifically written into the CMS 2018 Strategic Plan. *Strategic Plan 2018: For a Better Tomorrow* highlights six goals to be focused on through 2017-18 (Charlotte-Mecklenburg Schools, 2017) and includes one in particular about retaining the workforce (Goal 2: Recruit, develop, retain and reward a premier workforce)[4].
The retention rate for PL Cohort 1 teachers was 88.2% compared to 97.9% for the Comparison Group. The overall CMS District retention rate for 2015-16 was 86.1%, which the PL Group exceeded by 2.1 percentage points (see Figure 11). While the retention rate for PL teachers is lower than the rate for Comparison Group, it is worth noting that the net difference is only three teachers. That is, six teachers were not retained for the PL Group whereas three teachers were not retained for the Comparison Group.

While both the PL Group and the Comparison Group have retention rates that are slightly greater than the district average, there is still a more work to be done to reach the Strategic Plan 2018 target of a 95% teacher retention rate for the district.

[4] Goal 2: Recruit, develop, retain and reward a premier workforce, Focus Area III - Retention of effective employees/ quality performance appraisals: 1. Develop a performance-management approach to provide ongoing feedback to all employees, 2. Revise the employee evaluation system to incorporate multiple measures, 3. Transform compensation and recognition programs, 4. Create a culture of high-performance expectations to retain effective employees and address ineffective employees, 5. Study the engagement level of teachers and student-outcome data (achievement, disciplinary referrals, attendance, suspensions, etc.) to determine impact on school culture.

Figure 11. Teacher Retention SY 2014-15 to SY 2015-16



Summary and Conclusions

Q1. Personalized Learning and Student Growth

The current evaluation was conducted in order to quantify the influence of PL instruction at CMS. We conducted an evaluation after the first year that PL was brought into the school district, 2014-15, and followed it up with a more robust evaluation for the 2015-16 school year. For the 2014-15 evaluation, we compared the average movement students made in their class standing in math by whether they had taken a math course from a PL-trained teacher or not. The mean gain in class standing for math from the end of the 2013-14 to 2014-15 was consistently higher for students who took a math course from a PL-trained teacher than matched peers who had a traditional math instructor. The results showed a similar trend across race, AIG, LEP and SWD status. However, we could not make any claims regarding whether PL training was the reason for differences in student growth scores. We could only state with confidence that PL training and student growth were positively associated.

For the year two evaluation of 2015-16 data, we wanted to isolate teacher and PL influence on student growth. In order to do this, we used the SAS EVAAS system, a valid and reliable value-added model (VAM) to account for the multiple factors that influence student academic growth in order to isolate the influence of PL. This model is used across the United States, including in North Carolina by the Department of Public Instruction, to isolate teacher influence, and assess teacher performance in regards to student growth.

By using indices on student growth created by SAS EVAAS, and by following the same formula for calculating the growth index SAS uses for teacher assessments, we were able to isolate the unique influence of teachers and contrast the groups regarding whether PL training had an impact on student growth above and beyond the teacher.[5] Overall,

[5] Based on the underlying premise of the Central Limit Theorem, which is one of the fundamental principles in inferential statistics, random sampling from the same population should lead to approximations of the population average. Since both teacher groups were drawn from the same population (i.e., same schools and same student body), they should approximate the mean value of each other and the population in general. The SE is based on the standard deviation of the sample and the size of the sample. When the PL group is compared to the Comparison group, the average teacher influence in both groups is expected to be within two SEs of each other and the population 95% of the time. This means that by subtracting the mean of the comparison group plus two SEs from the PL group, we have accounted for the expected average influence of the

students who took math courses from PL-trained teachers showed significantly more growth than students who took math courses from teachers without PL training; the overall group differences were not significant in reading. Certain subgroups were responsive to the influence, specifically African American and Not Identified students. Both groups showed robust growth increases from PL in math and reading . Not Identified students showed more growth in math across all years and cohorts, and also in the combined cohort analysis for reading. African American students showed significantly more growth in both math and reading across cohort and year.

Results for Students with Disabilities were somewhat unexpected: on average, SWDs who took a math course from a PL-trained teacher showed signifianctly *less growth* than SWDswho had non-PL math teachers. This finding was consistent across cohorts and years, and was statistically significant. These results are worth consideration in order to ensure that all students are equally supported in PL classrooms.

Q2. Personalized Learning and Teacher Engagement

Coaching PL teachers may have a positive effect on teacher engagement. Teachers who received PL coaching had a lower absence rate compared to other teachers overall in 2014-15 and 2015-16. Furthermore, a greater percentage of the Comparison Group teachers were absent 10+% of school days compared to Personalized Learning teachers overall in 2014-15 and 2015-16. Finally, the retention rate for PL teachers is greater than the district average.

Discussion

Further analyses should seek to isolate the influence of PL from teacher influence in order to identify other mechanisms that may be influenceing student growth and interacting with PL. This would increase confidence that PL training leads to increased teacher influence on student growth. This could be done by assessing the extent to which teacher assignment to PL training is random versus systematic and ensuring that teachers in both PL and comparison groups are similar in teaching experience and demographic characteristics. Future research regarding moderating or mediating factors that influence the students who were more sensitive to the influence of PL should also be conducted. In particular, the influence of PL seems more robust with African American students than any other race/ethnicity and understanding the factors involved in this difference could lead to the development of better methods for closing achievement gaps.

Very few studies have been completed to evaluate PL. In the few that do exist, there are many limitations present in the research designs. Both Netoch (2017) and Basham (2016) discuss the void of knowledge in this area of research, with Basham stating, “a search of academic journal databases returns no articles related to design elements, classroom practices, and outcomes associated with personalized learning” (Basham, Hall, Carter Jr., & Stahl, 2016, p.126). Thus, the information contained in this evaluation may be the most robust information currently available regarding PL outcomes on student growth and teacher absenteeism and retention.

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teachers within that population plus potential estimation error. This means that the remaining difference between groups is the influence of PL on math and reading growth. This allows us to say with reasonable confidence that any group difference over two SEs is due to the influence of PL.

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Appendix A. Personalized Learning Schools by Cohort Year.

School Type	School Name	Cohort Year
Elementary Schools	Barringer Academic Center, Devonshire Elementary, Eastover Elementary, Grand Oak Elementary, Hawk Ridge Elementary, Lake Wylie Elementary, Newell Elementary, Pinewood Elementary, Tuckaseegee Elementary, Whitewater Academy	2014-15
	Bain Elementary, Highland Creek Elementary, Irwin Academic Center, Long Creek Elementary, Matthews Elementary, Montclaire Elementary, Pineville Elementary, River Gate Elementary, River Oaks Academy, Winget Park Elementary, Winterfield Elementary	2015-16
K-8 Schools	Ashley Park PreK-8 School, Morehead STEM Academy	2015-16
Middle Schools	Carmel Middle, Kennedy Middle, Martin Luther King Jr Middle, Ridge Road Middle	2014-15
	Whitewater Middle, Mint Hill Middle, Piedmont IB Middle, Sedgefield Middle	2015-16
High Schools	Olympic High - Renaissance School	2014-15
	North Mecklenburg High, Olympic High - Biotech Health Pub Admin	2015-16