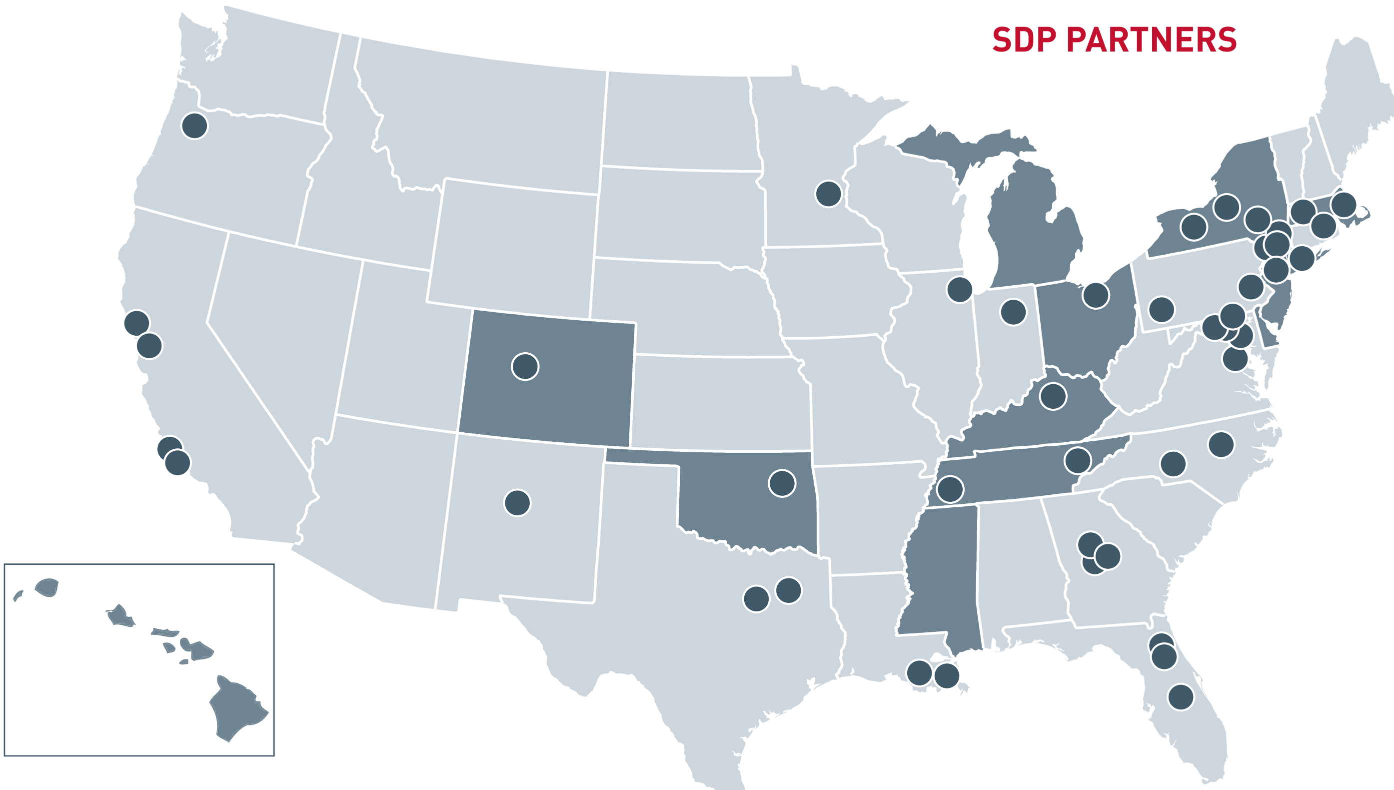
STRATEGIC DATA PROJECT

SDP HUMAN CAPITAL DIAGNOSTIC

Denver Public Schools

November 2014



THE STRATEGIC DATA PROJECT (SDP)

Since 2008, SDP has partnered with 56 school districts, charter school networks, state agencies, and nonprofit organizations to bring high-quality research methods and data analysis to bear on strategic management and policy decisions. Our mission is to transform the use of data in education to improve student achievement.

Part of the Center for Education Policy Research at Harvard University, SDP was formed on two fundamental premises:

1. Policy and management decisions can directly influence schools' and teachers' ability to improve student achievement.
2. Valid and reliable data analysis significantly improves the quality of decision making.

SDP's theory of action is that if we are able to bring together the right people, assemble the right data, and perform the right analysis, we can help leaders make better decisions—ultimately improving student achievement significantly.

To make this happen, SDP pursues three strategies:

1. building a network of top-notch data strategists who serve as fellows for two years with our partners (e.g., school district, charter management organization, nonprofit, or state education agency);
2. conducting rigorous diagnostic analyses of teacher effectiveness and college-going success using agency data; and
3. disseminating our tools, methods, and lessons learned to the education sector broadly.

The project is supported by the Bill & Melinda Gates Foundation.

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INTRODUCTION AND BACKGROUND

At the core of all the work that local and state education agencies aspire to accomplish is their educator workforce—the "human capital." There is widespread consensus among practitioners, researchers, and policymakers that teachers are the most important school-based factor that affects students' academic growth and development (e.g., see Rivkin, Hanushek, & Kain, 2005; Wright, Horn, & Sanders, 1997). Emerging evidence from recent research suggests that, in addition to helping academically struggling students catch up to their peers, effective teachers may influence students' long-term outcomes, such as their labor market earnings many years later (Chetty, Friedman, & Rockoff, 2011). Given teachers' critical role in influencing students' growth, it is imperative that education agencies be well informed about the functioning of their human capital systems and look closely at matters pertaining to teacher recruitment, effectiveness, development, and retention.

The Strategic Data Project (SDP) developed the Human Capital Diagnostic to provide agencies with vital information about these and other aspects of their teacher workforce. In 2013–14, SDP conducted this diagnostic in collaboration with the Denver Public Schools (DPS). The project investigated the five core components of the SDP Human Capital Diagnostic: recruitment, placement, development, evaluation/compensation, and retention/turnover.

Compensation is an important facet of human capital systems across all sectors. Using data from DPS' unique ProComp[1] teacher compensation system, we investigated the salaries and bonuses that teachers receive and the associations between teachers' salary and other aspects of their performance. These analyses have the potential to inform important education policy both in Denver and across the nation as education agencies consider revising traditional "lockstep" pay systems.

This report highlights key findings from the SDP–DPS Human Capital Diagnostic collaboration. Because of the uniqueness of the ProComp data and its relevance to current policy discussions, we describe the evaluation/compensation analyses in depth and summarize the key findings from the other components of the diagnostic.

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KEY FINDINGS

1. **In Denver Public Schools, students with lower prior achievement are disproportionately assigned to first-year teachers—a phenomenon that may exacerbate achievement gaps** given that novice teachers are generally less effective than teachers with more experience. This "placement pattern" can emerge when either or both of the following occur: 1) schools that serve students who are academically behind hire a larger share of novice teachers; 2) principals disproportionately assign students with lower prior achievement to novice teachers. In Denver, we find evidence of the former, but not the latter.

2. Despite the district's innovative ProComp system, **many aspects of DPS teachers' salaries mirror those of traditional step-and-lane compensation systems.** For instance, increases in teachers' salaries appear to be primarily related to teachers' gaining additional years of experience, and teachers' total salaries do not appear to differ substantially according to their median growth percentiles (MGP).

3. **Some individual ProComp incentives are positively related to teachers' MGPs and some are negatively related.** For example, math teachers whose MGPs are in the top half of the distribution are more likely to receive the following types of incentives: Exceeds Expectations, Growth Schools, and Top Performing Schools. Math teachers with higher MGPs are less likely to receive the Hard-to-Staff and Hard-to-Serve Schools incentives. Roughly the same percentages of math teachers with MGPs in the top and bottom half of the distribution receive the Advanced Degrees and Meets One Student Growth Objective incentives.

4. Because of its compounding effect on teachers' salaries, **the base-building incentive for participating in Professional Development Units (PDUs) cost the district roughly the same amount annually[2] as the costliest one-time bonus payments** (e.g., the bonuses for teaching in Hard-To-Serve Schools, Growth Schools, and Top Performing Schools). The estimated costs of the base building incentives were less than the payments DPS makes to individuals who Exceed Expectations (as measured by their gains in students' test scores).

5. When examining one-year retention rates across three recent school years, we find that **90% of math teachers whose MGPs were in the top quartile remained teaching in DPS, as compared with 81% of math teachers whose MGPs were in the bottom quartile. However, math teachers with lower MGPs were more likely to transfer between schools in the district** (14%, as compared with 8% among top-quartile math teachers), which may have negative consequences for the receiving schools. When teachers transferred between district schools, they tended to transfer to schools where the share of free/reduced lunch (FRL) students was about 6% lower than in the schools they left.

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ANALYSES: RECRUITMENT AND HIRING, PLACEMENT

Recruitment and Hiring

To gather foundational descriptive information about the DPS teacher workforce, we examined broad patterns in hiring over seven recent school years (2007–08 through 2013–14) and found that the DPS teacher workforce increased steadily over this period. In 2007–08, the district employed roughly 3,800 teachers; by 2013–14, this number had grown to over 4,600 teachers. With the exception of two years within this timeframe (2009–10 and 2010–11, both of which span the recent economic recession), the number of new hires generally increased, from 640 in 2007–08 to nearly 900 in 2013–14.

DPS administrators reported that this notable expansion of their teacher workforce was largely due to growth in student enrollment that occurred over the same time period and targeted increases in funding around special programs. Citing a study by Council for Great American Schools, DPS administrators reported that Denver is the fastest growing urban school district in the nation (Auge, 2012).

Placement

A common finding in teacher effectiveness research is that novice teachers are generally less successful at raising students' achievement than their more experienced peers (Rivkin et al., 2005; Rockoff, 2004).[3] Thus, placing students who are academically behind with novice teachers is likely to exacerbate achievement gaps among student groups. SDP's placement analysis examines the extent to which an agency assigns students with lower prior achievement to first-year teachers.

Across Denver schools, we found that first-year teachers were assigned students whose prior achievement was 0.26 standard deviations[4] below that of students in the classrooms of teachers with six or more years of experience.[5] However, this appeared to be due to the greater share of novices teaching in schools with low student achievement. When we conducted the same analysis within DPS schools—rather than across all schools in the district—we did not see statistically significant differences in the average prior achievement of students in novice and experienced teachers' classrooms. SDP has performed similar analyses in nine other school districts; in five of these nine, we have found that novice teachers are employed at schools with lower-achieving students and assigned to lower-achieving students within schools.

ANALYSES: DEVELOPMENT, EVALUATION/COMPENSATION

Development

Replicating a finding that is well documented in the teacher effectiveness literature, we found that both DPS math and reading teachers' impact on student achievement (as measured by SDP's estimate of teachers' value-added)[6] increased for their first four to five years on the job, after which it appeared to level off. Figure 1 (on page 7) depicts math teachers' average impact on student achievement as teachers gain additional years of experience. Relative to their first year on the job, math teachers in their fifth year raised students' performance by about 0.13 standard deviations—roughly the equivalent of four additional months of math learning.[7]

Reading teachers' impact on student achievement (not shown, see Appendix) followed a similar trajectory. By their fifth year, reading teachers had also made gains in student performance of 0.13 standard deviations. However, both math and reading teachers' impact on student achievement appeared to plateau after roughly their fifth year on the job. It is important to note that the 95% confidence interval (pictured in blue) widens for the groups with more experience due to smaller sample sizes.[8]

Evaluation/Compensation

The primary objective of the evaluation and compensation analyses we describe below was to investigate associations between various ProComp incentives and important teacher outcomes, such as student growth (i.e., teachers' MGP) and retention. To gain a foundational understanding of DPS teachers' compensation, we first examined the average salaries and ProComp incentives that teachers receive as they gain experience teaching in DPS. As Figure 2 depicts, similar to more traditional salary schedules, DPS teachers' total salaries increase as they gain experience teaching in district schools. The average amount of teachers' total salaries paid as one time bonuses (depicted in green) and as base-building salary incentives (depicted in light orange) appears roughly similar across the range of teacher experience.

It is important to note that the share of teachers' salaries comprised of base-building incentives does increase with experience for teachers with zero to six years of experience. This is likely due to the fact that these teachers were automatically enrolled in ProComp when they started teaching in the Denver Public Schools. For these teachers, the only route to salary growth is to accumulate base-building incentives, so teachers with more experience are likely to have had more years to earn base-building incentives. Most teachers with more than six years of experience could have chosen to opt into ProComp at any point after 2005–06, so we do not see any consistent trend with experience. In other words, teachers with a certain amount or range of experience—for example, veteran teachers with the most teaching experience—do not receive disproportionately large ProComp bonuses relative to their less experienced peers. Other research on ProComp aligns with these findings (see the yellow breakout box on pp. 8–9).

ProComp is a complex system that pays teachers different amounts for a variety of reasons (see the blue box on p. 7 for an overview of ProComp bonuses). For ease of exposition, we created two classifications to categorize the ProComp incentives that are paid out as one-time bonuses.[9] In the first classification, we differentiate between bonuses that are paid based on an assessment of performance (e.g., teaching in a school with exceptional growth in student achievement), as compared with bonuses associated with teachers' assignments or positions (e.g., teaching in a hard-to-staff grade or subject).

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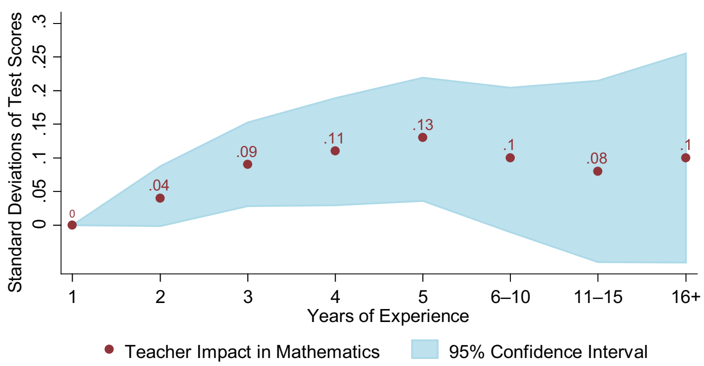
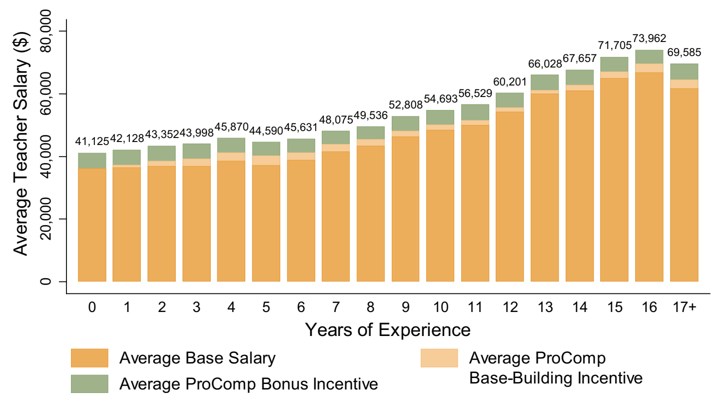
ANALYSES: EVALUATION/COMPENSATION

Figure 1. Average Within-Teacher Impact on Student Achievement in Mathematics, Compared to First-Year Teachers in Elementary and Middle Schools



Note. Sample includes teachers in the 2010–11 through 2012–13 school years, with teacher job codes and teacher effects estimates who are linked to Grade 4 through Grade 8 students with 965 teacher years and 519 unique teachers. Teacher effects are average within-teacher gains compared to novice teachers. All data are from DPS administrative records.

Figure 2. Average Total Salary of Classroom Teachers, by Total Years of Experience



Note. Sample includes teachers with teacher job codes in 2009–10 through 2011–12, with 8,879 teacher years and 4,075 unique teachers. All data are from DPS administrative records.

ProComp Bonus Overview

Implemented in 2006, Denver's ProComp is a complex array of incentives meant to reward teachers for their accomplishments, motivate teachers to strengthen their instructional practice, and help ensure that teachers are equitably distributed across district schools. The table below identifies the incentives that are paid out as one-time bonuses and groups them into two classifications systems that we created and refer to throughout this report. ProComp also includes incentives that are paid out in base-building increments, meaning that they continue to contribute to a teacher's annual salary after the initial payout. A more detailed overview of ProComp can be found here: http://www.denverprocomp.org

BONUS NAME	CLASSIFICATION I	CLASSIFICATION II
Hard-to-Staff	Position	Individual
Hard-to-Serve	Position	School
Exceeds Expectations	Performance	Individual
Met One Student Growth Objective (SGO)	Performance	Individual
Top Performing School	Performance	School
Growth School	Performance	School
Professional Development Units (Bonus)	Other	Individual
Tuition/Student Loan Reimbursements	Other	Individual

Comparing Salaries Under ProComp and the Single Salary Schedule

Colleagues at the Center for Education Data & Research have recently published research on ProComp's effects on student achievement (e.g., Goldhaber & Walch, 2012). In addition to the findings published in their report, Dan Goldhaber and Joe Walch have also investigated the degree to which teacher compensation under the ProComp system differed from compensation under the single salary schedule (SSS). With the authors' permission, we summarize their findings below.

For this comparison, Goldhaber and Walch constructed a sample of 945 teachers who opted into ProComp during the first opt-in window in 2005–06.[10] In each school year from 2005–06 to 2009–10,[11] the authors compared these teachers' actual earnings under ProComp with the hypothetical salaries they would have earned under the SSS in effect during these years.[12] The key takeaway from their analysis is that teachers' actual salaries were slightly higher, but overall quite similar, to the salaries they would have earned under the SSS.

In Table 1, they report the relationship between the dollars teachers earn under each salary system (the Pearson correlation) and the relationship between teachers' rank in the salary distribution under each system (the Spearman correlation). Across all years presented in the table, both types of correlations are generally high (i.e., over 0.9), indicating that, while teachers are being compensated via an alternative pay system, their compensation rank and total amount largely mirror those from the SSS system.

Table 1. Correlation Between ProComp Salary and Hypothetical Salary Under SSS

	Pearson Correlation	Spearman Correlation	*N*
2006	0.99	0.98	945
2007	0.99	0.98	847
2008	0.98	0.96	761
2009	0.94	0.92	687
2010	0.94	0.91	630

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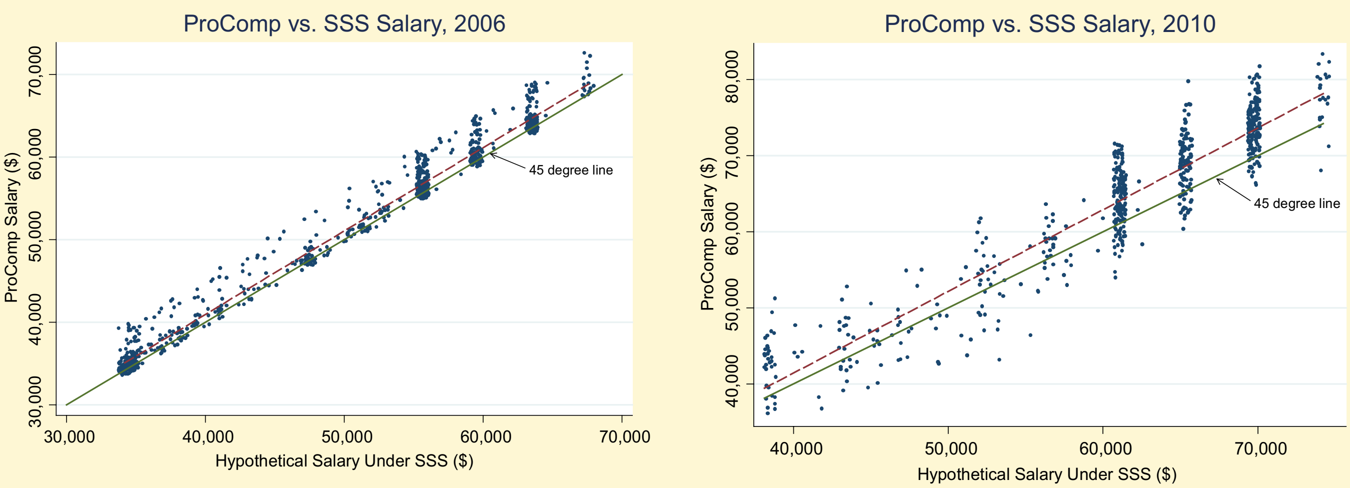
ANALYSES: EVALUATION/COMPENSATION

In Figure 2.1, Goldhaber and Walch present this relationship graphically for the first (2005–06) and last (2009–10) years in the authors' data. Were teachers' salaries the same under the ProComp and SSS systems, all teachers would lie on the solid 45 degree line. The dashed line represents the predicted ProComp salary from a linear regression of ProComp salary on SSS salary. In both years, the fitted line is above the 45 degree line, indicating that, on average, teachers had higher salaries under ProComp than they would have earned under the SSS. In 2006, the dashed fitted line is nearly parallel and quite close to the solid 45 degree line while the gap between lines is greater in 2010. There is also a higher degree of divergence in salaries in 2010, as shown by the increased spread of points, which echoes the drop in the correlations presented in Table 1.[13] From 2006 to 2010 the average absolute value of the difference in salary between ProComp and the SSS increases from about $1,000 to over $4,000; DPS policymakers must determine whether this magnitude of difference is in accordance with the theory of action undergirding the ProComp system.

Figure 2.1 Relationship Between ProComp Salary and Hypothetical Salary Under SSS, 2006 and 2010



Bonuses that fall into neither category—such as receiving tuition reimbursements—are identified as other in this classification system. In our second classification system, we differentiate between bonuses that are paid to the individual teacher as compared with bonuses that are paid to all teachers in a school. The analyses that follow refer to either or both of these classifications.

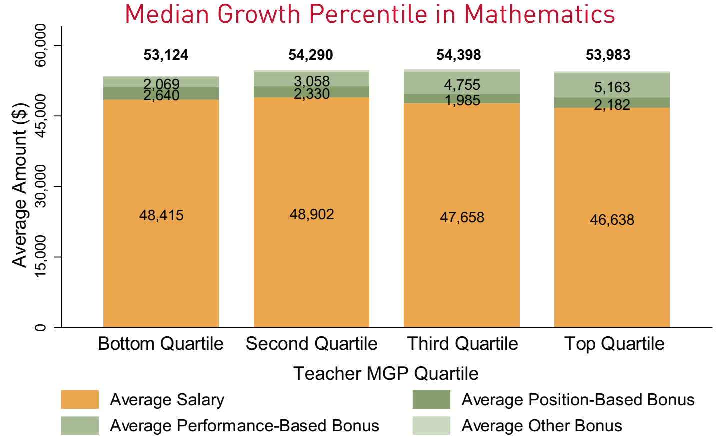
To further investigate which DPS teachers receive which types of ProComp bonuses, we examined whether math teachers'[14] average salaries differed depending on their MGP (a measure of the gains on standardized assessments of students in particular teachers' classes). This analysis allowed us to explore whether math teachers with higher MGPs received more, on average, in the form of ProComp bonuses than their peers with lower MGPs. Using DPS' MGP measure, we grouped mathematics teachers into four quartiles (i.e., those in the top quartile had the most student growth, those in the bottom quartile, the least) and then compared their average salaries and bonuses.

As Figure 3 reveals, DPS math teachers' average total salary differed little across the MGP quartiles. It is important to note that this would not be the case if more experienced DPS math teachers were associated with greater gains in student achievement. Given that more experienced teachers earn higher salaries (see Figure 2), if experienced math teachers had higher MGPs than their less experienced peers, the average salary (depicted in orange) of top MGP quartile teachers would be greater than the average salary of bottom quartile teachers.

While math teachers' total salary was similar across MGP quartiles, Figure 3 also reveals that teachers in the top MGP quartile received more of their salary through ProComp bonuses, particularly performance-based bonuses. Specifically, DPS teachers in the top-quartile of MGPs received an average of $5,163 in performance-based bonuses; teachers in the bottom MGP quartile received $2,069, on average, for the same bonuses. The story was somewhat different for position-based bonuses, such as those the district pays to teachers for filling vacancies in hard-to-staff positions. Math teachers in the bottom MGP quartile received about $500 more than top quartile teachers ($2,640 as compared with $2,182), on average, for position-based ProComp bonuses.

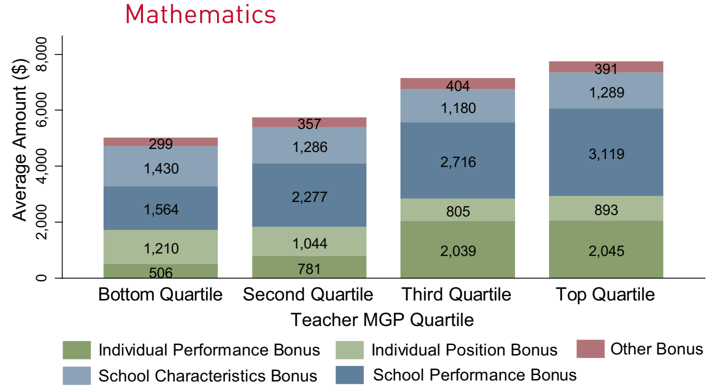
We conducted a series of more fine-grained analyses to gain additional insights into the types of bonuses that math teachers in different MGP quartiles receive. Figure 4 focuses solely on teachers' ProComp bonuses, removing

Figure 3. Average Classroom Teacher Salary, by Teacher Median Growth Percentile in Mathematics



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2010–11 through 2011–12, for whom student growth percentile data were available, with 838 teacher years and 565 unique teachers. All data are from DPS administrative records.

Figure 4. Average Classroom Teacher ProComp Bonus, by Teacher Median Growth Percentile in Mathematics

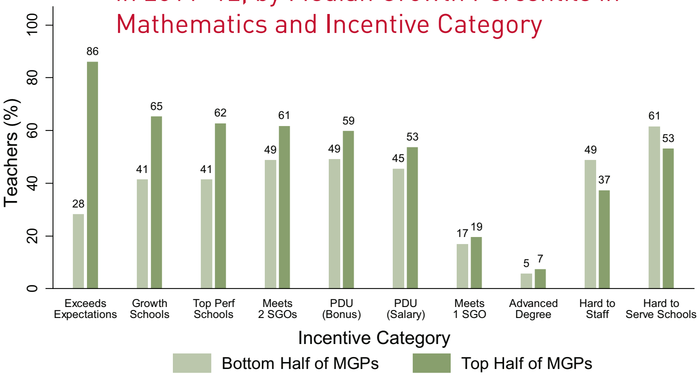


Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2010–11 through 2011–12, for whom student growth percentile data were available, with 838 teacher years and 565 unique teachers. Individual performance bonuses include Exceeds Expectations and Meets One SGO. Individual position bonuses include Hard-to-Staff bonuses. School-based performance bonuses include Growth Schools and Top Performing Schools bonuses, and school characteristics bonuses include Hard-to-Serve bonuses. Other bonuses include PDU, tuition and loan reimbursements, and manual adjustments. All data are from DPS administrative records.

the average salary information depicted in prior figures. Figure 4 reveals that math teachers in the top two MGP quartiles received more, on average, for performance-based ProComp bonuses, both for their individual and school performance. Specifically, per year, the district paid top quartile math teachers $2,045 and $3,119, on average, for individual and school performance bonuses, respectively. By comparison, math teachers in the bottom MGP quartile received annual payouts of $506 and $1,564, on average, for the same bonuses.

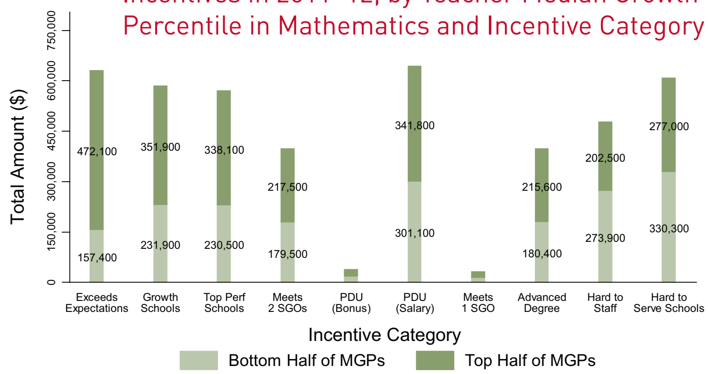
ANALYSES: EVALUATION/COMPENSATION

Figure 5. Share of Teachers Receiving ProComp Incentives in 2011–12, by Median Growth Percentile in Mathematics and Incentive Category



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2011–12, for whom student growth percentile data were available, with 401 teacher years and 401 unique teachers. PDU (bonus) refers to one-time bonuses paid out to teachers with more than 14 years of experience. Other bonuses include tuition and loan reimbursements, and manual adjustments. All data are from DPS administrative records.

Figure 6. Estimated Net Present Value of ProComp Incentives in 2011–12, by Teacher Median Growth Percentile in Mathematics and Incentive Category



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2011–12, for whom student growth percentile data were available, with 401 teacher years and 401 unique teachers. PDU (bonus) refers to one-time bonuses paid out to teachers with more than 14 years of experience. Other bonuses include tuition and loan reimbursements, and manual adjustments. DPS Pension Contribution Multiplier = 1.1375 and Discount Rate = .05. All amounts rounded to the nearest 100. All data are from DPS administrative records.

Interestingly, we did not see sizeable differences across the MGP quartiles in the average annual amount the district paid for teaching in hard-to-serve schools with high concentrations of students in poverty (depicted in light blue). Thus, while top quartile teachers were more likely to receive school-based performance bonuses, it did not appear that they were substantially less likely to teach in schools that DPS has designated as being hard to serve.

To examine the relationship between teachers' MGPs and the various ProComp incentives, we examined whether the percentage of teachers who received incentive payments differed according to their MGP. Figure 5 depicts the percentage of teachers who received each incentive in 2011–12, for teachers in two different groups: those whose mathematics MGPs were in the top and bottom half of the distribution. The relative height of the bars within each category reveals that the district awards some incentives much more frequently than others. For example, regardless of their MGP, few math teachers earned an advanced degree or received the Meets One SGO incentive on an annual basis while many teachers received payments for the following types of incentives: Exceeds Expectations, Growth Schools, and Top Performing Schools. Second, DPS awarded some incentives much more frequently to teachers with high MGPs relative to those with low MGPs, or vice versa. For example, 86% of teachers in the top half of MGPs received an Exceeds Expectations bonus, while 28% of bottom half teachers received the same bonus. Other bonuses, such as Hard-to-Staff and Hard-to-Serve, were more likely to be awarded to math teachers whose MGPs were in the bottom half of the distribution. The analogous analysis for reading teachers (see Appendix) yields generally consistent results with the exception that the Professional Development Units (PDU) bonus was awarded to more reading teachers whose MGPs were in the bottom half.

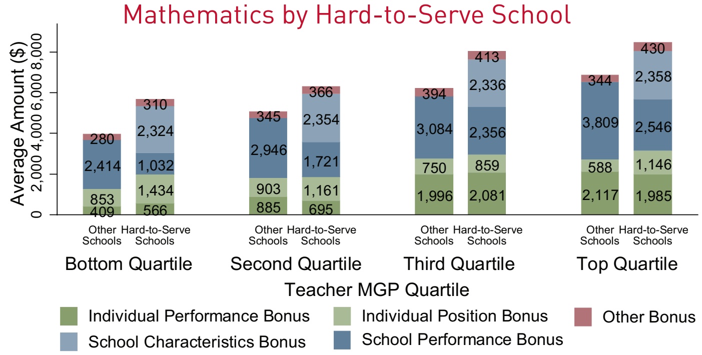
In Figure 6, we present the estimated amount of money that DPS committed to paying for incentives earned in the 2011–12 school year.[15] As shown in Figure 6, DPS awarded five incentives that each cost the district over $500,000 in net present value: Exceeds Expectations, Growth Schools, Top Performing Schools, Professional Development Units Base Building, and Hard-to-Serve Schools. Two incentives cost less than $50,000: the PDU bonus, and Meets One SGO bonus. See the Appendix for the analogous figure for reading teachers.

Extending this line of inquiry further still, in Figure 7, we grouped math teachers into quartiles based on their MGP and then subdivided them into two additional groups: 1) teachers who taught in hard-to-serve schools and 2) those who taught in other schools (i.e., schools not classified as hard-to-serve).[16] Figure 7 depicts several findings of note. First, as we would anticipate if the Hard-to-Serve bonus were functioning as designed, within each MGP performance quartile, the district pays more, on average, to math teachers with assignments in hard-to-serve schools than to teachers in non-hard-to-serve schools. The higher average bonus for teachers in hard-to-serve schools appears to be driven by three factors: 1) These teachers received the "school characteristics" bonus for teaching in hard-to-serve schools; 2) some taught in high-performing hard-to-serve schools and, thus, earned school performance bonuses in addition (albeit in smaller sums than their colleagues who taught in schools that were not designated hard-to-serve); and 3) teachers in hard-to-serve schools were slightly more likely to receive bonuses for teaching in hard-to-staff positions, such as secondary math and special education teaching positions. Related to teachers' individual performance, Figure 7 reveals that math teachers in the top two MGP quartiles received about $1,000 more per year, on average, in the way of individual performance bonuses than teachers in the second quartile, and about $1,500 more than teachers in the bottom MGP quartile.

It can also be instructive to look across the MGP quartiles to compare the average total amount of ProComp bonuses that teachers in different schools and at different MGP levels receive. For instance, math teachers in the top MGP quartile who did not teach in hard-to-serve schools earned, on average, $1,500 more per year in total ProComp bonus (i.e., the sum of all the bonuses that Figure 7 depicts) than bottom quartile teachers in hard-to-serve schools. It remains an open question whether an average difference of this size represents enough of an incentive to influence teacher behavior and help DPS optimize how teachers are allocated across the district's schools.

One potential policy lever that the Hard-to-Serve bonus might offer is the ability to reduce turnover in schools that serve high concentrations of students from minority and poverty backgrounds. While a comprehensive analysis examining whether the Hard-to-Serve bonus reduces teacher turnover is beyond the scope of this project, our exploratory analyses found some evidence that schools just above the cut-point for receiving the Hard-to-Serve bonus had somewhat higher retention rates than schools

Figure 7. Average Classroom Teacher ProComp Bonus, by Teacher Median Growth Percentile in Mathematics by Hard-to-Serve School



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2010–11 through 2011–12, with 838 teacher years and 565 unique teachers. Individual performance bonuses include Exceeds Expectations and Meets One SGO. Individual position bonuses include Hard-to-Staff bonuses. School-based performance bonuses include Growth Schools and Top Performing Schools bonuses. School characteristics bonuses include Hard-to-Serve bonuses. Other bonuses include PDU, tuition and loan reimbursements, and manual adjustments. All data are from DPS administrative records.

just below the cut-point.[17] In light of findings described earlier, it is important to keep in mind that hard-to-serve schools are staffed by a greater share of teachers whose MGPs are in the bottom quartile; thus, while increasing teacher retention in these schools may have some benefits, it may also have some costs if the district is paying bonuses to teachers who are not adept at raising students' performance. It is important to note, however, that we cannot disentangle whether lower average MGPs of teachers in hard-to-serve schools stems from these teachers being less capable practitioners or from teaching students whose performance is harder to raise (or any number of other factors that might influence teachers' MGPs, such as their schools' working conditions).

Additional research on this topic could help inform an important discussion about whether the benefits of any increases in teacher retention outweigh the costs associated with paying the Hard-to-Serve bonus to all teachers in these schools. Moreover, this line of analysis might also help the district consider whether to modify how it pays the Hard-to-Serve bonus, such as by tying it to a certain length of stay in schools or to teachers' MGP.

Retention/Turnover

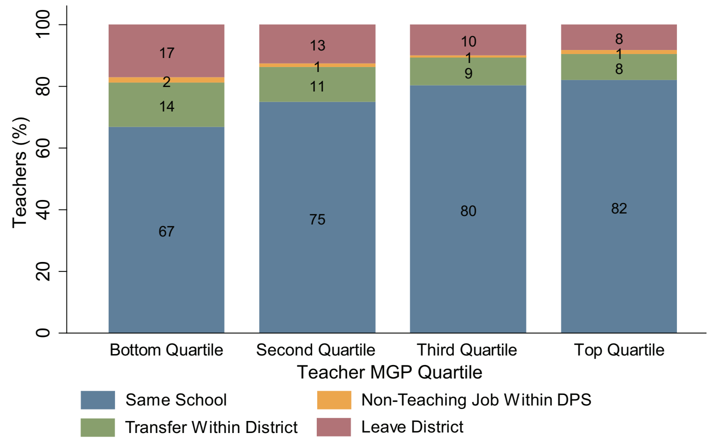
Analyses of teacher retention and turnover can help agencies identify patterns in teachers' movements into, across, and out of the district, which can, in turn, inform numerous human capital policies. In examining overall retention rates in DPS over time, we found that retention differed slightly over five recent cohorts of new hires. Specifically, 79% of the new teachers hired during the 2010–11 school year remained in district teaching assignments for a second year, compared to 74% of those hired in 2006–07. Looking three years out from the point of hire, 51% of those hired in 2010–11 and 53% of teachers hired in 2006–07 remained in district teaching assignments. Putting DPS' retention rates in context with eight other districts where SDP has conducted similar analyses,[18] DPS' 79% one-year retention rate is generally on-par with retention in other districts; DPS' roughly 50% three-year retention rate is lower than retention in five districts, comparable to two, and higher than one.

When considering the policy implications of turnover and retention, it is critical to consider which teachers leave and where they go. Figure 8 examines how one-year teacher retention rates vary for math teachers[19] in different MGP quartiles. The figure reveals that 90% of top-quartile math teachers remained teaching in DPS from one year to the next, as compared with 81% of teachers with MGPs in the bottom quartile. However, bottom-quartile math teachers were more inclined to transfer between Denver schools (14%) than their top-quartile counterparts (8%), which may have negative consequences for the schools into which bottom-quartile teachers transfer.

It is also important to consider these retention rates in absolute terms. While the districtwide retention rate among top-quartile math teachers was high (90%), roughly 17% of these teachers were not teaching in the same school from one year to the next (8% transferred between schools, 8% left the district, and 1% secured non-teaching jobs in DPS). How do these departure rates compare with the target retention rates that DPS would like to achieve in order to fulfill its educational objectives? Nineteen percent of bottom-quartile math teachers left teaching in the district. Is this rate higher, lower, or on-par with DPS' intended trajectories for its bottom-quartile math teachers?

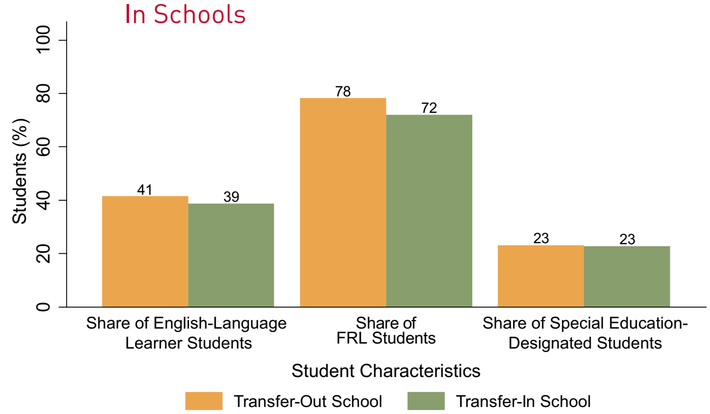
In one final series of retention-related analyses, we examined the characteristics of the schools that teachers leave and enter when they transfer between district schools. Figure 9 reveals that teachers transferred into schools where the share of FRL students was about 6% lower than in the schools they left (i.e., 72% FRL as compared with 78%). We also found that teachers transferred to where students had slightly higher average math and reading achievement (not shown).[20]

Figure 8. One-Year Classroom Teacher Retention Outcomes, by Teacher Median Growth Percentile in Mathematics



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2010–11 through 2012–13, for whom student growth percentile data were available, with 1,490 teacher years and 799 unique teachers. All data are from DPS administrative records.

Figure 9. Characteristics of Transfer-Out and Transfer-In Schools



Note. Sample includes teachers with teacher job codes in 2010–11 through 2012–13, with 741 teacher years and 684 unique teachers for whom student growth percentile data were available. Student demographic averages are based on 2010–11 and 2011–12 student-level data for elementary and middle schools and 2009–10 and 2010–11 student-level data for high schools. All data are from DPS administrative records.

CONCLUSION

Conclusion

In describing numerous facets of DPS' human capital system, the results from this diagnostic can help DPS policymakers continue to refine their human capital management system to serve the district's ultimate goals of promoting students' growth and development. This work comes at an important moment in the district's development, with student enrollment increasing rapidly and the district in the process of implementing LEAP—its new, multiple-measure teacher evaluation system (http://leap.dpsk12.org/LEAP-Components/Overview).

This analysis raises a number of findings that may have important policy implications for DPS. For example, our discovery that teachers' impact on student achievement appears to plateau after five years of classroom teaching may prompt DPS administrators to strategize about how to alter this trajectory. Would targeting professional development or specific opportunities for growth and leadership to at this stage in their tenure lead to increasing returns to experience? If so, what opportunities do teachers at this stage need to continue their growth and development?

One of the most striking findings from this study is also one of the most general—that the ProComp system, while innovative in many ways, largely mirrors that compensation that teachers receive under traditional step-and-lane systems, such as Denver's previous single salary schedule. Under ProComp, teachers receive bonuses and base-building incentives for many different services and accomplishments. However, if DPS teachers with similar experience and credentials earn within $1,000 to $2,000 of their peers, on average, regardless of their MGP, their service in hard-to-serve schools, etc., how likely is it that ProComp will prompt any number of desirable behavior changes, such as staying in one's school longer or strengthening one's teaching practice?

A final finding of note is that some ProComp incentives are positively related to teachers' MGPs, some are negatively related, and some are not particularly related at all. We would expect to see a positive relationship for bonuses that award teachers' individual performance. Perhaps more notable is that teachers with higher MGPs are less likely to receive the Hard-to-Staff and Hard-to-Serve Schools bonuses, and roughly the same percentage of teachers with MGPs in the top and bottom half of the distribution receive the Advanced Degrees and Meets One Student Growth Objective incentives. DPS administrators, practitioners, and public education stakeholders may find this evidence useful in helping to assess the degree of alignment between compensation and the district's objectives.

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ENDNOTES

1 Implemented in 2005–06, ProComp is a bargained agreement between the Denver Classroom Teachers Association and DPS designed to link teacher compensation more directly with the district's mission and goals.

2 It is important to note that our preliminary analyses only investigate the relative costs for payments to math and English language arts teachers. A district-wide analysis is critical for determining the total costs of the various ProComp incentives.

3 For examples of SDP's research on teacher effectiveness with other agencies, see: http://cepr.harvard.edu/sdp/diagnostics/published-findings.php

4 Roughly the equivalent of seven to eight months of mathematics learning.

5 SDP used DPS' estimated teacher experience variable for this and other analyses in the diagnostic. DPS reports that this new approximation of teachers' experience is more accurate and reliable than their previous measure. DPS can provide a thorough explanation of their estimation approach. In summary, DPS bases teachers' experience on the paygrade "step" (based on years of prior teaching experience and validated by district HR data management) that teachers are assigned when they opt-in or are automatically enroll in ProComp. To estimate teachers' experience on a date of interest, DPS identifies the elapsed years of service between the Procomp start date and the date of interest. This method may underestimate years of experience for teachers who have not opted in to ProComp, and for teachers who entered DPS with more than 10 years of prior teaching experience.

6 This report refers to two related but distinct teacher effectiveness outcomes: teachers' value-added and their median growth percentiles. Typically, SDP uses value-added when performing analyses that are part of our core Human Capital Diagnostic. Using a consistent methodology allows us to benchmark findings across agencies, which our partners report finding valuable. Thus, for the analyses that are usually conducted as part of our Human Capital Diagnostic (Figures 1 and 10), we use value-added. However, we also present many customized analyses related to the DPS ProComp system. For these analyses, we report teachers' median growth percentiles (MGPs), as MGPs are the district's preferred measure of teachers' impact on student achievement and, thus, the one with which DPS practitioners and policymakers are most familiar.

7 Conversion of effect sizes to months of learning used throughout this report is based on Hill, Bloom, Black, and Lipsey (2008).

8 Estimates of teacher effects by level of experience are based on a value-added model with teacher fixed-effects. In order to identify average within-teacher growth in effectiveness over time, we group teachers into experience categories. For the first five years of experience, the categories contain a single year of experience (e.g., the first category is all teachers with one year of experience). Due to smaller sample sizes, after five years of experience we group the teachers into categories with more than a single year of experience (e.g., teachers with six to 10 years of experience). Since we control for between-teacher time-invariant differences (i.e., teacher fixed-effects), our estimate of returns to experience is based only on differences as teachers move from one experience group to another. In this analysis, the following number of mathematics teachers move between the higher experience categories: five to six years of experience, 40 teachers; 10 to 11 years of experience, 16 teachers; 15 to 16 years of experience, 30 teachers.

9 The one-time bonuses are more prevalent than the base-building incentives and are, thus, the primary focus for many of our analyses.

10 Goldhaber and Walch's (2012) sample is drawn from administrative records from DPS. The researchers included employees with a teacher job code who are coded as opting into ProComp during the first opt-in window (November 11–December 31, 2005) and for whom they had SSS step-and-lane data (or data on years of prior teaching experience and degree level to infer step-and-lane).

11 The 2009–10 school year was the last year of data available to the researchers at the time they were analyzing the data for their study.

Continued on next page.

ENDNOTES CONTINUED

[12] Specifically, they calculated teachers' annual salary under ProComp by adding to the base salary the value of all the ProComp awards (one-time bonuses and base-building incentives) earned by each teacher. In calculating teachers' hypothetical salaries under the SSS, the authors assumed that teachers advanced a single step in each year and remained in the same lane unless they were coded in the dataset as having earned an advanced degree. For teachers with missing values for step, the researchers inferred using the teacher's prior years of experience; for teachers missing values for lane they coded teachers with a value of 1 for the "master's degree or higher" variable as being in the M.A. lane and code teachers with a value of 0 in the B.A. lane. They used the DPS 2006–07 salary schedule to compute the ProComp base salary and salaries under SSS in 2006, 2007, and 2008; the DPS 2008–09 salary schedule to compute SSS salaries in 2009; and the DPS 2009–10 salary schedule to compute SSS salaries in 2010. The researchers' dataset included an indicator for whether a teacher earned a ProComp bonus for an advanced degree, and teachers in a B.A. lane who were coded as receiving an advanced degree were bumped up into the M.A. lane. The researchers were unable to determine from their data whether teachers already in an M.A. lane who were flagged as earning an advanced degree (approximately 2% of the sample) earned an additional master's degree or a doctorate, but they assumed they remained on the same M.A. lane.

[13] Because many teachers had the same value for salaries, the researchers spaced the points that fall directly on top of each other in Figure 2.1 to show up as clumps of points rather than a single point.

[14] We conducted the same analysis for reading teachers and found similar results. For parsimony, we only present the results for math teachers in this brief.

[15] For one-time bonuses (e.g., Exceeds Expectations), the amount committed is simply the total amount of the bonuses plus an estimate of additional pension obligations. For base-building incentives, the amount committed is an estimate of the sum of the base-building amount over all the years that the teacher is expected to receive the base-building amount, plus additional pension obligations. Our estimate of DPS's pension contribution is 13.75% but is an underestimate of the true pension contribution since variable amortization equalization disbursements (AEDs) and supplemental amortization equalization disbursements (SAEDs) are not included. Future obligations are discounted back to the net present value using a discount rate of 5%.

[16] See Table 2 in the Appendix for the number of teachers in these schools, by MGP quartile.

[17] To determine which schools receive the Hard-to-Serve bonus, DPS first groups schools into grade-level categories (i.e., elementary, middle, high) and then identifies schools within each group where the percentage of the student body qualifies for free or reduced-price lunch is greater than the median. The district awards the Hard-to-Serve bonus to all of the teachers in these schools.

[18] SDP's Strategic Performance Indicators benchmark the findings from analyses across partners. For more information about the indicators and specific partners, please see http:/cepr.harvard.edu/sdp/diagnostics/spi/index.php

[19] We conducted a parallel analysis for reading teachers and found similar results.

[20] Math teachers transferred to schools where students had roughly four to five more months of learning in mathematics than the students in the schools they transferred from. Reading teachers transferred to schools where students had roughly five more months of learning in reading. These average differences in FRL status, math tests, and reading tests were statistically significant at the 5% level.

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REFERENCES

Auge, K. (2012, October 15). Denver is fastest growing large urban school district in the U.S. The Denver Post. Retrived from http://www.denverpost.com/ci_21777322/denver-is-fastest-growing-large-urban-school-district

Chetty, R., Friedman, J.N., & Rockoff, J.E. (2011). The long-term impacts of teachers: Teacher value-added and student outcomes in adulthood (NBER Working Paper No. 17699). Retrieved from http://www.nber.org.ezp-prod1.hul.harvard.edu/papers/w17699.pdf?new_window=1

Goldhaber, D., & Walch, J. (2012). Strategic pay reform: A student outcomes-based evaluation of Denver's ProComp teacher pay initiative. Economics of Education Review, 31, 1067–1083.

Hill, C.J., Bloom, H.S., Black, A.R., & Lipsey, M.W. (2008). Empirical benchmarks for interpreting effect sizes in research. Child Development Perspectives, 2(3), 172–177.

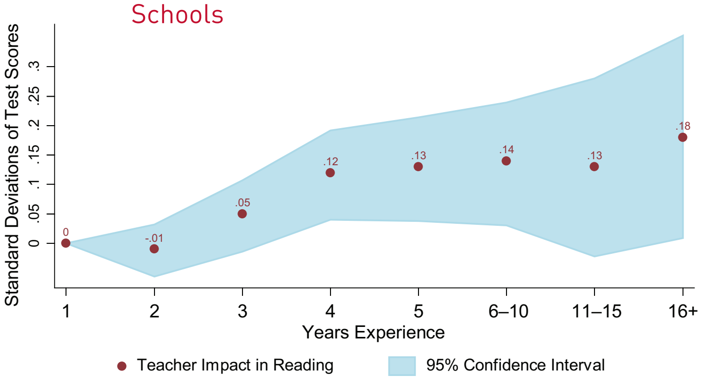
Rivkin, S.G., Hanushek, E.A., & Kain, J.F. (2005). Teachers, schools, and academic achievement. Econometrica, 73(2): 417–458.

Rockoff, J.E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. American Economic Review, 94(2), 247–252.

Wright, S. P., Horn, S. P., & Sanders, W. L. (1997). Teachers and classroom context effects on student achievement: Implications for teacher evaluation. Journal of Personnel Evaluation in Education, 11, 57-67.

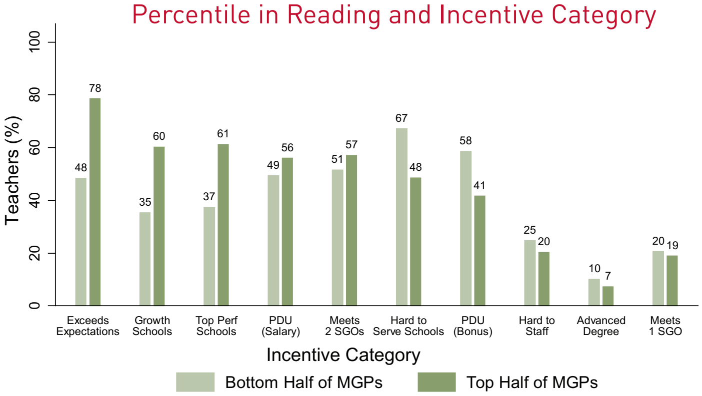
APPENDIX

Figure 10. Average Within-Teacher Impact on Student Achievement in Reading, Compared to First-Year Teachers in Elementary and Middle Schools



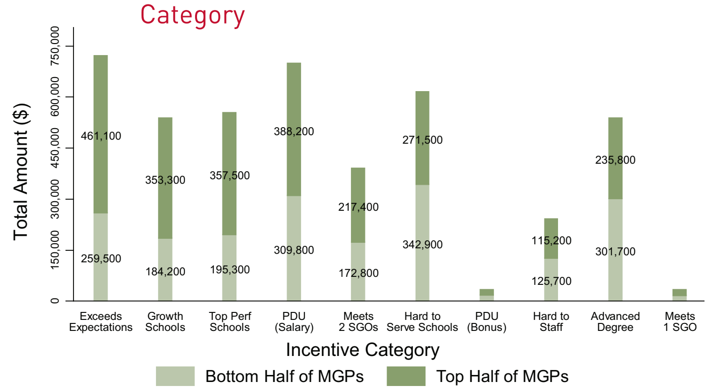
Note. Sample includes teachers in the 2010–11 through 2012–13 school years, with teacher job codes and teacher effects estimates who are linked to Grade 4 through Grade 8 students with 911 teacher years and 508 unique teachers. Teacher effects are average within-teacher gains compared to novice teachers. All data are from DPS administrative records.

Figure 11. Share of Teachers Receiving ProComp Incentives in 2011–12, by Median Growth Percentile in Reading and Incentive Category



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2011–12, for whom student growth percentile data were available, with 404 teacher years and 404 unique teachers. PDU (bonus) refers to one-time bonuses paid out to teachers with more than 14 years of experience. Other bonuses include tuition and loan reimbursements, and manual adjustments. All data are from DPS administrative records.

Figure 12. Estimated Net Present Value of ProComp Incentives in 2011–12, by Teacher Median Growth Percentile in Reading and Incentive Category



Note. Sample includes teachers with teacher job codes of students in Grade 4 through Grade 8 in 2011–12, for whom student growth percentile data were available, with 404 teacher years and 404 unique teachers. PDU (bonus) refers to one-time bonuses paid out to teachers with more than 14 years of experience. Other bonuses include tuition and loan reimbursements, and manual adjustments. DPS Pension Contribution Multiplier = 1.1375 and Discount Rate = .05. All amounts rounded to the nearest 100. All data are from DPS administrative records.

Table 2. Number of Teachers in Hard-to-Serve Schools, by Median Growth Percentile Quartile

	MATH TEACHERS		READING TEACHERS	
MGP Quartile	Number of Teachers in HTS Schools	Number of Teachers in non-HTS Schools	Number of Teachers in HTS Schools	Number of Teachers in non-HTS Schools
1	211	118	237	115
2	169	146	203	159
3	162	165	157	150
4	172	159	142	196

NOTES

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