Essential Programs and Services Component Review, FY2021

Final Report and Synthesis of Findings

Report to

Maine Department of Education

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Essential Programs and Services Component Reviews, FY2021
Final Report and Synthesis of Findings

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Syntheses and Summary of Reports

The Essential Programs and Services (EPS) funding formula is designed to estimate the minimum amount of money a school district needs to have in order to provide the programs and services necessary to enable all students have an equitable opportunity to achieve the Maine Learning Results standards. The model for determining this "total allocation" amount includes the recommended student-to-staff ratios, per pupil amounts for supplies and equipment, specialized services (e.g., professional development, student assessment, technology, instructional leadership support, co-curricular and extracurricular student learning) and district services (e.g., transportation, facilities management). The total amount is largely driven by district enrollment, which is adjusted for circumstances that have been determined to increase costs, such as differentiated populations including students with limited English proficiency, economically disadvantaged students and students with special needs. The EPS formula also adjusts personnel costs for differences in staff experience and education and regional differences in the cost of education as well as small school size and remote location.

By statute (Title 20-A, Section 15686-A), the EPS cost model is reviewed on an ongoing basis with technical support from the Maine Education Policy Research Institute. Our data analyses inform any updates or improvements that may be needed to maintain adequate funding allocations as conditions in our public schools change over time. Each major component of the model is reviewed in a standard three-year cycle; the Commissioner of Education has the flexibility to adjust the review schedule provided that each element is analyzed at least once every four years. MEPRI technical reports for each individual component are prepared for the Commissioner of Education, who then considers which elements should be updated. Some elements are under the Commissioner's discretion to change; others require legislative action, in which case the Commissioner prepares recommendations for the Education Committee to consider.

The full "reports of findings" that follow this introduction are the complete analyses that were delivered to the Commissioner under the contract for FY20201. These technical reports contain substantial detail. Because those analyses are lengthy, the summary table below is directed at policymakers and highlights the most significant findings across all of the FY2021 technical reports that may require future attention.

Summary of Major Findings

Major Findings	Recommendation & Cost Estimate(s)
Salary Matrices	
• Teacher salaries have increased at a greater rate than consumer inflation, and thus the amount allocated in the salary matrix is inadequate. • The teacher salary matrix has become more compressed over time; there is less of a spread from beginning, bachelor's degree teachers to experiences, advanced-degree holders.	The base salary needs to be increased to provide adequate funding. The index values of the teacher salary matrix also need to be updated at the same time the base salary is increased (including some streamlining of categories) in order to prevent overestimation at the higher end of the scale. The index values should be recalculated in summer 2022 to affirm their stability. **Cost: Significant**. Depends on selected base salary scenario (see spreadsheet). The statutory minimum teacher salary in FY2023 is $40,000. We recommend adjusting this base by the latest year of inflation, per standard practice, for FY2024 allocations.
• While salaried specialists (guidance counselors, social workers, librarians) earn slightly more on average than teachers, the difference may be due to regional variation rather than the labor market.	Additional study of staff salaries in the next cyclical review to compare pay of different professional job categories within districts. This will determine whether a separate salary matrix is appropriate and feasible.
• Educational technicians are the reverse of teachers. The base salary is adequate, but the range of index values has increased. Library media technicians should be combined into the educational technician matrix.	Update index values to reflect higher salaries for experienced Ed Tech IIIs compared to Ed Tech IIs. No change recommended to base salary. **Cost: Significant**.
• Administrator salaries have narrowed in spread, with relatively higher salary increases in schools with lower enrollments and flatter pay increases at the top size categories.	The matrix should be updated to consolidate some categories, and update index values. The base salary should be increased by 5.5%. **Cost:** TBD; needs to be modeled. Narrowing of the index values will somewhat offset the increased base salary.

<table>
<tr><td>Major Findings</td><td>Recommendation & Cost Estimate(s)</td></tr>
<tr><td colspan="2">School Staff Benefit Percentages</td></tr>
<tr><td>Since the inception of the EPS funding formula, the cost of providing benefits to public school staff has increased faster than increases in salaries. The percentages of salaries that are allocated to fund benefits are therefore inadequate. This pattern has been persistent over time and is consistent with national trends, in particular for rising health care costs.
Additional study is warranted to analyze the variation in benefit ratios across Maine school districts. If variation is large, then using state average percentages for each staff category may not be an optimal way to model these costs. For example, a fixed per-staff amount for benefits may be a better fit for adequacy, and thus avoid under- and over-funding in districts that are not close to the average patterns.</td><td>Benefit percentages should be increased at the same time as the updated base salaries and salary matrices for school staff positions. Cost: Significant.
Given the magnitude of the increased cost to use current state averages, additional study of district-level benefit percentage patterns should be conducted in summer 2022 to assess the degree of variation across the state. If the averages are skewed (i.e. the median benefit percentage is meaningfully lower than the average), it may be advisable to increase benefit percentages to the median value.</td></tr>
<tr><td colspan="2">Regional Adjustment</td></tr>
<tr><td>The regional adjustment indices have become out-of-date over time and are no longer adequate in some labor market areas.
The range of salaries across the state has grown over time; regional differences have increased.</td><td>The report of findings identifies various options for updating the regional index values to be closer to adequacy. The cost of the update will depend on the specific scenario that is selected. A purely mathematical update would approximately be cost-neutral because it merely re-centers the state average, but would result in substantial funding shifts (with some districts increasing allocations and a similar number of others receiving decreases). Implementing measures to constrain the spread of indices across the state and/or establish a minimum “floor” of adequacy would require additional investment.</td></tr>
</table>

Major Findings	Recommendation & Cost Estimate(s)
Staff Ratios	
• The current cost model is resulting overall in observed student-to-staff ratios that are below the EPS basic allocations. School districts are using the funds allocated in other EPS model components, such as the additional student weights or other adjustments, to invest in additional staff. Districts may also be raising additional local funds (above and beyond the EPS allocations) to further supplement their staff. • There is substantial variation in staff ratios across school districts. Across all grade levels and staff types, higher poverty schools generally have more students per staff member than lower poverty schools. The notable exception is that higher poverty elementary schools as a group have fewer students per teacher and educational technician – i.e. more favorable staff ratios. This may reflect the additional allocations those schools receive through the economically disadvantaged student weight. • While all schools report having teachers and educational technicians, some schools reported having zero of other staff categories (such as guidance, nurse / health staff, or library/media staff). This is most likely to occur in our smallest schools (fewer than 100 students) and higher poverty schools.	• Overall, the staff ratios are achieving adequate results. • No changes are recommended for teacher and education technician ratios. • Recommend lowering the staff ratio for elementary guidance to increase the number of schools employing those staff (including social workers) to support social-emotional health, with the goal of achieving staff ratios in higher-poverty schools that are at least at the level of lower-poverty schools. • Recommend additional study in small schools to understand how they are meeting students' guidance, health, and library needs without employees matching those job titles. If current staffing is inadequate, it may be advisable to add a minimum staff threshold (e.g. half-time staff member) for some position types. • Recommend additional discussion about improving or amending data collection to allow tracking teachers and educational technicians serving early grades (pre-K to 2), in order to analyze separate ratios from grades 3-5.

<table>
<tr><td>Major Findings</td><td>Recommendation & Cost Estimate(s)</td></tr>
<tr><td colspan="2">Gifted & Talented</td></tr>
<tr><td>The current expenditure-based method of allocating funding for gifted and talented (G&T) student programs is resulting in inequitable resources for economically disadvantaged students.
Economically disadvantaged students are 45% of Maine’s enrollment but only 21% of those identified as G&T in 2018.
In SY2020 and SY2021, just over half (54% and 53%) of districts reported any G&T students. Those districts had statistically lower poverty than those with zero G&T enrollment.
Those districts with G&T enrollments overall had about 5% of their enrollment identified as G&T, ranging from 0.1% to 16% across districts.
The available empirical research evidence on the impacts of participation in G&T programs is decidedly mixed. In the absence of universal testing and random assignment, rigorous research on G&T program participation is hard to do–because of selection bias, confounding factors, simultaneity—and because there is so much variation on the type, quality and intensity of G&T programming.
More exceptionally gifted students might benefit the most from dedicated G&T programs.
Universal screening may help to identify more students from disadvantaged backgrounds.</td><td>Maine should consider following the precedent set by the other New England states and reallocate G&T funding in more equitable ways, such as through a census-based mechanism like a staff ratio, rather than an expenditure-based system.
Recommend a personnel ratio in the EPS model to provide academic learning specialists who have the capacity to support students at both ends of the achievement spectrum. This would also alleviate the resource gap to Maine’s requirement for districts to provide Multi-Tiered System of Supports (MTSS).</td></tr>
<tr><td colspan="2">Small, Geographically Isolated School Adjustment</td></tr>
<tr><td>The EPS funding formula is working as intended to provide districts with small, isolated schools with additional funds. However, these districts are twice as likely to be minimum receivers, which means they must raise the additional dollars per student locally. SAUs with small and isolated schools need to raise $9,099 per student locally compared to the $5,949 that has to be raised on average by SAUs without small and isolated schools. These districts also have slightly higher rates of poverty and lower median incomes, which raises a concern as to whether they may struggle in terms of ability to pay.</td><td>No recommended changes to the EPS cost model. Recommend additional analysis of the subsidy distribution formula, and consideration of whether it is adequately providing state funds for geographically-isolated communities who need to educate students in very small schools.</td></tr>
</table>

EPS Report of Findings: Salary Matrices

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Overview

The Essential Programs and Services (EPS) funding formula is designed to estimate the minimum amount of money a school district needs to have in order to provide the programs and services necessary to enable all students have an equitable opportunity to achieve the Maine Learning Results standards. The model for determining this "total allocation" amount includes the recommended student-to-staff ratios, per pupil amounts for supplies and equipment, specialized services (e.g., professional development, student assessment, technology, instructional leadership support, co-curricular and extra-curricular student learning) and district services (e.g., transportation, facilities management). The total amount is largely driven by district enrollment, which is adjusted for circumstances that have been determined to increase costs, such as differentiated populations including students with limited English proficiency, economically disadvantaged students and students with special needs. The EPS formula also adjusts personnel costs for differences in staff experience and education and regional differences in the cost of living as well as small school size and remote location.

Personnel costs are the largest component of school expenditures. According to an analysis by the National Center of Education Statistics (NCES), salaries and benefits paid to school personnel make up 80% of all school spending (NCES, 2017).[1] Maine is no different, with nearly 75% of the state's expenditure on public education going to staff salaries and benefits (MEPRI, 2018).

Personnel costs for individual districts tend to vary depending on the profile of their staff. The EPS model adjusts a district's allocation for the educational attainment of its teachers and other educational specialists and for those with more years of professional experience. Paying higher salaries for more education and experience may help districts attract and retain staff.[2] Similarly, because districts generally pay higher salaries to administrators of larger schools, the EPS model adjusts for this also.

The EPS formula adjusts personnel costs for differences in staff and school profiles using a salary matrix. A salary matrix is a table that provides a measure of the salary differences for each category of staff based on experience and/or education, job classification or school size. The matrix is used to adjust a district's EPS allocation

[1] https://nces.ed.gov/pubs2017/2017144.pdf
[2] https://cepa.stanford.edu/content/can-district-level-teacher-salary-incentive-policy-improve-teacher-recruitment-and-retention
https://usm.maine.edu/sites/default/files/cepare/Teacher_Turnover_in_Maine_Analysis_of_Staffing_Patterns_2005-06_to_2016-17.pdf

according to the mix of education and experience levels or other cost factors such as school size or job classification of its staff. Salary matrices are developed for school-based essential staff positions including teachers, educational and media technicians, counselors and librarians, nurses, school administrators and administrative assistants. The teacher salary matrix produces a larger allocation for districts employing a greater number of teachers with higher levels of education and experience and the administrator matrix produces a larger allocation for districts employing more principals managing larger schools. A description of the calculations using the salary matrix is included in Appendix A. Salary matrices are used in the EPS formula for school personnel cost allocation only. Allocations for other costs, such as system administration, transportation, and operation and maintenance of facilities are addressed within other components of the EPS.

By statute, the EPS salary matrices are reviewed every three years. The data used to update the staff salary matrices comes from the 2019-2020 staff data file obtained from the Maine Department of Education. Districts utilize the state's NEO system to maintain a record of all employees engaged in a school's regular operations, including teaching, sports, health care, transportation, maintenance, and administration.[3] The data include an individual record for each position held by a staff member. Unique position codes and staff and school IDs enable the identification of individual staff across positons and schools. The staff record also includes information on each staff member's education and years of experience in Maine as well as FTE and salary for each position held.

In Part I of this report we provide a detailed explanation of how the salary matrices are calculated and the results of the updated analyses based on 2019-20 data. Previous salary matrices are included for comparison. In Part II we present an analysis of staff education and experience profiles across districts by district size, poverty level and rurality in order to investigate whether salary matrices are allocating funds in ways that support or undermine equity goals embedded in the EPS funding model. Part III presents analysis pertinent to Maine's recent policy change to increase minimum teacher salaries to $40,000. The increase is to be phased in over three years starting at $35,000 in 2020-21 and arriving at the full $40,000 in 2022-23. We analyzed salaries paid to teachers and other staff eligible for the new salary floor by comparing minimum salaries by education, experience, position and school type. Part III also includes descriptions of the number and percentage of staff currently earning below the minimum salaries by district size, poverty level and location to assess differential impacts of the $40,000 salary floor across district types.

[3] http://www.maine.gov/doe/data/staff/index.html

PART I

Teacher salary matrix

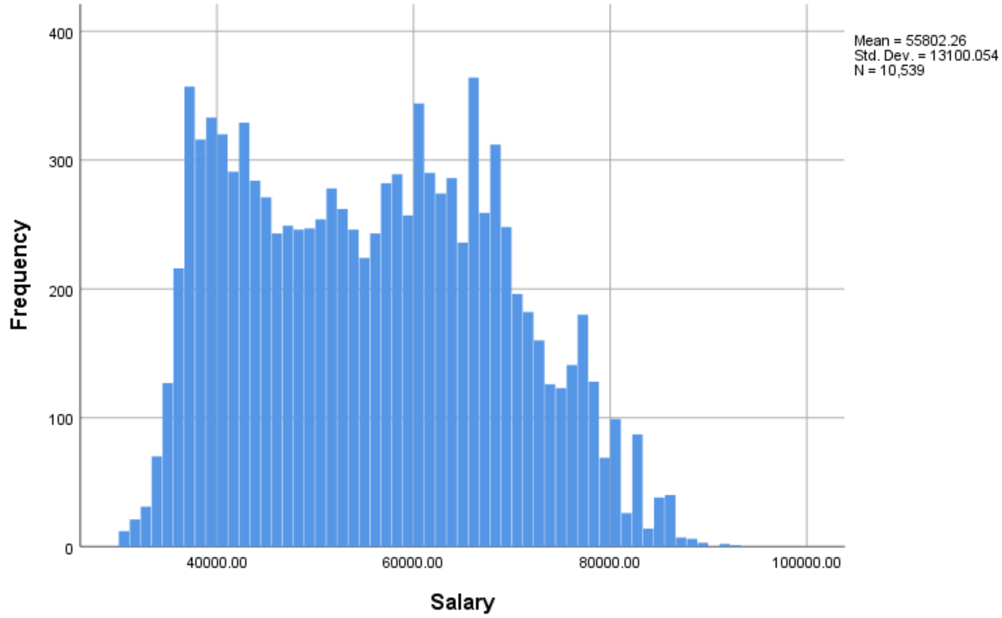
The teacher salary matrix is used to estimate how much money a particular school district needs in order to hire the number of teachers necessary to ensure that all students are provided an equitable opportunity to achieve the Maine Learning Results standards. The matrix adjusts a district's EPS allocation according to the mix of education and experience levels of its teachers.

The salary matrix for teachers was generated using only fulltime public school teacher positions. Private schools as well as state-operated schools, CTE/Vocational Technical schools, EUT schools and public charters were excluded. Following the lead of previous matrix reports, only regular classroom teachers, EL teachers, and Literacy Specialists are included in the salary matrix sample; Special education and Gifted and Talented teachers were not included. Note: in matrices calculated prior to the last report produced by MEPRI in 2019, Title I and Gifted and Talented teachers were included because the data did not reliably identify these teachers; the data now include a specific position code for Title I teachers (88) and Gifted and Talented teachers (112). Because they are funded through federal programs, Title I teachers and those teaching "military science" were also excluded. Teachers whose highest educational degree was listed as "Other" were also excluded from the matrix calculation.

The staff data are position level data. About 10% of the teachers have more than one position in the staff data. For example, a teacher who teaches Mathematics and Life and Physical Sciences within the same school or across two different schools may have two records. We include in the salary matrix data only those teachers with one full-time position (FTE=1.0) in one school. They may also have non-teaching positions in addition to their classroom role, such as Department Head or coach. Only the teaching positions are included in the salary matrix sample. After these exclusions, there were 10,539 full-time public school teacher positions with an average recorded salary of $55,802 and a standard deviation of $13,100. There were no outlier salaries with recorded salaries three times the standard deviation above the mean.

Notably, we also excluded teachers whose reported salaries were less than $35,000, the minimum teacher salary by the new statutory requirements that were in effect in 2019-20 (in the transition to a $40,000 minimum required in 2022-23). This had a significant impact on the sample. While teacher salaries have increased markedly since the prior review—presumably in response to the increased minimum salary—there were 179 teachers (1.7% of all full-time teachers) earning less than $35,000 in 2019-20 according to district-reported staff data. In practice, these teachers would have received an adjusted salary of $35,000 to meet state requirements, with the difference from their contractual salary paid with salary supplements provided from the state to the local district during the three- year phase-in period. Figures 1, 2, and 3 below profile all full-time teachers, but those below $35,000 were excluded from the salary matrix analyses.

Figure 1: Statewide Teacher Salaries, 2019-20

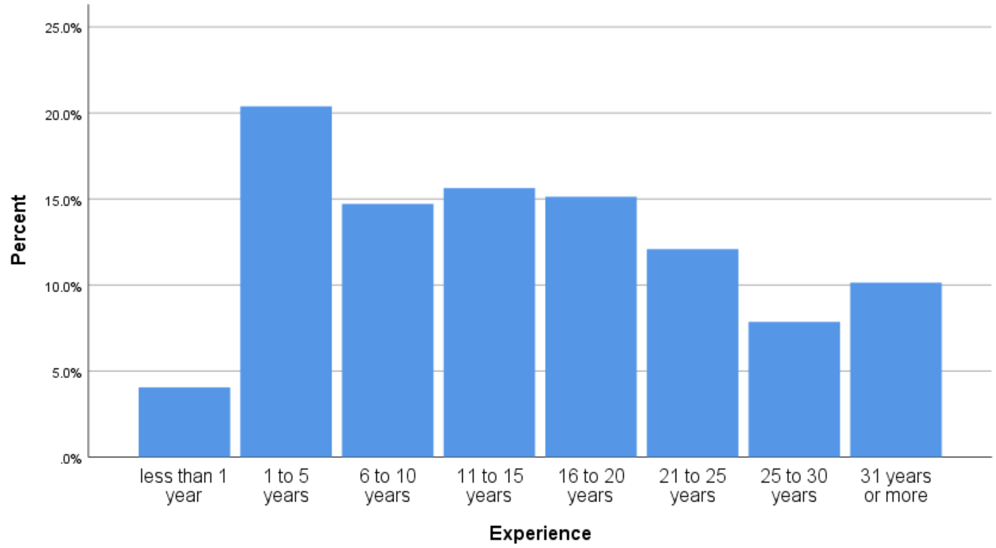


Both education and experience are used to calculate the teacher salary matrix. Regression analysis shows that years of experience is strongly correlated to salary, explaining 59% of the variation in teacher salary. Level of education is less predictive of salary, explaining only about 23% of salary variance. Together education level and experience level explain 67% of the variation in salary.

Highest educational degree was broken into 5 categories: Bachelor's degree, Bachelor's degree plus 15 or 30 hours of additional training, Master's degree or Master's degree plus 15 hours of additional training, Master's degree plus 30 hours of additional training or an Advanced Degree, and Doctorate. Based on "years of experience" information available in the staff data eight experience categories were computed: less than 1 year, 1 to 5 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 21 to 25 years, 26 to 30 years, and 31 or more years.

Overall, across the state the average number of years of experience in 2019-20 was 15.0, with a minimum of 0 years and a maximum of 57. The bar graph below displays the percentage of teachers within each experience category. About 4% of Maine's teachers were beginner teachers in their first year of teaching; an additional 20% had 1 to 5 years of experience, for a total of 24% who were relatively new teachers. Thirty percent have more than 20 years of experience and 10% of teachers have been working as teachers for 31 years or more.

Figure 2: Statewide Teacher Experience, 2019-20



Fifty-five percent of teachers across Maine hold a Bachelor's degree and about 45% have a Master's degree or an advanced certificate. Very few teachers in Maine (0.5%) have a doctorate, as seen below in Figure 3.

Figure 3: Maine Teacher Education Profile, 2019-20

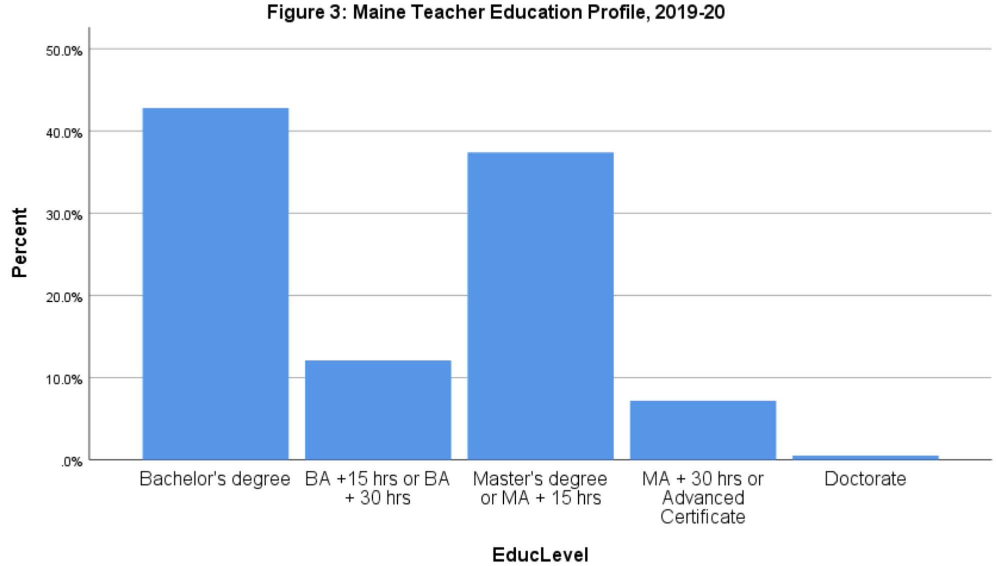


Table 1a displays the number of full-time teachers in each of the 40 education-experience categories. The final row identifies the number of these teachers who had a contracted salary less than $35,000 as reported by the districts; these were removed from further matrix calculations, as described above.

Table 1a: Number of teachers in each category, 2019-20 (all Full-time FTE salaries)

	Education Category					
Experience Category	BA only	BA + 15 hours or + 30 hours	MA or MA + 15 hours	MA + 30 hours or Advanced Cert	Doctorate	Total
0	320	22	78	6	1	427
1-5	1,472	169	472	28	7	2,148
6-10	702	169	612	60	8	1,551
11-15	584	194	765	98	7	1,648
16-20	482	197	727	180	9	1,595
21-25	387	183	555	139	10	1,274
26-30	233	139	344	105	7	828
31 plus	331	201	390	142	4	1,068
Total	4,511	1,274	3,943	758	53	10,539
Number $35,000 or above	*4,343*	*1,270*	*3,936*	*758*	*53*	*10,360*
Number earning below $35K	*168*	*4*	*7*	*0*	*0*	*179*

Note that there are only 6 beginner teachers with a Master's plus 30 hours or an Advanced Certificate, and there are only 53 teachers with doctorates in the salary matrix sample. Given the small numbers in these categories, their average salaries produced some unexpected or counterintuitive results such as beginning teachers earning more than teachers with at least 10 years of experience within the same level of education, or teachers with doctorates earning less than those with similar experience and less education. The numbers of cases of doctorates are therefore insufficient to support a separate education category, and we combined the top two educational levels (teachers with doctorates and those with Master's degrees plus 30 hours) into one category.

Table 1b shows the resulting number of full-time teachers who were earning at least 35,000 and thus were able to be included in the sample for matrix calculations, with all advanced (post-Master's) combined and resulting in four education categories.

Table 1b. Teacher Salary matrix sample –N's (sample excludes those w/ salaries lt $35,000)

Experience Category	Education Category			
	BA only	BA +15 or +30	MA or MA +15	MA +30 or Adv Cert or Doctorate
0 years	263	21	77	7
1-5 years	1367	166	467	35
6-10 years	700	169	612	68
11-15 years	584	194	765	105
16-20 years	482	197	727	189
21-25 years	387	183	555	149
26-30 years	230	139	343	112
31 + years	330	201	390	146
Total	4343	1270	3936	811

Table 2 displays the average, minimum and maximum salaries for teachers in each of the resulting 32 education-experience categories.

Table 2: Actual average (minimum and maximum) salary for teachers by education and experience, 2019-20

	Education Category				
Experience Category	BA only	BA + 15 hours or + 30 hours	MA or MA + 15 hours	MA + 30 hours, CAS or Doctorate	Overall
0	$38,523 (35,000-62,479)	$41,798 (35,000-64,843)	$46,297 (35,000-74,080)	$60,775 (49,324-71,080)	$40,760 (35,000-74,080)
1-5	$40,403 (35,000-69,483)	$43,263 (35,000-75,604)	$46,913 (35,000-86,583)	$50,417 (40,000-72,720)	$42,302 (35,000-86,583)
6-10	$45,100 (35,000-68,111)	$47,339 (37,000-86,583)	$51,136 (37,389-76,551)	$55,107 (41,337-87,733)	$48,168 (35,000-86,583)
11-15	$51,698 (37,648-73,857)	$56,739 (40,635-86,583)	$58,283 (37,180-81,410)	$63,995 (42,000-83,915)	$56,132 (37,179-86,583)
16-20	$57,521 (37,093-80,794)	$61,701 (39,575-88,508)	$63,544 (39,332-82,737)	$68,926 (44,784-88,508)	$62,134 (37,093-88,508)
21-25	$62,113 (42,685-85,180)	$64,616 (48,961-86,583)	$68,268 (47,057-86,838)	$72,975 (51,609-89,343)	$66,424 (42,685-89,343)
26-30	$64,507 (35,000-86,583)	$65,729 (48,632-92,892)	$69,774 (35,000-86,583)	$75,277 (42,979-89,343)	$68,369 (35,000-92,892)
31 plus	$65,867 (35,000-86,583)	$67,365 (51,466-86,583)	$71,147 (46,531-88,716)	$74,152 (58,500-91,430)	$69,213 (35,000-91,430)
Overall	$49,611 (35,000-86,583)	$58,050 (35,000-92,892)	$60,196 (35,000-88,716)	$68,816 (40,000-91,430)	$56,170 (35,000-92,892)

The resulting salary matrix is shown below in Table 3. Index values increase at every higher level of experience within each education level, and the rate of increase is approximately the same across education levels. Between a beginner teacher and the most experienced teacher, the salary allocation increases by 71% and between the lowest and highest levels of education, salary allocations increase by 28%. The change in the size of indices between experience levels and thus the increase in allocation is larger for the categories between 1-5 and 21-25 years than for the lower and higher levels of experience. For example, the salary allocated for teachers with 1-5 years of is about 5% more than the amount allocated for beginner teachers while the amount allocated for those 6-10 years is 1~~2~~% more than the salary allocated for those with 1-5 years.

Table 3: Teacher Salary Matrix, 2019-20

	Base Salary: $38,523			
Experience Category	BA only	BA +15 or +30	MA or MA +15	MA +30 or Adv Cert or Doctorate
0 years	1.00	1.07	1.16	1.28
1-5 years	1.05	1.12	1.21	1.33
6-10 years	1.17	1.25	1.33	1.45
11-15 years	1.34	1.42	1.50	1.62
16-20 years	1.49	1.57	1.65	1.77
21-25 years	1.61	1.69	1.77	1.89
26-30 years	1.67	1.75	1.83	1.95
31 + years	1.71	1.78	1.87	1.99

To verify that the salary matrix is accurate, the statewide salary total was recalculated using the matrix (i.e., the sum of base salary $38,523 times the matrix value multiplied by the number of teachers in each education-experience category). When compared to the actual statewide total of teacher salaries, there was no difference, thus validating the accuracy of the calculations.

Table 4 translates these indices into salary allocation amounts. Actual average salaries are included for comparison. Because the matrix is calculated using mathematical smoothing techniques which hold salary increments for experience constant and equal to the salary increments for Bachelor's-only teachers across all levels of education, actual average salaries will differ somewhat from those generated by the matrix.

Table 4: Teacher Salary Allocations (actual average salary), 2019-20; base salary $38,523

Experience Category	Education Level Category			
	BA only	BA +15 or +30	MA or MA +15	MA +30 or Adv Cert or Doctorate
0 years	38,523 (38,523)	41,220 (41,798)	44,687 (46,297)	49,309 (60,775)
1-5 years	40,449 (40,403)	43,146 (43,263)	46,613 (46,913)	51,236 (50,417)
6-10 years	45,072 (45,100)	48,154 (47, 339)	51,236 (51,136)	55,858 (55,107)
11-15 years	51,621 (51,698)	54,703 (56,739)	57,785 (58,283)	62,407 (63,995)
16-20 years	57,399 (57,521)	60,481 (61,701)	63,563 (63,544)	68,186 (68,926)
21-25 years	62,022 (62,113)	65,104 (64,616)	68,186 (68,268)	72,808 (72,975)
26-30 years	64,333 (64,507)	67,415 (65,729)	70,497 (69,774)	75,120 (75,277)
31 + years	65,874 (65,867)	68,571 (67,365)	72,038 (71,147)	76,661 (74,152)

The range of indices narrowed very slightly between the 2016-17 matrix calculated in our prior review (range of 1.00 to 2.02) and the 2019-20 matrix (range of 1.00 to 1.99, Table 3). Both matrices demonstrated the same general pattern of allocations, with the increase in allocations between experience levels larger for the mid-level experience categories and smaller for the lower and higher levels of experience. However, the 2016-17 updated matrix was not implemented. The next section compares the updated salary matrix calculated in this review to the actual matrix that was applied in practice in FY2020.

Updated Teacher Salary Matrix compared to actual use in FY2020

By statute, the amount allocated through the salary matrix has been increased each year to keep up with rising salaries by automatically adjusting the base salary by an inflation factor based on the Consumer Price Index. This practice helps to maintain adequate resources over time. The matrix indices have not been updated since they were initially developed for 2006-07. Updated index values have been calculated and recommended in prior component reviews, but changing the indices requires legislative action and has not happened. Table 5 summarizes the matrix that was implemented in practice in FY20 with the index values that have been in place since FY2007.

Table 5. Actual Salary Matrix Implemented in 2019-20

Experience Category	Base Salary: $35,735				
	BA only	BA +15 or +30	MA or MA +15	MA +30 or Adv Cert	Doctorate
0 years	1.00 ($35,735)	1.04 ($37,164)	1.16 ($41,452)	1.24 ($44,311)	1.25 ($44,668)
1-5 years	1.07 ($38,236)	1.11 ($39,665)	1.23 ($43,954)	1.31 ($46,812)	1.32 ($47,170)
6-10 years	1.22 ($43,596)	1.27 ($45,383)	1.38 ($49,314)	1.47 ($52,530)	1.47 ($52,530)
11-15 years	1.39 ($49,671)	1.44 ($51,458)	1.55 ($55,389)	1.63 ($58,248)	1.64 ($58,605)
16-20 years	1.56 ($55,746)	1.60 ($57,176)	1.72 ($61,464)	1.80 ($64,323)	1.81 ($64,680)
21-25 years	1.68 ($60,034)	1.73 ($61,821)	1.84 ($65,752)	1.93 ($68,968)	1.93 ($68,968)
26-30 years	1.74 ($62,178)	1.79 ($63,965)	1.90 ($67,896)	2.00 ($70,755)	1.99 ($71,112)
31 + years	1.76 ($62,893)	1.80 ($64,323)	1.92 ($68,611)	2.02 ($71,470)	2.01 ($71,827)

The salary matrix that is currently in use (and was in place for the EPS allocations in FY2019-20) is provided below in Table 6 alongside the updated matrix values that were calculated from FY20 data. The matrix that was used had a lower base salary, but generally higher index values than the matrix that was calculated empirically from that year's actual salary patterns. Index values in green are an increase from the current matrix, and those in red represent a decrease.

Table 6: Comparison of Updated to Current Salary Matrix Indices

Updated Base salary: $38,523; Implemented Base Salary (FY20): $35,735										
Experience Category	BA only		BA +15 or +30		MA or MA +15		MA +30 or Adv Cert		Doctorate	
Years	Update	Current	Update	Current	Update	Current	Update	Current	Update	Current
0	1.00	1.00	1.07	1.04	1.16	1.16	1.28	1.24	1.28	1.25
1-5	1.05	1.07	1.12	1.11	1.21	1.23	1.33	1.31	1.33	1.32
6-10	1.17	1.22	1.25	1.27	1.33	1.38	1.45	1.47	1.45	1.47
11-15	1.34	1.39	1.42	1.44	1.50	1.55	1.62	1.63	1.62	1.64
16-20	1.49	1.56	1.57	1.60	1.65	1.72	1.77	1.80	1.77	1.81
21-25	1.61	1.68	1.69	1.73	1.77	1.84	1.89	1.93	1.89	1.93
26-30	1.67	1.74	1.75	1.79	1.83	1.90	1.95	1.98	1.95	1.99
31 +	1.71	1.76	1.78	1.80	1.87	1.92	1.99	2.00	1.99	2.01

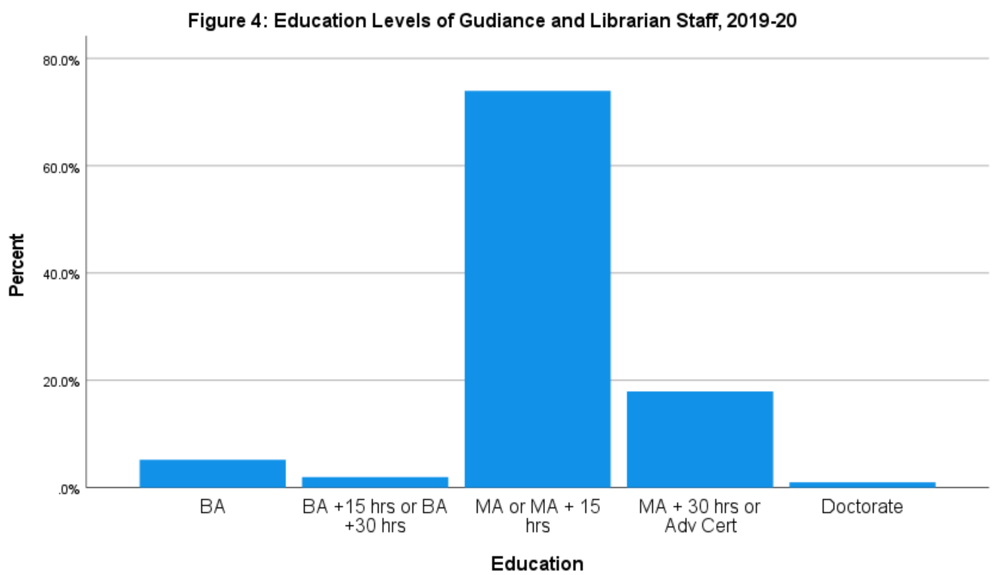
Although the individual index values are almost all lower in the updated matrix, the net effect of implementing it would increase allocations because of the substantially higher base salary in the updated calculations.

It is noteworthy that the base salary resulting from our FY20 calculations ($38,523) is substantially higher than the base salary that was implemented for that funding year ($35,735), which resulted from the annual practice of inflating the base salary by a measure of consumer inflation. The gap of $2,788 (or 7.8%) conveys that teacher salaries in practice have increased more than the cumulated adjustments for consumer inflation. This is due to the two policy initiatives that have increased the minimum teacher salary since the implementation of EPS – first to $30,000 in FY2008 and then to $35,000 for FY2200, on the way to the $40,000 minimum for FY2023. This means that in order to maintain adequacy in the formula, the base salary must be increased by more than just inflation to catch up to the policy minimum established in state statute. Recommendations for updating the matrix values for FY2024 are included in the summary section of this report.

Guidance Counselors and Librarians

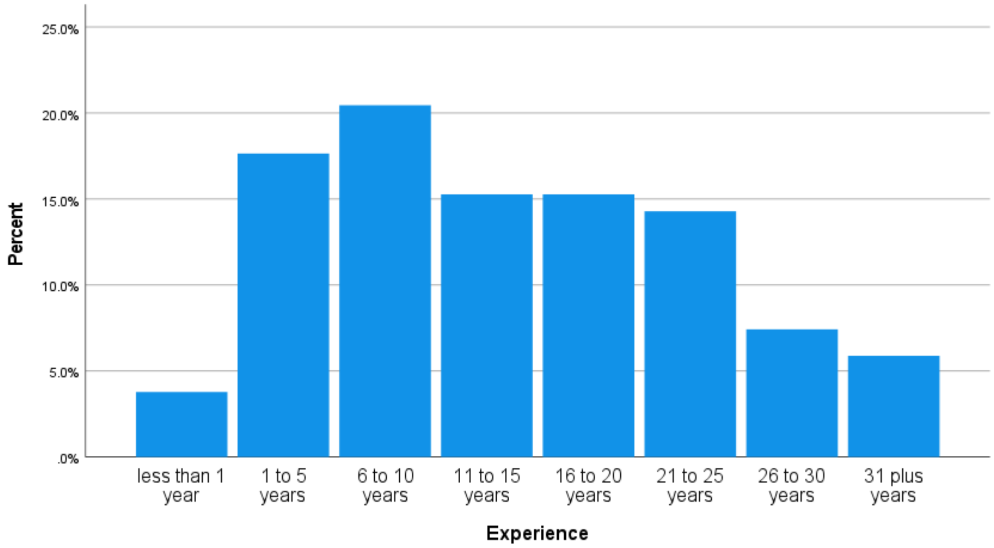
The teacher salary matrix is also used as the matrix for guidance staff and librarians. Specifically, the same set of indices—generated using teacher salaries—is used to calculate EPS salary allocations adjusted for education and experience profile for school social workers, guidance counselors, directors of guidance, and librarians/media specialists. This is primarily because there were not enough fulltime school social workers, guidance counselors, directors of guidance, and librarians/media specialist positions with which to generate a stable matrix with the same experience and education categories (see Table 7 below). Also, staff in these positions hold similar levels of education and were generally on the same contract as teachers at the time the EPS formula was developed. Thus this practice was deemed appropriate.

After excluding those who worked in more than one school, there were 941 school social workers, guidance counselors, directors of guidance, and librarians/media specialist positions working in regular public or Indian schools in 2019-20. Eighty-five percent (802) were EPS funded and of those, 716 worked full-time. We excluded two additional staff because their recorded salaries were unusually low (less than $20,944, which is more than 3 times the standard deviation below the mean). Of the 714 remaining staff, the average salary was $60,527, with a range of $29,968 to $99,707. Due to credentialing requirements, 93% of guidance and librarian staff have Master's degrees or higher compared to 45% of teachers, as shown below.



While counselors and librarians/media specialists tend to have significantly higher levels of education, the pattern of experience is generally similar to that of teachers. About 4% of Maine's counselors and librarians/media specialists are in their first year (same as the % of teachers) and 42% have 10 years or less (compared to 39% of teachers). Almost 28% of counselors and librarians/media specialists have more than 20 years of experience' (compared to 30% of teachers) and 6% have 31 years or more (compared to 10% of teachers), as shown below.

Figure 5: Experience Levels of Gudiance and Librarian Staff, 2019-20



Because there is relatively less variation among counselors and librarians, especially in terms of education, education and experience have somewhat less power in predicting salary amounts compared to teachers. Regression analysis indicates that experience explains about 46% of the variation in salary and education level explains about 11%.

Table 7 displays the number of social workers, guidance counselors, directors of guidance, and librarians/media specialists in each of the 40 education-experience categories. Note that many of the individual cells contain fewer than 5 staff members.

Table 7: Number of school social workers, guidance counselors, librarians/media specialists in each education-experience category, 2019-20

Experience Category	Education Category					
	BA only	BA + 15 hours or + 30 hours	MA or MA + 15 hours	MA + 30 hours or Advance Cert	Doctorate	Total
0	7	2	14	4	0	27
1-5	15	2	98	11	0	126
6-10	6	0	124	16	0	146
11-15	6	2	88	12	1	109
16-20	2	4	74	29	0	109
21-25	1	3	67	28	3	102
26-30	0	1	36	14	2	53
31 plus	0	0	27	14	1	42
Total	37	14	528	128	7	714

As with teachers, the doctorate category is combined with the Master's + 30 group in order to achieve sufficient numbers. However, because the guidance / library staff are allocated using the teacher salary matrix, the education levels must remain aligned and it is not feasible to combine the first two education levels. Table 8 displays the actual average salaries for social workers, guidance counselors, directors of guidance, and librarians/media specialists in each of the 32 education-experience categories for which there are 5 or more staff, as well as the accompanying allocated salaries (which are from the teacher salary matrix allocations described in Table 4).

Table 8: Actual average salary for guidance staff and librarians and the amount allocated by the teacher salary matrix, by education-experience category, 2019-20, base salary $38,523

	Education Level Category			
Experience Category	BA only	BA +15 or +30	MA or MA +15	MA +30, Adv Cert, Doctorate
0 years				
actual	$37,110	**	$48,336	**
allocated	$38,523	$41,399	$44,628	$49,205
1-5 years				
actual	$47,321	**	$48,629	$56,197
allocated	$40,403	$43,279	$46,508	$51,085
6-10 years				
actual	$51,845	**	$53,962	$55,108
allocated	$45,100	$47,976	$51,206	$55,783
11-15 years				
actual	$56,735	**	$60,924	$62,170
allocated	$51,698	$54,574	$57,804	$62,381
16-20 years				
actual	**	**	$64,848	$70,340
allocated	$57,521	$60,396	$63,626	$68,203
21-25 years				
actual	**	**	$68,060	$73,539
allocated	$62,113	$64,989	$68,218	$72,795
26-30 years				
actual	**	**	$71,164	$76,015
allocated	$64,507	$67,383	$70,612	$75,189
31 + years				
actual	**	**	$72,395	$76,291
allocated	$65,867	$68,743	$71,973	$76,550

** Category contains fewer than 5 staff members

Notably, there are many cells – including all of the Bachelor's +15 or +30 levels – that do not have an adequate number of staff data points upon which to base a reliable calculation. For those that do have data, the actual average salaries are generally higher than the salary allocations assigned by using the teacher matrix—in some cases considerably so. The overall average salary paid to guidance staff and librarian positions ($60,527) was $4,725 more than the average salary paid to teachers ($55,802; see Table 2), as is expected due to their higher educational attainment. However, in the 2016-17 report, the statewide average salary for the guidance staff and library/ media specialist sample was $3,907 more than the average salary for the sample of teachers, indicating that the wage gap between these positions is widening. This raises the question about whether guidance staff and library/media specialists should continue to be funded using the teacher salary matrix. Employment conditions for these staff may have changed since the implementation of the EPS funding model, and assumptions of similar contractual treatment may no longer hold true. However, Table 7 and the number of missing data points in Table 8 illustrate that the small number of staff in some matrix categories would make it problematic to construct a robust matrix using these same education-experience categories. To construct a separate, reliable matrix for guidance and library/media specialist positions, it would require that fewer categories be used.

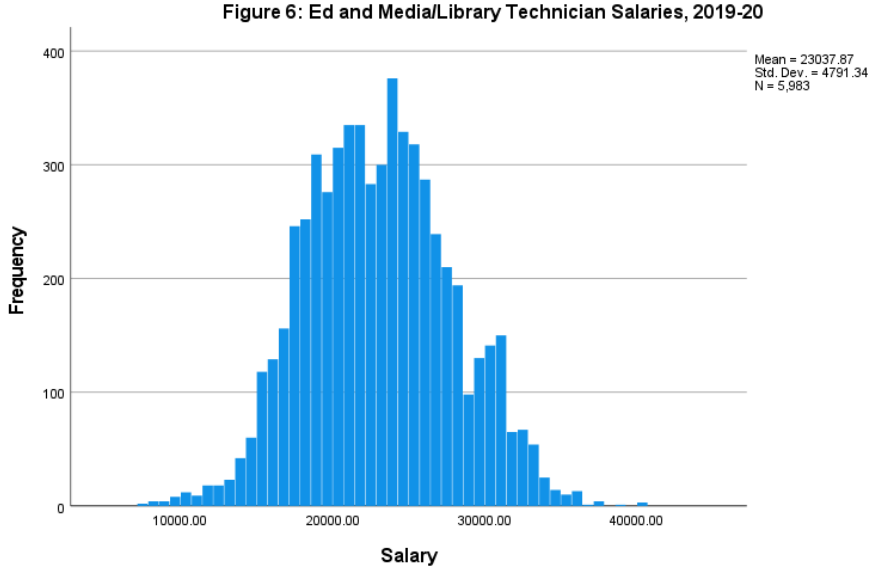
Further analysis was conducted to discern whether there are other patterns within the guidance/librarian staff that might explain the average salary gap between teachers. We found that high poverty and rural districts are less likely to employ full-time guidance/librarian staff: over half of the high poverty districts (13 out of 23) had no full-time staff member, compared to 27% of low poverty and 30% of average poverty districts. Moreover, low poverty districts also pay their guidance/librarian staff more than other districts ($64,612 mean salary for FT staff compared to $55,273 in average poverty districts and $55,848 in high poverty districts). City and suburban schools also pay their fulltime guidance/librarian staff more than rural districts ($64,115 in city districts, $65,885 in suburban districts, $57,280 in towns and $54,676 in rural districts). Almost half (46%) of rural districts did not employ a full-time guidance or librarian staff member compared to 0% of city districts, 10% of suburban and 5% of town districts. This staffing pattern is likely explained by the smaller total enrollments in rural districts, making it difficult to achieve an economy of scale that would make it feasible to hire full-time personnel in these roles. Because the salary matrix is only based on full-time staff, this means any attempt to create a separate matrix for guidance and library staff would be challenged by the underrepresentation of rural districts.

Educational Technicians and Library/Media Technicians

The data used to update the educational and library/media technician salary matrix also come from staff data file obtained from Maine DOE for the school year 2019-20. Technician positions include educational technicians and library/media technicians at level I, II or III. In 2019-20 there were a total of 6,006 technicians working fulltime in one school.

Following the approach used in previous matrix calculations, fulltime technicians with salaries less than $7,354 (inflated from the $6,250 used in 2010) were also excluded from the matrix sample (this included 14 staff, including 4 with recorded salaries of $100 and 2 with salaries recorded as $15.75). This left 5,992 technicians with an average salary of $23,088 (minimum $7,399 and maximum $71,584) and a standard deviation of $4,979. After excluding 9 high-salary outliers that had recorded salaries more than four standard deviations above the mean (i.e., with salaries ranging from $43,056 to $71,584), the sample used to calculate the matrix for education and media/library technicians included 5,983 technicians with an average salary of $23,038 (minimum $7,399 and maximum $40,430).

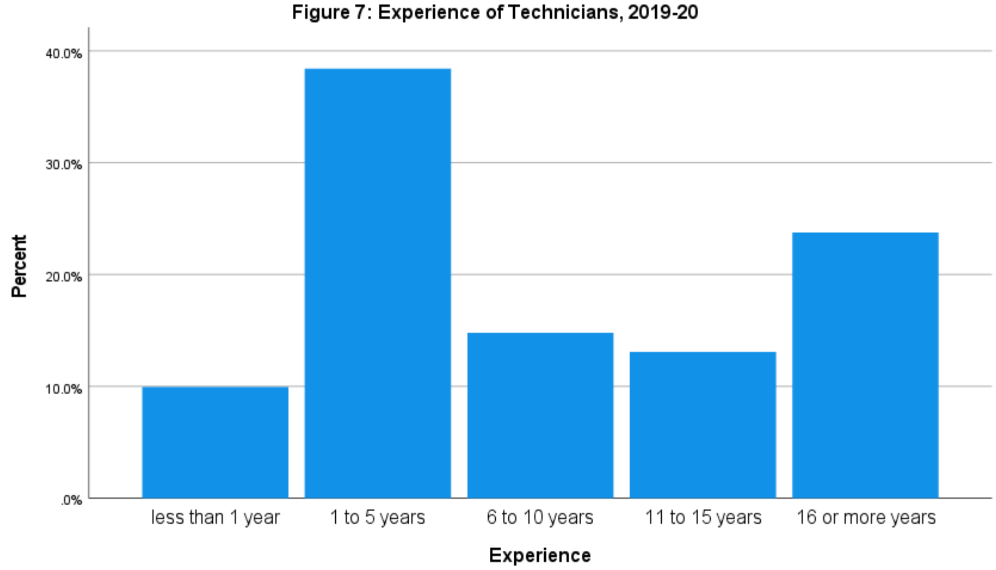
Figure 6: Ed and Media/Library Technician Salaries, 2019-20



The salary matrix developed for educational and library/media technicians uses experience and job classification rather than experience and education because technician pay is typically based on job classification rather than a particular employee's education level. The different job classifications require different levels of education and certification, however, and thus are related to education level. Six job classifications (Educational Technician I, II and III and Library/Media technician I, II, and III) and 5 experience categories (less than one year, 1 to 5 years, 6 to 10 years, 11 to 15 years and 16 or more years) are used, creating a 5x6 matrix with 30 experience-position indices.

About 10% of education and library/media technicians were beginners in 2019-20 having worked for less than one year. Another 38% were relatively new with 1 to 5 years of experience. Nearly 24% had 16 or more years of experience.

Figure 7: Experience of Technicians, 2019-20



The majority of technicians are educational technicians and most are classified as level III.

Figure 8: Job Classification of Technicians, 2019-20

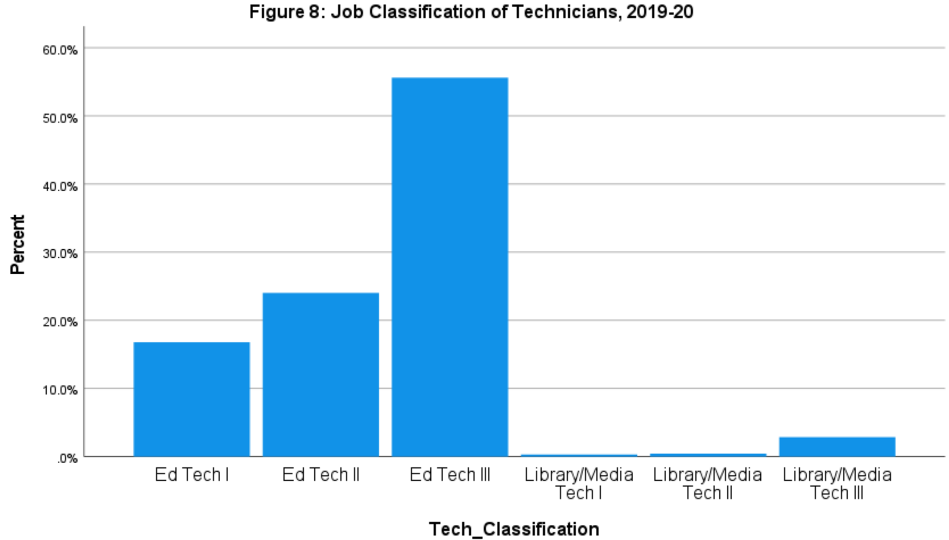


Table 9 displays the actual average, minimum and maximum salary for technicians in each of the 30 job type-experience categories.

Table 9: Actual average (minimum and maximum) salary for technicians by experience and job classification, 2019-20

	Ed Tech I	Ed Tech II	Ed Tech III	Media Tech I	Media Tech II	Media Tech III	Overall
Less than 1 year	16,032 (8,082-24,613)	17,537 (7,714-29,959)	21,206 (7,399-40,000)	**	**	23,628 (18,390-29,140)	19,374 (7,399-40,000)
1-5 years	17,401 (10,380-25,695)	20,145 (9,034-36,923)	23,041 (9,689-38,635)	22,576 (18,144-28,788)	24,059 (18,014-35,370)	24,118 (16,708-33,883)	21,498 (9,034-38,635)
6-10 years	18,642 (11,517-26,082)	22,538 (11,971-37,731)	24,757 (14,660-35,382)	**	**	26,372 (18158-40430)	23,431 (11,517-40,430)
11-15 years	20,375 (14,386-33,251)	24,078 (12,366-31,047)	26,505 (17,228-35,414)	**	**	28,268 (22,076-40,093)	25,043 (12,366-40,093)
16 or more years	21,692 (9,662-30,993)	24,781 (15,128-32,690)	27,575 (14,696-37,615)	21117 (18449-25696)	27,202 (21,319-33,948)	29,046 (18,150-36,086)	25,710 (9662-37,615)
Overall	18,894 (8,082-33,251)	22,027 (7,714-37,731)	24,539 (7,399-40,000)	21,428 (7,974-28,788)	24,518 (14,130-35,370)	26,594 (16,708-40,430)	23,038 (7,399-40,430)

** Category contains fewer than 5 staff members

Unlike other staff positions, the majority of education technician positions are not EPS-funded. In 2019-20 just 27% (1,608) of technicians were EPS-funded. In the past, rather than using only EPS-funded positions, all technicians were used in our calculations in order to ensure a more robust matrix. Additionally, the average salary for beginner Ed Tech II's was used as the base salary because Tech II's were more common than Ed Tech I's. As can be seen from Tables 10 and 11, using only EPS-funded positions results in small numbers of staff in some of the categories, which can amplify the effect of underlying salary irregularities on the matrix. Using the full sample of technicians regardless of funding source will mute these effects. Moreover, the full 2019-20 sample includes a sufficient number of beginner Ed Tech I's for generating an adequate distribution and thus a reliable base salary. The number of beginner Ed Tech I's has increased since the last report (in 2016-17 there were 68 Ed Tech I's and 116 Ed Tech II's). Note that because almost all of the Media/Library technicians are EPS-funded, using the full sample of technicians does not solve the small numbers problems for those positions.

Table 10: Technicians, number of staff in each experience band, 2019-20, EPS-funded only (n=1,608)

Experience	Position					
	Ed Tech I	Ed Tech II	Ed Tech III	Media I	Media II	Media III
0 years	19	27	88	1	3	14
1-5	42	126	292	5	7	52
6-10	9	51	149	0	3	23
11-15	20	48	117	2	3	33
16 plus	56	127	223	10	10	48
Total	146	379	869	18	26	170

Table 11: Technicians, number of staff in each experience band, 2019-20, includes all positions (n=5,983)

Experience	Position					
	Ed Tech I	Ed Tech II	Ed Tech III	Media I	Media II	Media III
0 years	127	121	329	1	3	14
1-5	366	532	1,336	5	7	52
6-10	119	213	527	0	3	23
11-15	119	195	431	2	3	33
16 plus	273	376	704	10	10	49
Total	1004	1437	3327	18	26	171

Below we show the results of the updated salary matrix using the mean salary of beginner Ed Tech II's as the base, as is current practice. A second set of analyses that describe the matrix based on Ed Tech I as the base is included in the appendix for comparison. As indicated above, the index values for media tech I and II positions are based on small numbers of staff data points and should be considered accordingly; these values are italicized to emphasize that they are less robust than other calculated values.

Table 12: Salary Matrix created using all tech positions (N=5,983) and Ed Tech II mean salary as base salary ($17,537)

	Position					
Experience	Ed Tech I	Ed Tech II	Ed Tech III	Media I	Media II	Media III
0 years	0.83	**1.00**	1.16	*0.91*	*1.12*	1.24
1-5	0.98	1.15	1.31	*1.06*	*1.27*	1.39
6-10	1.12	1.29	1.44	*1.19*	*1.41*	1.53
11-15	1.21	1.37	1.53	*1.28*	*1.50*	1.62
16 plus	1.25	1.41	1.57	1.32	1.54	1.66

If the average salary for beginner Ed Tech II's continues to be used as the base the resulting matrix allocates a lower salary for early career technicians but the increases in allocation between experience start off higher and decline at higher levels of experience: there's an 15% increase in the indices between 0 years and 1-5 years, a 13-14% increase between 1 to 5 and 6 to 10 years of experience, an 9% increase between 6 to 10 years and 11 to 15 years, and an 4% increase after 16 years or more.

Also note that the increase in indices between levels I and II for Media/Library techs is larger than the increase between levels II and III: Using the Ed Tech II salary as the base, the increase in allocation between levels I and II is almost twice as large (22%) as the increase in allocation between levels II and III (12%); when the base salary is the Ed Tech I's, the increase between levels I and II is 23% and the increase between levels II and II is 14%. This is because the number of Media/Library techs, especially at levels I and II, is small and the underlying salary data more irregular. For Ed Techs the increases in indices between levels I and II and II and III are more consistent (16-19%).

In Table 13 we display the allocated salaries resulting from the updated matrix and the actual mean salaries. Using the mean salary for beginner Ed Tech I's as the base would allocate relatively more to technicians with less experience, especially beginners, compared to the matrix developed using the Ed Tech II salary as the base.

Table 13: Actual Average salaries vs Proposed Updated Allocations, 2019-20 Data

	Position					
	Ed Tech I	Ed Tech II	Ed Tech III	Media I	Media II	Media III
0 years						
Ed Tech II as base	14,556	17,537	20,343	15,956	19,641	21,746
Actual avg salary	16,032	17,537	21,206	**	**	23,628
1-5 years						
Ed Tech II as base	16,835	20,167	22,973	18,589	22,272	24,376
Actual avg salary	17,401	20,145	23,041	22,576	24,059	24,118
6-10 years						
Ed Tech II as base	19,641	22,623	25,253	20,869	24,727	26,832
Actual avg salary	18,642	22,538	24,757	**	**	26,372
11-15 years						
Ed Tech II as base	21,220	24,026	26,832	22,447	26,305	28,410
Actual avg salary	20,375	24,078	26,505	**	**	28,268
16 plus years						
Ed Tech II as base	21,921	24,727	27,533	23,149	27,007	29,111
Actual avg salary	21,692	24,781	27,575	21,117	27,202	29,046

** Fewer than 5 staff data points

Educational Technician Salary Matrix compared to actual implemented values:

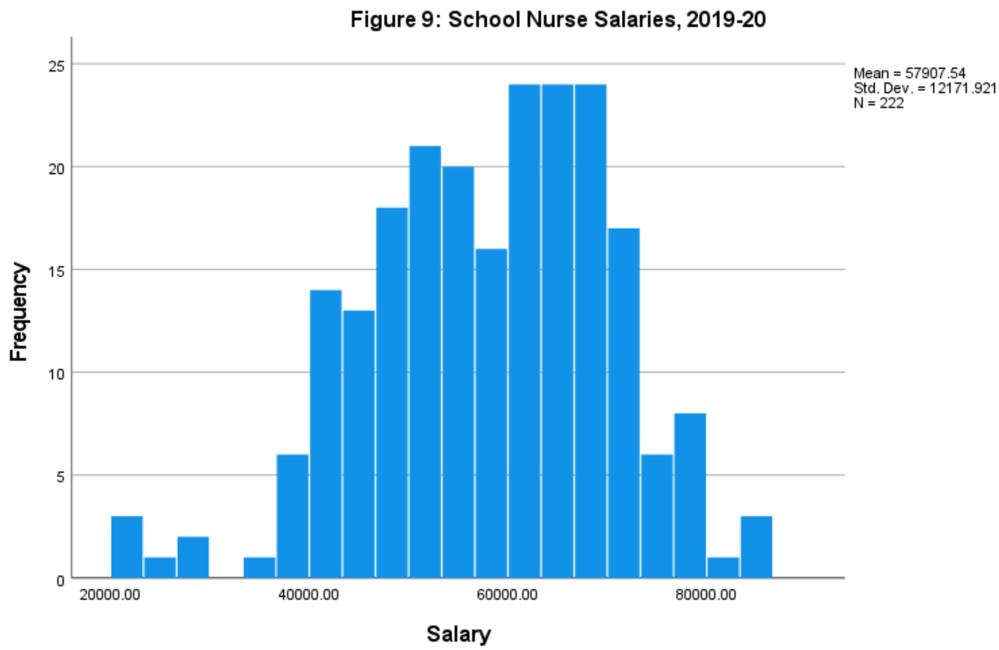
Table 14. Comparison of Recommended Update (Base salary 17,537) to Actual Matrix Indices Implemented in FY20 (Base salary 17,613)

Experience	Ed Tech I		Ed Tech II		Ed Tech III	
	Used in EPS (FY20)	Update	Used in EPS (FY20)	Update	Used in EPS (FY20)	Update
0 years	0.84	0.83	**1.00**	**1.00**	1.13	1.16
1-5	0.88	0.98	1.04	1.15	1.18	1.31
6-10	0.95	1.12	1.12	1.29	1.25	1.44
11-15	1.04	1.21	1.21	1.37	1.34	1.53
16 plus	1.06	1.25	1.22	1.41	1.35	1.57

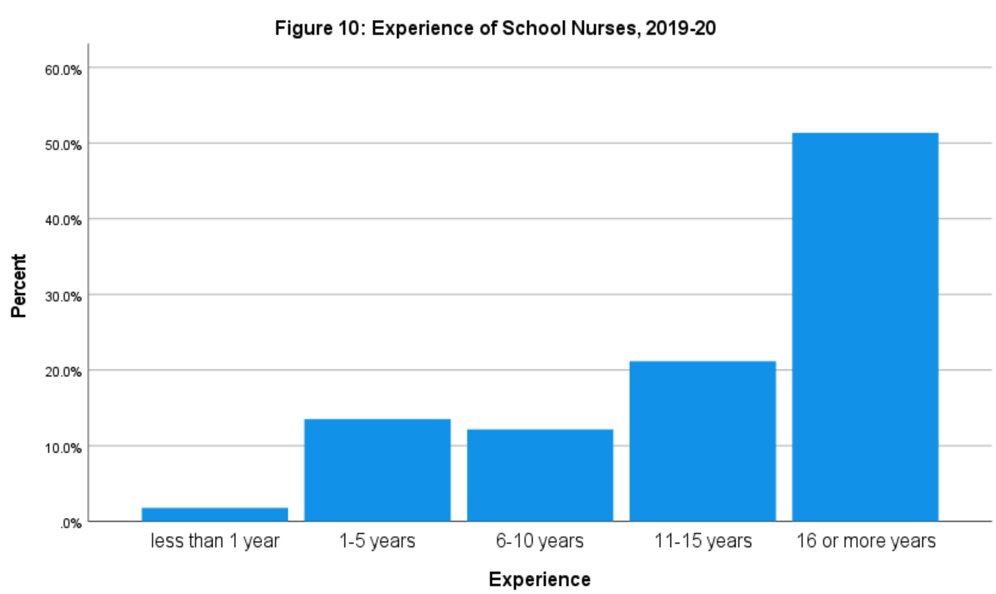
The updated ed tech salary matrix based on FY20 reported data shows that the salary scale has expanded substantially since the initial matrix values were developed. The maximum index value (ed tech III with 16+ years of experience) has increased from 1.35 (actual implemented allocation of $24,306) to 1.57 (model allocation of $27,652). Updating the ed tech matrix to these recommended values in order to achieve adequacy will therefore have notable cost implications.

Nurses/Health Staff

In 2019-20 there were 414 school nurses working in one public or Indian school, 97% (402) of whom were EPS-funded. Of those, 224 were working full-time. There were no nurses with exceptionally high outlier salaries (greater than $97,249, 3 times the standard deviation above the mean). After excluding the two nurses with salaries recorded as $100, the average salary was $57,907, with a range of $20,848 to $85,467.



Experience is the only factor used in calculating the nurse matrix because the education levels of nurses does not vary enough to permit calculation of a reliable matrix using both education and experience. The majority of nurses (77%) have bachelor's degrees while only 13% have Master's degrees. Years of experience is moderately correlated with salary, explaining about 29% of the variation in salaries. The experience categories used in previous matrices are the same as used for technicians: less than one year, 1 to 5 years, 6 to 10 years, 11 to 15 years and 16 or more years.



About half (51%) of school nurses in our matrix sample had 16 or more years of experience. Less than 2% (n=4) were beginner nurses in their first year. The fact that so few nurses are "beginners" with less than one year of experience may suggest that schools are counting experienced accrued before coming to the school setting, rather than that there are no nurses who are new to working in schools. In the past, using as the base salary the statewide average instead of the average salary for nurses with less than 1 year of experience has produced a stable matrix, with allocations increasing with experience. In 2019-20, however, the 4 nurses recorded as having less than one year of experience were paid, on average, more than nurses with 1-5 years of experience. In fact, they were paid on average what nurses with 6 to 10 years of experience were earning. This would lead to a matrix that allocates more for nurses with less experience (Table 15).

Table 15: Actual average (minimum and maximum) salaries, number of nurses, by experience (5 levels), and matrix values, 2019-20

	Number of nurses	Actual salary, average (minimum-maximum)	Matrix Index Value	Resulting salary allocation
Less than 1 year	4	** (43,138-62,674)	**0.88**	$50,958
1-5 years	30	$46,785 (37,339-59,803)	0.81	$46,905
6-10 years	27	$51,260 (22,600-70,667)	0.89	$51,537
11-15 years	47	$57,173 (43,565-77,235)	0.99	$57,328
16 or more years	114	$62,948 (20,848-85,467)	1.09	$63,119
Overall	222	$57,907 (20,848-85,467)	– – –	

** Fewer than 5 staff data points

To avoid generating a matrix that allocates less for more experienced nurses, we recommend reducing the experience categories used and combining nurses with 0 to 5 years of experience. This produces a more robust matrix with allocations increasing with increased experience (See Table 16).

Table 16: Actual average (minimum and maximum) salaries, number of nurses, by experience (4 levels), and matrix values, 2019-20

	Number of nurses	Actual salary, average (minimum-maximum)	Matrix Index Value	Allocated salary
0 to 5 years	34	$47,300 (37,339-62,674)	0.82	$47,484
6-10 years	27	$51,260 (22,600-70,667)	0.89	$51,537
11-15 years	47	$57,173 (43,565-77,235)	0.99	$57,328
16 or more years	114	$62,948 (20,848-85,467)	1.09	$63,119
Overall	222	$57,907 (20,848-85,467)	———	

Nurse Salary Matrix over time

The range of indices narrowed slightly between 2016-17 and 2019-20 with an increase in the index values at the lowest experience level and a decrease in the index value at the highest experience level.

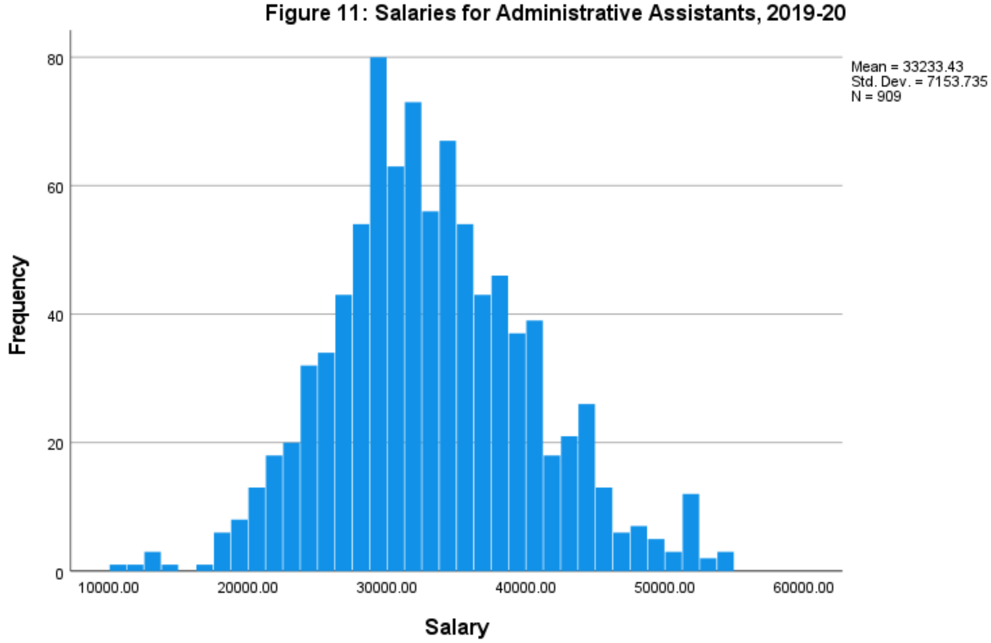
Table 17: Salary matrices for nurses over time: indices (allocated salaries)

<table>
<tr><th rowspan="2">Base salary</th><th>2007 matrix values (current practice)</th><th>2016-17 matrix values (allocated salary)</th><th>2019-20 matrix values (allocated salary), 5 exp levels</th><th>2019-20 matrix values (allocated salary), 4 exp levels</th></tr>
<tr><th></th><th>$53,483</th><th>$57,907</th><th>$57,907</th></tr>
<tr><td>0 years</td><td>0.85 ($45,919)</td><td>0.78 ($41,717)</td><td>0.88 ($50,958)</td><td rowspan="2">0.82 ($47,484)</td></tr>
<tr><td>1-5 years</td><td>0.93 ($50,240)</td><td>0.83 ($44,391)</td><td>0.81 ($46,905)</td></tr>
<tr><td>6-10 years</td><td>0.94 ($50,781)</td><td>0.87 ($46,530)</td><td>0.89 ($51,537)</td><td>0.89 ($51,537)</td></tr>
<tr><td>11-15 years</td><td>1.06 ($57,263)</td><td>0.99 ($52,498)</td><td>0.99 ($57,328)</td><td>0.99 ($57,328)</td></tr>
<tr><td>16 or more years</td><td>1.11 ($59,964)</td><td>1.11 ($59,366)</td><td>1.09 ($63,119)</td><td>1.09 ($63,119)</td></tr>
</table>

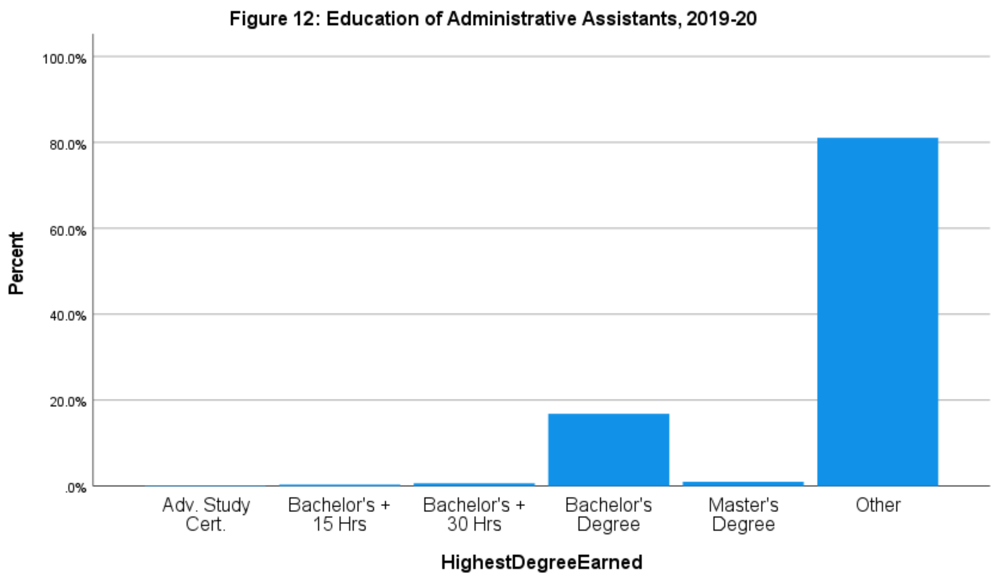
Administrative Assistant/Secretary

The salary matrix for clerical staff used 2019-20 staff data and included all full-time "administrative assistant" positions. There were 1,212 administrative assistant positions in regular public and Indian schools, 917 of which were EPS funded and full-time. There were 8 staff with atypically low or high recorded salaries (3 times the standard deviation, $7,603, outside the mean, $33,409), less than $10,600 and greater than $56,218. The final sample used for the salary matrix computation included 909 administrative assistants with an average salary of $33,233 (minimum of $11,168 and a maximum of $54,254).

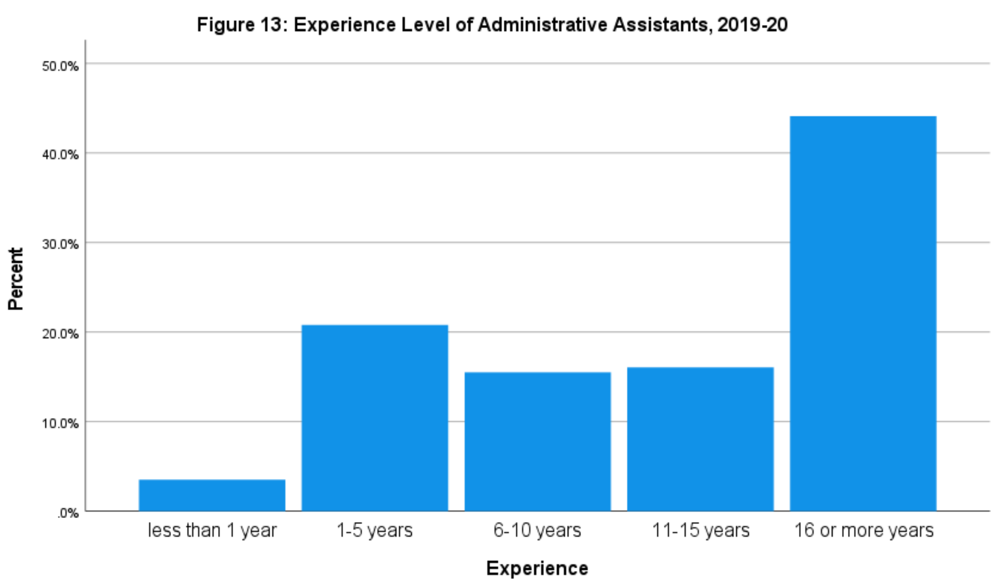
Figure 11: Salaries for Administrative Assistants, 2019-20



Most administrative assistants (81%) have "Other" recorded as their highest degree. This likely includes high school diplomas and Associate degrees. Eighteen percent have a Bachelor's degree and 1% have a Master's degree.



Experience is the only factor used in calculating the salary matrix for clerical staff. While years of experience is weakly correlated with salary, explaining only 10% of the variation in average salaries, education has no statistically significant relationship to salary amounts ($p=0.715$). The experience categories used in previous matrices are the same as for technicians and nurses: less than one year, 1 to 5 years, 6 to 10 years, 11 to 15 years and 16 or more years.



Less than 4% of administrative assistants were in their first year in 2019-20 and 44% had 16 or more years of experience.

Table 18 displays the number of administrative assistants in each experience category and the average and range of salaries paid at each level. The average salary paid to beginner administrative assistants is typically used as the base salary. Note, however, that the number of beginning administrative assistants has declined from 53 in 2009-10 to 37 in 2016-17 to 32 in 2019-20. If this number continues to decline, future salary matrices should use the statewide average for all administrative assistants rather than the average salary paid to beginning staff.

The index for each experience category is calculated by dividing the mean salary for each experience category by the average salary for beginner administrative assistants (i.e., those with less than one year of experience), which in 2019-20 was $28,003.

Table 18: Actual average salaries, matrix index values and allocated salaries, Administrative Assistants, 2019-20 (base salary: $28,003)

	Number of admin assistants	Actual salary, average (minimum-maximum)	Matrix Index Value	Updated salary allocation
Less than 1 year	32	$28,003 (12,356-38,771)	1.00	$28,003
1-5 years	189	$30,246 (11,168-53,014)	1.08	$30,243
6-10 years	141	$30,994 (14,280-51,654)	1.11	$31,083
11-15 years	146	$33,892 (18,580-50,773)	1.21	$33,884
16 or more years	401	$35,606 (13,598-54,254)	1.27	$35,564
Overall	909	$33,233 (11,168-54,254)	----	---

The range of indices narrowed between 2016-17 and 2019-20 because the average salary for beginner clericals increased during that time (from $25,821 to $28,003) while the average salaries for more experienced administrative assistants saw more modest increases and in some cases even declines. As a result, except for beginners, the increase in allocations from 2016-17 to 2019-20 are modest and in some cases, staff are allocated less in the 2019-20 matrix.

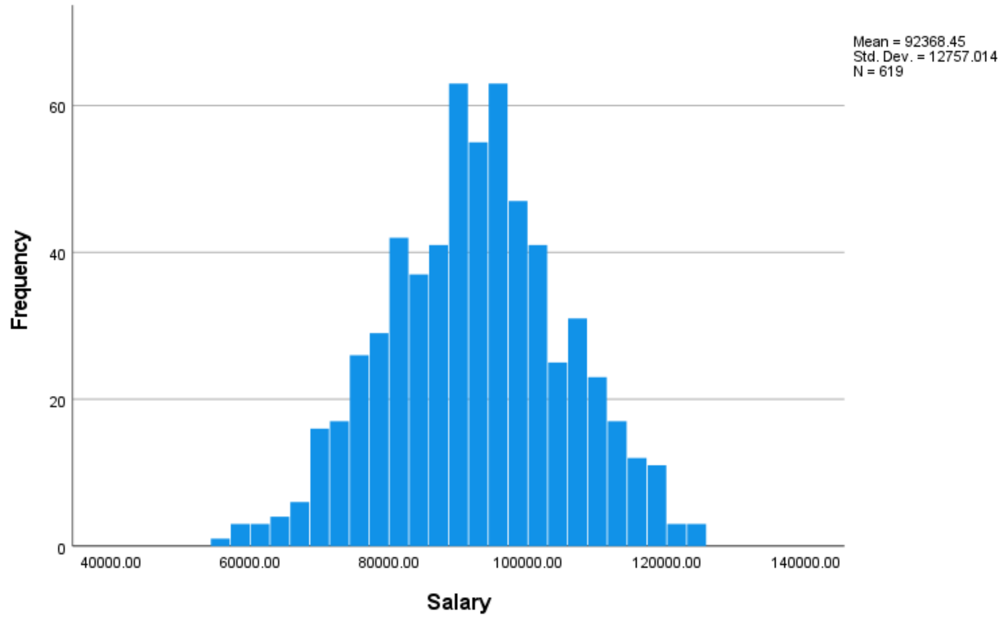
Table 19: Salary Matrices for Administrative Assistants, Actual Implementation in 2019-20, compared to updated values (actual average salary, indices)

	FY 20 Actual EPS (Implemented) Base salary: $28,022		Calculated Update based on 2019-20 data Base salary: $28,003		
	Index	Allocated salary	Index	Actual average	Allocated salary
0 years	1.00	$28,022	1.00	$28,003	$28,003
1-5 years	1.08	$30,264	1.08	$30,246	$30,243
6-10 years	1.18	$33,066	1.11	$30,994	$31,083
11-15 years	1.27	$35,588	1.21	$33,892	$33,884
16 or more years	1.30	$36,429	1.27	$35,606	$35,564

School Administrators

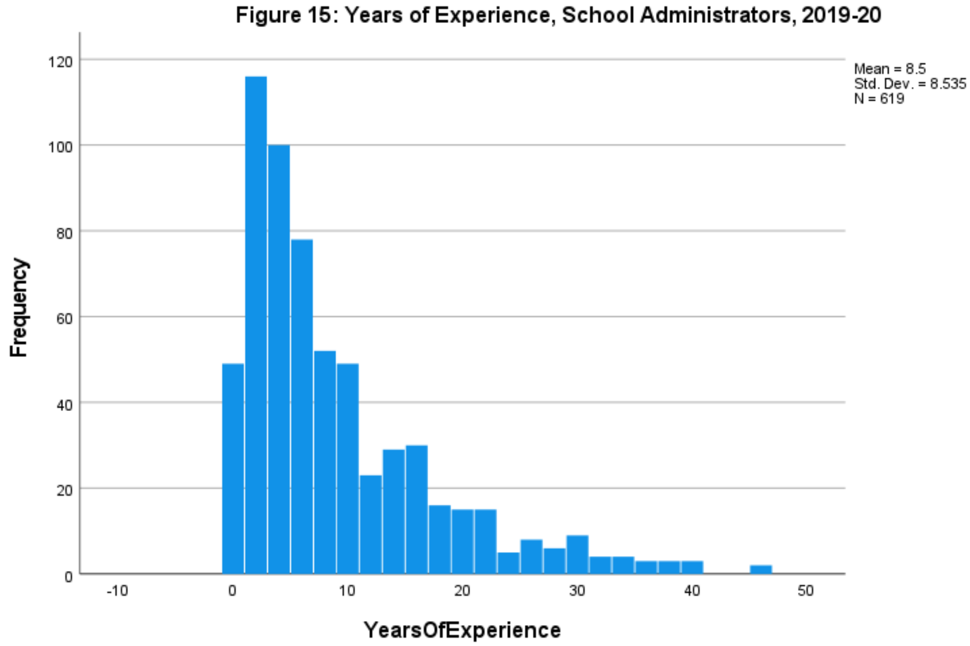
The salary matrix for school administrators used 2019-20 staff data for assistant principals and principals. Of the 828 school administrators employed in regular public or Indian schools, 620 were both full-time and EPS funded. There was only one principal with an unusually low salary: less than $53,759, which is the 3 times the standard deviation ($12,848) below the mean of $92,304; there were no high-salary outliers with salaries greater than $130,848 (3 times the standard deviation above the mean). The final sample used for the salary matrix computation included 619 administrators, 65% of whom are principals and 35% assistant principals, with an average salary of $92,369 and a minimum of $54,750 and a maximum of $125,606.

Figure 14: Salaries, School Administrators, 2019-20

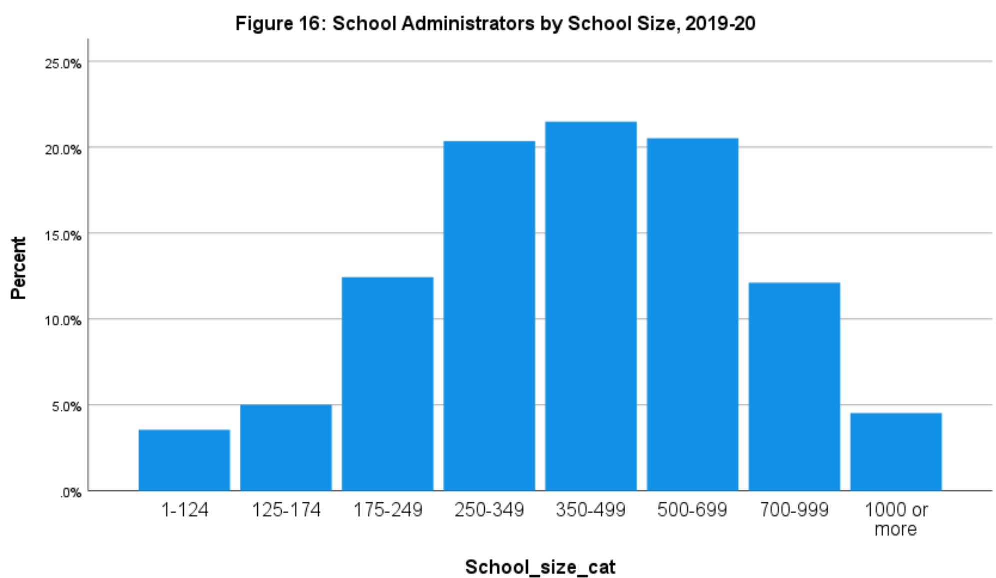


The majority of school administrators (84%) have a Master's degree or advanced certificate. About 11% percent have a Bachelor's degree and 5% have a doctorate. Because there is very little variation in education level, it explains only 2% of the variation in salary level.

The average number of years of experience is 8.5. About 49% of school administrators are relatively new (5 years or less), and about 17% have 16 or more years of experience. Years of experience explains only about 7% of the variation in salaries. Figure 15 is noteworthy for its atypical shape compared to other staff types. A disproportionate number of administrators are in their first 5 years of experience as an administrator. In 2016-17, 26% of school administrators had 16 or more years of experience; by 2019-20 that number had dropped to 17%.



The salary matrix for school administrators is calculated using position (assistant principal vs principal) and school size rather than education and experience. School size and position together explain about 40% of the variation in salary among school administrators. There are 8 school size categories: 1 to 125, 126-175, 176-250, 251-350, 351-500, 501-700, 701-1,000, and 1,001 plus.



The number of assistant principals and principals by school size and their salary averages and ranges are displayed below in Table 20.

Table 20: Actual average (minimum and maximum) salaries and number of school administrators by school size

School size	Assistant Principals N	Assistant Principals Average salary (minimum-maximum)	Principals N	Principals Average salary (minimum-maximum)
1-124	0	**	22	$82,320 (54,750-103,094)
125-174	2	** (64,000-66,162)	29	$86,335 (68,819-110,512)
175-249	8	$68,004 (57,650-86,467)	69	$90,007 (65,933-112,407)
250-349	24	$76,853 (60,953-95,473)	102	$92,729 (69,485-11,5344)
350-499	52	$84,543 (70,000-102,662)	81	$97,686 (73,909-124,589)
500-699	63	$88,226 (64,223-110,420)	64	$104,689 (73,777-125,606)
700-999	46	$90,967 (59,222-104,300)	29	$108,567 (74,933-122,240)
1000 or more	19	$94,298 (84,478-100,233)	9	$109,117 (98,587-117,163)
Overall	214	$86,212 (57,650-110,420)	405	$95,622 (54,750-125,606)

** Fewer than 5 staff data points

The matrix for school administrators uses the statewide average salary for all assistant principals and principals combined as the base salary, which in 2019-20 was $92,369.

Table 21: Salary Matrix for School Administrators, 2019-20 (base salary $92,369)

School Size	Assistant Principal	Principal
1-124	0.72	0.89
125-174	0.76	0.93
175-249	0.80	0.97
250-349	0.83	1.00
350-499	0.88	1.06
500-699	0.96	1.13
700-999	1.00	1.18
1000 or more	1.01	1.18

Table 22 displays the actual average salaries and the matrix allocated salaries using the 2019-20 matrix. Note that the increase in allocation for assistant principals of schools with 1,000 or more students is very small (1%) and that there is no increase in the allocation for principals of the largest schools.

Table 22: Actual average salary vs allocated salaries for school administrators by school size, 2019-20

School size	Assistant Principals		Principals	
	Allocated salary	Actual average salary	Allocated salary	Actual average salary
1-124	$66,506	-	$82,204	$82,320
125-174	$70,200	$65,081	$85,903	$86,335
175-249	$73,895	$68,004	$89,598	$90,007
250-349	$76,666	$76,853	$92,369	$92,729
350-499	$81,285	$84,543	$97,911	$97,686
500-699	$88,674	$88,226	$104,377	$104,689
700-999	$92,369	$90,967	$108,995	$108,567
1000 or more	$93,293	$94,298	$108,995	$109,117

School administrator salary matrix over time:

The overall span of indices remains about the same between the 2016-17 and 2019-20 matrices. In the 2016-17 salary matrix the allocations do not increase initially with school size. This is because of the small number of very small schools and skewed underlying salary distributions. In 2016-17 the average salary of the 25 principals at schools with 125 to 174 students ($78,845) was slightly below the average salary for the 23 principals at schools with 1 to 124 students ($78,920). The underlying salary distribution in 2019-20 is no longer skewed, with the average paid to principals at schools with 125-174 students $4,015 more than the average paid to those at schools with less than 125 students. Also note that with the 2016-17 matrix the increase in allocation for principals of schools with 1,000 or more students is very small (1%). This issue persists with the 2019-20 salary matrix, which allocates the same salary for principals at schools with 700 to 999 students and those with 1,000 or more students and only 1% more for assistant principals at schools with 1,000 or more students. Given the decreased variation in allocations at low and high ends of the school size bands, a more robust matrix would be generated if the school size spans at the low and high ends were combined. However, this becomes a trade-off with sharper changes in allocation when schools near the boundary of an enrollment band category change.

Table 23: Proposed Updated Salary matrices for Principals compared to Actual EPS allocations in 2019-20

	EPS allocations provided in FY20 (Base $87,514)		Recommended updated values (FY20 Base salary value $92,369)			
Size	Index	Allocated salary	N	index	Actual avg salary	Allocated salary
1-124	0.88	$77,012	22	0.89	$82,320	$82,204
125-174	0.92	$80,513	29	0.93	$86,335	$85,903
175-249	0.96	$84,013	69	0.97	$90,007	$89,598
250-349	1.01	$88,389	102	1.00	$92,729	$92,369
350-499	1.05	$91,980	81	1.06	$97,686	$97,911
500-699	1.11	$97,141	64	1.13	$104,689	$104,377
700-999	1.18	$103,267	29	1.18	$108,567	$108,995
1,000 +	1.24	$108,517	9	1.18	$109,117	$108,995

Table 24: Proposed Updated Salary matrices for Assistant Principals compared to Actual EPS allocations in 2019-20

	EPS allocations provided in FY20 (Base $87,514)		Recommended updated values (FY20 Base salary value $92,369)			
Size	index	Allocated salary	N	index	Actual avg salary	Allocated salary
1-124	0.70	$61,260	0	0.72	-	$66,506
125-174	0.73	$63,885	2	0.76	$65,081	$70,200
175-249	0.78	$68,261	8	0.80	$68,004	$73,895
250-349	0.83	$72,637	24	0.83	$76,853	$76,666
350-499	0.87	$76,137	52	0.88	$84,543	$81,285
500-699	0.93	$81,388	63	0.96	$88,226	$88,674
700-999	0.99	$86,639	46	1.00	$90,967	$92,369
1,000 +	1.06	$92,765	19	1.01	$94,298	$93,293

As with teachers, the base salary that was applied in the EPS district allocations in FY2020 was substantially lower than the base that would have been recommended in hindsight ($87,514 compared to $92,369). It would appear that the practice of using the prior year's statewide average salary produced a substantial underestimate. We recommend increasing the base salary for FY2024 to catch up with actual data, while also updating the index values to reflect an overall compression in the scale.

PART II

In this section we compare teacher education and experience profiles across districts by district size, poverty rate and location to investigate the impact of these differences on salary allocations. Because salary matrices for teachers are generated using current education and experience profiles, the salary matrix, in effect, compensates districts that employ more teachers, guidance staff and librarian/media specialists with higher degrees and more experience. Districts employing more experienced and/or more highly educated (e.g., Master's degrees) teachers will be allocated more funding than districts employing less experienced or educated staff in recognition of the additional costs of paying such employees. If the education-experience profiles differ by SAU size, poverty level, or rurality, the allocations resulting from the salary matrices will reflect those patterns. For example, if rural districts systematically employ staff with lower levels of education and less experience than suburban districts, the salary matrix will allocate less funding on the whole to rural districts than it does to suburban districts. Thus the purpose of these analyses is to describe Maine's staffing patterns to inform policy discussions about the role and impact of the salary matrix component on funding allocations.

This analysis was first conducted using 2016-17 staff data and reported in the previous MEPRI report (Morris and Johnson, 2019). Then we found that higher poverty districts and rural districts, particularly small rural districts, employed less experienced and less educated staff.

The data used to update the analysis come from the 2019-20 staff data files, NCES code rankings from the National Center for Education Statistics (SAU urban-to-rural category), 2019-20 information from Maine DOE on student enrollment (SAU size category) and 2018-19 information on the % of students eligible for FRPL (poverty level). The sample includes the population of Maine public school districts and administrative units with data available on enrollment, %FRPL, and NCES locale, excluding those in unorganized territories and on tribal reservations as well as small island districts (N=182).

<u>Poverty</u>: Districts were categorized according to three levels of poverty: lower, average and higher. Lower poverty districts had less than 30% of students eligible for free or reduced priced lunch, or one standard deviation below the mean percent eligible of 47.6%. The average rate of eligibility for FRPL among low poverty districts was 19% (range: 4% to 29%). Average poverty districts had 30% to 67% FRPL eligibility, one standard deviation from the statewide average, and a mean FRPL eligibility rate of 49%. Higher poverty districts included those districts with a FRPL eligibility rate one standard deviation above the statewide mean. The average FRPL rate among these high poverty districts was 80% with a range of 70% to 99%.

Table 25: Districts by Poverty level, 2019-20

	N	%	Mean poverty rate (range)
Low poverty (0% to 29%)	31	17%	19% (4% to 29%)
Average Poverty (30% to 67%)	128	70%	49% (30% to 67%)
High Poverty (68% to 100%)	23	13%	80% (70% to 99%)

District size: We also categorized districts by size, with smaller districts defined as those with fewer than 300 attending students (n=74), medium sized districts as those with 300 to 1,200 attending students (n=51), and larger districts as those with 1,201 or more (n=57). The average student enrollment for small districts was 126 (with a range of 7 to 288), for medium sized districts the average size was 641 (with a range of 307 to 1,187) and for large districts, the average size was 2,281 (range 1,201 to 6,779).

Table 26: Districts by size, 2019-20

	N	%	Mean Size (range)
Less than 300 students	74	41%	126 (7 to 288)
300 to 1,199 students	51	28%	641 (307 to 1,187)
1,200 or more students	57	31%	2,281 (1,201 to 6,779)

Rurality: Districts were also categorized according to their NCES locale code, a measure of rurality produced by the National Center for Education Statistics, which includes three levels within each category of city, suburban, town, and rural.

Table 27: Districts by location 2019-20

	N	%
City	5	3%
Suburb	19	10%
Town	20	11%
Rural	138	76%

*For definitions of codes, got to: https://nces.ed.gov/programs/handbook/data/pdf/appendix_d.pdf

Maine is a heavily rural state with 76% of the school districts located in a rural area. Of the 138 rural school districts, 51 (37%) are designated remote, which is defined as more than 25 miles from an urbanized area and also more than 10 miles from an urban cluster. Only 5 districts (3%) are located in an area defied as a city, another 10% (19 districts) are in suburban areas and 11% are in a town.

Staff Education and Experience by District Characteristics

From the 2019-20 staff files obtained from the Maine DOE we extracted data on "years of experience" and "highest educational degree". Highest educational degree was broken into 5 categories: Other, Bachelor's degree, Bachelor's degree plus 15 or 30 hours of additional training, Master's degree or Master's degree plus 15 hours of additional training, Master's degree plus 30 hours of additional training, an Advanced Degree, or a Doctorate. Based on "years of experience" information available in the staff data eight experience categories were computed: less than 1 year, 1 to 5 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 21 to 25 years, 26 to 30 years, and 31 or more years. This information was aggregated up to the SAU level and used to assess the % of staff (teachers, including regular classroom teachers, ELL teachers, and Literacy Specialists and school social workers, guidance counselors, directors of guidance, and librarians/media specialists) at each education and experience level across districts by size, poverty level, and urban-rural locale.

Overall, the results are the same as the previous MEPRI report (Morris and Johnson, 2019): teachers and other professional staff employed in higher poverty districts and small districts are less experienced and less likely to have a Master's degree or higher. Rural districts also employ teachers and other professional staff with lower levels of education compared to other districts and both urban and rural districts tend to have less experienced teachers but differences disappear once district size (enrollment) and poverty rate are taken into account.

Profiles by District Poverty Level

Finding #1: The staff employed by high poverty districts are less experienced and less likely to hold a Master's degree compared to other districts.

High poverty districts employ fewer staff with Master's degrees or more, compared to low poverty and average poverty districts. On average, the proportion of staff with a Bachelor's degree among low poverty districts is 34.8% compared to 54.6% among high poverty districts. The percentage of staff with a Master's degree or a Master's degree plus 15 hours of additional training is on average 44.2% among low poverty districts, 33.5% among average poverty districts and 28.6% among high poverty districts. The typical profile among low poverty districts contains 10.5% of staff with a Master's degree plus 30 additional hours of training (or an Advanced Certificate or a doctorate) compared to 5.9% among average poverty districts and 3.2% among high poverty districts.

Table 28: Percentage of staff at each education level by district poverty level, 2019-20

	Other	BA only	BA plus 15 or 30 hours	MA or MA plus 15 hours	MA plus 30 hours, advanced certificate or PhD
Low poverty	0.2%	34.8%	10.3%	44.2%	10.5%
Average poverty	1.4%	46.4%	12.8%	33.5%	5.9%
High poverty	3.1%	54.6%	10.5%	28.6%	3.2%
Overall	1.4%	45.3%	12.0%	34.8%	6.5%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

Using correlation and regression analysis, we confirm that percentage of students eligible for FRPL is significantly associated with the staff's education profile. The percentage of students eligible for FRPL is positively correlated with the percentage of BA-only staff and the percentage of staff with education recorded as "other" (presumed to be an Associate's degree) and negatively correlated with the percentage of staff with a Master's degree or higher. The strength of the correlation is weak-to-moderate, with the student poverty rate explaining about 13% of the variation in staff education profile. The significance between the student poverty rate and the percentage of staff with a BA-only and the percentage with a Master's degree or higher remains statistically significant even after controlling for district size and rurality. The FRPL rate and the percentage of staff with a BA plus 15 or 30 hours of additional training are not significantly correlated.

Experience profiles: Low poverty districts have fewer beginning career staff compared to higher poverty districts. On average, the percentage of staff with 5 or fewer years of experience among low poverty districts is 23.4% compared to 28.6% among average poverty districts and 33.4% among high poverty districts. Low poverty districts have higher percentages of mid-career staff: on average, 43.4% of staff at low poverty districts have 11 to 25 years of experience compared to 38.0% among average poverty districts and 36.9% among high poverty districts. Higher poverty districts, on the other hand, have on average slightly lower percentages of staff with 26 years or more: 15.5% compared to 20.1% among low poverty districts.

Table 29: Percentage of staff at each experience level by district poverty level, 2019-20

Years →	< 1	1-5	6-10	11-15	16-20	21-25	26-30	31+
Low poverty	2.3%	21.1%	13.3%	14.9%	15.6%	12.9%	9.1%	11.0%
Average poverty	4.7%	23.9%	15.8%	14.5%	12.8%	10.7%	7.6%	10.1%
High poverty	5.2%	28.2%	14.1%	15.6%	10.0%	11.3%	7.8%	7.7%
Overall	4.3%	23.9%	15.1%	14.7%	12.9%	11.2%	7.9%	10.0%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

Using correlation and regression analysis, we confirm that percentage of students eligible for FRPL is significantly associated with the staff's experience profile. The student poverty rate is positively correlated with percentage of staff with 5 years or less and negatively correlated with the percentage of staff with 6 to 25 years of experience, even after controlling for district size and rurality. The strength of the correlation between experience profiles and student poverty rate is statistically significant but weak, with the student poverty rate explaining only 3% of the variation in staff experience profile. The differences in percentage of staff with 26 years or more are small and not statistically significant.

Profiles by District Size

Finding #2: The staff employed in small districts tend to have less experience and are less likely to hold a Master's degree compared to larger districts.

Education profiles: Small districts have fewer staff with Master's degrees or more compared to medium size and large districts. On average, the percentage of teachers with a Bachelor's degree is 63.8% among small districts compared to 59.3% among medium sized districts and 47.1% among large districts. About half (51.8%) of staff in the typical large districts have a Master's degree, an Advanced Certificate or a Doctorate compared to only 34.4% for small districts and 39.5% for medium sized districts.

Table 30: Percentage of staff at each education level by district size, 2019-20

	Other	BA only	BA plus 15 or 30 hours	MA or MA plus 15 hours	MA plus 30 hours to doctorate
< 300 students	1.9%	51.2%	12.6%	29.5%	4.9%
300-1,199	1.2%	46.8%	12.5%	34.7%	4.8%
1,200 or more	1.0%	36.2%	10.9%	42.0%	9.8%
Overall	1.4%	45.3%	12.0%	34.8%	6.5%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

Size (student enrollment) is negatively correlated with the percentage of staff with Bachelor's degrees and positively correlated with the percentage with a Master's degree or more. These correlations remain statistically significant even after controlling for the district's poverty rate and location. The correlation between enrollment and the percentage of staff with a BA only or a Master's degree or higher are relatively weak in strength, with enrollment explaining about 8-11% of the variation in staff education profile.

Experience profiles: Small districts tend to have more beginner staff (0 to 5 years) and fewer mid-career staff (6 to 25 years). On average, the percentage of staff with 5 years or less of experience among small districts is 32.8% compared to 26.2% among medium size districts and 23.1% among large districts. In the typical small district, 50.5% of staff have 6 to 25 years compared to 53.6% in medium sized districts and 58.8% in large districts. The difference in the average percentage of staff with 26 years or more is less pronounced: on average 16.6% among small districts, 19.2% among medium sized districts and 18.1% among large districts.

Table 31: Percentage of staff at each experience level by district size, 2019-20

Years →	< 1	1-5	6-10	11-15	16-20	21-25	26-30	31+
Students								
< 300	4.4%	28.4%	15.5%	13.7%	10.8%	10.5%	8.0%	8.6%
300-1,199	3.9%	22.3%	15.5%	14.9%	12.8%	10.4%	7.3%	11.9%
1,200 or more	3.6%	19.5%	14.3%	15.8%	15.9%	12.8%	8.1%	10.0%
Overall	4.3%	23.9%	15.1%	14.7%	12.9%	11.2%	7.9%	10.0%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

Size (student enrollment) is negatively correlated with the percentage of staff with 5 or fewer years of experience and positively correlated with the percentage with 6 to 25 years of experience. These correlations remain significant even after controlling for the district's poverty rate and location. The differences in percentage of staff with 26 years or more are small and not statistically significant.

Profiles by Rurality

Finding #3: Rural districts, particularly small rural districts, are more likely to have a staff profile with fewer Master degrees and less experience.

Education profiles: Rural districts tend to have staff with lower levels of education compared to city-based and suburban districts. On average, 60.2% of staff in rural districts have a Bachelor's degree compared to 46.8% in urban districts and 44.6% in suburban districts. Rural districts have fewer staff with Master's degrees or higher. On average, the percentage of staff with a Master's degree, Advanced Certificate or a doctorate in rural districts is 38.3% compared to 54.6% in suburban districts and 51.8% in urban districts.

Table 32: Percentage of staff at each education level by district locale, 2019-20

	Other	BA only	BA plus 15 or 30 hours	MA or MA plus 15 hours	MA plus 30 hours, advanced certificate or PhD
City	1.4%	35.8%	11.0%	40.5%	11.3%
Suburb	0.7%	32.6%	12.0%	42.6%	12.0%
Town	1.6%	39.6%	12.5%	39.0%	7.4%
Rural	1.5%	48.2%	12.0%	33.0%	5.3%
Overall	1.4%	45.3%	12.0%	34.8%	6.5%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

However, after controlling for district size and poverty rate, location is not in and of itself significantly correlated to differences in staff education profiles (even when comparing rural districts to all others), except for the percentage of highly educated staff (MA plus 30 hours or Advanced Certificate or Doctorate), which remains statistically significant even after holding district size and poverty rate constant, explaining about 13% of the percentage of the difference between rural and other districts.

Experience profiles: Rural districts have somewhat more beginner staff and fewer mid-career staff especially compared to suburban districts. Nearly 30% of staff in the average rural district have 5 or fewer years of experience compared to 25.1% of the staff employed in districts based in towns, 22.3% in suburban districts and 26.9% in urban districts. At 52.9%, rural districts have, on average, the lowest percentage of mid-career staff (6 to 25 years of experience) compared to 59.5% of the staff in suburban districts and 57.3% in city-based districts.

Table 33: Percentage of staff at each experience level by district locale, 2019-20

Years →	< 1	1-5	6-10	11-15	16-20	21-25	26-30	31+
City	5.8%	21.1%	15.3%	14.2%	15.3%	12.5%	7.3%	8.5%
Suburb	3.3%	19.0%	13.8%	16.6%	15.9%	13.2%	8.8%	9.4%
Town	3.9%	21.2%	14.1%	14.8%	13.6%	12.5%	7.9%	12.0%
Rural	4.5%	25.1%	15.5%	14.4%	12.3%	10.7%	7.8%	9.8%
Overall	4.3%	23.9%	15.1%	14.7%	12.9%	11.2%	7.9%	10.0%

*Note: Staff include teachers, guidance counselors, Directors Guidance, school social workers, and librarians/media specialists. The sample of districts includes all regular public school districts with available data, except island districts.

After controlling for district size, rural location is not in and of itself significantly correlated to differences in staff experience profiles (even when comparing rural districts to all others). Small rural districts are significantly more likely to have a staff profile with less experience.

As we found in 2016-17, staff in low poverty districts and larger, non-rural districts have more experience and are more likely to hold advanced degrees (e.g., Master's degrees, Advanced Certificates, doctorates) while staff in high poverty districts and small rural districts have less experience and are less likely to hold advanced degrees. While the differences are not dramatic, teachers and other professional staff in high poverty districts and small rural districts tend to be less experienced and have less education staff compared to other districts. Next we examine how these differences in staff profiles impact EPS allocations.

Staff education and experience profiles and EPS Allocations

Using our sample of 182 public school districts and administrative units and the 2019-20 teacher salary matrix generated in Part I, we calculate the per student teacher salary allocation by district size, poverty level and location in order to visualize the impact of differences in teacher education-experience profile. We produce these figures for district poverty level as follows:

- Step 1: Obtain the % of teachers in each experience-education category for low, average, and high poverty districts
- Step 2: Calculate EPS total teachers = actual enrollments * teacher ratios from 279 form
- Step 3: Calculate EPS total allocation = % of teachers in each experience-education category * EPS # of teachers * salary matrix index * base salary ($37,361)
- Step 4: Calculate the per student teacher salary allocation = total EPS allocation / total student enrollment

The above is repeated for district size and location. Table 34 below summarizes the results of these estimations:

Table 34: Per student teacher salary allocations by district poverty level, location and size, 2019-20

	Number of districts	Per-Pupil teacher salary allocation
District poverty Level		
Low	32	$3,541
Average	128	$3,353
High	22	$3,260
District size		
Small	74	$3,260
Medium	51	$3,663
Large	57	$3,415
District location		
City	5	$3,346
Suburb	19	$3,462
Town	20	$3,419
Rural	138	$3,350
Combined district demographics		
Rural and small	72	$3,267
Rural and high poverty	19	$3,314
Non-rural, medium and large districts	42	$3,419
Overall – all districts	182	$3,389

Because higher poverty districts employ more teachers with lower levels of education and less experience, the salary matrix allocates poorer districts less funding relative to other districts. Based on the 2019-20 salary matrix, high poverty districts – those with 68% or more of their students FRPL-eligible - receive $93 per student less than average poverty districts and $281 per student less than low poverty districts.

This effect is mitigated by the economically disadvantaged component of the school funding formula, which currently provides an additional 0.15 weight for FRPL-eligible students in each district. For example, Lewiston Public School district is a high poverty district with over 70% of its students designated as economically disadvantaged in 2019-20. The EPS calculated per student allocation for the 2019-20 school year was $6,333 for elementary students and $6,782 for middle and high school students (page 1 of the 279 report). Based on the number of economically disadvantaged students in 2019-20, Lewiston was allocated an additional $3,830,214 (0.15 x $6,333 x #of PK-8 students plus

0.15 x $6,782 x # of 9-12 grade students, page 2 of the 279 report)[4], which works out to be about $702 per student, more than offsetting the lower allocation due to their patterns of staff experience and education level.

Small districts have fewer staff with Master's degrees compared to medium sized and large districts. Small districts also tend to have more beginner staff (0 to 5 years) and fewer mid-career staff (6 to 25 years). Based on the 2019-20 salary matrix, small districts receive $155 per student less than large districts and $403 per student less than medium-sized districts. Almost all the small districts (those with fewer than 300 districts), are rural. Based on the 2019-20 salary matrix and their teacher education-experience profile, small, rural districts are allocated $3,267 per student, $152 less than medium and large districts located in non-rural locations. This effect will be mitigated for eligible districts by the small and isolated school adjustment (see page 2 of the 279 report).[5] About 40% of small, rural districts contained schools that were eligible for the small and isolated school adjustment. For example, Georgetown Public Schools received an adjustment of $46,095 in 2019-20, which works out to be about $429 per student. RSU85/MSAD19 was allocated an additional $60,570 through the small and isolated adjustment, $555 per student. The majority of the small, rural schools in our sample did not, however, qualify for the small and isolated school adjustment in 2019-20.

The differences in education and experience profiles for other staff – social workers, counselors, directors of guidance and librarian/media specialists – are small, compared to differences in teacher profiles, resulting in much smaller per-pupil allocation differences.

Conclusion: Staff in low poverty districts and larger, non-rural districts have more experience and are more likely to hold advanced degrees (e.g., Master's degrees, Advanced Certificates, doctorates) compared to high poverty districts and small, rural districts. Because salary matrices for teachers, social workers, guidance counselors, directors of guidance and librarians/media specialists are generated using current education and experience profiles, the salary matrix provides more funding to lower poverty and larger, non-rural districts than to higher poverty and small, rural districts. While these effects will be offset by the economically disadvantaged component of the EPS funding formula and by the small and isolated component for qualifying districts, they undermine the equity intent of these components.

[4] https://neo.maine.gov/doe/neo/eps/public/ed279.aspx
[5] https://neo.maine.gov/doe/neo/eps/public/ed279.aspx

Part III

Beginning in 2020-21, the State will provide each qualifying school administrative unit with the funding necessary to achieve the minimum salary for certified teachers established in Title 20-A, §13407. All types of teachers are eligible for the minimum salary supplement including long-term substitutes and specialized teachers (e.g., EL, special education, gifted and talented) as well as those paid with federal funds or state and local grants. School social workers, guidance counselors and librarians and media specialists are also included in the minimum salary increase. The salary increase will be phased in over three years. Districts will be required to pay salaries of at least $35,000 starting in 2020–2021. The following year, the minimum salary increases to $37,500. The full $40,000 minimum will be required beginning in the school year of 2022-2023. The minimum amount will be prorated for part-time staff in proportion to their full–time equivalency (FTE). The State will provide districts the necessary funding to close the gap between what each staff is earning now and the minimum salary required (i.e., $35,000 in SY2021, $$37,500 in SY2022, and $40,000 in SY2023). Funding for the difference will be calculated using base salaries exclusive of stipends. [6]

In this section we use staff data obtained from the MDOE from school years 2019-20 and 2020-21 to gauge the number of staff that will be impacted by the minimum salary increase and to compare minimum salaries by experience, education, position and district characteristics including poverty rate, size and location. In this analysis the sample includes staff working in regular public schools, public charters and CTEs. In both school years about 1% worked in more than one district; they were excluded from the sample. Also excluded were 12 full-time classroom teachers with salaries recorded as $101 and 12 other staff who were recorded as working more than 1.0 FTE. Salaries for part-time staff were prorated.

In SY2020, the percentage of staff earning less than $35,000, the minimum required salary beginning in SY2021, was 2.5%, just over 3 times more than it was by the next year (0.8%). Note that fewer staff were also being paid below $40,000, the eventual minimum beginning in SY2023, indicating that some districts were foregoing the phase-in.

Table 35: % and # of staff below salary minimums, SY2020 and SY2021

	SY 2020	SY 2021
% (#) less than $35,000	2.5% (404)	0.8% (116)
% (#) less than $37,500	7.5% (1,221)	3.2% (486)
% (#) less than $40,000	14.3% (2,323)	8.5% (1,278)

Less experienced staff, those without more advanced degrees and those working part-time were more likely to be earning less than the minimum required salary ($35,000

[6] https://mainedoenews.net/2020/10/16/priority-notice-verification-of-minimum-teacher-salaries/
https://www.mainelegislature.org/legis/statutes/20-a/title20-Asec13407.html

in SY2021 and $40,000 by SY2023) compared to full-time staff (FTE=1.0) and those with more education and experience. Long-term substitutes (of which there are few) were a lot more likely to be earning less than the minimum required salaries ($35,000 in SY2021 and $40,000 by SY2023). Librarian/media specialists were slightly more likely to be earning less than the minimum required salary compared to teachers, social workers and guidance counselors. Staff at Maine's public Charter school are also more likely than staff at regular public schools or CTEs to be earning less than the minimum salaries.

Table 36: Education and the likelihood of being paid less than $35,000 and $40,000, SY 2020

	Less than $35,000	Less than $40,000
Other	13.7%	40.4%
Bachelor's degree	4.0%	24.4%
Master's degree or MA + 15 hours	0.6%	3.3%
MA +30 hours, Advanced Certificate or doctorate	0.6%	0.9%

Table 37: Experience and the likelihood of being paid less than $35,000 and $40,000, SY 2020

	Less than $35,000	Less than $40,000
Less than 1 year	17.3%	65.5%
1-5 years	6.1%	43.5%
6-10 years	1.1%	9.2%
11 or more years	0.3%	0.7%

Table 38: FTE and the likelihood of being paid less than $35,000 and $40,000, SY 2020

	Less than $35,000	Less than $40,000
FTE = 1.0	2.3%	14.3%
FTE < 1.0	6.0%	14.8%

*Note: All salaries were prorated by FTE.

Table 39: School type and the likelihood of being paid less than $35,000 and $40,000, SY 2020

	Less than $35,000	Less than $40,000
Regular Public	2%	14%
Charter	15%	34%
CTE	3%	9%

Table 40: Types of staff being paid less than $35,000 and $40,000, SY 2020

	Less than $35,000	Less than $40,000
Regular Classroom Teacher	2.4%	15.0%
G&T Teacher	2.2%	4.3%
Special Education Teacher	2.5%	16.4%
Literacy Specialist	0%	0%
EL Teacher	1.1%	8.2%
Title I Teacher	1.4%	8.3%
Long-term Substitute	65.9%	80.5%
School Social Worker	2.4%	4.8%
Guidance Counselor	0.7%	5.5%
Librarian/Media Specialist	5.8%	10.4%
Overall	2.5%	14.3%

On average, the percentage of eligible staff earning less than the $35,000 is higher in rural districts, smaller districts and in higher poverty districts. The same is true of the percentage earning less than $40,000.

Table 41: Mean percentage (range of percentages) of eligible staff being paid less than $35,000 and $40,000, by district, SY 2020

	Less than $35,000	Less than $40,000
Location		
City	< 1% (0-0.4%)	9% (0.7-24%)
Suburb	<1% (0-3%)	8% (0-48%)
Town	3% (0-16%)	14% (0-50%)
Rural	8% (0-83%)	25% (0-100%)
Poverty level		
Low poverty	1% (0-29%)	6% (0-43%)
Average poverty	6% (0-50%)	23% (0-87%)
High poverty	13% (0-83%)	36% (0-83%)
SAU Size		
Less than 300 students	10% (0-83%)	27% (0-100%)
300 to 1,199	5% (0-29%)	23% (0-53%)
1,200 or more	2% (0-15%)	12% (0-37%)

Summary of Findings and Conclusions

Teachers

- Teacher salaries are increasing more rapidly than inflation on average. Legislation increasing the minimum teacher salary in Maine to $30,000 for FY2008 and to $40,000 for FY2023 has likely contributed to this trend. This means that the practice of annually increasing the base teacher salary by a consumer inflation measure is inadequate to keep pace with actual salaries, and the base salary will need to be reset to a new and higher level. This change should be implemented for FY2024, the first year when transitional salary supplements pursuant to Title 20-A Section 15689, 7-A will no longer be in place to ensure adequate funding.

- As anticipated, the statutory increase in minimum salaries has brought up the lower end of the salary range, but has not proportionally increased salaries at the upper end. This means that the overall salary matrix is more compressed than in prior years; there is a smaller range between the entry-level positions and the staff with the highest educational attainment and years of experience. This makes it important to also update the index values for FY2024 (and not just the base salary) to avoid overestimating the funding needed for the positions at the higher end of the scale.

- A separate accompanying spreadsheet has been prepared to assist the Department in comparing rough cost estimates of various base salary scenarios for FY2024.

- Salary matrix indices should be recalculated in summer 2022 (using FY2022 staff data) in order to have an additional transitional year of data to ensure that the updated matrix values to be implemented for FY2024 allocations are stable.

- There are not enough teachers with doctorate degrees (53) to sustain a separate education category; the matrix should also be modified in future to combine them with Master's +30 hours or advanced certificates. We recommend combining all beginning teachers (0 to 5 years) into one experience category at the same time.

Guidance Counselors/Librarians

- We did not find sufficient and compelling evidence that guidance counselors, social workers, and librarian / media specialist staff positions should have their own separate salary matrix rather than receiving allocations based on the teacher matrix. While these staff positions did earn slightly more on average than teachers with similar levels of education and experience, a preliminary investigation revealed that this may be explained by the greater proportion of guidance and library staff hired by higher-salary districts. Additional study is needed to determine whether these staff are paid commensurate with teachers *in their same districts*. Otherwise, the additive effect of the regional adjustment on top of higher salaries would overestimate actual costs.

- If further study reveals that there is a lingering effect of increased salary above and beyond district hiring patterns, then a separate matrix may be justified. However, the resulting matrix would need to have fewer staff categories in order to have sufficient data points to calculate reliable values, which would have its own trade-offs. Each broader category would by necessity have a wider range of salaries, which means variance from actual could be substantial in some districts.

Education technicians / media technicians

- The salary matrix in use in the EPS model no longer reflects the spread of salaries between beginning and experienced ed tech staff observed in FY20 data. We recommend updating the matrix to the values in Table 12. Because the updated base salary is similar to that used in EPS allocations, changing the top index value from 1.35 to 1.57 will have substantial cost implications that must be modeled.

- There is an insufficient number of EPS-funded media technicians to sustain separate matrix values. We recommend combining media techs into the educational technician matrix. Furthermore, as with guidance and librarian positions, the slightly higher index values for these positions may be attributable to the pattern districts that disproportionately hire these types of staff positions. Additional study would be warranted if a separate matrix is to be maintained in the future.

Nurses / Health Staff

- Because there are so few beginner nurses represented in the salary data (i.e. less than 1 year of reported experience) we combined all staff with 0 to 5 years of experience into the same category in order to achieve reliable results.

Administrative assistants

- The calculated salary matrix using FY20 salary data is remarkably similar to the actual matrix in use for that year. This matrix appears to be stable over time; minor adjustments to update the index values may be warranted but would reduce allocations overall.

School Administrators

- The average salary calculated in hindsight for FY20 based on reported data was substantially higher than that used in allocations based on a projected average. For FY24, the averages should be recalculated and compared before finalizing the number used in the district allocations to see if they have come back into better alignment. We also recommend updating the index values, which have compressed somewhat at the higher ends of the scale but increased at the lower ends, where they are most needed.
- We recommend decreasing the number of size categories at the bottom and top of the scale to increase the Ns in each cell and make the matrix more stable and reliable.

Part II

- Staff in low poverty districts and larger, non-rural districts have more experience and are more likely to hold advanced degrees (e.g., Master's degrees, Advanced Certificates, doctorates) compared to high poverty districts and small, rural districts. This means that there likely is an interaction between the salary matrix and the regional adjustment, since Maine's smaller, rural districts are predominantly in lower-cost regions of the state and vice versa.
- We recommend a fresh look at the methodology for determining regional adjustments that would better account for the non-random distribution of less-experienced teachers. A revised methodology could also ensure that the final allocations resulting from the combined effect of the salary matrix and the regional adjustment do not allocate less than $40,000 for any full-time teacher.

Part III

- In the transition to the minimum $40,000 teacher salary, there were teachers who were lagging in their salary increases and were contracted for less than $35,000 in FY2020 (and were thus recipients of state adjustments in that phase-in period). These staff were more likely to be teaching in rural, smaller, and/or higher poverty districts. Therefore, these districts will be getting more assistance from state to close the gap during the transition years. Because the state minimum salary adjustments will be discontinued after FY23, it will critically important to implement the updated salary matrix with a higher base salary in FY2024 in order to provide adequate minimum funding to all districts.

APPENDIX

Education Technician Notes

Using the beginner Ed Tech I's average salary as the base instead of beginner Ed Teach II would produce a matrix (Table A42) that allocates more to early career technicians and a more uniform rate of increase in salary allocations for additional experience: there's an 8-9% increase in the indices between 0 years and 1-5 years, a 7-9% increase between 1 to 5 and 6 to 10 years of experience, an 11% increase between 6 to 10 years and 11 to 15 years, and a 8% increase after 16 years or more. This is an overall "smoother" pattern than using Ed Tech II salary as the base. This may be an overall improvement in the cost model if more substantial updates are considered in a future review cycle.

Table A42: Salary Matrix created using all tech positions (N=5,983) and Ed Tech I mean salary as base salary ($16,032)

	Position					
Experience	Ed Tech I	Ed Tech II	Ed Tech III	Media I	Media II	Media III
0 years	**1.00**	1.19	1.36	*1.09*	*1.32*	1.46
1-5	1.09	1.27	1.45	*1.17*	*1.41*	1.54
6-10	1.16	1.35	1.52	*1.25*	*1.48*	1.62
11-15	1.27	1.46	1.63	*1.36*	*1.59*	1.73
16 plus	1.35	1.54	1.71	1.44	1.67	1.81

School Administration Notes

The number of assistant principals and principals by school size and their salary averages and ranges are displayed below in Table A43.

Table A43: Actual average (minimum and maximum) salaries and number of school administrators by school size

School size	Assistant Principals		Principals	
	N	Average salary (minimum-maximum)	N	Average salary (minimum-maximum)
1-249	10	$64,419 (57,650-86,467)	120	$87,710 (54,750-112,407)
250-349	24	$76,853 (60,953-95,472)	102	$92,729 (69,485-115,344)
350-499	52	$84,543 (70,000-102,662)	81	$97,686 (73,909-124,589)
500-699	63	$88,226 (64,223-110,420)	64	$104,689 (73,777-125,606)
700 plus	65	$91,940 (59,222-104,300)	38	$108,697 (74,933 -122,240)
Overall	214	$86,212 (57,650-110,420)	405	$95,622 (54,750-125,606)

The matrix for school administrators uses the statewide average salary for all assistant principals and principals combined as the base salary, which in 2019-20 was $92,369. When 8 school size categories were used, the index for assistant principals of the largest schools (1,000 or more students) was only 1% more than the next smaller school size category (700 to 999 students) and there was no difference in the allocation for principals of the two largest school sizes. Using fewer school size categories creates a smoother matrix with more uniform increases between school size categories.

Table A44: Salary Matrix for School Administrators, 2019-20 (base salary $92,369)

School Size	Assistant Principal	Principal
1-249	0.78	0.95
250-349	0.83	1.00
350-499	0.89	1.06
500-699	0.96	1.13
700 plus	1.01	1.18

Table A45 displays the actual average salaries and the matrix allocated salaries using the 2019-20 matrix.

Table A45: Actual average salary vs allocated salaries for school administrators by school size, 2019-20

School size	Assistant Principals		Principals	
	Allocated salary	Actual average salary	Allocated salary	Actual average salary
1-249	$72,048	$64,419	$87,750	$87,710
250-349	$76,666	$76,853	$92,369	$92,729
350-499	$82,208	$84,543	$97,911	$97,686
500-699	$88,674	$88,226	$104,377	$104,689
700 plus	$93,293	$91,940	$108,995	$108,697

Essential Programs and Services Component Review Report of Findings:
School Staff Benefits Percentages

Background

This report presents the analysis and review of the school staff benefits percentages used in the Maine Essential Programs and Services (EPS) funding formula. The EPS funding formula is designed to estimate an appropriate amount of funds a school district needs to provide the programs and services necessary to ensure that all students are provided adequate opportunities to achieve the Maine Learning Results standards. The estimated amount that a district should need to spend is based on student enrollment and student-staff ratios set by the Maine DOE and include amounts for a variety of services (per pupil amounts for supplies and equipment, specialized services such as professional development, student assessment, instructional leadership support, co-curricular and extra-curricular student learning, and district services (e.g., transportation, facilities management). Adjustments are made to the allocation based on circumstances determined to increase costs, including the size of specialized student populations (e.g., students with limited English proficiency, economically disadvantaged students and students with special needs) as well as school size, geographic location and cost of living differences. The EPS formula also adjusts personnel costs for differences in staff experience and education and regional differences in the salaries and the cost of living.

School employee compensation, comprised of salaries and the cost of employee benefits, including group insurance (health, life, dental, etc.), Social Security/Medicare, unemployment compensation, and workers' compensation, make up the bulk of school district expenditures. Benefit expenditures are paid by the school administrative unit on behalf of employees, meaning they are not paid directly to the employee as part of their gross salary but are in addition to that amount. In the EPS formula, the allocation for employee benefits is calculated as a proportion of salary. Different ratios are used for different categories of staff because the relative costs of benefits differ when calculated as a percentage of salaries. The EPS model uses four categories of school staff: classroom teachers, guidance/counseling staff, school administrators, and clerical support staff. Although the benefits ratios have been reviewed several times in the past as part of the scheduled EPS Component Review process, the original EPS benefits ratios have been in place since the initial implementation of the formula in 2005 and have not been updated in the formula.

In this component review we have updated benefit percentages using data from fiscal year 2018-19. Benefit percentages include all school personnel benefits, except tuition reimbursement for instructional staff, which are included in the Professional Development component of EPS. Note: Employee benefits costs of system personnel are included in their respective components (school administration, student transportation, operation and maintenance of plant, special education, or CTE). In addition to updating benefit percentages for EPS school staff, we examined benefit percentage changes over time and estimated the cost of updating current EPS benefit percentages. Because teacher compensation is the largest component of school district expenditures, we also took a closer look at changes over time in teacher benefit and salary expenditures and the teacher benefit percentages.

Size and scope of benefits expenditures

Employee benefits are one of the largest operating expenditure categories for Maine school districts after salaries and wages. Employee compensation, which includes both salaries and benefits, is the largest expenditure of Maine SAUs. Among regular public school districts across Maine (excluding public charters and specialized schools) employee compensation accounted for $1.9 billion out of the total operating expenditure of $2.6 billion, which represented 73% of SAU operating expenditures in FY 2019. Employee benefits alone were 17% of the total operating expenditure of $2.6 billion.

The EPS Benefits Percentages that are the main subject of this report are used directly in the School Staff Benefits component of EPS. This funding allocation appears on page 1 of each SAU's annual "ED 279" funding report. Benefits included are group insurance (health, life, dental, etc.), Social Security/Medicare, unemployment compensation, and workers' compensation. Tuition reimbursement and professional development are also included in the calculation of benefits percentages for clerical personnel. However, tuition reimbursement and retirement costs are not included as employee benefits for instructional personnel (teachers, education technicians, library staff, guidance, school administrators), as there is a separate EPS component to fund these expenditures.

The EPS Benefits Percentages are used in several parts of the EPS cost model. Primarily they are applied to the school staff salaries calculated according to the recommended school staff ratios. Unlike salaries, benefits are not subject to the regional adjustment. The same percentages also influence other EPS components, including the calculation of the Isolated Small School Adjustment as well as the Special Education and CTE cost allocations. A detailed explanation of the places within the EPS model that Benefit Percentages are used, may be found in a previous MEPRI benefit percentages report by Johnson and Sloan (2019).[1] The Johnson and Sloan report also details how funding for benefits paid to other

[1] EPS Reports and Presentations | Department of Education (maine.gov)

types of staff (e.g. district-level staff and certain non-instructional staff) are included in separate calculations of other EPS model elements.

As described above, tuition reimbursement and professional development costs are not included as employee benefits for instructional personnel (teachers, education technicians, library staff, guidance, school administrators). Instead, they are funded in a separate Professional Development component as a per pupil amount (EPS 279 Sec. 1.D. line 3). Retirement expenditures for school instructional staff are also not included in the Benefit Percentage. They are funded by an allocation on a separate line of the ED 279 (Sec. 3.B.) according to the normalized cost for each SAU from the Maine Public Employees Retirement System. The amounts of the tuition reimbursement and retirement expenditures for FY2019 are shown below in Table 1.

Table 1: School Staff Benefits Included in Other EPS Components (in $ millions), FY 2018-19

	Professional Development Tuition Reimbursement	Retirement Contribution
Teachers, Guidance/Counseling, Librarians, and Health Staff	$4.4	$30.1
Educational Technicians and Library/Media Assistants	$0.5	$3.9
School Administrative Staff	$0.3	$2.3

*Note: Private schools, public charters and specialty schools not included.

Updated Ratios

MEPRI computed updated benefits percentages for school staff categories using Fiscal Year 2018-19 SAU expenditure data. Results are shown below in Table 2. The percentages are calculated by determining the ratio of the benefits to the total salaries.

Table 2. Salary, Benefits, and Benefits Percentages by EPS Staff Grouping, FY 2019 ($millions)

	Salary	Benefits	Percentage
Teachers, Guidance/Counseling, Librarians, and Health Staff	$860.9	$225.1	26%
Educational Technicians and Library/Media Assistants	$124.9	$49.7	40%
Clerical Staff	$34.0	$13.6	40%
School Administrative Staff	$68.5	$14.4	21%
Total EPS School Staff (excludes system functions)	$1,088.3	$302.8	28%
Note: The benefits amount for clerical staff includes $0.7 million in retirement contributions and $17 thousand in tuition reimbursement, which are excluded for other staff types as they are funded via other EPS components (see Table 1).			

*Note: Private schools, public charters and specialty schools not included.

Table 3 includes the percentages from the original EPS model, which are also the current rates used in calculating EPS cost components each year. Also included in the table are the updated rates from previous MEPRI analyses as part of the ongoing 3-year review of EPS components, as well as the an estimate of the approximate impact on total allocations if the EPS benefits rates, established in 2005, were updated to the FY2019 ratios. The total EPS school staff difference of $75 million is based on actual 2016 statewide school staffing levels and salaries rather than EPS recommended staffing levels, salaries, pupil weights, and adjustments. It is used as a preliminary estimate of the difference in total allocation that would occur if updated benefits percentages were adopted within the EPS funding model. However, the exact difference in allocation will be affected by the EPS recommended personnel ratios, salary matrices, increases for inflation, and other factors.

Table 3. Comparison of EPS Benefits Percentages to FY19 Expenditure Percentages ($millions)

	Current EPS Benefits % (2005-06)	2008-09	2015-16	2018-19	Proposed Increase (Current to FY19)	Difference ($millions)
Teachers, Guidance/Counseling, Librarians, and Health Staff	19%	22%	25%	26%	7%	$60.3
Educational Technicians and Library/Media Assistants	36%	33%	38%	40%	4%	$5.0
Clerical Staff	29%	32%	39%	40%	11%	$7.5
School Administrative Staff	14%	19%	20%	21%	7%	$2.4
Total EPS School Staff	21%	23%	27%	28%	7%	$75.2
Total State Share					*55% state*	*$41.4*
Total Local share					*45% local*	*$33.8*

*Note: Private schools, public charters and specialty schools not included.

In summary, spending on staff benefits as a percentage of salaries has continued to increase since the initial ratios were implemented in the EPS model, but the percentages in the EPS model have not changed from the original 2005-06 EPS rates. This raises concerns about the adequacy of the model allocations. The following section further discusses this trend.

Further Analysis of the Change in Teacher Benefits Percentage

Classroom teachers comprise the largest single position type within the EPS school staff categories. Teacher salaries - $794 million in FY2019 - were 73% of the total EPS school staff salaries of $1,088 million. Teacher benefits ($209 million) were 69% of total EPS school staff benefits. The benefits percentage for classroom teachers alone was 26%, the same as the group including teachers, guidance, librarians, and health staff.

The observed benefits percentage for teachers changed from 25% to 26% between FY2016 and FY2019, an increase of 1% of salaries or 4% from the FY16 updated rates. To explain the change, we analyzed changes in total salary and benefits expenditure. As shown in Table 4, total teacher benefits expenditure increased by 11% from FY16 to FY19 and total salaries increased by 7%, which yielded the 4% increase in the benefits percentage (1.11 ÷ 1.07 = 1.04).

Table 4: Teacher Salary and Benefit Changes ($ millions)

	FY2016	FY2019	Change FY2016 to FY2019
Benefit expenditures	$188	$209	+11%
Salary Expenditures	$744	$794	+7%
Benefits Percentage	25%	26%	+4%

*Note: Private schools, public charters and specialty schools not included.

To further explore the changes in teacher salary and benefits expenditure, we next examined the changes in average per-teacher salaries and benefits expenditure, and the number of teachers employed. Full-Time Equivalent (FTE) teacher counts and average full-time teacher salaries were computed using staff data provided by SAUs to the state. In an FTE teacher count, each part-time teacher position counts as part of a full-time teacher. For example, a half-time teacher counts as 0.5 FTE teachers. Average teacher benefits amounts were calculated as total benefits expenditure divided by the FTE teacher count.

As reported in Table 5, the number of FTE teachers in Maine decreased by 9% in the three years between FY 2016 and FY 2019, the same rate of decrease that occurred in 8 years between FY 2008 and FY 2016, as reported in the earlier MEPRI benefits percentages report (see Johnson and Sloan, 2019).

Table 5. Change in FTE Teacher Counts and Average Salaries and Benefits

	FY 2016	FY 2019	Change
FTE Teacher count	15,524	14,107	-9%
Average FT Teacher Salary	$49,871	$54,116	+9%
Average Teacher Benefits	$12,121	$14,815	+22%

Note: FTE count includes regular classroom, special education, ELL and G&T teachers as well as literacy specialists; excludes long-term substitutes. Average FT salary includes teachers who are FTE=1 and whose reported earnings are at least $25,000. Private schools, public charters and specialty schools not included.

Declines in teacher FTE are consistent with declining enrollments and school reorganizations. However, the statewide decline in publicly funded student counts between FY2016 and FY2019 was only 0.7% (181,742 to 180,472[2]), significantly smaller than the 9% drop in teacher FTE counts. Given that there are approximately 16 students per teacher, it was anticipated that enrollment drops would be larger than declines in teacher FTE counts. The difference may reflect teacher retirement and recruitment shortages (Morris and Johnson, 2018).

[2] see https://www.maine.gov/doe/data-reporting/reporting/warehouse/enrollment

Meanwhile, the average teacher salary saw a 9% increase while the amount paid in benefits per FTE teacher increased by 22%. This is consistent with state and national trends for increasing benefits costs, primarily driven by rising costs of health insurance.

The 9% increase in teacher salaries is somewhat higher than inflation when compared to cumulative inflation of 6.6% between July 2016 and July 2019 according to the Consumer Price Index. This cannot be explained by an increase in teacher experience: average experience of teachers between 2016 and 2019 dropped slightly by 0.3 years (15.1 versus 14.8). If older, more experienced teachers were retiring one would expect average salaries to decline not increase. This is a similar data dynamic found by the last report by Johnson and Sloan (2019). As they explained, one potential explanation is that the decline in FTE teacher counts between FY16 and FY19 occurred disproportionately in rural areas of the state, where average teacher salaries are lower. Research conducted by Morris and Johnson (2008) showed that in addition to school closings and reorganizations, rural districts have slightly higher rates of teacher turnover.

Conclusion

In summary, the compensation patterns in Maine have changed since the inception of the EPS funding formula. The cost of providing benefits to public school staff has increased relative to the cost of salaries. This trend has been consistent and is not likely to be reversed based on state and national trends for rising costs of benefits including health care insurance.

In June 2019, Maine's legislature passed L.D. 898 "An Act to Provide for a Professional Wage and Support to New Educators," which will raise the minimum teacher salary to $40,000. The increase will be phased in over three fiscal years: the minimum salary will be $35,000 for the school year 2020-21, $37,500 for 2021-22, and $40,000 for 2022-23.[3] In theory, increasing teacher salaries could slow the increase in benefit percentages or even put downward pressure on benefit percentages, since benefit rates are calculated as a ratio of benefits to salary. However, the 2019 MEPRI report (Johnson and Sloan, 2019) produced a rough estimate of the effect of the $40,000 minimum salary using conservative assumptions about the impact of the minimum salary increase (zero increase in benefit costs), and found only small changes (-0.4%) in the benefit percentage.

Based on the continuous upward trajectory observed in the actual expenditure data and the Johnson and Sloan's estimates, we speculate that while the $40,000 increase in base pay for teachers could slow the increase in benefit percentages, it is unlikely to reduce them back to the initial EPS

[3] http://legislature.maine.gov/legis/statutes/20-A/title20-Asec13407.html

benefit percentage (19%). Thus, it is the recommendation of MEPRI researchers that it would be appropriate to update the benefits ratios to levels that are more reflective of actual benefit costs. One way to possibly mitigate the immediate effects of the increases would be to phase in the increase over a three-year time period so that the new rates would be in effect before the next scheduled review of the benefits cost component in the EPS formula. Subsequent reviews of the EPS formula will capture the impacts of increasing the minimum teacher salary using actual data rather than simulated estimates, and will inform further refinements to the model.

EPS Regional Adjustment Component Report of Findings

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This report of findings is presented in three sections. The first section provides a description of the methodology used to calculate Maine's regional adjustment component, and the next two sections divide the findings of our analyses into two separate categories. Section two describes an updated calculation of the regional adjustment using the most recent available pre-pandemic salary data (FY2020). These updated regional adjustment calculations are compared to prior reviews and to the current EPS regional adjustment, which was based on 2004-05 salary data. Section three presents policy options in light of the updated calculations, which include keeping or removing the adjustment, updating or not updating the calculations, and adding a floor or ceiling to the adjustment. Cost estimates provided for several policy options to aid in evaluation and decision making regarding the EPS Regional Adjustment.

Method: Updating the Regional Adjustment Calculation

Geographic Regions in EPS Regional Adjustment: Labor Market Areas (LMAs)

The cost of providing an education varies from place to place depending on the local prices of necessary resources used in providing education services. The most significant input resource is personnel. To account for regional variation in local salary prices, an adjustment is made in the EPS cost model to school personnel salary allocations. Each Labor Market Area (LMA) in Maine has a regional adjustment factor which is applied to the school salary allocation in each SAU within the LMA.[1]

In the current review, regional adjustments were recalculated using updated teacher salary data for the same LMA groupings used in the original computation of the adjustment and in each of the past reviews, which are summarized in Box 1. The LMAs for the EPS regional adjustment were designated by the Maine Department of Labor. They were based on commuting

[1] The regional adjustment's underlying basis of *price* is distinctly different from a *cost of living* construct. Pricing uses actual salary data to reflect the current cost of educator labor in each area of the state. A cost of living basis would use an external index and may result in different patterns across the state. Some selected cost of living measures are provided by county in appendix Table A4 for general information.

patterns revealed in data from the 1990 US Census. Before calculating the regional adjustment, the geographic units needed to be modified in two ways. First, many Maine School Administrative Units (SAUs) such as RSUs (Regional School Units) and MSADs (Maine School Administrative Districts) contain towns in more than one LMA. Each SAU was assigned to the LMA where most of its resident students live. The second reason the geographic units needed to be modified is that the smallest LMAs did not have enough SAUs or full-time teachers to perform a reliable regression analysis of teacher salaries. Regression is a statistical method used in calculating the regional adjustment. Small LMAs were combined with each other or with a larger LMA to form an LMA group to use as a geographic unit. Twenty-five LMAs were held to be large enough to have their own regional adjustment. The other ten LMAs were combined into four LMA groups, two groups of two LMAs and two groups of three LMAs. A Regional Adjustment was calculated for each of these 29 LMAs and LMA groups during the initial calculation of the EPS Regional Adjustment and during each periodic review thereafter.

Box 1. Geographic LMAs and LMA Groups

LMAs and Groups in Current EPS Model
29 Modified LMA Groups
Based on 35 LMAs from 1990 Census
Modified due to: o Regional SAUs crossing LMA borders o Combined if too few SAUs or teachers

Maine has not updated the geographic units in the EPS Regional Adjustment following prior component reviews of the EPS Regional Adjustment. The US Department of Labor released updated LMAs following the decennial US Censuses of 2000 and 2010. MEPRI presented the estimated effects of using each of geographic region updates for the EPS Regional Adjustment. MEPRI recommends revisiting the possibility of updating the geographic units after LMA updates based on the 2020 US Census are released.

Updated Regional Adjustment Calculations Based on FY 2020 Salary Data

During the original computation and each subsequent review, a regional adjustment for each LMA or LMA group was calculated based on the salaries of full-time teachers in all SAUs within the LMA groups. Some LMAs have teachers with more experience and education than others, meaning they will be at different points on the local salary scales. The regional adjustment takes this into account by adjusting each LMA average salary to what it would be if the LMA had the same experience and education profile as the state as a whole. The adjusted average salary for each LMA or LMA group was calculated using regression analysis, based on the salaries of teachers within the LMA at different levels of experience and education. The detail calculations by LMA are available in Appendix Table A1.

Results: Updating the Regional Adjustment Calculation

The overall summary results of recalculating a regional adjustment for each LMA with 2019-20 teacher data are shown in Table 1. The highest and lowest average annual teacher salary is shown as a dollar amount as well as indexed to the state, where 1.00 represents the statewide average annual teacher salary. For example, the 1.20 index for the highest unadjusted LMA (Kittery-York LMA) means that the average teacher salary there was 20% higher than the statewide average teacher salary. The regional adjustment in the rightmost column is the adjusted average salary indexed to the state, where a 1.00 represents the state average teacher salary. The 1.15 in the regional adjustment column for the highest area (Kittery-York LMA) means that, after adjusting for the experience and education levels in the LMA, averages salaries are 15% higher than the state average. If the adjusted average salary is lower than the unadjusted average salary—such as in the Kittery-York LMA, $64,340 adjusted compared to $67,124 unadjusted — this means that the teachers in that LMA have on average more years of experience and/or a higher average educational attainment than in the state as a whole.

The calculated regional adjustments range from a low of 0.81 in the Lincoln-Howland LMA based on a $45,423 adjusted average salary to 1.15 in the Kittery-York LMA based on a $64,340 adjusted salary. This is a smaller range than the unadjusted average salaries, which range from a 0.76 index in the Machias-Eastport LMA based on a $42,280 average salary to 1.20 in the Kittery-York LMA at $67,124.

Note that the EPS cost allocation model also accounts for the teacher experience and education level within each individual SAU. This item is not included within the regional adjustment component of EPS but rather in the teacher salary matrix component. The combination of the two components is designed to yield a sufficient allocation to pay for enough school staff, given local labor costs.

(See accompanying spreadsheet and Appendix for more details on the calculation of the EPS Regional Adjustment.) Table A2 in the Appendix provides average salaries and adjusted salaries for each LMA group.

Table 1. Unadjusted and Adjusted Average Teacher Salary Range by LMA

		Unadjusted	Adjusted
LMA	Lowest	Machias - Eastport LMA	Lincoln - Howland LMA
	Highest	Kittery - York LMA	Kittery - York LMA
Teacher Salary	Lowest	$ 42,280	$ 45,423
	Highest	$ 67,124	$ 64,340
	Gap	$ 24,843	$ 18,917
Index to State	Lowest	0.76	0.81
	Highest	1.20	1.15
	Gap	0.44	0.34

Comparison to Current EPS Regional Adjustment and to Prior Reviews

The EPS regional adjustment was initially calculated using 2004-05 data. The results of the original calculation are still used in computing SAU EPS allocations on the ED 279 reports which determine state subsidy. Since the initial calculation, the regional adjustment has been recalculated five times with newer data during periodic reviews, including the current review. The data for the recalculations were from 2006-07, 2008-09, 2013-14, 2016-17, and 2019-20. The results of the highest and lowest LMAs are shown in Table 2. Each time, the range of the adjustments has been greater than the 2004-05 data. The largest range, which was in the 2016-17 data, was a difference of 0.36 from a low of 0.80 to a high of 1.16. The difference reflected in the 2004-05 data was only 0.25, from a low a 0.84 to a high of 1.09. The most recent update closed the gap slightly from 2016-17 with a low of 0.81 and max of 1.15, a range of 0.34. It is likely that this modest narrowing is due to the statutory increase in the state minimum teacher salary that was partially implemented in that fiscal year, thus bringing up the lowest end of salaries.

The changes in the calculated regional adjustments for each review reflected actual changes in teacher salaries in different areas of the state. As a result of these calculations we can conclude that the differences in teacher salaries across different areas of Maine have indeed become larger since the date of the adoption of the EPS funding model. The results do not show that the changes were necessarily *because of* the EPS funding model; keeping the prior funding formula may have also resulted in increased salary disparity.

Table 2. Calculated Regional Adjustment Range 2004-05 to 2019-20

Data Year	Low	High	Gap	Lowest LMA	Highest LMA
2004-05	0.84	1.09	0.25	Machias - Eastport LMA	Biddeford LMA
2006-07	0.81	1.09	0.28	"	"
2008-09	0.83	1.09	0.26	"	Biddeford/Greater Portland
2013-14	0.77	1.13	0.35	"	Kittery - York LMA
2016-17	0.80	1.16	0.36	Lincoln - Howland LMA	"
2019-20	0.81	1.15	0.34	"	"

The calculated regional adjustment change from 2004-05 to 2019-20 for each LMA is provided in Appendix Table A3.

The EPS model has not been updated to reflect the newer data and the larger differences in actual salaries. This raises the concern that the formula is not providing adequate funding for all SAUs.

Policy Options and Estimated Costs

There are several policy options for the EPS Regional Adjustment: keep it as it is, eliminate it, or change it. Possible changes include the following.

- Update the regional adjustment based on recent salary data.
- Implement a minimum adjustment as a floor.
- Implement a maximum adjustment as ceiling.
- A floor or ceiling can be a fixed number, or a soft number that averages the actual adjustment with the target number.

Table 3 outlines several options for how these changes may be combined.

Table 3. Policy Options Analyzed

Option 1	Remove the Regional Adjustment from EPS
Option 2	Status Quo: No change
Option 3	Update Salary data
Modified Options	A. Add a floor
	B. Add a floor and a fixed ceiling
	C. Add a floor and a soft cap

Cost Estimates

Cost estimates for each policy option are provided in Table 4. The amounts were based on actual total full-time equivalent (FTE) teacher counts within each area and increased to estimate allocations for all EPS school staff positions. Increased cost allocations would be borne in part by the state through higher subsidies and in part by local governments through a higher property tax mill rate expectation and required local share. The state share is the estimated net increase (or decrease) in state subsidy assuming a 55% state share percentage. The local share is the estimated increase in local required amount assuming a 45% local share percentage. The numbers of LMAs with increases and decreases along with the estimated amounts are also shown, as is the range of regional adjustments under each policy option.

Option 2, the *status quo*, is listed as no cost, because it is the option to which the others were compared. Some of the options are estimated to lower the total allocation. Option 3, for example, updating the adjustment to reflect more recent salary data, would result in an estimated $7.3 million lower total allocation than the *status quo*. Assuming a 55% state share and a 45% local share, this would amount to a lower state share by $4.0 million and a lower local share by $3.3 million.

The options affect the allocations of each LMA differently, as shown in the columns of Table 4 showing LMA increases and decreases. Option 1 for example, eliminating the regional adjustment, has a modest estimated net cost reduction of $1.1 million. But figuring into that modest reduction are a substantial increase of $23.5 million in 19 LMAs along with a reduction of $24.6 million in 9 LMAs.

Table 4. Estimated Change in Cost Allocation ($millions)

Policy Option Simulation		Total Cost	State Share	Local Share	LMA Increases		LMA Decreases		Range
1. Remove Adjustment (all 1.00)		**-$ 1.1**	**-$ 0.6**	**-$ 0.5**	**19**	**$ 23.5**	**9**	**-$ 24.6**	**all 1.00**
2. *Status Quo* (no update)		**$ 0.0**	**$ 0.0**	**$ 0.0**	**0**	**$ 0.0**	**0**	**$ 0.0**	**0.84–1.09**
2A.1	Floor = 1.00	$ 23.5	$ 12.9	$ 10.6	19	$ 23.5	0	$ 0.0	1.00–1.09
2A.3	Floor = 0.93	$ 3.9	$ 2.1	$ 1.8	6	$ 3.9	0	$ 0.0	0.93–1.09
3. Update Salary Data, Old LMAs		**-$ 7.3**	**-$ 4.0**	**-$ 3.3**	**5**	**$ 9.6**	**21**	**-$ 17.0**	**0.81–1.15**
3A.1	Floor = 1.00	$ 30.2	$ 16.6	$ 13.6	23	$ 32.8	4	-$ 2.6	1.00–1.15
3A.3	Floor = 0.93	$ 2.2	$ 1.2	$ 1.0	11	$ 13.5	15	-$ 11.3	0.93–1.15
3B	Floor = 0.93, hard cap 1.09	-$ 2.9	-$ 1.6	-$ 1.3	11	$ 8.4	15	-$ 11.3	0.93–1.09
3C.1	Floor = 0.93, soft cap 1.07	-$ 2.9	-$ 1.6	-$ 1.3	11	$ 8.9	16	-$ 11.8	0.93–1.11
3C.2	Floor = 0.93, soft cap 1.09	-$ 0.3	-$ 0.2	-$ 0.2	11	$ 11.0	15	-$ 11.3	0.93–1.12

Note: To determine the cost with "hold harmless," read from the "SAUs with Increase" column.

Evaluation & Discussion of Policy Options

General Discussion

This analysis was conducted to aid in evaluation of the policy options, keeping in mind (1) that the purpose of the EPS funding model is to provide adequate educational resources to give every student an equitable opportunity to achieve the state learning standards and (2) that the purpose of the Regional Adjustment Component of EPS is to make sure that the allocation dollars are sufficient to purchase the necessary educational human resources for providing this equitable educational opportunity in all areas of the state.

One finding that is common to all reviews of the regional adjustment is that salary gaps across the state have generally grown wider over time. Two factors that may contribute to the divergence over time are changing underlying differences in labor markets and the differing ability of individual districts to raise funds to hire and retain highly-qualified teachers. Increases in the minimum teacher salary appear to moderate the trend of widening salary gaps, including both the previous increase to $30,000 in FY2008 and the increase to $40,000 that is in the process of being implemented.

The goal of the Essential Programs and Services funding model is to provide the resources necessary to provide equitable educational opportunity to all students. The challenge with accounting for regional differences is to establish a geographic index that adjusts for labor market realities without respect to community wealth. In districts where teacher salaries are lower (or higher) than what is needed to attract and retain enough qualified teachers, those actual salaries may not be valid estimates of a fair and adequate labor market. In that case, using them as indicators of labor market variation would introduce error, which may in turn exacerbate inequities based on ability to pay. However, there is no data source that exists to make it possible to readily identify whether the teachers that are paid by a given district's salaries are adequate. Anecdotal reports suggest that smaller, lower-income, and rural schools have a harder time retaining qualified teachers; these were corroborated by a recent MEPRI study of Maine teacher turnover (MEPRI, 2019), which discerned a pattern of teacher movement toward higher paying districts. If the salaries themselves are inadequate, then the regional adjustments that are calculated from them will not improve the situation.

A concept that has been discussed with increasing frequency (in the face of Maine's inability to implement updates to the regional adjustment indices despite growing regional wage differences) is the potential to switch to an external indicator such as cost of living as the underlying basis for regional adjustments. This is a topic that merits further analysis in a future review. At the time EPS was developed, an adjustment based upon cost of living data was not feasible due to numerous issues including quality of data, questionable assumptions about the relationship to salaries, and ability to calculate values for rural areas with few data points. It may be worthwhile to revisit those analyses to see whether those challenges have abated.

As noted in prior reviews, increasing the EPS cost allocation for salaries does not guarantee an increase in actual local salaries. Because the regional adjustment is determined by an LMA average salary, approximately half of the actual salaries are lower and half are higher. In SAUs where the allocation provides more funding than the district needs to cover its contractual salary commitments, it may choose to spend the surplus allocation on other local priorities. With those issues in mind, the following sections evaluate the results of each of the proposed policy options.

Option 1: Remove adjustment

Option 1 would set all regional adjustment factors to the state average of 1.00, effectively removing the regional adjustment. This option would bring more allocation and subsidy to the lower cost areas of the state, and has a slightly lower estimated cost than the *status quo*. Although the total net cost reduction is small, there would be a large reduction in cost allocations in the higher cost areas of the state ($24.6 million in 9 LMAs). The EPS cost allocation dollars would be insufficient to provide the EPS recommended level of staffing in higher cost geographic areas. This inadequacy is contrary to the purpose of the regional adjustment and the EPS cost model to provide equitable access to education resources for students in all areas of the state. Option 1 does not guarantee that additional funds are spent on raising salaries. Regional variation in actual salaries may continue to widen. MEPRI researchers do not recommend Option 1, as it undermines the goals of adequacy and efficiency for the EPS funding formula.

Option 2: Status quo

Option 2, keeping the status quo, is designated as the no-cost option, as the other options are evaluated relative to it. This option has been chosen by policymakers during each of the previous review cycles. The regional adjustment has not been updated since its initial inclusion in the original implementation of EPS for Fiscal Year 2005-06. The primary reason given for keeping the status quo has been the widening of the geographic variation in actual salaries and the resulting widening of the range of updated regional adjustment calculations. While retaining the *status quo* prevents widening the range of adjustments, this option does not reflect current reality of regional variation in teacher salaries. Salaries in some areas have increased more than the state average, and some less. The current regional adjustments based on Fiscal Year 2004-05 salaries do not reflect these changes.

Under Option 2A, a floor is added to the current model. Option 2A.1 is a floor of 1.00. All areas with an adjustment below 1.00 would be raised to 1.00, while those above 1.00 would receive their current adjustment. The advantage of this option is that it would provide increased allocation in all areas of the state with below-average salary costs. The drawback is the high cost estimated at $23.5 million, including a state subsidy increase of $12.9 million and an increased required mill rate resulting in a $10.6 million increase in the local required share.

Option 2A.2, a floor of 0.93, is a lower cost alternative to the floor of 1.00. At a total cost estimate of $3.9 million it would provide an estimated additional subsidy of $2.1 million to the lowest salary areas of the state with an increase of $1.8 million in the required local share.

MEPRI researchers do not recommend retaining the status quo permanently, due to concerns that widening pay disparities are resulting in inequities for teachers in the current funding system. Instituting a floor would mitigate the risk of underfunding in the areas of the state with below-average teacher salaries. Option 2.A.1, a floor of 1.00, is not recommended due to its higher cost and that it likely over-estimates adequate salary costs for much of the state. Options 2.A.2, a floor of 0.93, may be a preferred option in that it provides additional funding to the areas of the state with the lowest teacher salaries.

Option 3: Update Salary Data

Option 3, updating the indices to reflect recent salary data, has the advantage of reflecting current salary cost differences. It would result in an estimated cost reduction of $7.3 million, which is a net total of allocation increases of $9.6 million in 5 LMAs and decreases of $17.0 million in 21 LMAs. The updated regional adjustment would widen the regional adjustment a range of 0.81 to 1.15 as a result of the increasing actual geographic differences in salaries.

Several Option 3 modifications were examined, including floors as well as hard and soft caps. The lowest cost areas would receive an increased cost allocation from a floor. The caps are not intended to reduce the regional adjustments of higher cost areas but rather to limit the increases. Higher cost areas would still see an increased cost allocation compared to the current EPS regional adjustment but not as much as the actual salary increases.

Options 3A.1 and 3A.2 provide floors similar to those under Option 2A. The primary advantage of these options modifications is in providing increased subsidies to lower salary areas of the state. The main disadvantage of Option 3A.1, a floor of 1.00, is the cost of 30.2 million. Option 3A.1, a floor of 0.93 is a lower cost option at an estimated $2.2 million intended to provide more subsidy to lower cost areas of the state, where salaries are not keeping pace with the rest of the state.

Option 3B provides a minimum adjustment floor of 0.93 and caps the maximum adjustment at 1.09, which is equal to the highest current adjustment. Capping the adjustment lowers the total cost, resulting in an overall estimated allocation reduction of $2.9 million. The advantages of this option are that a floor provides additional subsidy to the lowest cost areas of the state, and current reality of regional cost differences are better reflected among other areas. Necessarily, some areas will experience lower adjustments, including 15 LMAs with an estimated reduction of $11.3 million in allocation. As a caution, one possible drawback is that the cap may result in allocations that are inadequate to provide equitable educational resources in some of the highest cost areas. Compared to the status quo, however, the highest cost areas would see increases in their regional adjustment.

Option 3C.1 and 3C.2, which have a floor of 0.93 and a soft cap of 1.07 or 1.09, are an attempt to provide a balanced approach, recognizing the increasingly higher cost of labor in parts of the state, while at the same time acknowledging some portion of the salary increases may be due to the higher local ability to pay rather than strictly higher salary requirements of teachers. LMAs above the soft cap of 1.07 or 1.09 receive an adjustment halfway between the respective cap and the calculated adjustment. For example, the calculated adjustment for Kittery - York LMA is 1.15. Under Option 3C.1, it would receive an adjustment halfway between 1.07 and 1.15, which is 1.11. The result of option 3C.1 is a range of adjustments from 0.93 to 1.11 with an estimated cost savings of $2.9 million. For Option 3C.1, the estimated cost savings is $0.3 million. The advantages of these options is that the floor provides an increase to the lowest cost areas, and the cost is more reflective of actual salary. As in Option 3B, there are areas whose salaries have not kept pace with the state average, resulting in reduced adjustments under this option. They are the same 15 LMAs and $11.3 million as in Option 3B. It is possible that this option also provides inadequate resources in the highest cost areas. However, allocations in those areas would be higher than either Option 3B or the *status quo*.

Summary of MEPRI Recommendations

As detailed in the evaluation and discussion above, using salary data as a measure of regional differences in labor markets is imperfect. Salaries are influenced by labor market factors, e.g. cost of living differences, regional competition for jobs, etc. This is demonstrated by the finding that there are high-poverty districts in some parts of the state that pay at or above the state average, and low-poverty districts elsewhere that pay below the state average. Salaries also depend on each district's ability to raise taxpayer funds. This can be seen in the comparative salaries within each labor market area, with poorer districts generally paying lower salaries than neighboring wealthy districts. Thus salaries at the lowest and highest ends of the spectrum can reasonably be presumed to be influenced by community wealth, and are not solely a reflection of regional differences. Accordingly, MEPRI recommends the following options.

1. In the spirit of an adequacy-based funding formula, we recommend retaining a regional adjustment index to promote equitable and adequate educational human resources statewide.
2. To counter the lesser ability of lower-income communities to raise funding adequate to attract teachers, it would be beneficial to institute a minimum floor. This floor should be less than 1.00 (where 1.00 is the state average), as regional labor market variation means that some districts can attract teachers with below-average salaries. Such communities should not be required to raise more taxpayer funds than are needed to provide adequate resources.
3. If the regional adjustment is updated with new salary data, it is also valid to institute a maximum adjustment cap. The communities at the top of the pay scales in any geographic area have a greater ability to raise taxpayer funds to pay higher salaries to attract and retain teachers, and thus incorporating the full amount of salary differences is an expenditure-based (rather than adequacy-based) methodology. This could be instituted as either a fixed or soft cap. If the regional adjustment is not updated to reflect recent salary data, a maximum cap is not necessary, only a floor.
4. MEPRI should continue to monitor geographic variation in teacher salaries during future periodic reviews of the EPS Regional Adjustment. When new labor market areas are generated based on 2020 Census data, changes to the geographic unit in the regional adjustment should be explored.
5. MEPRI may also investigate the feasibility and potential impacts of instituting a different methodology based on one or more external indices (such as cost of living, housing costs, etc.) to adjust for regional labor market variation. Appendix Table A4 provides example data using three such county-level measures.

Table A1. Regional Adjustment Calculation Detail by LMA Group
For 35 Labor Market Areas (2019-20 Staff Data)

Labor Market Area (LMA)		Intercept (First Year Bachelors Degree)	Experience Coefficient (First 20 Years)	Experience Coefficient (Beyond 20 Years)	Education Coefficient	Average Salary Adjusted for Education and Experience	Regional Adjustment (Updated Data)
1	Kittery - York LMA	$ 44,370	$ 1,326	$ 0	1.104	$ 64,340	1.15
2	Sanford LMA	36,832	1,363	217	0.517	55,854	1.00
3	Biddeford LMA	40,233	1,422	288	0.691	60,766	1.09
4	Greater Portland LMA	40,805	1,396	295	0.925	61,839	1.11
5	Bath - Brunswick LMA	35,964	1,191	690	1.124	56,265	1.01
6	Boothbay Harbor LMA	38,686	1,499	446	0.473	59,856	1.07
7/10	Sebago Lake LMA Norway - Paris LMA	34,944	936	317	0.934	50,455	0.90
8	Lewiston - Auburn LMA	36,921	979	477	0.841	53,074	0.95
9	Rockland LMA	38,891	1,271	320	0.835	58,156	1.04
11	Stonington LMA	35,530	762	564	0.899	49,479	0.89
12	Augusta LMA	34,237	1,146	621	0.476	51,593	0.92
13	Waterville LMA	36,239	939	839	0.420	51,480	0.92
14	Belfast LMA	34,907	1,390	0	0.555	53,782	0.96
15	Bucksport LMA	34,249	909	659	0.503	48,906	0.88
16	Jonesport - Milbridge LMA	34,900	649	338	0.484	45,423	0.81
17	Bangor LMA	34,297	1,509	234	1.008	56,822	1.02
18	Machias - Eastport LMA	32,860	759	184	0.872	45,626	0.82
19	Dexter - Pittsfield LMA	32,394	1,351	404	0.567	51,953	0.93
20	Ellsworth - Bar Harbor LMA	36,295	983	464	0.503	51,303	0.92
21	Outer Bangor LMA	33,711	1,052	438	0.168	48,357	0.87
22	Rumford LMA	35,472	1,144	526	0.554	52,806	0.95
23	Lincoln - Howland LMA	33,387	736	755	0.289	45,460	0.81
24	Farmington LMA	35,032	1,040	451	0.230	49,771	0.89
25	Calais LMA	35,024	1,110	151	0.723	51,471	0.92
26/27/28	Patten - Island Falls LMA Millinocket - East Millinocket LMA Houlton LMA	33,307	907	624	0.430	47,595	0.85
29	Skowhegan LMA	37,204	1,025	423	0.649	53,116	0.95
30/31	Greenville LMA Dover - Foxcroft LMA	34,381	1,022	410	0.480	49,640	0.89
32	Presque Isle - Caribou LMA	33,877	1,036	319	0.898	50,488	0.90
33/34/35	Van Buren LMA Fort Kent LMA Madawaska LMA	34,911	1,043	444	0.871	51,858	0.93
	Lowest	$ 32,394	$ 649	$ 0	0.168	$ 45,423	0.81
	Highest	$ 44,370	$ 1,509	$ 839	1.124	$ 64,340	1.15
	Maine	$ 34,044	$ 1,150	$ 347	1.000	$ 55,789	1.00

* Due to the small number of teachers in each of these LMAs, data was combined into the following groups: 7/10; 26/27/28; 30/31; and 33/34/35.

Table A2. Regional Adjustment Calculation by LMA Group (2019-20 Teacher Salary Data)

Labor Market Area (LMA)		Average Teacher Salary	Indexed to State	Average Salary Adjusted for Education and Experience	Regional Adjustment
1	Kittery - York LMA	$ 67,124	1.20	$ 64,340	1.15
2	Sanford LMA	54,057	0.97	55,854	1.00
3	Biddeford LMA	61,619	1.10	60,766	1.09
4	Greater Portland LMA	63,521	1.14	61,839	1.11
5	Bath - Brunswick LMA	60,087	1.08	56,265	1.01
6	Boothbay Harbor LMA	59,477	1.07	59,856	1.07
7/10	Sebago Lake LMA Norway - Paris LMA	49,490	0.89	50,455	0.90
8	Lewiston - Auburn LMA	50,184	0.90	53,074	0.95
9	Rockland LMA	57,578	1.03	58,156	1.04
11	Stonington LMA	49,253	0.88	49,479	0.89
12	Augusta LMA	51,855	0.93	51,593	0.92
13	Waterville LMA	53,671	0.96	51,480	0.92
14	Belfast LMA	54,083	0.97	53,782	0.96
15	Bucksport LMA	50,501	0.91	48,906	0.88
16	Jonesport - Milbridge LMA	44,847	0.80	45,423	0.81
17	Bangor LMA	58,113	1.04	56,822	1.02
18	Machias - Eastport LMA	42,280	0.76	45,626	0.82
19	Dexter - Pittsfield LMA	50,998	0.91	51,953	0.93
20	Ellsworth - Bar Harbor LMA	49,643	0.89	51,303	0.92
21	Outer Bangor LMA	46,839	0.84	48,357	0.87
22	Rumford LMA	52,630	0.94	52,806	0.95
23	Lincoln - Howland LMA	44,896	0.80	45,460	0.81
24	Farmington LMA	50,211	0.90	49,771	0.89
25	Calais LMA	48,445	0.87	51,471	0.92
26/27/28	Patten - Island Falls LMA Millinocket - East Millinocket LMA Houlton LMA	46,529	0.83	47,595	0.85
29	Skowhegan LMA	53,269	0.95	53,116	0.95
30/31	Greenville LMA Dover - Foxcroft LMA	46,406	0.83	49,640	0.89
32	Presque Isle - Caribou LMA	50,346	0.90	50,488	0.90
33/34/35	Van Buren LMA Fort Kent LMA Madawaska LMA	52,143	0.93	51,858	0.93
	Lowest	$ 42,280	0.76	$ 45,423	0.81
	Highest	$ 67,124	1.20	$ 64,340	1.15
	Maine	$ 55,789	1.00	$ 55,789	1.00

Table A3. Calculated Regional Adjustment Change
By Labor Market Areas 2004-05 to 2019-20

	Labor Market Area (LMA)	Regional Adjustment Calculations						Change 2004-05 to 2019-20
		2004-05 Data (Current EPS Model)	2006-07 Data	2008-09 Data	2013-14 Data	2016-17 Data	2019-20 Data	
1	Kittery - York LMA	1.06	1.07	1.06	1.13	1.16	1.15	+.09
2	Sanford LMA	1.03	1.04	1.02	1.00	0.99	1.00	-.03
3	Biddeford LMA	1.09	1.09	1.09	1.09	1.08	1.09	-.00
4	Greater Portland LMA	1.08	1.08	1.09	1.10	1.10	1.11	+.03
5	Bath - Brunswick LMA	1.02	1.04	1.03	1.05	1.02	1.01	-.01
6	Boothbay Harbor LMA	1.03	1.02	1.05	1.06	1.11	1.07	+.04
7/10	Sebago Lake LMA Norway - Paris LMA	0.94	0.94	0.93	0.91	0.90	0.90	-.04
8	Lewiston - Auburn LMA	0.98	0.97	0.96	0.95	0.96	0.95	-.03
9	Rockland LMA	1.00	1.01	1.00	0.97	1.04	1.04	+.04
11	Stonington LMA	0.95	0.98	0.94	0.94	0.92	0.89	-.06
12	Augusta LMA	0.95	0.96	0.94	0.93	0.92	0.92	-.03
13	Waterville LMA	0.97	0.97	0.96	0.94	0.92	0.92	-.05
14	Belfast LMA	1.01	1.01	0.99	0.98	0.97	0.96	-.05
15	Bucksport LMA	0.94	0.92	0.90	0.88	0.87	0.88	-.06
16	Jonesport - Milbridge LMA	0.84	0.84	0.83	0.81	0.82	0.81	-.03
17	Bangor LMA	1.02	0.99	1.02	1.04	1.02	1.02	-.00
18	Machias - Eastport LMA	0.84	0.81	0.83	0.77	0.84	0.82	-.02
19	Dexter - Pittsfield LMA	0.94	0.96	0.96	0.96	0.95	0.93	-.01
20	Ellsworth - Bar Harbor LMA	0.93	0.93	0.91	0.89	0.92	0.92	-.01
21	Outer Bangor LMA	0.89	0.89	0.89	0.88	0.87	0.87	-.02
22	Rumford LMA	0.93	0.92	0.92	0.94	0.94	0.95	+.02
23	Lincoln - Howland LMA	0.86	0.85	0.84	0.82	0.80	0.81	-.05
24	Farmington LMA	0.96	0.95	0.96	0.90	0.92	0.89	-.07
25	Calais LMA	0.96	0.97	0.98	0.95	0.90	0.92	-.04
26/27/28	Patten - Island Falls LMA Millinocket - East Millinocket LMA Houlton LMA	0.88	0.90	0.87	0.87	0.86	0.85	-.03
29	Skowhegan LMA	1.03	1.02	1.05	1.02	0.96	0.95	-.08
30/31	Greenville LMA Dover - Foxcroft LMA	0.95	0.95	0.94	0.92	0.91	0.89	-.06
32	Presque Isle - Caribou LMA	0.90	0.90	0.89	0.89	0.90	0.90	+.00
33/34/35	Van Buren LMA Fort Kent LMA Madawaska LMA	0.99	1.00	0.98	0.97	0.95	0.93	-.06
	Lowest	0.84	0.81	0.83	0.77	0.80	0.81	-.08
	Highest	1.09	1.09	1.09	1.13	1.16	1.15	+.09
	Maine	1.00	1.00	1.00	1.00	1.00	1.00	~

Table A4. Example Cost of Living Index Measures by Maine County

	Median Housing Cost Index		Living Wage Index		Family Budget Index	
County	Median Rent ($)[1]	Resulting Index	Living Hourly Wage ($)[2]	Resulting Index	Annual Family Budget[3]	Resulting Index
Androscoggin	915	0.94	20.66	0.98	78,029	0.98
Aroostook	762	0.78	18.71	0.89	77,180	0.97
Cumberland	1,096	1.12	23.58	1.12	92,425	1.16
Franklin	1,054	1.08	19.53	0.92	73,897	0.93
Hancock	984	1.01	20.47	0.97	83,702	1.05
Kennebec	919	0.94	20.14	0.95	74,033	0.93
Knox	974	1.00	20.38	0.96	80,240	1.01
Lincoln	831	0.85	21.16	1.00	81,053	1.02
Oxford	878	0.90	20.50	0.97	74,720	0.94
Penobscot	910	0.93	20.53	0.97	80,069	1.01
Piscataquis	1,110	1.14	19.64	0.93	74,737	0.94
Sagadahoc	925	0.95	21.48	1.02	82,548	1.04
Somerset	989	1.01	19.89	0.94	74,695	0.94
Waldo	968	0.99	20.33	0.96	78,375	0.99
Washington	911	0.93	20.05	0.95	79,273	1.00
York	1,053	1.08	22.47	1.06	85,865	1.08
Maine	*976*	*1.00*	*21.14*	*1.00*	*79,428*[4]	*1.00*

1 Median cost of 2 bedroom apartment rental including utilities; 2017 data at https://www.mainehousing.org/policy-research/housing-data/affordability-indexes

2 Hourly rate that an individual in a household needs to earn to help support a family of four (two working adults and two children); 2019 data at https://livingwage.mit.edu/states/23/locations

3 Income that a household needs to support a family of four at a “modest yet adequate” standard of living; 2017 data at https://www.epi.org/resources/budget/

4 An annual budget was not available for Maine overall. This base amount (79,428) is an average with each county weighted equally. This underestimates the denominator and thus produces index values that are artificially inflated to an unknown extent.

EPS Report of Findings: Staff Ratios

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Background

Staffing ratios are a key component of the Essential Programs and Services (EPS) funding model. When multiplied by student enrollment, they determine a large proportion of a district's total funding allocation. The EPS formula establishes the number of full-time equivalent (FTE) staff necessary per student to ensure all students have an opportunity to achieve the Maine Learning Results. This includes staff positions for several school-level functions deemed essential to student learning and school management, including teachers, guidance counselors, librarians, education technicians ("education technicians"), library/media technicians, school health professionals (nurses), administrative assistants, and school administrators (principals and assistant principals). The ratios vary by grade level. Until recently, ratios were provided for three grade levels: preK-5, 6 to 8, and 9 to 12. Beginning in FY2019, a separate teacher ratio was created for grades pre-K and K.

When the EPS model was initially developed, staff ratios were established after review of several data sources. Empirical data from available staff and student enrollment information were used to calculate existing student-to-staff ratios as a first step. Because some types of administrative data were limited, a survey was also conducted to collect additional data from school districts to fill in gaps. However, the goal of the EPS "adequacy-based" funding model was to provide sufficient staff to help schools provide a comprehensive education as proscribed by the Maine Learning Results, and merely looking at existing staffing patterns was not necessarily an indicator of adequacy. Some schools may have had more than enough staff, while others were understaffed. Therefore, the model development process also consulted existing research literature to inform the optimal proportions of various types of staff positions. For several staff position types, there was no published research to guide policymakers' decisions. Thus as an additional step, the model development consulted professional experts, including Maine practitioners as well as national professional organizations, to establish appropriate ratios of students to staff.

The teacher and education technician ratios were modified for FY2019 as part of a related policy change to remove Title I-funded staff and thus redefine those ratios as including only EPS-funded positions. In this change, a separate (and lower) ratio of 15:1 was created for grades PreK and K, the ratio for grades 1 to 5 remained the same at 17:1, the ratio for grades 6-8 was raised from 16:1 to 17:1, and the ratio for grades 9-12 was raised from 15:1 to 16:1. The education technician ratios were also increased to proportions equal to those reported in the 2015 ratio review: 114:1 for grades PreK-8, 312:1 for grades 6-8, and 316:1 for grades 9-12. All other staff ratios have remained the same since the inception of the model.

It is important to note that the staff ratios are not the only source of funding for staff in the EPS model. For example, the model provides an additional weight of 0.10 for each pupil in grades PreK, K, 1, or 2. The funds are "targeted" in that they must be used to support education in those grades, but there are no further restrictions; school districts can choose to use these supplemental resources to pay for additional staff. Conceptually, a school with only grades preK though 2 would have 100% of its students eligible for the early childhood student weight, and would thus have an additional 10% of its base funding amount available to hire additional teachers – an effective ratio of 13.5:1 for grades PreK-K and 15.3 in grades 1-2 if all the supplemental funds were used for that purpose. Elementary schools with grades K-5 would only be able to spend the 0.10 student weight amount on grades K to 2, but because there is no restriction on the *base* funding amount, they can redirect a portion of the base funding from the earlier grades to grades 3-5. Thus the 0.10 early elementary weight can indirectly result in lower ratios in other grades. The EPS formula also has an additional student weight of 0.20 for each economically disadvantaged student, 0.15 of which is non-targeted and could be used for paying for additional teachers in any grade. (The remaining .05 weight has targeted restrictions that may or may not include staff; each district must have an approved plan for the funds.) This makes it difficult to use the actual staff ratios found in Maine schools to directly inform the ratios in the EPS model.

Approach to Component Review

As dictated by Maine statute, the components of the EPS funding formula are subject to review every three years. Staff ratios were last analyzed in 2019 using 2016-2017 data. The previous review examined ratios for all essential positions, including teachers, guidance counselors, librarians, education technicians ("education technicians"), library/media technicians, school health professionals (nurses), administrative assistants, and school administrators (principals and assistant principals). In this review, we focus on teachers, educational, school nurses, and guidance staff (which include school social workers as well as guidance counselors). Library/media technicians are described selectively. We compare the EPS ratios to actual ratios and by school characteristics (size, poverty level, and location). Tracking the same schools over time, we also examine ratios to see if there have been changes resulting from recent policy changes and the COVID19 pandemic, including the hiring of additional student support staff. Finally, using SY2020 data we estimate the cost of adding a full-time nurse and social worker to every school and explore the cost effects of variations on this staffing proposal (e.g., exempting smaller schools; adding a nurses' aides instead of a registered nurse).

Method

We use staff and enrollment data obtained from the Maine DOE for the school years 2016-2017, 2019-2020 and 2020-2021. The sample of schools used to calculate ratios includes only regular public schools with both staff and enrollment data reported and made available to us by the Maine DOE. Maine Indian Education, state operated, CTE, unorganized territory and charter schools were excluded from the analysis, as were private town academies. Also excluded from ratio calculations were island schools and other schools designated as "small and isolated" as well as stand-alone PK and PK/KG programs. The analysis included 492 schools in SY2020 and 483 schools in SY2021. When examining whether schools have been hiring additional student support staff, we track schools using the sample of schools (N=457) with data available for both SY2017 and SY2020; and when examining effects of the pandemic on ratios we use the same sample of schools (n=474) with data available for both SY2020 and SY2021. When estimating the cost of bringing all schools up to at least 1.0 FTE social worker and 1.0 FTE nurse and variations on this staffing proposal, we used staff data from the school year 2019-20. While “small and isolated” schools and stand-alone PK and PK/KG programs were excluded from the sample of schools used to conduct ratio calculations, they were included in the sample used to conduct these cost estimates.

Only positions that are funded via the staff ratios in the EPS formula are included in the ratio calculations. As of FY2018, Title I classroom teachers are no longer considered part of the EPS teacher ratios and are included only when relevant for comparison purposes. Student-to-staff ratios were calculated for Elementary (grades K thru 5 or 6), Middle (grades 6 thru 7 or 8) and High (grades 9 thru 12) as well as for schools with alternative grade configurations including K-8. Schools with narrower grade ranges, such as K-5 or 7-8, were placed within the closest EPS school type. The category labeled “Other” includes schools that cross two different EPS types, for example, 6-12 schools as well as K-12 schools.

We report ratios at both the state and school levels. Statewide ratios include schools without staff (i.e., zero FTE). As was done in previous ratio reviews, we examined ratios by school size, poverty level, and urban-rural location. In previous reports we have also examined ratios by school proficiency level controlling for poverty level to assess whether schools that are “beating the odds” (i.e., schools with both higher rates of student poverty and proficiency) have lower student-to-staff ratios. However, because small sub-sample sizes make this analysis unreliable, we do not include this analysis in this report.

Another limitation of the data relates to counting FTE by grade level for staff who teach across grades. As described above, the recently-revised ratios in the EPS model segregate pre-K and K teachers from grades 1-5 to provide fewer students per teacher in the earliest grades. Whereas previously the EPS ratio was the same for grades PK-5 (17 students per teacher), the new ratios are 15 students per teacher for grades PK and K and 17 for grades 1-5. However, we were unable to distinguish between the implemented ratios for PK-K and 1-5 because many teachers teach across more than one grade; the staff data reported by SAUs do not apportion teacher FTE by grade level. We include tables in the Appendix examining ratios for the nine stand-alone PK-KG schools and for the 56 “small and isolated” schools.

Findings

Staff Ratios by Grade Level

Tables 1 and 2 display overall statewide ratios by school grade configuration observed in the most recent data, compared to the ratios used in the EPS formula. As noted in the introduction, the EPS personnel ratios are not the only source of funding for staff. Therefore, actual ratios are anticipated to be at or below the EPS ratios.

Table 1: Statewide Teacher and Education Technician Ratios, EPS and SY2020

	Elementary (Grades p/K-5)		Middle Schools (Grades 6-8)		High Schools (Grades 9-12)		**Total FTE staff statewide***
Number of schools	227		77		88		483
	EPS	**SY20**	**EPS**	**SY20**	**EPS**	**SY20**	**FY20**
Teacher ratio	17	14.9	17	14.4	16	14.4	11,416.2
Ed Tech ratio	114	71.7	312	268.5	316	256.5	1,504.5

Notes: Only EPS funded positions are included in ratio calculations. Teachers include Regular Classroom teachers, Literacy Specialists, ELL teachers and long-term substitutes. Sample includes only EPS funded positions. Schools without any staff in a position category (i.e., zero FTE) are included in statewide ratios. The sample of schools includes only regular public schools with reported data; schools eligible for "small and isolated" designation were excluded as were stand-along PK and PK_KG programs. *The total statewide FTE includes schools with atypical grade configurations (e.g., K-8, K-12).

Table 2: Non-Instructional Staff Ratios, EPS and SY2020

	Elementary (Grades p/K-5)		Middle Schools (Grades 6-8)		High Schools (Grades 9-12)		Total FTE staff statewide*
	EPS	**SY20**	**EPS**	**SY20**	**EPS**	**SY20**	**SY20**
Guidance	350	297.1	350	255.6	250	177.1	686.2
School nurse	800	504.4	800	646.9	800	747.5	282.3

Note: Only EPS funded positions are included in ratio calculations. Guidance staff includes school social workers, guidance counselors and guidance directors. Schools without any staff in a position category (i.e., zero FTE) are included in overall ratios. The sample of schools includes only regular public schools with reported data; schools eligible for "small and isolated" designation were excluded as were stand-along PK and PK-KG programs. *The total statewide FTE includes schools with atypical grade configurations (e.g., K-8, K-12).

Table 1 shows that both teacher and ed tech ratios in 2019-20 were below the EPS level at all grade levels. Table 2 demonstrates that the student-to-staff ratios for all other staff were also lower than EPS. In other words, schools are employing more staff than provided by the EPS ratios; they are supplementing hiring with funds from other parts of the EPS formula, or with additional local funds above the EPS model allocation.

Table 3 is an expanded depiction of staffing levels that includes the percent of schools without each type of EPS staff position, school-level median ratios and ranges, and the percent of schools with ratios below those provided in the EPS funding model, to provide important context for interpreting the ratios.

Table 3: SY2020 Staff Ratios, Statewide Ratios, School-Level Median and Range Of Ratios, Percent of Schools Without Staff and Percent with Ratios Below EPS Ratio

Number of schools 2019-20	227	77	88
Total enrollment 2019-20	67,336	30,212	44,404
	Elementary Schools	**Middle Schools**	**High Schools**
Teacher ratio	**14.9**	**14.4**	**14.4**
% schools with no Teachers	0%	0%	0%
Median (Range) of School ratios	14.7 (10-31)	14.5 (10-22)	14.1 (8-19)
EPS ratio (% schools below)	15 or 16:1 (88%)	17:1 (90%)	16:1 (75%)
Educational Tech	**71.7**	**268.5**	**256.5**
% schools with no Ed Tech	3%	26%	16%
Median (Range) of School ratios	69.5 (20-602)	199.3 (35-1,170)	256.6 (34-836)
EPS ratio (% schools below)	114:1 (78%)	312:1 (65%)	316:1 (61%)
Guidance ratio	**297.1**	**255.6**	**177.1**
% schools with no Guidance	7%	1%	5%
Median (Range) of School Ratios	282.0 (79-1,480)	265.9 (159-1,680)	177.8 (77-405)
EPS ratio (% schools below)	350:1 (71%)	350:1 (82%)	250:1 (85%)
School nurse ratio	**504.4**	**646.9**	**747.5**
% schools with no Nurse	29%	33%	27%
Median (Range) of School Ratios	392.0 (127-1,380)	488.5 (180-1,680)	577.0 (206-1,583)
EPS ratio (% schools below)	800:1 (95%)	800:1 (90%)	800:1 (75%)

Note: Only EPS funded positions are included in ratio calculations. Teachers include Regular Classroom teachers, Literacy Specialists, ELL teachers and long-term substitutes. Guidance staff includes school social workers, guidance counselors, and guidance directors. Statewide ratios are bolded. They include schools with zero staff. Ratio ranges, medians, and percent of schools below the EPS ratio are at the school level and include only schools with relevant staff positions. The sample of schools includes only regular public schools with reported data; schools eligible for "small and isolated" designation were excluded as were stand-alone PK and PK-KG programs.

While the likelihood of not having a school nurse is about the same across schools, among those that have nursing staff, elementary schools have more nurse FTE as evidenced by lower student-to-nurse ratios. The opposite is true of guidance staff, with high schools having the lower student-to guidance ratios.

Variation in Ratios

The additional descriptions in Table 3 illustrate several important factors. First, ratios varied substantially from school to school. Even with small and isolated and island schools excluded from the sample, there were wide ranges in schools' student-to-staff ratios across all EPS positions and at each grade span. At one end of the spectrum, some schools had zero staff in some of the EPS position categories. For example, 29% of elementary schools, 33% of middle schools and 27% of high schools did not have school nurses; and 7% of elementary schools did not have guidance staff positions compared to 1% of middle schools and 5% of high schools. During the 2019-20 school year, across our sample of regular public schools, there were 2,822 education technician positions statewide, but only 26% were EPS positions paid with state or local funds. Once funding source was considered, 3% of elementary schools, 26% of middle schools and 16% of high schools did not have any state or locally funded ed tech staff.

At the other end of the ranges, some schools operated with as few as 8 or 10 students per full-time teacher, 20 students per full-time ed tech and 77 students per full-time guidance staff. Except for elementary school guidance staff, a strong majority of schools (more than 75%) had actual staff ratios below those in the EPS funding model. The EPS staff ratios are lower than actual staffing patterns in only a few selected areas (see Table 2).

Teacher ratios were below the EPS funding model ratio across all grade levels. The statewide teacher ratio was below the EPS funding ratio by 2.1 students per full-time teacher for elementary schools, 2.6 students per teacher for middle schools, and 1.6 students per full-time teacher for high schools. School districts are using other resources to fund additional teachers, drawing either from other allocations within the EPS formula (such as the disadvantaged student weight) or from additional revenue raised locally.

Stabilizing Ratios

Table 4 displays student-to-teacher ratios reported in earlier MEPRI reports for school years 2013-14 and 2016-17, including schools with non-prototypical grade configurations. We add the updated ratios using data from the school year 2019-20 to examine changes over time. Statewide teacher ratios declined somewhat (i.e., there were fewer students per teacher FTE) across all school types between SY2014 and SY2017. Overall, in 2016-17 there were 0.7 fewer students per teacher FTE (15.1 versus 14.4) compared to 2013-14. Teacher ratios declined the most during this period for elementary and middle schools, with ratios down by 1.0 and 0.9 students per teacher FTE, respectively, compared to 0.5 fewer students per teacher FTE for high schools. Extending the timeline out to SY2020 indicates that teacher ratios may be stabilizing at around 14 to 15 students per teacher FTE. Between SY2017 and SY2020 teacher ratios changed by only smaller amounts: teacher ratios declined by 0.1 for elementary schools and increased by 0.2 for middle schools and 0.1 for high schools.

Table 4: Statewide Student-Teacher Ratios By Grade Span Between 2013-14 and 2019-20

	PK/K-5/6	6-8/7-8	9-12	K-8	K-12	Other	All schools
2013-14							
Number of schools	270	82	89	88	10	26	565
Total enrollment	71,900	31,122	45,978	16,174	1,993	7,649	174,816
FTE teachers	4,515	2063	3065	1,213	180	540	11,575
Teacher ratio	15.9	15.1	15.0	13.3	11.1	14.2	15.1
2016-17							
Number of schools	271	83	89	75	10	31	559
Total enrollment	71,919	30,932	45,064	14,867	1,835	7,925	172,542
FTE teachers	4,814	2,118	3,107	1,132	172	564	11,972
Teacher ratio	14.9	14.2	14.5	13.1	10.6	14.0	14.4
2019-20							
Number of schools	263	78	88	81	9	29	548
Total enrollment	70,688	30,294	44,404	15,783	1,609	9,620	172,398
FTE teachers	4,777	2,101	3,035	1,215	148	639	11,915
Teacher ratio	14.8	14.4	14.6	13.0	10.9	15.0	14.5

*The ratios for 2013-14 and 2016-17 come from previous MEPRI reports. Teachers include Regular Classroom teachers, Literacy Specialists, ELL teachers and long-term substitutes. Following the methods of the earlier report that calculated ratios using 2013-14 data (MEPRI, 2015), the sample used to calculate ratios included small and isolated schools. Thus the ratios in this table are not identical to those depicted above.

In Table 5 we recalculate teacher ratios using the same sample of schools for school years 2016-17 and 2019-20 to make sure ratio changes are not being masked by the use of different samples and variation in school data reporting across MEPRI reports. We also exclude small and isolated schools, island schools and stand-alone PK and PK/KG programs to make sure their inclusion above in Table 4 is not driving results.

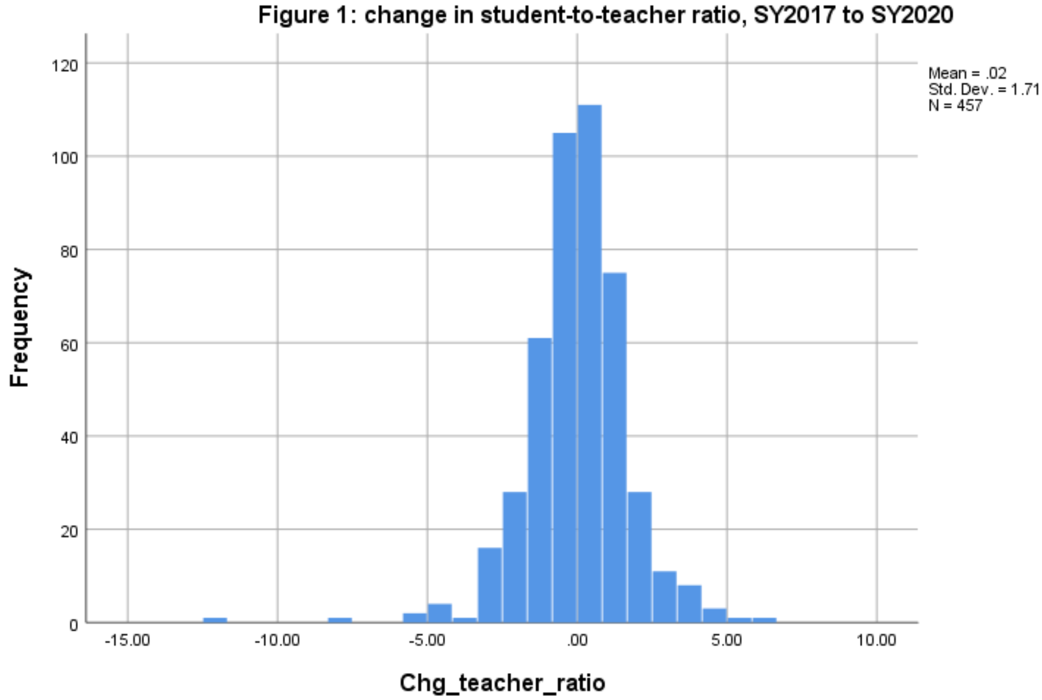
Table 5: Student-Teacher Ratios by Grade Span for 2016-17 and 2019-20 Tracking the Same Sample of Schools

Teachers	Elementary	Middle	High	K-8	Other, including K-12	All schools
Number of schools	212	75	86	61	23	457
2016-17						
Enrollment	62,738	28,914	44,259	13,796	8,184	157,891
FTE total teachers	4,164.9	2,049.7	3,048.6	1,026.2	570.1	10,859.5
Statewide ratio	15.1	14.1	14.5	13.4	14.3	14.5
2019-20						
Enrollment	62,447	29,306	43,767	13,688	8,730	157,938
(% change)	(-0.5%)	(+1.3%)	(-1.1%)	(-0.8%)	(+6.7%)	(+0.03%)
FTE total teachers	4,168.3	2,039.6	2,995.5	1,033.1	559.9	10,796.4
(% change)	(+0.1%)	(-0.5%)	(-1.7%)	(+0.7%)	(-1.8%)	(-0.6%)
Statewide ratio	15.0	14.4	14.6	13.3	15.6	14.6

Note: Only EPS funded positions are included in ratio calculations. Teachers include regular classroom teachers, Literacy Specialists, long-term substitutes, ELL teachers. The sample of schools includes those with data made available to MEPRI researchers by MDOE for both school years. The sample excludes schools who are designated "small and isolated" by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools. There were only 2 K-12 schools; they are included in with "Other".

Restricting the sample to the same schools for both SY2017 and SY2020 and excluding small and isolated schools, island schools and stand-alone PK/KG schools yields a similar pattern of results to those taken directly from previous MEPRI reports (Table 4). Teacher ratios for elementary schools and K-8 schools declined slightly because enrollments declined while teacher FTE increased. The teacher ratio for middle schools increased by 0.3 students per teacher FTE (because enrollments increased while teacher FTE decreased) and by 0.1 students for high schools (because teacher FTE declined more than enrollments).

At the school level, the small statewide changes between SY2017 and SY2020 mean that most schools had almost no change in their student-to-teacher ratios (see Figure 1 below). The average school-level change between school years 2016-17 and 2019-20 was 0.02 students per teacher FTE, the median, a measure less impacted by outliers, was 0.07, and the standard deviation was 1.71.



Using the same sample of schools for both school years, we provide enrollment, staff FTE and ratio changes between 2016-17 and 2019-20 for the other EPS positions. Over the course of this three-year period, the use of education technicians increased a bit at the elementary school level leading to a slight decrease in the ratio by 5 students per FTE. There was a decline in ed tech FTE among high schools – leading to a 24 student per FTE increase – while the ed tech ratio at the middle school level remained almost unchanged.

Table 6: Staff Ratios, 2016-17 and 2019-20, Tracking the Same Sample of Schools

	Elementary	Middle	High	All schools
Number of schools	212	75	86	457
Enrollment 2017	62,738	28,914	44,259	157,891
Enrollment 2020	62,447	29,303	43,767	157,938
% change in enrollment between 2017 and 2020	-0.5%	+1.3%	-1.1%	+0.03%
Education Technicians				
Statewide ratio 2017 and 2020	**78 to 73**	**267 to 268**	**231 to 255**	**118 to 113**
FTE 2017 to 2020	805.7 to 855.1	107.5 to 109.2	191.8 to 171.9	1,339.5 to 1,392.2
% chg in FTE 2017-2020	+6.1%	+1.6%	-10.4%	+3.9%
% (#) w/o education technicians in 2017	7% (15)	27% (20)	15% (13)	14% (62)
% (#) w/o education technicians in 2020	4% (8)	27% (20)	15% (13)	10% (46)
Guidance Staff (social workers, guidance counselors, guidance directors)				
Statewide ratio 2017 and 2020	**357 to 296**	**246 to 250**	**185 to 177**	**263 to 240**
FTE 2017 to 2020	175.6 to 211.1	117.5 to 117.0	238.7 to 247.9	599.7 to 657.5
% chg in FTE 2017-2020	+20.2%	-0.4%	+3.9%	+9.6%
% (#) w/o guid. staff 2017	10% (22)	0%	6% (5)	12% (56)
% (#) w/o guid. staff 2020	7% (14)	1% (1)	5% (4)	9% (42)
School Nurses				
Statewide ratio 2017 and 2020	**579 to 514**	**645 to 636**	**777 to 737**	**634 to 588**
FTE 2017 to 2020	108.4 to 121.5	44.8 to 46.1	57.0 to 59.4	249.1 to 268.7
% chg in FTE 2017-2020	+12.1%	+2.9%	+4.2%	+7.9%
% (#) w/o nurse 2017	33% (70)	31% (23)	28% (24)	32% (148)
% (#) w/o nurse 2020	29% (61)	33% (25)	26% (22)	29% (135)

Note: Only EPS funded positions are included in ratio calculations. The sample of schools includes those with data made available to us by MDOE for both school years. The sample excludes schools who are designated "small and isolated" by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools. The final column includes all schools including those with atypical configurations such as K-8 or K-12.

The MDOE is particularly interested in the expansion of guidance and health capacity. Between the school years 2017 and 2020, there was an almost across the board increase in the staffing levels of both positions, the exception being a slight contraction (0.5 FTE) in guidance staffing at the middle school level. The biggest changes were at the elementary school level. Over the course of this three-year period, elementary schools added enough staff to cause statewide ratios to decline by 61 students per guidance FTE and 65 students per nurse FTE. While the guidance ratio for middle schools inched up a bit, the nurse ratio across middle schools declined slightly by 9 students per nurse FTE. Among high schools, the guidance ratio declined by 8 students per FTE while the nurse ratios declined more substantially by 40 students per FTE.

Comparison by School Characteristics

The analysis also examined student-to-teacher ratios comparing SY2020 ratios by school size, poverty level and location.

School Size

Table 8 depicts this effect of school size on teacher ratios. For both elementary and middle schools, small schools were those with on average less than 15 per grade, medium schools 15-28 students per grade, and larger schools, 29 or more students per grade. For high schools, size was measured at the school level: small schools had 99 or fewer students, medium schools had 100 to 199 students, and large schools had 200 or more.

Table 7: Number of Schools by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	11	0	4
Medium	26	1	12
Large	190	76	72

There's a statistically significant and positive correlation between school size and all student-to-staff ratios except for the guidance ratio. Student-to-teacher ratios for most EPS staff positions increase with increasing school size. The school-level relationships between teacher ratio and school size are generally reflected in the statewide ratios (which include schools with zero FTE) as well.

Table 8: Statewide Teacher Ratios by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	11.8	-	10.9
Medium	13.3	11.0	11.4
Large	15.1	14.0	14.9

This effect is generally attributed to the economies of scale that can only be achieved in schools with a certain number of students. For example, small elementary schools—defined as having fewer than 15 students per grade level—typically provide one classroom per grade level. They must provide comprehensive instruction to the students who are enrolled, and thus may need to deliver classes that are smaller than would be desirable. Strategies such as multi-age classrooms and online learning may help to optimize student to teacher ratios, but options are limited.

For non-teaching EPS positions, smaller schools were, not surprisingly, more likely to be without staff. For example, it appears that fewer smaller elementary schools can justify the cost of non-teaching staff such as a guidance counselor, a library/media ed technician, or a nurse. An exception to that rule is the use of education technicians at elementary schools: all 11 small elementary schools employed education technicians while there were a handful of larger elementary schools that do not. Another exception is the use of nursing staff at the high school level: while 2 of the 4 small high schools employ a school nurse, 9 of the 12 medium sized high schools do not. Note, however, that none of the small or medium sized high schools employed a full-time nurse while a majority of the large high schools did.

Table 9: Statewide Ed Tech Ratios (% w/o) by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	53 (0%)	-	327 (75%)
Medium	64 (11%)	35 (NA)	127 (25%)
Large	73 (3%)	275 (26%)	268 (11%)

Table 10: Statewide Lib/Media Tech Ratios (% w/o) by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	286 (45%)	-	(100%)
Medium	515 (39%)	106 (NA)	435 (50%)
Large	439 (17%)	740 (43%)	874 (31%)

Table 11: Statewide Guidance Ratios (% w/o) by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	261 (18%)	-	273 (50%)
Medium	304 (15%)	1,060 (NA)	208 (17%)
Large	297 (5%)	255 (1%)	175 (0%)

Table 12: Statewide Nurse Ratios (% w/o) by School Size, SY2020

	Elementary Schools	Middle Schools	High Schools
Small	467 (45%)	-	654 (50%)
Medium	507 (35%)	353 (NA)	1,438 (75%)
Large	505 (27%)	649 (33%)	733 (18%)

Poverty Level

Statistically, after controlling for school size and location, the percentage of students eligible for free or reduced-price lunch is positively correlated to student-to-staff ratios (i.e., there are more students per staff FTE at higher poverty schools) across all staff types except for education technicians and teacher ratios at the elementary level (higher-poverty schools tend to hire more education technicians and teachers). Despite the substantial variation in ratios across schools (discussed above), these statistical school-level relationships between staff ratios and school poverty rates are generally reflected in the statewide ratios (which include schools with zero staff FTE) shown in Tables 14 through 18. Ratios were disaggregated based on the percent of students that were eligible to receive free or reduced priced lunch. Schools within ½ standard deviation (10.6%) of the statewide mean of 48.0% poverty were considered of average poverty.

Table 13: Number of Schools by Poverty Level, SY2020

	Elementary Schools	Middle Schools	High Schools
Lower (0 to 37%)	73	26	34
Average (38 to 59%)	75	32	40
Higher (60 to 100%)	76	18	12

Statewide teacher ratios varied only a little bit by school poverty level among elementary schools: higher poverty schools had slightly *lower* ratios: 0.1 fewer students per teacher FTE than lower poverty schools, and 0.3 fewer students per teacher than average poverty schools (Table 14). The ratios decrease significantly when the supplemental elementary teacher positions that are paid through federal Title I are included, particularly in higher poverty schools.

Table 14: Statewide EPS Teacher Ratios (and Including Title I teachers) By School Poverty Level, SY2020

	Elementary Schools (EPS)	Elementary (Incl Title I)	Middle Schools	High Schools
Lower (0 to 37%)	14.9	14.7	13.9	14.3
Average (38 to 59%)	15.1	14.5	14.4	15.1
Higher (60 to 100%)	14.8	13.9	15.1	15.1
All schools	14.9	14.4	14.4	14.4
EPS ratio	*15:1 PK/K; 17:1 for 1-5*		*17*	*16*

Ratios at the middle and high school levels increased with increasing poverty level (i.e., schools with higher rates of student poverty had more students per teacher FTE). The ratio among high schools with higher rates of student poverty (15.1) was close to the EPS funding level of 16 students per teacher, while for low poverty high schools the ratio (14.3) was well below the EPS ratio. Higher ratios (i.e., more students per teacher FTE) among higher poverty schools is generally considered to be a reflection of increased budget constraints in communities with lower property wealth, which raise fewer local dollars for education through each mil of property taxes. That the teacher ratio at the elementary level was lowest among high poverty schools suggests that higher poverty districts may be using the additional funds from the disadvantaged student weight to target hiring at the elementary level.

Teacher ratios that include Title I funded teachers are included for additional context. When Title I teachers are included in the ratio, higher poverty elementary schools had nearly one fewer student per teacher; these schools had 0.8 fewer students per FTE compared to low poverty schools and 0.6 fewer students than average poverty schools. The effect of Title I is only seen at the elementary level. Forty-five percent of Maine's public elementary schools had a Title I teacher while only 4% (3 schools) of middle schools had a Title I teacher; these supplemental staff do not affect overall ratios at the middle level.

From Table 15 we can see that high poverty schools hired more education technicians than lower poverty schools, and as a result had lower student-to-staff ratios. This is particularly evident at the middle and high school levels. This may be another example of higher poverty school districts' use of the additional funds from the EPS economically disadvantaged student weight, in this case to hire additional staff to support teachers in the classroom. One thing to note, however, is that while the statewide education technician ratio for high poverty schools was well below the EPS ratio, still 25% of high poverty high schools and 22% of high poverty middle schools were without any education technician staff.

Table 15: Statewide Education Technician (Ed Tech) Ratios by School Poverty Level (% without staff). SY2020

	Elementary Schools	Middle Schools	High Schools
Lower (0 to 37%)	75 (3%)	334 (31%)	290 (15%)
Average (38 to 59%)	75 (1%)	300 (25%)	261 (15%)
Higher (60 to 100%)	66 (7%)	170 (22%)	163(25%)
All schools	72 (3%)	269 (26%)	257 (16%)
EPS ratio	*114*	*312*	*316*

Using the same three categories for lower, average, and higher poverty schools, Tables 16 through 18 provide statewide ratios for the other staff positions by school poverty level. The percentage of schools with no reported staff in each position type is also provided. In most cases, higher poverty schools were more likely to have fewer (or zero) staff per student and thus higher statewide ratios (i.e., more students per staff FTE).

Table 16: Elementary School Statewide Ratios (% without staff) by School Poverty Level, SY2020

Position Type	*EPS Ratio*	Lower Poverty	Average Poverty	Higher Poverty	All Schools
Guidance	*350*	295 (4%)	297 (8%)	307 (9%)	297 (7%)
School nurse	*800*	438 (18%)	478 (24%)	635 (48%)	504 (29%)

Table 17: Middle School Statewide Ratios (% without staff) by School Poverty Level, SY2020

Position Type	*EPS Ratio*	Lower Poverty	Average Poverty	Higher Poverty	All Schools
Guidance	*350*	268 (0%)	236 (0%)	263 (5%)	256 (1%)
School nurse	*800*	527 (23%)	613 (25%)	1,156 (61%)	647 (33%)

Table 18: High School Statewide Ratios (% without staff) by School Poverty Level, SY2020

Position Type	*EPS Ratio*	Lower Poverty	Average Poverty	Higher Poverty	All Schools
Guidance	*250*	179 (3%)	177 (5%)	187 (8%)	177 (5%)
School nurse	*800*	670 (15%)	783 (27%)	1,145 (67%)	747 (29%)

In 2019-20 high poverty schools were only slightly more likely than other schools to be without guidance staff. As a result, statewide guidance ratios did not differ as much by school poverty level and all are below the EPS ratio (350 students per guidance FTE for elementary and middle schools and 250 students per FTE for high schools). This is not the case for health staff. Student-to-nurse ratios were substantially higher among schools with higher rates of student poverty. This was true across all grade levels and primarily because higher poverty schools were much more likely to have zero nursing FTE (i.e., more schools with zero FTE were used in the calculations). Moreover, even though the nurse ratio was below the EPS ratio of 800 students per full-time nurse at the elementary level, still nearly half of all high poverty elementary schools had no school nurse in SY2020. At the high school level, 8 out of 12 high poverty schools were without a school nurse.

We also examined changes in statewide ratios between the school years 2016-17 and 2019-20 by school poverty level, again using the same sample of public schools for both school years. We include the percentage change in both enrollment and staff FTE to show the dynamics behind changes in student-to-staff ratios.

Table 19: Changes in Statewide Ratios Between 2017 and 2020, by Poverty Level

	Elementary Schools	Middle schools	High schools
Teachers			
Low poverty	15.1 to 15.0	13.6 to 13.9	14.0 to 14.3
(%change enroll/ FTE)	(+1.6%/+2.1%)	(+1.7%/-0.7%)	(+0.8%/-1.6%)
Average poverty	15.3 to 15.3	14.4 to 14.4	15.0 to 15.0
(%change enroll/ FTE)	(-0.7%/-0.3%)	(-0.9%/-1.1%)	(-2.8%/-2.9%)
High poverty	14.9 to 14.7	14.5 to 15.1	15.7 to 15.2
(%change enroll/ FTE)	(-2.4%/-1.6%)	(+5.3%/+1.1%)	(-2.4%/+0.9%)
All schools	15.1 to 15.0	14.1 to 14.4	14.5 to 14.6
Education technicians			
Low poverty	89 to 78	366 to 333	232 to 290
(%change enroll/ FTE)	(+2%/+16%)	(+2%/+11%)	(+1%/-19%)
Average poverty	76 to 76	249 to 310	244 to 259
(%change enroll/ FTE)	(-1%/+0.3%)	(-1%/-20%)	(-3%/-9%)
High poverty	70 to 66	206 to 170	167 to 157
(%change enroll/ FTE)	(-2%/+3%)	(+5%/+28%)	(-2%/+4%)
Guidance staff (guidance counselors, social workers, Directors of Guidance)			
Low poverty	323 to 294	244 to 268	176 to 179
(%change enroll/ FTE)	(+2%/+11%)	(+2%/-7%)	(+1%/-1%)
Average poverty	369 to 289	242 to 231	193 to 176
(%change enroll/ FTE)	(-1%/+27%)	(-1%/+4%)	(-3%/+7%)
High poverty	404 to 313	259 to 263	212 to 183
(%change enroll/ FTE)	(-2%/+26%)	(+5%/+4%)	(-2%/+13%)
School Nurse			
Low poverty	501 to 454	529 to 527	691 to 670
(%change enroll/ FTE)	(+2%/+12%)	(+2%/+2%)	(+1%/+4%)
Average poverty	646 to 498	644 to 602	813 to 764
(%change enroll/ FTE)	(-1%/+29%)	(-1%/+6%)	(-3%/+3%)
High poverty	638 to 611	1,060 to 1,156	1,287 to 1,099
(%change enroll/ FTE)	(-2%/+2%)	(+5%/-3%)	(-2%/+14%)

Note: Only EPS funded positions are included in ratio calculations. The sample of schools includes those with data made available to us by MDOE for both school years. The sample excludes schools who are designated "small and isolated" by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools. The final column includes all schools including those with atypical configurations such as K-8 or K-12.

At the elementary school level, the teacher ratio dropped a bit more among high poverty schools - 0.2 fewer students per teacher FTE compared to 0.1 among low poverty schools – but only because enrollments declined more than teacher FTE. Among elementary schools, only low poverty schools added teacher FTE. At the middle and high school level, high poverty schools added teaching staff while low and average poverty schools did not. However, the additional FTE among high poverty middle schools did not keep pace with enrollments and the teacher ratio increased (0.6 more students per FTE) and among high poverty high schools, the 0.5 student per FTE drop was driven primarily by declines in enrollment.

As shown above, high poverty schools, especially middle and high schools, use more education technicians (Table 15). Between school years 2016-2017 and 2019-2020, high poverty schools at all grade levels continued to add more ed tech staff. Low poverty districts also added ed tech staff but only at the elementary and middle school levels. The biggest gain was among high poverty middle schools where ed tech FTE increased by 28% while enrollment increased by 5% resulting in 36 fewer students per ed tech FTE.

Between the school years 2016-2017 and 2019-2020 expansions in guidance staffing occurred primarily among higher poverty schools. As shown above in Table 6, elementary schools added guidance staff and as shown in Table 19, this occurred across all poverty levels, with larger changes occurring among average and high poverty schools. While low poverty elementary schools added enough staff to reduce the ratio by 29 students per guidance FTE, the guidance ratio at average and high poverty elementary schools declined by 80 and 91 students, respectively. Higher poverty high schools also expanded guidance staff: there were 17 fewer students per FTE in 2020 compared to 2017 among average poverty high schools and 29 fewer students among high poverty high schools. Average and high poverty middle schools also expanded guidance capacity but among high poverty middle schools the increased hiring did not keep pace with enrollment increases. Still, while high poverty schools are expanding guidance staff, higher poverty schools are still a bit more likely to be without guidance staff compared to low poverty schools (see Tables 16-18).

In Table 6 above we showed that nurse ratios declined between SY2017 and SY2020 and in Table 19 we see that this decline occurred across all poverty levels with the exception of high poverty middle schools where enrollments increased while FTE declined and the ratio increased by almost 100 students per nurse FTE. Still, higher poverty schools are much more likely to be without nurses. In SY2020, 19% of low poverty schools had zero nurse FTE compared to 27% average poverty schools and 50% high poverty schools (for the break-out by school level, see above Tables 16-18).

Rural Schools

In this section we examine ratios based on school location broken into the four categories of urbanicity/rurality (known as "locale" codes) as designated by the National Center for Educational Statistics. The codes are based on existing definitions of "urbanicity", which include overall population, population density, and distance to the nearest urban center. Statistically, differences in staffing by school location are driven largely by school size and poverty level. Once school size and poverty level are controlled for, a school's location is no longer statistically correlated to its student-to-staff ratio. Student-to-staff ratios by location, therefore, tend to reflect a mix of school size and poverty rate effects. On average, schools located in cities have higher rates of poverty, especially compared to suburban schools, and schools located in rural areas are smaller. The negative correlation between size and rurality is stronger than the positive correlation between poverty rate and rurality. So, for example, lower teacher ratios among schools in rural areas are primarily due to the fact that rural schools are smaller while lower ratios in suburban schools reflect the fact that these schools are less likely to be in poor communities. In general, the patterns produced by statewide ratios displayed below in Tables 20-22 reflect a synthesis of the effects of school size and poverty rate described above.

Table 20: Ratios for Elementary Schools by Locale, SY 2019-20

	City	Suburb	Town	Rural
# of schools	27	31	35	128
Total enrollment	9,559	10,829	10,622	33,978
Avg enrollment	354	349	303	269
Median (mean) % FRPL	66%	27%	57%	50%
Teacher ratios (ratio w/ Title I)				
Statewide ratio	**15.0 (14.6)**	**14.7 (14.3)**	**15.7 (15.1)**	**14.8 (14.3)**
School level median (range)	15.2 (12-19)	14.8 (11-18)	15.7 (11-24)	14.5 (10-31)
Ratio (range) including Title I Teachers	14.4 (12-19)	14.7 (10-18)	15.3 (11-21)	14.0 (9-21)
% below EPS ratio (17)	85% (89%)	93% (93%)	71% (83%)	91% (94%)
Ed Tech ratios				
Statewide ratio	**89**	**89**	**70**	**65**
School level median (range)	98 (30-396)	81 (36-602)	68 (20-443)	65 (20-380)
% (#) w/o education technicians	4% (1)	3% (1)	3% (1)	4% (5)
% below EPS ratio (114)	54%	70%	79%	83%
Guidance staff ratios				
Statewide ratio	**321**	**268**	**306**	**299**
School level median (range)	313 (159-750)	241 (165-588)	272 (104-694)	285 (79-1,480)
% (#) w/o guidance	0%	3% (1)	14% (5)	7% (9)
% below EPS ratio (350)	56%	80%	80%	70%
School Nurse ratios				
Statewide ratio	**673**	**513**	**439**	**507**
School level median (range)	456 (281-1,110)	432 (223-817)	305 (143-1,040)	389 (130-1,380)
% (#) w/o nurse	33% (9)	19% (3)	23% (8)	33% (43)
% below EPS ratio (800)	89%	96%	93%	97%

Table 21: Ratios for Middle Schools by Locale, SY 2019-20

	City	Suburb	Town	Rural
# of schools	8	14	11	43
Total enrollment	3,736	6,970	4,296	14,640
Avg enrollment	467	498	390	341
Avg % FRPL	54%	25%	51%	48%
Teacher ratios				
Statewide ratio	**14.0 (NA)**	**14.4 (NA)**	**13.9 (13.9)**	**14.6 (14.5)**
School level median (range)	13.9 (12-17)	14.6 (11-22)	13.7 (12-17)	14.7 (1-21)
% below EPS ratio (17)	100%	79%	91%	91%
Ed Tech ratios				
Statewide ratio	**239**	**279**	**263**	**268**
School level median (range)	158 (136-1,010)	348 (89-660)	191 (128-542)	197 (35-1,170)
% (#) w/o education technicians	13% (1)	36% (5)	27% (3)	26% (11)
% below EPS ratio (312)	57%	44%	75%	72%
Guidance staff ratios				
Statewide ratio	**225**	**286**	**250**	**248**
School level median (range)	244 (159-400)	271 (162-660)	275 (163-1,680)	259 (161-1,060)
% (#) w/o guidance	0%	0%	0%	2% (1)
% below EPS ratio (350)	75%	77%	73%	86%
School Nurse ratios				
Statewide ratio	**747**	**601**	**573**	**659**
School level median (range)	488 (361-789)	529 (347-660)	365 (241-1,680)	489 (180-1,083)
% (#) w/o nurse	37% (3)	21% (3)	27% (3)	37% (16)
% below EPS ratio (800)	100%	100%	87%	89%

Table 22: Ratios for High Schools by Locale, SY 2019-20

	City	Suburb	Town	Rural
# of schools	7	16	14	51
Total enrollment	6,800	9,714	8,615	19,275
Avg enrollment	971	607	615	378
Avg % FRPL	52%	26%	40%	48%
Teacher ratios				
Statewide ratio	**16.0**	**14.3**	**15.0**	**14.2**
School level median (range)	16.3 (14-17)	14.0 (9-18)	15.0 (12-17)	13.6 (8-19)
% below EPS ratio (16)	71%	75%	57%	84%
Ed Tech ratios				
Statewide ratio	**210**	**275**	**299**	**251**
School level median (range)	252 (132-544)	233 (145-540)	377 (131-836)	213 (34-768)
% (#) w/o education technicians	14% (1)	19% (3)	0%	20% (10)
% below EPS ratio (316)	50% (3 out of 6)	77%	71%	66%
Guidance staff ratios				
Statewide ratio	**192**	**161**	**190**	**176**
School level median (range)	182 (115-252)	168 (89-349)	187 (122-313)	183 (77-405)
% (#) w/o guidance	0%	0%	0%	8% (4)
% below EPS ratio (250)	86%	87%	86%	83%
School Nurse ratios				
Statewide ratio	**907**	**694**	**836**	**698**
School level median (range)	874 (390-1,583)	650 (265-933)	637 (418-1,078)	497 (206-1,132)
% (#) w/o nurse	0%	18% (3)	21% (3)	35% (18)
% below EPS ratio (800)	29% (2 out of 7)	77% (10 out of 13)	73% (8 out of 11)	85%

*Note: Only EPS funded positions are included in ratio calculations. The sample excludes schools who are designated “small and isolated” by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools. Median and ratio ranges are at the school level and include only those schools with staff.

Changes Over Time by Locale

As we did above by school poverty level, we examine changes in statewide ratios between SY2017 and SY2020 by school location level using the same sample of public schools for both years. The results are displayed below in Table 23.

Table 23: Changes in Statewide Ratios Between 2017 and 2020, by Locale

	Elementary	Middle	High
Teachers			
Cities	15.6 to 15.0	13.8 to 14.0	15.9 to 16.0
(%change enroll/ FTE)	(-3.3%/+0.1%)	(-0.3%/-2.1%)	(+3.2%/+2.5%)
Suburbs	14.9 to 14.7	14.4 to 14.4	14.2 to 14.3
(%change enroll/ FTE)	(+1.3%/+2.7%)	(+1.1%/+1.1%)	(+1.0%/+0.6%)
Towns	15.3 to 15.5	13.7 to 13.9	14.9 to 14.9
(%change enroll/ FTE)	(+0.5%/-1.3%)	(+4.6%/+3.6%)	(-4.0%/-4.0%)
Rural areas	14.9 to 14.9	14.1 to 14.6	14.1 to 14.2
(%change enroll/ FTE)	(-0.7%/-0.4%)	(+1.0%/-1.9%)	(-2.3%/-3.2%)
Education technicians			
Cities	88 to 87	187 to 239	181 to 210
(%change enroll/ FTE)	(-3.3%/-3.0%)	(-0.3%/-22.0%)	(+3.2%/-11.0%)
Suburbs	102 to 89	319 to 279	268 to 274
(%change enroll/ FTE)	(+1.3%/+15.7%)	(+1.1%/+15.7%)	(+1.0%/-1.7%)
Towns	71 to 69	335 to 283	273 to 296
(%change enroll/ FTE)	(+0.5%/+3.7%)	(+4.6%/+23.9%)	(-4.0%/-11.5%)
Rural areas	72 to 67	265 to 268	221 to 248
(%change enroll/ FTE)	(-0.7%/+6.6%)	(+1.0%/0%)	(-2.3%/-13.2%)
Guidance staff (guidance counselors, social workers, Directors of Guidance)			
Cities	366 to 317	240 to 225	194 to 192
(%change enroll/ FTE)	(-3.3%/+11.6%)	(-0.3%/+6.4%)	(+3.2%/+4.1%)
Suburbs	346 to 268	252 to 286	164 to 161
(%change enroll/ FTE)	(+1.3%/+30.7%)	(+1.1%/-10.9%)	(+1.0%/+2.7%)
Towns	382 to 307	280 to 233	200 to 190
(%change enroll/ FTE)	(+0.5%/+25.2%)	(+4.6%/+25.9%)	(-4.0%/+1.0%)
Rural areas	350 to 300	237 to 248	189 to 175
(%change enroll/ FTE)	(-0.7%/+15.9%)	(+1.0%/-3.3%)	(-2.3%/+5.6%)

(Table 23, Continued)

School Nurse			
Cities	656 to 692	577 to 747	941 to 907
(%change enroll/ FTE)	(-3.3%/-8.3%)	(-0.3%/-23.1%)	(+3.2%/+7.0%)
Suburbs	512 to 513	638 to 601	628 to 694
(%change enroll/ FTE)	(+1.3%/+1.0%)	(+1.1%/+7.4%)	(+1.0%/-8.5%)
Towns	424 to 416	541 to 543	709 to 792
(%change enroll/ FTE)	(+0.5%/+2.5%)	(+4.6%/+4.3%)	(-4.0%/-14.2%)
Rural areas	669 to 525	707 to 659	861 to 692
(%change enroll/ FTE)	(-0.7%/+26.3%)	(+1.0%/+8.3%)	(-2.3%/+21.6%)

* Note: Only EPS funded positions are included in ratio calculations. The sample of schools includes those with data made available to us by MDOE for both school years. The sample excludes schools who are designated "small and isolated" by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools. Median and ratio ranges are at the school level and include only those schools with staff.

Locations where teacher FTE did not keep pace with enrollments leading to increased teacher ratios – either declining more than enrollments or not keeping up with increasing enrollments - occurred in cities (middle and high schools), towns (elementary and middle schools) and rural areas (middle and high schools). The largest increase – 0.5 more students per teacher FTE - occurred in rural middle schools because teacher FTE declined by 2% while enrollments grew by 1%. Among suburban schools, increases in teacher FTE kept pace with increased enrollments among middle and high schools and eclipsed enrollments at the elementary school level. Declining ratios among suburban schools may reflect the fact that these schools are less likely to be in poor communities and thus face fewer budget constraints. Suburban districts may also face fewer challenges recruiting and retaining teachers (Morris and Johnson, 2018).

On the other hand, schools in Maine's more rural areas did not appear to face exceptional constraints in expanding nursing and guidance capacity. In fact, the statewide decline in nurse ratios (see Table 6) was driven almost exclusively by rural schools. The nurse ratio among rural elementary schools declined by 144 students per nurse FTE and by 169 students per nurse FTE among rural high schools. The increase in nursing staff among rural middle schools was a bit more modest, with 48 fewer students per nurse FTE in 2020 compared to 2017. On the other hand, school nurse ratios increased among elementary and middle schools in urban areas because nurse FTE declined significantly more than enrollment. Among middle schools, the decline in nursing staff resulted in 170 more students per full-time nurse while at the elementary level the decline in nursing staff was a more modest 36 more students per nurse FTE. Urban high schools were able to increase health staff levels, but the increase was relatively modest resulting in only 34 fewer students per nurse FTE. Rural schools have generally been able to increase FTE and lower ratios, yet are still more likely to have no nurse. Among schools located in rural areas, 36% had no nurse, compared to 18% of suburban schools, 23% of schools located in towns and 29% of schools in cities.

While rural schools were still more likely to be without any guidance staff (12% compared to 8% of schools in towns, 1% of suburban schools and 2% of suburban schools), they were able to expand guidance capacity at least at the elementary and high school levels. With the exception of rural and suburban middle schools, all guidance ratios declined between SY2017 and SY2020, and in all cases across all locations it was because either rising guidance FTE outpaced increasing enrollments or continued despite declining enrollments. In other words, in no case did the guidance ratio decline just because enrollments declined.

The Pandemic Effect

In this next section we used data for the school years 2019-20 and 2020-21 from the same sample of schools (n=474) to examine the effect of the pandemic on enrollment, staff FTE and ratios. Overall enrollment dropped by 5%, with the largest declines in enrollment occurring at elementary level. Except for high schools, statewide teacher ratios dropped between the school years 2019-20 and 2020-21 driven almost exclusively by pandemic-induced declines in enrollment. Teacher FTE remained nearly steady during the pandemic.

Table 24: Before and During the Pandemic, SY2020 and SY2021

Teachers	Elementary	Middle	High	K-8	K-12 + Other	All schools
Number of schools	222	77	87	64	24	474
2019-20						
Enrollment	66,379	30,212	44,221	14,751	8,698	164,261
FTE total teachers	4,455.7	2,096.6	3,021.4	1,109.1	576.6	11,259.4
Statewide ratio	**14.9**	**14.4**	**14.6**	**13.3**	**15.1**	**14.6**
2020-21						
Enrollment	60,467	29,261	44,188	13,622	8,274	155,812
(% change)	(-8.9%)	(-3.1%)	(-0.7%)	(-7.7%)	(-4.9%)	(-5.1%)
FTE total teachers	4,406.0	2,091.6	3,013.7	1,107.8	568.7	11,187.8
(% change)	(-1.1%)	(-0.2%)	(-0.3%)	(-0.1%)	(-1.4%)	(-0.6%)
Statewide ratio	**13.7**	**14.0**	**14.6**	**12.3**	**14.5**	**13.9**

Note: Only EPS funded positions are included in ratio calculations. Teachers include regular classroom teachers, Literacy Specialists, long-term substitutes, ELL teachers; Title I teachers are not included. The sample of schools includes those with data made available to us by MDOE for both school years. The sample excludes schools who are designated "small and isolated" by the EPS model as well as stand-alone pre-Ks, island schools and Maine Indian Education, state operated, unorganized territory and charter schools.

We also looked at whether there was a change in other EPS positions before and during the pandemic including other health and support type positions such as health assistants, school psychologists, and licensed clinical professional counselors. Changes in the staffing levels of non-teaching EPS positions during the pandemic year were generally smaller than the decline in enrollment. Any increases in staffing were focused on positions providing services related to student health and emotional wellbeing. However, the increases were small and driven by only a handful of schools.

Among the 474 regular public schools with data available for both SY2020 and SY2021, student enrollment decreased by 5% between school years 2020 and 2021 while nursing staff FTE increased by about 2%. While nursing staff increased relative to enrollment and the nurse ratio dropped by 40 students per nurse FTE, the net change in nursing FTE between SY2020 and SY2021 amounts to less than 5 full-time nurses statewide: 46 schools increased their nurse FTE by a combined 21.7 FTE and 37 schools decreased their nursing staff by a combined 16.8 FTE. In SY2020 69% (329) of our sample of 474 schools had at least a part-time nurse; 145 schools had no nursing staff. In SY2021, 147 schools had no nursing staff.

Table 25: Before and During Pandemic: FTE (ratio), Change and Percentage Change, All Schools, Statewide (n=474 schools)

	SY 2019-20 FTE (ratio)	SY 2020-21 FTE (ratio)	Change (% change)
Student enrollment	164,261	155,812	-8,449 students (-5.1%)
EPS staff			
Teachers (w/o Title I)	11,259.4 (14.6)	11,187.8 (13.9)	-71.6 FTE (-0.6%)
Guidance Staff	676.7 (243)	681.2 (229)	-4.5 FTE (-0.7%)
Nurses	278.1 (591)	283.0 (551)	+4.9 FTE (+1.8%)
Education technicians	1,481.3 (111)	1,393.8 (112)	-87.5 FTE (-5.9%)
Selected Other Student Support Staff			
Health Assistants	19.4 (8,467)	19.1 (8,158)	-0.3 FTE (-1.5%)
School Psychologists	26.3 (6,245.7)	33.9 (4,596)	+7.6 FTE (+28.9%)
Licensed Clinical Professional Counselors	12.3 (13,355)	14.3 (10,896)	+2.0 FTE (+16.3%)

*Note: The sample of schools (n=474) includes only regular public schools with reported data for both SY2020 and SY2021; schools eligible for "small and isolated" designation were excluded as were stand-along PK and PK_KG programs. Statewide ratios include schools without staff (i.e., zero FTE).

There were larger relative increases in staff who provide mental and emotional support. Compared to the year before the pandemic, there was a 29% increase in school psychologist FTE and a 16% increase in licensed clinical professional counselor FTE. However, again, while large in terms of % changes and relative to changes in student enrollment, the increases are modest in terms of actual hiring: 7.6 FTE school psychologists and 2 FTE counselors statewide. These changes are being driven by a handful of schools.

Most public schools do not have psychologists on staff. In SY2020, only 12% (n=57) of the 474 schools in our sample had a school psychologist on staff; in SY2021 16% (n=74) had a school psychologist on staff. Most school psychologists work part-time at multiple schools. The statewide increase in school psychologist FTE between SY2020 and SY2021 by 7.6 was driven by 33 schools: 11 schools (2%) had less school psychologist FTE in SY2021 compared to SY2020, 33 (7%) had more and the rest (430, 91%) remained the same (i.e., either they still had none or the FTE did not change). The 33 schools that increased their staff hired 11.2 FTE school psychologists: 2 schools hired a full-time psychologist while the rest hired part time psychologists. Eleven schools reduced their psychologist staff by a combined 3.6 FTE.

Even fewer schools have licensed clinical professional counselors on staff: in SY2020 only 18 (4%) of the 474 schools had a licensed counselor on staff; and in SY2021 only two additional schools had a counselor on staff. No schools reduced counseling staff between SY2020 and SY2021. The statewide increase in licensed clinical counseling staff by 2 FTE was the result of staffing changes at 4 schools: one school hired a new full-time counselor, one school increased counseling staff to 0.8 FTE and the remaining two schools both increased counseling by only 0.10 FTE.

Estimating the Cost of Funding a Nurse Per School

In this section we estimate the cost of adding a full-time nurse to all schools (compared to standard staffing based on EPS model and to actual staffing in SY2020). We also explore the cost effects of variations on this staffing proposal (e.g., exempting smaller schools; a nurses' aide at smaller schools, etc.).

Of the 548 public schools (including small and isolated and stand-alone PK/K programs), 59% (325) do not have at least one full-time (FTE 1.0) nurse on staff, including 170 schools which do not have any nursing staff and 223 which have only a part-time nurse. Among the typically grade configured schools, there's little difference in the percentage without nursing staff but among those with nursing staff, high schools and middle schools are more likely to have to have at least one full time nurse.

Table 26: School Nurses, by School Type, SY2019-20

	Elem	Middle	High	K-8	K-12	Other, including PK/K stand-alones	All schools
Number of schools	254	78	88	81	9	38	548
% (#) w/o any nurse	30% (77)	32% (25)	27% (24)	25% (20)	4 of 9	53% (20)	31% (170)
% (# of schools) with either no nurse or less than 1.0 FTE	60% (153)	51% (40)	43% (38)	72% (58)	6 of 9	79% (30)	59% (325)
Of those with nursing staff, the % (# of schools) with at least FTE=1.0	57% (101 of 177)	72% (38 of 53)	78% (50 of 64)	38% (23 of 61)	3 of 3	44% (8 of 18)	41% (155 of 378)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Smaller schools are less likely to have a nurse on staff and are more likely to utilize part-time nursing staff when they do. Note: The EPS ratio is 800 students per one full-time nurse. Only 19 schools have 800 or more students and all 19 have at least one full-time nurse.

Table 27: School Nurses by School Size, SY2019-20

Number of students	Number of schools	% (# schools) w/ zero nurse FTE	% (# of schools) with either no nurse or less than 1.0 FTE	Of those with some nursing staff, the % (# of schools) with at least FTE=1.0
Less than 100	70	40% (28)	97% (68)	5% (2 of 42)
100 – 299	237	41% (98)	75% (179)	42% (58 of 139)
300 – 499	143	25% (36)	43% (62)	76% (81 of 107)
500 - 799	79	10% (8)	20% (16)	89% (63 of 71)
800 or more	19	0%	0%	100% (19)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

High poverty schools are significantly less likely to have a nurse on staff and more likely to have a part-time nurse when they do.

Table 28: School Nurses by School Poverty Level, SY2019-20

	Low poverty	Average poverty	High poverty
Number of schools	168	212	155
% (#) w/o any nurse	15% (26)	27% (58)	53% (82)
% (# of schools) with either no nurse or less than 1.0 FTE	42% (71)	59% (125)	77% (119)
Of those with nursing staff, the % (# of schools) with at least FTE=1.0	68% (97 of 142)	57% (87 of 154)	49% (36 of 73)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Although rural schools saw the biggest increases in nurse FTE between SY2017 and SY2020 (Table 23), they are still less likely to have a nurse on staff and more likely to have a part-time nurse when they do.

Table 29: School Nurses by School Locale, SY2019-20

	City	Suburb	Town	Rural
Number of schools	42	66	69	362
% (#) w/o any nurse	21% (9)	18% (12)	25% (17)	36% (131)
% (# of schools) with either no nurse or less than 1.0 FTE	45% (19)	35% (23)	43% (30)	69% (249)
Of those nursing staff, the % (# of schools) with at least FTE=1.0	70% (23 of 33)	80% (43 of 54)	75% (39 of 52)	50% (113 of 231)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Not surprisingly, schools officially designated as small and geographically isolated are less likely to have a nurse on staff; and, if they do, they are much more likely to be part-time.

Table 30: School Nurses by "Small and Isolated" Designation, SY2019-20

	Small and geographically isolated	Not Small and geographically isolated
Number of schools	56	492
% (#) w/o any nurse	39% (22)	30% (148)
% (# of schools) with either no nurse or less than 1.0 FTE	91% (51)	56% (274)
Of those nursing staff, the % (# of schools) with at least FTE=1.0	15% (5 of 34)	63% (218 of 344)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Among regular public schools, there were 222 full time (FTE = 1.0) nurses with salaries that were not outliers (there were three nurses with salaries recorded as $100 and one non-EPS nurse who was paid $96,188). Among the 222 full time nurses (excluding outliers), the mean salary was $57,907 (median: $59,514, range: $20,848 to $85,467). Their average years of experience was 16.4 (median: 16.0, range: 0 to 39). Only 4 of the 222 nurses were beginner nurses (year =0); 10 were in year 0-1; 24 were in years 0-3. There's a moderately strong positive correlation between years of experience and salary ($r = 0.537$, $p < 0.001$); years of experience explains about 30% of salary. The average salary paid to the 4 beginner nurses (i.e., those with less than 1 year experience) working full-time was $51,161. The average salary paid to 144 "typical" nurses – i.e., those with years of experience within one standard deviation (9.6) of the mean years of experience (16.7), 7.1 years to 26.3 years, was $56,579.

Of the 548 public schools in our SY2020 data set, 325 had less than 1.0 FTE nurse. We use the average salaries to estimate how much it would cost to bring them up to 1.0 FTE in nursing staff. If all newly hired nurses were beginner nurses, the estimated cost for a school going from zero nursing FTE to 1.0 FTE is $51,161, The estimated cost for schools going from, say, a half-time nurse to a full-time nurse is $25,580, assuming the school moved a beginner part-time nurse to a full-time nurse or hired a beginner nurse to work part-time. Assuming all 325 schools hired beginner nurses to get to FTE 1.0, the estimated cost to bring all 325 schools up to 1.0 FTE is **$13,404,182.**

However, assuming all schools hire beginner nurses is unrealistic. A more likely scenario is that schools will increase the hours of current nursing staff, almost all of whom will have more experience and command higher wages, or newly hired nurses will be given credit in salary negotiations for previous work experience outside education. The fact that so few nurses are "beginners" with less than one year of experience suggests that a more realistic estimate for the cost of bringing all schools up to at least 1.0 FTE is obtained using the statewide average salary for the "typical" school nurse: one with years of experience ranging from 7 to 26. The average salary for this group of nurses was $56,579. Using the statewide average salary for full-time nurses in SY2020 with the typical amount of experience, the estimated cost to bring all 325 schools up to 1.0 FTE is: **$14,823,698.**

Next, we explore the cost effects of variations on this staffing proposal (e.g., exempting smaller schools; a nurses' aides at smaller schools). We assume the cost to hire a nurse is $56,579 per 1.0 FTE, the average salary paid to a typically experienced full-time nurse in SY2020. The estimated costs of different proposals are summarized in Table 31 below.

Table 31: Cost Implications of Policy Options for Increasing Nursing Staff in all Public Schools

Policy	Number of schools assisted (of 548)	Estimated cost
Bring all schools up to at least 1.0 FTE using only beginner nurses	325	**$13,404,182**
Bring all schools up to at least 1.0 FTE using typically experienced nurses	325	**$14,823,698**
Exempt smaller schools		
Bring schools with at least 100 students up to 1.0 FTE nurses	257	$11,411,984
Bring schools with at least 200 students up to 1.0 FTE nurses	149	$6,574,480
Bring schools with at least 300 students up to 1.0 FTE nurses	78	$3,332,503
Hire health assistants instead of nurses		
Bring all schools up to at least 1.0 health care staff (nurses and/or health assistants) using health assistants to close the gap	315	$6,868,002
Hire health assistants instead of nurses for smaller schools		
Close the gap by hiring nurses for larger schools and health assistants for schools with fewer than 100 students	325	$13,069,209
Close the gap by hiring nurses for larger schools and health assistants for schools with fewer than 200 students	325	$10,534,780
Close the gap by hiring nurses for larger schools and health assistants for schools with fewer than 300 students	325	$8,732,912
Exempt smaller schools and hire health assistants instead of nurses in larger schools		
Exempt smaller schools and hire health assistants to bring schools with 100 or more students to FTE=1.0 in health care staffing (nurses and/or health assistants)	247	$5,210,777
Exempt smaller schools and hire health assistants to bring schools with 200 or more students to FTE=1.0 in health care staffing (nurses and/or health assistants)	140	$2,907,701
Exempt smaller schools and hire health assistants to bring schools with 300 or more students to FTE=1.0 in health care staffing (nurses and/or health assistants)	72	$1,467,592

There are 68 schools with fewer than 100 students. If they were to be treated differently and not expected to maintain a full-time nurse, there would be 257 schools requiring additional funds. The estimated cost is **$11,411,984**, a savings of about $3.4 million from the cost of funding all 325 schools. If schools with fewer than 200 students were exempted from the policy, 149 would receive additional funding to hire nurses and the total cost is estimated to be **$6,574,480**, a savings of about $8.8 million compared to the cost of helping all 325 schools achieve 1.0 FTE nursing staff. Exempting schools with fewer than 300 students would reduce the cost to **$3,332,503**, a savings of about $11.5 million.

Another policy option is to hire health assistants instead of nurses to close the 1.0 FTE gap in school health staffing. In this section we explore the cost if instead of hiring nurses to bring their healthcare staff (nurses and/or health assistants) up to 1.0 FTE, schools hired health assistants. Note: in SY2020 there were not many schools hiring "health assistants" instead of nurses. Of the 170 schools without any nursing staff, only 10 schools had a health assistant on staff: 9 of the schools had a full-time health assistant and one school had a 0.50 FTE health assistant. Of the 155 with less than 1.0 FTE nursing, only 6 schools had a part time health assistant, 4 half-time and 2 less than half-time. If this is a labor supply issue, then it might be difficult to close health care staffing gaps with these less expensive paraprofessionals. Assuming there is not a labor supply issue, we estimate the cost of closing the health care staffing gap with health assistants instead of nurses.

There were only 28 health assistant positions statewide during the SY2020 and only 14 were full-time. The average salary paid to these full-time health assistants was $27,483 (median: $27,635; range: $17,776 to $37,355). Years of experience ranged from zero to 25 years. The one health assistant who is a "beginner" (zero years of experience) earned $19,656. Because there are so few health assistant positions, we use the statewide average salary, $27,483, to estimate the costs.

When we include health assistants and nurses (i.e., healthcare staff) there are 233 schools with at least 1.0 FTE of health care staffing; and 315 schools with less than 1.0 FTE in health care staff. If all 315 schools with less than 1.0 FTE of healthcare staff (nurses and/or health assistants) hired health assistants instead of nurses to bring up the total health care staff to 1.0 FTE, the estimated cost would be: **$6,868,002**.

Another policy option is to use health assistants to close the gap at smaller schools and school nurses to close the gap at larger schools. It would cost the 68 small schools with fewer than 100 students with less than 1.0 FTE nursing an estimated $3,411,714 to reach 1.0 FTE if they hired nurses to close the gap compared to $1,657,225 to achieve 1.0 FTE of "health care" staffing (some combination of nurses and health assistants), an estimated savings of $1,754,489. The estimated cost of bringing all 325 schools up to 1.0 FTE in health care staff using nurses to close the gap in schools with 100 or more students and health assistants to close the gap in schools with fewer than 100 students is **$13,069,209**, about $1.75 million less than if all schools hired nurses to achieve 1.0 FTE. The estimated cost of bringing all 325 schools up to 1.0 FTE in health care staff using nurses to close the gap in schools with 200 or more students and health assistants to close the gap in schools with fewer than 200 students is: **$10,534,780,** a savings of approximately $4.3 million. The estimated cost of bringing all 325 schools up to 1.0 FTE in health care staff using nurses to close the gap in schools with 300 or more students and health assistants to close the gap in schools with fewer than 300 students is: **$8,732,912,** a savings of $6.1 million.

Finally, there is also the option of exempting small schools altogether and using health assistants rather than the more expensive nurses to bring larger schools up to at least 1.0 FTE in health care staffing (nurses and/or health assistants). The estimated cost of those scenarios are displayed in the last three rows of Table 31: the savings – compared to the policy option of funding all schools to hire a full-time nurse which is estimated to cost **$14,823,698 –** range from $9.6 million to $13.3 million.

Estimating the Cost of Funding a Social Worker Per School

We conducted a similar process to estimate the cost to enable every public school in Maine to hire a full-time social worker, in addition to guidance and school psychologist staff. Of the 548 public schools in our SY2020 data set, 250 (46%) had no social worker on staff. Of the 298 that did have social work staff, 34% had less than 1.0 FTE. High schools and middle schools are more likely to have social workers and to have at least one full time social worker.[1]

Table 32: School Social Workers by School Type, SY2019-20

	Elem	Middle	High	K-8	K-12	Other, including PK/K only	All schools
Number of schools	254	78	88	81	9	38	548
% (#) w/o any social worker	42% (106)	33% (26)	35% (31)	74% (60)	6 of 9	55% (21)	46% (250)
% (#) w/o at least FTE = 1.0	67% (171)	49% (38)	48% (42)	86% (70)	7 out of 9	68% (26)	64% (351)
Of those w/ social work staff, the % (# of schools) with at least FTE=1.0	56% (83 /148)	83% (43/52)	81% (46 / 57)	52% (11 /21)	2 of 2	70% (12 /17)	66% (197/ 298)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Smaller schools are less likely to have a social worker on staff and are more likely to utilize a part-time social worker when they do.

Table 33: School Social Workers by School Size, SY2019-20

Number of students	Number of schools	Percent (# schools) w/ zero social work FTE	Percent (# of schools) with either no social worker or less than 1.0 FTE	Of those with some social work staff, the Percent (# of schools) with at least FTE=1.0
Less than 100	70	81% (57)	99% (69)	8% (1 of 13)
100 – 299	237	54% (129)	80% (190)	43% (47 of 108)
300 – 499	143	34% (48)	50% (72)	72% (71 of 98)
500 - 799	79	18% (14)	20% (16)	97% (63 of 65)
800 or more	19	10% (2)	21% (4)	88% (15 of 17)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Higher poverty schools are less likely to have a social worker on staff and more likely to have a part-time social worker when they do.

[1] This analysis does not include the handful of Licensed Clinical Professional Counselors (LCPCs) on staff in public schools although these individuals often provide similar services. If actions are taken to increase resources provided to public schools to hire additional mental health professionals, the discussion should clarify the types of positions (and their qualifications) that would be eligible or encouraged.

Table 34: School Social Workers by School Poverty Level, SY2019-20

	Low poverty	Average poverty	High poverty
Number of schools	168	212	155
% (#) w/o any social worker	37% (62)	46% (98)	55% (86)
% (# of schools) with either no social worker or less than 1.0 FTE	59% (99)	63% (134)	72% (111)
Of those with some social work staff, the % (# of schools) with at least FTE=1.0	65% (69 of 106)	68% (78 of 114)	36% (25 of 69)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Rural schools are significantly less likely to have a social worker on staff and more likely to have a part-time social worker when they do.

Table 35: School Social Workers by School Location, SY2019-20

	City	Suburb	Town	Rural
Number of schools	42	66	69	362
% (#) w/o any social worker	33% (14)	32% (21)	32% (22)	53% (190)
% (# of schools) with either no social worker or less than 1.0 FTE	50% (21)	44% (29)	51% (35)	73% (263)
Of those with some social work staff, the % (# of schools) with at least FTE=1.0	75% (21 of 28)	82% (37 of 45)	72% (34 of 47)	57% (99 of 172)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Again, not surprisingly, schools officially designated as small and geographically isolated are significantly less likely to have a social worker on staff and more likely to have a part-time social worker when they do.

Table 36: School Social Workers by "Small and Isolated" Designation, SY2019-20

	Small and geographically isolated	Not Small and geographically isolated
Number of schools	56	492
% (#) w/o any social worker	75% (42)	42% (208)
% (# of schools) with either no social worker or less than 1.0 FTE	96% (54)	60% (297)
Of those with some social work staff, the % (# of schools) with at least FTE=1.0	14% (2 of 14)	67% (195 of 284)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Of the 548 public schools in our SY2020 data set, 351 had less than 1.0 FTE social worker. We estimated how much it would cost to bring all 351 schools up to 1.0 FTE in social work staff. The average statewide salary in SY2020 based on the sample of social workers working full-time in a public school setting was $59,674. There's a moderately strong positive correlation between years of experience and salary ($r = 0.639$, $p < 0.001$); years of experience explains about 40% of salary. The average salary paid to the 7 beginner social workers (i.e., those with less than 1 year experience) working full-time was $43,929. The average salary paid to the 162 "typical" full-time social workers – those with years of experience within one standard deviation (9.96) of the mean years of experience (14.11), 4 years to 24 years, was $58,520.

Of the 548 public schools in our SY2020 database, 351 (64%) had either no social worker on staff or a part-time social worker (less than 1.0 FTE). Assuming all 351 schools hired beginner social workers to get to FTE 1.0, the estimated cost is **$13,578,454.** If instead schools hired experienced social workers and the average wage they paid was the average paid to the typically experienced social worker (years of experience 4 to 24) - $58, 520 - then the estimated cost would be **$18,088,532.** As we did above with nurses, we assume social workers will be able to negotiate a salary that gives them credit for prior experience and use the average wage paid to the typically experienced social worker - $58,520 – for the estimated costs of various policy measures summarized in the table below.

Table 37: Cost Implications of Policy Options for Placing a Full-Time Social Worker in All Public Schools

Policy	Number of schools assisted (of 548)	Estimated cost
Bring all schools up to at least 1.0 FTE using beginner social workers	351	$13,578,454
Bring all schools up to at least 1.0 FTE using experienced social workers	351	$18,088,532
Exempt smaller schools		
Bring schools with at least 100 students up to 1.0 FTE social worker	282	$14,167,692
Bring schools with at least 200 students up to 1.0 FTE social worker	171	$8,333,248
Bring schools with at least 300 students up to 1.0 FTE social worker	92	$4,447,520

Directing additional funding for schools to hire more nurses and social workers would target higher poverty and rural schools, since these schools are less likely to have full-time staff. As shown below, exempting small schools will, in fact, leave out a higher percentage of higher poverty and rural schools.

Table 38: Percent and Number of Small Schools by School Poverty Level

Policy	Low poverty (n=168)	Average poverty (n=212)	High poverty (n=155)
Exempt schools smaller than 100	8% (14)	10% (21)	18% (28)
Exempt schools smaller than 200	23% (39)	37% (78)	43% (66)
Exempt schools smaller than 300	45% (75)	57% (121)	66% (102)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Likewise, exempting smaller schools from the additional funding will disproportionately exclude rural schools.

Table 39: Percent and Number of Small Schools by School Locale

Policy	City (n=42)	Suburb (n=66)	Town (n=69)	Rural (n=362)
Exempt schools smaller than 100	0%	0%	0%	19% (69)
Exempt schools smaller than 200	5% (2)	6% (4)	12% (8)	48% (173)
Exempt schools smaller than 300	31% (13)	27% (18)	38% (26)	68% (246)

*Note: The sample includes all the regular public schools for which we obtained staffing data for the SY2020, including small and isolated schools and stand-along PK and PK/KG programs.

Summary and Implications

Overall staffing levels

- Teacher ratios, which declined between SY2014 and SY2017, appear to have stabilized at around 14 to 15 students per teacher. Teacher ratios were below the EPS funding model ratio across all grade levels.
- Student-to-staff ratios for all other EPS positions analyzed – e.g. education technicians, guidance staff and school nurses - were also lower than EPS. In other words, schools are employing more staff than provided by the EPS ratios.
- It is not feasible with existing data to calculate the actual teacher ratios for grades PreK/K separately from grades 1 to 5. Thus although the EPS model provides more funding for teachers for those earliest grades, we are unable to analyze whether and how the additional resources are impacting actual staffing levels. This limitation has been more thoroughly described and discussed in the component review for the PreK–2 pupil weight, which is a separate element in the cost model.

Conclusion: The staffing levels in Maine public schools are adequate. They are achieving at least the ratios allocated in the model, and in most cases providing even more staff per student. This is achieved by supplementing the resources allocated though the ratios, either with funds from other parts of the EPS formula (for example, with allocations from the economically disadvantaged or the PK-2 pupil weights), or with additional local funds above the EPS model allocation. We continue to recommend that the MDOE amend the guidance and requirements for reporting teacher staff FTE, as outlined in our recent preK-2 pupil component review, to enable more detailed analysis of staffing levels in the early elementary grades compared to grades 3-5.

School size

- Student-to-staff ratios for most EPS staff positions increased with increasing school size. This effect is generally attributed to the economies of scale that can only be achieved in schools with a certain number of students.
- Some smaller schools are below EPS staffing levels for certain non-teaching staff positions. For example, smaller elementary schools are more likely than medium and large schools to lack non-teaching staff such as a guidance counselor, a library/media technician, or a nurse. None of the small or medium-sized high schools employed a full-time nurse while a majority of the large high schools did.

Conclusion: Many of Maine's schools have enrollments that are smaller than the non-teacher staff ratios in the formula. This means they are allocated less than a full-time person for roles such as nurses and librarians (1 FTE per 800 students) or guidance (1 FTE per 250 or 350 students depending on the grade level). Districts with small schools must hire part-time staff, hire full-time staff and share them among multiple schools, or supplement the allocation with other resources to hire more staff than the model ratio provides. However, the district-reported data show a non-trivial number of schools with zero assigned nurses—not even part-time; a smaller number have no assigned guidance staff. This merits more targeted follow-up with these schools to determine whether the data are accurate, and to understand what alternatives they are employing to meet their students' needs.

Poverty level

- Teacher ratios varied slightly by school poverty level among elementary schools across the state, with higher poverty schools having slightly ***lower*** ratios (i.e fewer students per teacher, akin to smaller class sizes): 0.1 fewer students per teacher FTE than lower-poverty schools and 0.3 fewer students than average poverty schools.

These ratios are even more favorable in higher poverty schools when federally-funded Title I teachers are considered.

- Unlike the trend for elementary schools, ratios at the middle and high school levels ***increased*** with increasing poverty level (i.e., schools with higher rates of student poverty had more students per teacher FTE). The ratio among high schools with higher rates of student poverty (15.1) was close to the EPS funding level of 16 students per teacher, while for lower-poverty high schools the ratio (14.3) was well below the EPS ratio.
- High-poverty schools also hire more education technicians than lower poverty schools, and as a result had lower student-to-staff ratios at all levels (elementary, middle and high school).
- On the other hand, after controlling for school size and location, the student-to-staff ratios for guidance staff and nurses is positively correlated to the percentage of students eligible for free or reduced-price lunch (i.e., there are fewer of these staff at higher poverty schools). High poverty schools were more likely to have fewer (or zero) nursing and guidance staff per student. However, between the school years 2016-2017 and 2019-2020 expansions in guidance occurred, primarily among higher poverty schools.

Conclusions: Higher staff ratios (i.e., more students per staff FTE) among higher poverty schools (given comparable size) is generally considered to be a reflection of increased budget constraints in lower-income communities. Where there is less property wealth, less local funds for education are raised through each mil of property taxes. Thus the findings that higher poverty middle and high schools have more students per teacher, and have more students per other staff types at all school levels, is as expected. However, the finding that the teacher and ed tech ratios at the elementary level were more favorable among higher poverty schools is less intuitive. This encouraging finding suggests that higher poverty districts may be directing the additional funds they are allocated from the EPS disadvantaged student weight component to hire teachers and educational technicians at the elementary level. Additionally, higher poverty elementary schools benefit more than lower-poverty schools from federal Title I funds. Those funds directly allow hiring more teachers from federal funds, as shown in the lower ratios when Title I teachers are included. The finding that even EPS-funded teacher ratios are lower in higher poverty schools suggests that the federal funds do supplement EPS funding and thus allow the state and local dollars to stretch further and support more staff.

School Nurses & Social Workers

- From 2017 to 2020 there was an almost across the board increase in staffing levels of both nursing and guidance positions, the exception being a slight contraction (0.5 FTE) in guidance staffing at the middle school level. The biggest increases were at the elementary school level. Over the course of this three-year period, elementary schools added enough staff to cause the statewide ratios to decline by 61 students per guidance FTE and 65 students per nurse FTE.
- While the likelihood of not having a school nurse is about the same across grade levels, among those that do have nursing staff, elementary schools have more nurse staff (i.e. lower student-to-nurse ratios). The opposite is true of guidance staff, with high schools having the lower student-to guidance ratios.
- How much would it cost to staff every school with a full-time nurse? There were 325 public schools in Maine that had less than a 1.0 FTE nurse in SY2020. The estimated cost to bring all 325 schools up to 1.0 FTE ranges from $13.4 to $14.8 million, depending on the level of experience of the nurses**.** We explored the cost effects of variations on this staffing proposal (e.g., exempting smaller schools or using health assistants instead of nurses) and identified options ranging from $1.5 to $11.4 million.
- How much would it cost to staff every school with a full-time social worker? There were 351 public schools who in SY2020 had either no social worker on staff or a part-time social worker (less than 1.0 FTE). The estimated cost to bring all 325 schools up to 1.0 FTE ranges from $13.6 to $18.1 million depending on the experience mix of the social workers. Exempting smaller schools could reduce the cost down to between $4.5 and $14.2 million, depending on where the size cutoff is set.

Conclusion: Expanding funding to enable all schools to hire full-time nurses and social workers may disproportionately target higher poverty and rural schools, since these schools are less likely to already have full-time staff. However, the policy may only result in increased staff if coupled with constraints that direct the spending on these staff roles, rather than simply increasing the total EPS allocation for the SAU to budget at their own discretion. Additional study to describe the unmet student needs in schools with less than full-time staff is recommend in order to yield insights into the types of services that are most needed in these small schools. This would clarify the types of skills that are needed (with implications for credentialing), and whether other alternative policy interventions could be equally impactful – such as supporting the creation of school-based health centers or community partnerships.

Early Pandemic Staffing Impacts

- During the pandemic overall enrollment dropped by 5%, with the largest declines in enrollment occurring at elementary level. Except for high schools, statewide teacher ratios dropped between the school years 2019-20 and 2020-21 driven almost exclusively by pandemic-induced declines in enrollment. Teacher FTE remained nearly steady during the pandemic.
- Changes in the staffing levels of non-teaching EPS positions during the pandemic year were generally smaller than the decline in enrollment. Any increases in staffing were focused on positions providing services related to student health and emotional wellbeing (nurses, health assistants, school psychologists, licensed clinical professional counselors). However, the increases were small and driven by only a handful of schools.

School Locale

- Statistically, differences in staffing by school location are driven largely by school size and poverty level. Once school size and poverty level are controlled for, a school's location (city, suburb, town, or rural) is no longer statistically correlated to its student-to-staff ratio. Student-to-staff ratios by locale at the school level tend to reflect a mix of school size and poverty rate effects.

APPENDIX

In both SY2020 and SY2021 there were nine (9) schools that only had PK or KG (or both) enrollments.

Stand-alone KG and PK programs, SY 2021 and SY 2021:

Staff FTE and enrollments and ratios

	SY 2019-20	SY 2020-21	% change
Student enrollment	1,012	859	-15%
Regular teachers FTE			
Regular classroom teacher	62.8	62.7	
Literacy Specialist	1.0	1.0	
Long-term sub	0	0	
ELL teacher	1.5	1.8	
Total EPS teacher FTE	65.3	65.5	+0.3%
Teacher ratio	15.5	13.1	
Other teacher FTE			
Title I teacher	0	0	-
G&T teacher	0	0	-
Special Ed teacher	8.3	8.3	0
All teacher FTE	73.6	73.8	+0.3%
All teacher ratio	13.7	11.6	
Other staff FTE			
Education technicians	36.2	34.0	-6%
Ed tech ratio	27.9	25.3	
Library/Media Techs	2.3	1.3	-43%
Library/Media tech ratio	440.0	660.7	
Guidance staff	1.1	1.5	+36%
Guidance ratio	920.0	572.7	
School Nurse	1.5	2.3	+53%
Nurse ratio	674.7	373.5	

There were 56 schools that qualified as "small and isolated" in SY2020/21.

Small and isolated schools, SY 2021 and SY 2021:

Staff FTE and enrollments and ratios

	SY 2019-20	SY 2020-21	% change
Student enrollment	4,635	4,307	-3.4
Regular teachers FTE			
Regular classroom teacher	428.7	414.2	
Literacy Specialist	3.2	1.2	
Long-term sub	1.0	1.0	
ELL teacher	0.1	0.2	
Total EPS teacher FTE	433.0	416.6	-3.8
Teacher ratio	10.7	10.3	
Other teacher FTE			
Title I teacher	12.4	13.9	
G&T teacher	3.2	3.5	
Special Ed teacher	53.0	56.0	
All teacher FTE	501.6	490.0	-2.3
All teacher ratio	9.24	8.9	
Other staff FTE			
Education technicians	92.0	106.3	+15.5
Ed tech ratio	50.4	40.5	
Library/Media Techs	11.2	11.0	-1.8
Library/Media tech ratio	413.8	391.5	
Guidance staff	14.2	14.4	+1.4
Guidance ratio	326.4	299.1	
School Nurse	10.8	11.0	+1.9
	429.2	391.5	

EPS Component Review Report of Findings:

Gifted & Talented Education Funding

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Report Overview

This review of the Gifted and Talented (G&T) funding component within the Essential Programs and Services (EPS) education cost model begins with a summary of our most recent (2019) analyses of the G&T funding patterns and trends in Maine. Next we provide updated data (Part I) about G&T program implementation and enrollment in Maine public schools in FY2020 and FY2021 to confirm that trends from prior studies persist. We then provide a summary of the available research literature on the rationale and effectiveness of G&T programming in order to revisit the underlying tenets of this aspect of Maine's funding model and evaluate whether it remains consistent with the EPS model's overall goals of adequacy and equity.

Background

Maine provides an annual allocation in the EPS formula for districts that successfully apply and receive approval from the Maine Department of Education for their Gifted and Talented (G&T) program plans. In FY2021, the total allocation to the 156 Maine SAUs with approved G&T programs was $13.49 Million, with amounts ranging from $147 to $427,570 per district (averaging $86,457).

Once a district's program is approved, they are provided funding that is based on the amount actually spent on G&T in the most recent fiscal year. This expenditure-based approach means that the amount of funding is not based on pre-established criteria such as the number of students participating in G&T programs or a fixed ratio for hiring staff. Rather, the allocations are directly related to prior spending, so that districts who spend more on G&T services receive larger program allocations (and vice versa). In general, expenditure-based funding raises concerns about equity because it tends to disproportionately benefit districts with greater ability to raise funds through local property taxes (i.e. wealthier communities).

The findings in the most recent MEPRI review of the Gifted and Talented funding component (2019)[1] corroborated those concerns about equity. Students identified as Gifted and Talented are disproportionately white, female, and *not* economically disadvantaged compared to the general population of Maine students. The underrepresentation of economically disadvantaged students is particularly stark, with such students representing 45.0% of all Maine students but only 21.1% of G&T identified students in 2018.

This pattern is not unique to Maine as detailed in the national scan included in the 2019 component review. States are beginning to respond to concerns about equity and the potential unequal opportunities for high-achieving learners of all backgrounds to benefit from supplemental G&T programs. Currently, 16 states do not provide any G&T funding, including New York and all of the New England states except for Maine. Others have shifted in recent years to make G&T programming optional and/or reduce financial support.

Because this recent and comprehensive G&T component review was based on 2018 student and expenditure data, it was decided to shift the focus of the current study rather than repeat the same analyses. This is because it was not desirable to analyze data from FY2020 or FY2021 due to the likely impact of the pandemic on program expenditures. Repeating the 2018 analyses with FY2019 data – just one year more recent -- was deemed unlikely to be fruitful and not the highest priority for investigation. Thus the current study instead provides only a brief overview of G&T program enrollment in FY2020 and FY2021. The remainder of the report is a detailed analysis of the existing empirical (quantitative) national research on the overall outcomes and impacts of providing separate pull-out services and programs to student who are identified as Gifted and Talented. This is intended to examine the underpinnings of Maine's funding model in light of other emerging trends, such as using a Multi-Tiered System of Support (MTSS) framework to serve students whose academic needs may not always be adequately addressed solely through differentiated instruction in the regular classroom.

[1] https://www.maine.gov/doe/sites/maine.gov.doe/files/inline-files/GiftedTalentedAppendixA_FinalApril2019.pdf

Part I: Analyses of Participation in Maine G&T Programs (FY2020 and FY2021)

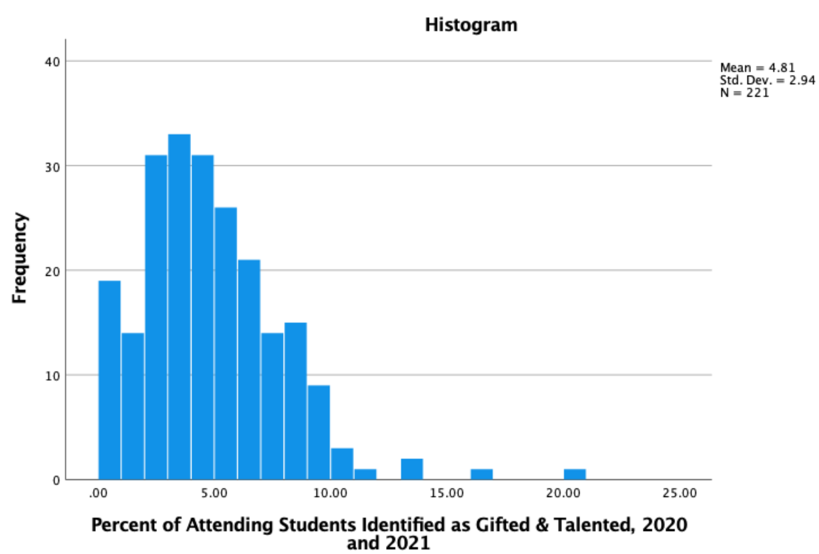
In academic years 2019-20 and 2020-21, just over half of Maine public school districts reported enrollment of students identified as Gifted and Talented (Table 1).

Table 1. Descriptive Information on SAUs with Enrolled Attending G&T Students

	AY2019-20	AY2020-21
Number (%) of SAUs reporting G&T students	112 of 207 (54%)	109 of 206 (53%)
Total Number of G&T Students	7,197	6,495
Mean % Enrolled G&T students	4.97%	4.65%
Range of G&T Enrollment %s	0.1% to 14%	0.1% to 16%

Table 1 also describes a large variation in the proportion of students identified as Gifted and Talented. Among districts that reported one or more G&T students, the overall identification rate was about 4.5% to 5% but rates in individual districts ranged from nearly zero (0.1%) to about 15%. Figure 1 depicts the G&T identification rates in districts with one or more reported G&T student.

Figure 1. % of Attending Students Identified as Gifted & Talented, FY2020 and FY2021*



*Excludes SAUs that did not report any students identified as G&T

When analyzing the demographics of the districts that reported enrolled G&T students compared to those that did not report any students, we found similar trends to prior reports. Namely, there was a significant difference with respect to the proportion of students considered economically disadvantaged (Table 2).

Table 2. Average Poverty Levels in Schools With and Without Enrolled G&T Students

	Average % Economically Disadvantaged Students	
	2019-20	2020-21
SAUs with reported G&T students	41.7%	39.1%
SAUs without reported G&T students	49.3%	45.6%
Statistically significant difference?	Yes (p=.004)	Yes (p=.009)

These findings continue to raise concerns about the equitable allocation of funds through this component of the EPS cost model. The summary and conclusion section of this report provides additional recommendations for next steps based on these implications.

Part II: Background and Existing Literature on Gifted & Talented Programs

General background

Part II contains a comprehensive review of the existing quantitative research related to Gifted and Talented education programs in the United States. Guiding questions for the literature review included:

- Are gifted and talented programs effective?
- Do students assigned to gifted and talented programs achieve academic gains above and beyond what they would have achieved in regular educational programs?
- Do benefits of G&T participation depend on the type of G&T program? I.e. do some students benefit while others do not (by race, gender, economic dis/advantage, marginally gifted vs exceptionally gifted)?
- What are the socioeconomic characteristics of students selected for G&T programs?
- Do G&T programs help compensate for the lack of advantages and supports low-income families can provide their gifted children, or the lower expectations that some teachers have for economically disadvantaged students or students of color?

How G&T programs are theorized to work

There is a lot of variety in how G&T programs are designed. Some schools create separate classrooms for students identified as gifted, some group students within the regular classroom and provide them more advanced content. Some are "pull-out" enrichment programs where gifted students are taken out of the regular classroom to participate in project-based, independent study. Other programs provide students with acceleration options, skipping a grade or taking more senior classes or college courses while still in high school.[2] G&T programs are presumed to help participating students offering more challenging and faster paced curricula commensurate with their abilities as well as more opportunities for independent work, creative and critical thinking. Students participating in G&T programs are also theorized to benefit from peer effects: their fellow G&T classmates are higher achieving, more academically motivated, etc. and they rise to the occasion, are more supported. Indirect effects of being in a class of

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[2] https://www.nagc.org/resources-publications/resources/frequently-asked-questions-about-gifted-education

higher achieving peers result from the teacher teaching at a higher level, as long as the student can keep up.[3]

When budgets are tight there is a tendency to focus scarce resources on struggling students, the assumption being that gifted students are generally able to reach their full academic potential on their own, or that at least they will not fall irreparably behind. Because socioeconomically advantaged (white and/or rich) students are more likely to be identified as gifted, there's also the argument that their families will be able to provide compensatory supports and outside-of-school enrichment activities, and that G&T programs are merely adding to existing advantages as well as elitist and even segregationist.[4]

On the other hand, if all gifted students were identified as such and G&T programs are effective (and if they were to be particularly in lifting the academic achievement of disadvantaged students) then eliminating them will hit gifted poor, EL and racial minority students hardest because their families are less likely to have the means to provide compensatory support (tutors, enrichment activities, summer camps, etc.) or to send them to private schools with accelerated and advanced curricula.[5]

Proponents argue that if gifted students are not sufficiently challenged by regular curricula they will not reach their full academic potential, resulting not only in personal losses in earning power and life and career satisfaction but losses to society as well, the argument being that well-educated gifted students are more likely to go on to become exceptionally productive workers, effective leaders and innovators who invent valuable new products and services.[6]

"*We assert that aspiring to fulfill one's talents and abilities in the form of transcendent creative contributions will lead to high levels of personal satisfaction and self-actualization as*

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[3] http://jhr.uwpress.org/content/early/2021/02/03/jhr.58.4.0920-11170R1.refs
https://journals.sagepub.com/doi/10.1177/01623532110340030
[4]https://journals.sagepub.com/doi/10.1177/00169862211002535?icid=int.sj-abstract.similar-articles.2 High-Achieving Students in the Era of No Child Left Behind (brookings.edu)
https://www.nytimes.com/2019/08/26/nyregion/gifted-programs-nyc-desegregation.html
Gifted and Talented Programs Aren't the Problem - The Atlantic
[5] https://fordhaminstitute.org/national/commentary/we-are-squandering-talents-too-many-low-income-high-achievers How talented low-income kids are left behind - kappanonline.org https://www.nber.org/papers/w21519
[6] https://journals.sagepub.com/doi/10.1177/1529100611418056 https://www.nagc.org/resources-publications/gifted-education-practices/why-are-gifted-programs-needed https://www.nagc.org/myths-about-gifted-students

well as produce yet unimaginable scientific, aesthetic, and practical benefits to society (Subotnik, Olszewski-Kubilius, & Worrell, 2011)."[7]

The Maine Educators of the Gifted and Talented (MEGAT) website reads: "*The MEGAT Mission is to further the common good of gifted education in the State of Maine by supporting the development of programs for gifted and talented youth in Maine."*[8]

The belief that gifted and talented programs will yield social benefits and level the playing field by helping socioeconomically disadvantaged gifted students is a powerful policy argument even when educational resources are scarce.

However, the empirical evidence in support of G&T program benefits is best described as mixed.

While there are a bunch of studies showing a positive correlation between G&T program participation and academic outcomes including higher test scores, grades, and educational attainment it is not clear that these outcomes are due to G&T programs themselves.[9]

Participation in gifted programs is not randomly assigned. Students identified as gifted and assigned to G&T programs are by definition a selected group. The observed positive outcomes produced by correlational studies could be due to G&T programming (causation) or to higher levels of ability, motivation, confidence, socioeconomic advantages, and family support (selection).

Is their higher achievement the result of their participation in a G&T program or is it due to a mix of factors including natural ability, motivation and drive, confidence, exposure to high expectations (e.g., teacher presumptions regarding their ability), access to support (e.g., teacher and parent encouragement and assistance, tutors), participation in extracurricular enrichment activities (e.g., summer camps, internships) and lower levels of socioeconomic stress and distractions (e.g., stable housing, food security, parents with less work-family conflict, fewer responsibilities for younger siblings)?[10]

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[7] https://journals.sagepub.com/doi/10.1177/1529100611418056
[8] http://www.megat.org/about.html
[9] https://ies.ed.gov/ncee/edlabs/regions/northeast/AskAREL/Response/72 https://www.nagc.org/resources-publications/gifted-education-practices/why-are-gifted-programs-needed
https://files.eric.ed.gov/fulltext/EJ746290.pdf https://medium.com/age-of-awareness/do-gifted-and-talented-programs-work-aaee7dcaaa30
[10] https://www.nagc.org/blog/no-child-just-born-gifted-creating-and-developing-unlimited-potential

In other words, it is plausible that students who were selected to participate in G&T programs had higher academic skills, were more motivated, and/or provided with more support. These characteristics would have helped them to prosper in any school program.

If all students were tested and all gifted children were accurately identified and assignment to the treatment (G&T program) was random (i.e., there was no systematic difference between the two groups in terms of ability, motivation, access to support, etc.) then we could validly determine program effects by comparing the differences in academic outcomes between the two groups.

In the absence of random assignment researchers need to use statistical techniques to try and isolate causal effects by reducing endogeniety bias caused by omitted variables (unobserved and thus uncontrolled confounding variables), simultaneity (when a predictor variable is correlated with both assignment to G&T programming *and* subsequent academic achievement) and measurement error.

Even using lots of control variables, regular regression techniques (OLS) will produce biased results. If students assigned to G&T programming are of higher ability and more highly motivated, supported, encouraged, etc. the bias will be upward, making G&T program participation look more beneficial than it actually is.

While we found a couple of studies that benefited (more or less) from random assignment, most of the studies investigating the impact of G&T program participation used statistical techniques to try and control for bias. In the absence of random assignment to the treatment, researchers typically used the following approaches to reduce selection bias– instrumental variables, regression discontinuity models, propensity score matching and student fixed effects.

Primer on quantitative research methods and their limitations

When there is a test (IQ or achievement) or some other type of score (i.e., a continuous index of tests and other factors) used to select which students are assigned to G&T programming researchers are able to use regression discontinuity techniques to try and isolate causal program effects. This approach compares students just above the eligibility cut-off to those who are just

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https://www.journals.uchicago.edu/doi/abs/10.1086/444275 https://us.sagepub.com/sites/default/files/upm-assets/38607_book_item_38607.pdf below the cut-off, the assumption being that the two groups of students are very similar in terms of both ability as well as other unobserved/able characteristics and factors that impact subsequent academic outcomes. Researchers must decide how far out from the eligibility cut-off to go: If they use observations from more points out from the cut-off their sample is larger and therefore, they are more likely to find a statistically significant difference but the further out the move the more they risk introducing bias (i.e., the two groups of students become less similar). Parametrically, researchers use standard linear regression with the dependent variable the subsequent academic outcomes of interest (e.g., post-participation achievement test score, % who went on to college) with the predictor variables of interest being the index score (i.e., the test or index score used to assign students to G&T) and a dummy variable that indicates whether the student's score is above the cut-off (the coefficient on this variable is the estimate of the G&T program effect).

It is often the case that not all the students who score above the cut-off participate in the G&T program (and some who score below do). Participation in G&T programs is voluntary, and some students opt out. In some instances, there are limited G&T program slots and so not all qualifying students are able to participate. In some cases, students who score below the cut-off are able to participate because their parents or teachers advocate on their behalf. In this case researchers use what is called "fuzzy" regression discontinuity design (RDD), a two-stage estimation technique in which in the first stage produces and estimates the likelihood the student participated based on their test or index score and a dummy that indicates whether their score is above the cut-off. The estimated likelihood is then used as a predictor in the second stage where you estimate the effects of program participation on achievement outcomes.

To test the validity of using RDD, researchers should provide a comparison of the two groups of students using the available data to see if there are "discontinuities" between the two groups in terms of characteristics and factors prior to the G&T program participation (or not). The only discontinuity you want to see between the two groups is on the dependent variable (in which case you can conclude there is a causal program effect). In other words, they should compare the two groups in terms of observable data like student demographics and prior achievement test scores. If there are no statistically significant differences (or no discontinuities in graphical plots) then the researchers can conclude the two groups are similar enough to isolate an estimate of causal effects of G&T participation. If they find significant differences, they need to at least include these variables as controls in their estimation models. If they find too many differences between students just above and just below the eligibility cut-off, then RDD is not appropriate.

While RDD is generally more robust than instrumental variables techniques (described below) a possible source of bias with RDD occurs when there are spillover effects (which "contaminate" the comparison group). Negative spillover occurs when the comparison group (the students below the cut-off) suffer in ways that negatively impact their academic performance (e.g., upset about not making the cut-off; teachers in regular classrooms teach to lower ability students once G&T students are removed from the classroom and these higher ability students left behind in the regular classroom suffer from not being challenged). Negative spillover effects will inflate the estimated effects of G&T class participation (i.e., the comparison group will be made worse off making the students above the cut-off in the G&T classroom look better even if there were no positive program impacts). There is also the possibility of positive spillover effects which will have the opposite effect on estimated program effects (i.e., will make the G&T program look less effective than it actually is). This might occur if students below the cut-off benefit from now being the top students in the regular class because the slightly higher achieving students went to the G&T class (confidence boost; teacher adjusts his/her pace and level in ways that better suit their needs; their parents provide more support – tutors, outside school enrichment - perhaps in hopes they make the cut next year or to at least make up for the fact that they aren't getting extra from the G&T program). If average achievement scores for the students just below the cut-off decline that is a sign there may be negative spillover effects; if they increase, there may be positive spillover effects.

The most obvious limitation of RDD is that it examines program effects only on the marginal students (i.e., those just above the eligibility cut-off); it does not enable accurate analysis of the effects on more highly gifted students (because the further you move away from the eligibility cut-offs, the less similar become your comparison groups).

Another way of addressing the potential for endogeneity bias is to use *instrumental variables.* Instead of using a G&T participation (yes/no) variable to estimate the program effect, researchers use some other variable – referred to as the instrumental variable (IV) - that is correlated with the treatment (G&T program) but not directly correlated with the outcome (subsequent academic achievement), i.e., the IV affects academic achievement only indirectly through G&T program participation. The estimation technique is two-staged. In the first stage the IV is used to predict the probability of being placed in a G&T program. The estimated probability of program participation is then used as a predictor variable in the second stage where you estimate the effects of program participation on achievement outcomes. The rub with this technique is that good IVs are hard to come by and there is no direct way to measure if they are good or bad (i.e., there is no way to statistically test whether the IV is both a strong predictor of G&T program participation and only correlated with subsequent academic outcomes via the G&T program). Choice of IVs is based on theory and logic. At best, researchers in certain cases can use statistics (like the F statistic or R-squared) associated with the first stage equation to assess the strength of the IV in predicting program participation. Weak IVs can lead to both biased and imprecise estimation of program effects. Note, however, a strong IV could still be biased (i.e., it may be strongly correlated with the participation but also correlated with the achievement outcomes used to assess program effectiveness).[11]

Propensity score (PS) matching is another technique used to try and reduce endogeneity bias. Using logistic or probit regression (usually), a propensity score (the probability a student participated in a G&T program) is estimated for all students using variables correlated with program participation available in the data. The resulting score is used to create matched comparison groups (i.e., very similar in terms of their PS) of G&T program participants and non-participants. There are a number of matching techniques (nearest neighbor closet score; with and without replacement, etc.) and researchers evaluate the quality of the matching by comparing the two groups on the covariates (differences of means t-tests, comparing of distributions graphically, etc.). Program effects are estimated by comparing the means on the outcome variable between the two groups, using regression to control for the variables that were "unbalanced" (i.e., on which the two groups did not match well) and in some cases including the PS as a covariate. The limitation of this technique is that is that the two groups are matched based on observable factors (i.e., variables in the available data); there remains a risk of bias

[11] https://www.statisticshowto.com/instrumental-variable/
https://www.nber.org/system/files/working_papers/t0284/t0284.pdf http://economics.mit.edu/files/15326

related to unbalanced unobserved/unmeasured confounding factors (e.g., family support, motivation, etc.).[12]

Finally, when researchers have access to longitudinal data with repeated measures on the same students (i.e., panel data) they can use student-fixed effect analysis. The analysis of repeated measures on the same student allows for the control of bias resulting from time-invariant unobserved confounding factors. Instead of comparing participating and non-participating students, this approach basically uses the individual student as their own control, comparing achievement outcomes during the years they received G&T services to the years during which they did not receive G&T services. To the extent that unmeasured confounding factors like motivation and parent support remain fixed (time-invariant), selection bias is controlled. The obvious limitation of this approach is that some unobserved confounding factors are not time-invariant. For example, wealthy parents may invest more time and resources to provide a child with outside school support once the child has been assigned to a G&T program (or maybe when they do not make the cut-off, hoping to help them do so in the next school year). On the other hand, parents with less resources may provide less support once their child is assigned to G&T (resources are scarce and they assume the G&T program will meet their child's educational needs). Another limitation of this technique is that the reduction in bias (by estimating effects of repeated within-student measures) may come at the expense of precision (i.e., it will be harder to achieve statistical significance), particularly if there is little change in observed program participation over time (i.e., if the observation period is relatively short and most of the students in the sample are either always in G&T or always out of G&T).

Summary and Critique of Available, Rigorous Studies

We conducted a search for studies examining the effects of G&T program participation academic achievement. Below is a summary of these studies. We do not include correlational studies that do not attempt to control for bias and isolate causal effects. We begin by describing the more rigorous studies, those that were able to benefit from random assignment, use RDD or panel data and student fixed effects. After that we include those using the less robust methods: instrument variables and propensity score matching. Overall, the results are mixed with some

[12] https://link.springer.com/article/10.1007/s12350-017-1012-y

studies finding positive effects and others finding no effects, some finding benefits for disadvantaged students, others finding net gains only for advantaged students.

The most rigorous U.S.-based studies were conducted by Bui, Craig and Imberman (2014) and Card and Guiliano (2014 and 2016). Both use data from one district (one concern about studies using national data is that program variability is masking program effects from higher quality G&T programs), employ RDD and run an extensive set of validity checks and sensitivity analyses. Bui et al also are able to confirm the results obtained using RDD by analyzing data from a lottery that more or less replicates random assignment.

Card and Giuliano (2016) Can Tracking Raise the Test Scores of High-Ability Minority Students?[13]

Summary: Except for studies employing random assignment or benefiting from lotteries, this is the strongest study methodologically. It is published in one of the top peer-reviewed journals in economics by a Nobel prize-winning economist. Taking advantage of extensive student level information, they use two different analytic approaches to test for the effects of assignment to separate G&T classrooms, RDD and a between school/cohort analytic design. Using data on multiple cohorts of students from one large urban district, they estimate the effect of being assigned to a separate G&T classroom on high-achievers (students who did not pass the IQ test cut-off but who were top-ranked according to the previous year's achievement tests). Using RDD, which examines the effects of G&T program participation on marginal, just-above-the-cut-off students as compared to just below the cut-off students who remain in regular classrooms, they find strong positive effects for students of color but not for white students (poor or not). Their findings persist when they use a between school/cohort analytic design as well as to a battery of alternative model specifications, validity checks and sensitivity analyses, including tests for potentially biasing spillover effects. They conduct additional analysis using student level data to show that racial minority students have lower achievement scores in the 3rd grade (prior to participating in the G&T program) than white students with the same cognitive ability (as measure by NNAT in 2nd grade) and that placement in a G&T class all but eliminates the achievement gap. They speculate that the reasons the program has valued-added impacts for minority students and not white students relates to minority students obtaining more support and higher teacher expectations in the G&T classroom: higher ability minority students do better in G&T classrooms because they are more supported (additional analysis also showed a reduction in absences and suspensions), have higher ability and more female peers (less flack for "acting white") and that teacher expectations are higher (in another paper they showed that before universal screening was adopted, teachers in the same district systematically under-refer black and Hispanic students for G&T programs) and that students rise to the occasion.

[13] https://www.aeaweb.org/articles?id=10.1257/aer.20150484

- **Data, Method, Sample:** The data used in this study come **from a large urban school district** in the U.S. Starting in 2004 the District required elementary schools to set up separate classrooms for gifted students (identified using IQ tests: non-disadvantaged students with IQ scores ≥130; subsidized lunch participants and English language learners with IQ scores ≥116) in fourth and fifth grades, with any open seats allocated to students with the highest scores on the previous year's achievement tests. Since most schools have only a handful of gifted children per grade, and class sizes are maintained at 20-24 pupils, most gifted classrooms in the district contained a mixture of high IQ students and high-achievers (the students who didn't make the IQ test cut-off but they scored in the top ranks of achievement tests). In this paper, the researchers focus on the effects on high achievers - the students who were assigned to the separate G&T classrooms based on their achievement test scores (in another study, described below, they look at the effects on students assigned to G&T classrooms based on their IQ tests). The researchers conduct two types of analyses: (1) **using regression discontinuity design (RDD)** based on the eligibility rules for the 4th grade G&T classroom, which estimates the effect of being in a separate G&T classroom by comparing students just above the achievement score cutoff (eligible for the G&T class) to those just below (remain in regular classrooms). They estimate separate models for white and minority students and examined whether there was evidence that teacher quality and peer characteristics impacted the estimates of program effects. (2) **they used a between school/cohort design to create a counterfactual scenario in order to test for spillover effects** (i.e., do students ranked just below the cutoff do worse when there is a separate G&T classroom in their school to which the higher ranked students are assigned compared to when there is no separate G&T classroom and the higher ranked students remain in the regular classroom). Note: it is important to check for spillover effects; negative spillover will inflate estimated effects of G&T class participation (i.e., the comparison group will be made worse off making the students above the cut-off in the G&T classroom look better even if there were no positive program impacts); positive spillover effects will produce a downward bias on estimated effects (if students below the cut-off benefit from being the top students in the regular class because the slightly higher achieving students went to the G&T class). The school/cohort design also enables them to test how different ranks of students performed on 4th grade tests when there is a G&T classroom option and when there is not. This approach enabled them to test whether effects differ by student rank (they ranked students according to their 3rd grade test scores, 1-20 were high ranked; 25-44 were low ranked) and as a confirmation of the RDD analysis.

- They tracked all students (N=4,144) who completed 3rd grade in the years from 2008 to 2011 and entered the 4th grade the following year at one of the district's 140 elementary schools. They follow the students into the 5th and 6th grades as long as they remain in the district. To construct their RDD sample they selected 4th graders in schools with a separate G&T classroom (i.e., the school had at least one student identified as gifted using IQ tests) and restrict their sample of students to those who scored within 10 points on either side of the eligibility cut-off. For the between-school analysis (schools with and without separate G&T classrooms), there were 4,767 students who they ranked 1-20 (who were likely to move to a G&T classroom if their school had one) and 5,016 who ranked 25-44 (who were likely to remain in the regular class regardless of the availability of a separate G&T class). All models include student controls (age, gender, race, median income for the zip code in which they live) as well as school and year fixed effects (dummies for all years and schools).
- **Results:** They first confirm the validity of using RDD by showing that students just below and above the achievement score cut-off are very similar (according to 3rd grade reading score, 3rd grade math score, 2nd grade NNAT score). They also show that there are no differences in attrition from their sample (a threat to their analysis would result if students assigned to the separate G&T class were more or less likely to remain in the district). Their RDD results show positive and statistically significant effects from being assigned to a separate G&T classroom on 4th grade reading and math test scores (but not on writing test results); the magnitude of the estimated effects are quite similar with and without student controls (gender, age, race and median household income for their zip code) or school fixed effects (school dummy variables). They estimate the net positive effects to be in the range of 0.3 standard deviations. They estimate effects separately for white and racial minority students and find that almost all the positive effects are

accruing to students of color: they find no statistically significant differences in test scores between white students above and below the cut-off. They check whether this is the result of white students above the cut-off topping out on exams – i.e., scoring so high in 3rd grade they can't go any higher – but find no indication of this (only 2% of white students achieved the top score in reading and 10% earned the top score in math). As a double check on the topping out possibility they estimate program effects using Tobit regression models (which account for censoring that might happen if a high enough number of white students were topping out) and confirm the linear RDD results. They found similar sized impacts for poor and non-poor students of color, and somewhat larger effects for male students compared to female students. When they compared poor and non-poor white students, they found no significant effects for either group. The positive effects of program participation on minority students appears to persist: in the 5th grade the effects of G&T classrooms on reading scores are positive but insignificant, larger for math test outcomes though only marginally significant; in the 6th grade, the results are more clearly positive, with marginally significant impacts on reading test scores of about 0.2 standard deviations and about 0.4 standard deviations for math. They also run a bunch of models looking into the effects of classroom-level differences: While they found no significant differences in teacher effects, they did find that students in G&T classes had a higher percentage of female peers, peers with higher average scores, and peers slightly fewer suspensions and that these differences had small effects: no effects on reading outcomes and small effects on math achievement.

- The results of their between school/cohort analysis indicate that the presence of a separate G&T class at the school has a positive impact on the top 20 students (ranked 1-20 based on 3rd grade test scores) and no effect on students ranked lower (24-44) and that the effects of being in a G&T classroom are smaller for highly ranked students and larger for those who are lower ranked (just above the cut-off), from which they conclude that students in G&T classes are not suffering from mismatch or invidious comparison. They also find no evidence of negative or positive spillover effects: lower ranked students in schools with a separate G&T class (i.e., they get left behind because their higher ranked peers are moved out of the regular classroom) do not do any better or worse than lower ranked students in schools without a separate G&T classroom (i.e., they are together with the higher ranked students in the regular classroom).

- Additional analyses using student level data show that minority students have lower achievement scores (3rd grade) than white students with the same cognitive ability (measure by NNAT in 2nd grade) and that placement in a G&T class all but eliminates the achievement gap.

- **Discussion:** This is a very rigorously conducted study. It is published in one of the top peer reviewed journals in economics by a Noble prize-winning economist. Taking advantage of extensive student level information, they use two different approaches, and both show positive program effects but only for minority students. They also provide compelling evidence that the program closes the achievement gap between white and racial minority students. They speculate that the reasons the program has valued-added impacts for minority students and not white students relates to minority students obtaining more support and higher teacher expectations in the G&T classroom: higher ability minority students do better in G&T classrooms because they are more supported (additional analysis also showed a reduction in absences and suspensions), have higher ability and more female peers (less flack for "acting white") and that teacher expectations are higher (in another paper they showed that before universal screening was adopted, teachers in the same district systematically under-refer black and Hispanic students for G&T programs) and that students rise to the occasion.

Card and Giuliano (2014) Does gifted education work? For which students?[14]

Summary: A more extensive version of the study conducted for the National Bureau of Economic Research (NBER) reports no positive benefits from being placed in a separate G&T classroom for students who were assigned based on IQ testing. Positive program effects only accrue to racial minority students assigned based on the previous year's achievement test results. They find no significant impact on subsequent math and reading achievement tests for the students assigned to the separate G&T classrooms based on their IQ scores – neither economically advantaged students or FRPL eligible or EL students (although they found a marginally significant positive benefit on the writing test scores for boys and students attending schools with high rates of FRPL eligibility). The authors speculate that students selected to participate in G&T classroom on the basis of previous standardized test scores may have a combination of cognitive abilities and non-cognitive traits (i.e., not captured IQ tests) that cause them to do even better on achievement tests after participating in the G&T program (traits that high IQ students do not have, such as a willingness to meet social expectations, attention to task).

- **Data, Method, Sample:** The data used in this study come from the same large urban school district in the U.S. used above. Starting in 2004 the District required elementary schools to set up separate classrooms for gifted students in fourth and fifth grades, with any open seats allocated to students who didn't make the IQ cut-offs (see below) but were among the top-ranked according to the previous year's achievement tests. Using the same methods in their published paper (described above) - RDD and a bunch of alternative specifications to conduct sensitivity analyses - they examine the effects of being placed in a separate G&T classroom on three groups of students: Plan A: 2,679 non-disadvantaged students with IQ scores ≥130; Plan B: 4,472 subsidized lunch participants and English language learners with IQ scores ≥116; and Plan C: 4,144 students who miss the IQ thresholds but scored highest among their school/grade cohort in state-wide achievement tests in the previous year, 2,098 of whom are not poor and 2,046 of whom are poor.
- **Results:** They find no significant impact on subsequent math and reading achievement tests for the students assigned to the separate G&T classrooms based on their IQ scores –

[14] https://www.nber.org/papers/w20453

neither economically advantaged students or FRPL eligible or EL students (although they found a marginally significant positive benefit on the writing test scores for boys and students attending schools with high rates of FRPL eligibility). But, as described in the published paper (see above), they do find positive effects for minority students placed in G&T classrooms based on previous achievement test scores.

- **Discussion:** They provide possible explanations – for why they find no program effects for students identified as gifted using IQ testing: (1) the statewide annual standardized test may not be capturing the effects of G&T participation on these students (because these students are already performing well academically, teachers in G&T classrooms may be teaching other stuff that's not measured by the achievement tests); (2) students selected to participate in G&T classroom on the basis of previous standardized test scores may have a combination of cognitive abilities and non-cognitive traits (i.e., not captured IQ tests) that cause them to do even better on achievement tests after participating in the G&T program (traits that high IQ students do not have, such as willingness to meet social expectations, attention to task); (3) students placed in G&T classes based on their IQ tests results may be topping out on achievement tests while those placed based on achievement tests still had room to grow (this argument works for the economically advantaged Plan A students but not for the disadvantaged Plan B students, whose 3rd grade achievement test scores were not as high as Plan A's and so they had room to grow by their 4th grade achievement test) (4) small fish deeper pond effect (marginal students – those with IQs just above cut-off – may experience invidious comparison effects – they went from being the top of their class to the bottom of the G&T class).
- They also used survey data that measured student responses to: my teacher(s) believe I can succeed; my teacher(s) answer my questions in a way I can understand, I enjoy learning at my school, I am accepted and feel like I belong at this school. To the extent that 4th graders self-report reliably (a possible limitation here)….again using the RDD to the compare students on either side of the cut-off they find that among Plan A students (not poor, IQ>129) just above the cut-off were more satisfied with their learning environment compared to those below the cut-off and left back in the regular classroom while Plan B students (poor and/or IQ>115) above the cut-off were no different in their

average responses compared to those just below the cut-off. Plan C students (missed IQ but scored high on 3rd grade achievement tests) just above the cut-off expressed about the same level of satisfaction with their learning environment as the comparison students just below the cut-off and in regular classrooms.

Is Gifted Education a Bright Idea? Assessing the Impact of Gifted and Talented Programs on Students (Bui, Craig, Imberman, 2014)[15]

Summary: This is another rigorously conducted study using a lot of student level data from one large urban school district in the southwestern U.S. It's actually two studies in one. The first study employs a RDD, which examines the effects of G&T program participation on students just above the eligibility cut-off to non-participating students just below the cut-off. The second study tests for program effects by comparing achievement outcomes of students randomly assigned to a specialized G&T magnet school compared to those who remain behind in G&T programs in regular schools. Neither study finds evidence of positive gains to program participants, even the magnet school lottery which targets more highly gifted students. Their initial findings persist under a number of alternative model specifications and sensitivity analyses. While their data come from one district there is variation across schools in terms of how their G&T programs is implemented (some offer separate G&T classrooms; some offer pull-out enrichment activities; some offer advanced course material called Vanguard, etc.). They conduct additional analysis to see if G&T participation effects differ by type of G&T program (whether or not the student attends a G&T magnet, whether or not their school offers the more advanced curriculum classes vs receiving additional materials within the standard AP classroom) and find no evidence of heterogeneous effects by G&T treatment type. They also examine whether estimated program effects differ in terms of the "intensity" with which a school provides G&T programming and find no clear pattern by program intensity. They also test whether program effects differ by student ability (to check if it's the very marginal students just above the cut-off who aren't making any gains) and find no difference in achievement results between the lower ability G&T participants and students just below the cut-off who remained in regular classrooms (i.e., does not appear that their finding of no program benefits is the result of very marginal students suffering from invidious comparison issues). They also test whether program effects differ by gender, race, economic status, or prior gifted status and find no statistically significant program effects by student type. A limitation of the RDD study is that they didn't rule out spillover effects; positive spillover effects accruing to students just below the eligibility cut-off – perhaps they do better when G&T participating students leave the regular classroom - could

[15] https://www.nber.org/system/files/working_papers/w17089/w17089.pdf
https://www.aeaweb.org/articles?id=10.1257/pol.6.3.30

downwardly bias estimates of program effects, although given that there is variation in G&T program type across schools it is less likely that positive spillover is masking a global program effect. The lack of additional benefits from attending a G&T magnet school may be the result of weak treatment effects (i.e., the G&T program at the G&T magnets may not have been that much more intensive than what lottery losers received back in the regular schools).

- **Data, Sample and Method:** This study is really two studies in one. The first study uses a **regression discontinuity design (RDD)** and compares students just above and below the G&T program eligibility cut-off. The second study takes advantage of a **lottery** that **randomly assigned** gifted students to specialized G&T magnet schools and compares achievement outcomes of lottery winners to lottery losers (gifted students left behind in regular G&T programs). The data they used are from **one large urban school district in the southwestern U.S.** where all 5th graders are evaluated to determine eligibility for G&T services starting in the 6th grade. The district generates a matrix score for each student based on standardized test results (SAT, Aprenda, NNAT), average course grades, teacher recommendations, and indicators for socio-economic status (5 extra points for being poor, 3 extra points for students of color). Students above the cut-off are eligible for G&T services. The regular **G&T program varies** across schools but, according to administrators surveyed by the researchers, most schools provide a more advanced curriculum (called Vanguard) that delves deeper into subjects and are geared towards developing creative and critical thinking as well as analytical skills although some provide students with other options (e.g., additional material within the regular AP class). In some schools G&T students are in their own classrooms; in others they are in mixed classrooms.
  - **The RDD study:** Because not all students above the cut-off participate in the G&T program and some below the cut-off do, they use a “fuzzy” RDD. After restricting their sample to a 15-unit band above and below the cut-off there are 4,055 students in the 7th grade who were evaluated for G&T in the 5th grade (1,509 were eligible for G&T and 2,546 were not). They test for the validity of RDD: they test to see how similar students above and below the cut-off are in observable characteristics (including race, gender, EL status, special education status, FRPL eligibility, achievement test scores from 5th grade in math, reading,

science and social studies, any missing data, teacher characteristics, school size, %FRPL) and find only one statistically significant difference at the student level (5^{th} grade math scores). They "fix" this by adding 5^{th} grade scores as a control variable in their models. They make sure students above the cut-off are actually receiving "treatment" and find that they were more likely to attend a G&T magnet school, take advanced Vanguard courses and their peers are higher achieving (their estimates show that G&T students were not more likely than the students just below the cut-off to have a G&T certified teacher or a teacher with an advanced degree). They find no difference in achievement test scores in reading, language, social studies, science, or math using Stanford Achievement Test between students just above the eligibility cut-off (G&T participants) and those just below the cut-off (non-participants). They conduct additional analysis to see if G&T participation effects differ by type of G&T program (whether or not the student attends a G&T magnet, whether or not their school offers the more advanced curriculum classes vs receiving additional materials within the standard AP classroom) and find no evidence of heterogeneous effects by G&T treatment type. They also examine whether estimated program effects differ in terms the "intensity" with which a school provides G&T programming (measured in terms of achievement scores of classmates, percentage of students that take advanced curriculum classes and percentage of students identified as gifted). They find no clear impact of program intensity (G&T program effects are mixed – some positive, some negative – at both high and low intensity schools). Their findings stand up to additional sensitivity analyses including school fixed effects (to control for unobserved school level factors), alternative cut-offs for G&T eligibility, and using different sized bandwidths around the cut-off. They test for ceiling effects (because if the G&T students have no room to improve program estimates will be biased downward and make it look like the G&T program is less/not effective) and conclude this is not what is causing them to find no positive program effects (the majority of G&T students had room to improve). Their results do not change if they include a baseline control (prior standardized test scores in the tested subject). They also test whether program effects differ by gender, race, economic status, or prior gifted status and generally find no statistically significant program effects by student type (except for non-poor students for which there is a marginally significant small negative effect on math scores; and students who were previously identified as gifted, for whom there is also a small negative effect on math scores).

- **The lottery study:** Conditional on meeting the district-wide GT eligibility requirements and completing an application, students were randomly offered admission to the district's premier magnet schools (versus staying behind in regular schools and receiving regular G&T services). In this part they are able to examine the effects of G&T program participation over the full range of G&T students (at least those that apply to get into the lottery, anyway), not just marginal students just above the cut-off (in fact, they mention that the students applying to magnet schools were more exceptionally gifted, scoring significantly higher on pre-tests than other gifted students). They compare the achievement test results of students who win the lottery and attend one of the magnet GT programs to those who lose the lottery and either attend a neighborhood GT program in the district, a magnet school based on a different specialty, or a charter school. In order to try and control for selection bias related to whether or not an eligible student applied or not, they use a 2SLS model to estimate program effects conditional on applying for admission to magnet program. Control variables included race, gender, special education status, EL status, FRPL eligibility and the baseline 5th grade achievement test score. They find no differences in math, reading, social studies scores between the lottery winners attending G&T magnet schools and lottery losers who remained behind in regular schools; they do find a positive effect on science achievement test scores (around 0.28 standard deviations higher) but it does not always hold its significance under different model specifications and sensitivity tests. To control for higher attrition among lottery losers (perhaps parents change schools when their child does not make it into the G&T magnet) they run weighted regressions (weighted by the inverse of the estimated probability of remaining in the data) and their initial results stand.

- **Discussion:** This a rigorous study. The researchers used two different approaches – RDD and lottery sample – and find, for the most part, confirmation of no program effects. All their baseline OLS models (which don't control for endogeneity bias) estimated positive and statistically significant program effects but the size of their RDD estimated program effects are all much smaller and never statistically significant. This indicates that achievement benefits observed using regular OLS are primarily explained by unobserved student traits and other factors (motivation, support, etc.) and reflect upward bias caused by selection. While RDD studies are inherently limited in that they only look for program effects for marginally gifted students (those just above the eligibility cut-off) the researchers note that the marginal students in the RDD sample still represented a range of giftedness: students right at the eligibility threshold ranged from 45 to 97 in national percentile rankings in reading and between 55 and 98 percentiles in math. Also, their lottery sample included a broader range of gifted students and skewed towards the higher end of gifted and presumably academically motivated (i.e., motivated enough to apply to get into the G&T magnet in the first place). They confirm significant "treatment" effects for their RDD sample (students above the cut-off were more likely to attend a G&T magnet and/or take advanced courses, they did have higher-achieving classmates) to make sure their results were not being drive by no real differences in "treatment". The treatment effects for their lottery sample appear smaller: students attending the G&T magnet schools did have stronger peers but that they were as likely as lottery losers to take advanced (Vanguard) courses. The authors speculate as to why they did not find much by way of significant program effects: (1) if parents of students who did not make the cut-off invested in more support for their children (perhaps hoping they'd test higher and get in next year), for example, by hiring a tutor or outside school enrichment activities (2) The school district may have set eligibility cut-off too low (research shows getting into a G&T program keeps parents from removing their children from the school), which would mean that more marginal students would be in the G&T program and they either bring down the achievement scores and/or cause teachers to teach a less rigorous curriculum (3) since they found that G&T participating students had academically stronger peers (at least those in separate classrooms or at the G&T magnet), maybe the marginal just above-the-cut-off students suffered from invidious comparison (their confidence is shaken; they were the top students in the regular classroom and now they are the bottom students in the G&T program) or the marginal students suffer because the teachers teach to the average or higher ranked students' level and they can't keep up. I would add to this the possibility of weak treatment effects, especially for the lottery sample: while students attending the G&T magnet schools had higher achieving peers than the lottery losers, they weren't more likely to take advanced Vanguard courses.

Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya (Dufflo, Dupas, and Kremer, 2011)[16]

Summary: While this study uses data from Kenya which has a much different education system than the U.S. it is included because of its rigorous methodology and use of experimental data. It is also important because it evaluates a specific type of G&T programming: tracking. In addition to regular regression techniques (which would be sufficient because they have experimental data), they also conduct RDD comparing two students – the one just above the eligibility cut-off and the one just below - from each of the 60 randomly selected schools that employed tracking. Their results suggest that all students benefit from tracking, both those in the upper and lower parts of the ability distribution. They found that these gains persisted one year later, after the experimental tracking program was concluded. They also show that the results were similar for boys and girls (although girls got a bit of a larger boost from tracking on their math test results). They also find interesting evidence suggesting that teacher type matters: They show differences in the benefits of tracking were influenced by whether the student had a contract teacher (no job security) or a civil service teacher (tenured; promotion based on seniority not performance), with all students benefiting if their teacher was a contract teacher and only initially high scoring students benefiting from tracking if their teacher was a civil service teacher (they provide additional analysis and some speculation that suggests that this is because tracking induced civil service teachers to increase their effort when they were assigned to teach upper track students but not when they were assigned to teach lower track students while contract teachers – hoping to be hired as civil service teachers - exerted high effort no matter what types of students they were assigned to teach). Since this is a top tier journal, they do a bunch of sensitivity analyses and model specifications to make sure their results are robust.

- **Data, sample, methods:** In 2005, 140 primary schools in western **Kenya** received funds to hire an extra first grade teacher. Of these schools, 121 had a single first-grade class, which they split into two sections, with one section taught by the new teacher. These are the schools they use for their study. **In 60 randomly selected** schools, students were assigned to sections based on initial achievement (tracking schools: those scoring in top

[16] https://www.aeaweb.org/articles?id=10.1257/aer.101.5.1739

half of the distribution go into one class, those scoring in the bottom half into another). In the remaining 61 schools, **students were randomly assigned to one of the two sections** (non-tracking schools). After students were assigned to sections, the teachers by type (contract vs civil-service) were randomly assigned to their sample includes 589 students in tracking schools, and 549 in non-tracking schools. They compare end of year achievement test scores for students in the tracking schools to those in the non-tracking schools; they also conduct regression analysis (using all students and a dummy variable indicating whether the student attended a tracking or non-tracking school) and control variables include the baseline achievement test scores, age and gender, teacher type (contract vs civil servant, the latter has union-like protections and tenure like job security), school size, student-teacher ratio. They compare effects based on whether the student was in the bottom or top half of the distribution (so these aren't just marginal students like in the RDD studies). They test for peer effects by estimating models with the average baseline test score of classmates and school fixed effects (school level dummy variables to control for school conditions not observable in the data like school culture, setting, etc.). In addition to regular regression, they also employ RDD using the students in tracking schools to assess peer effects and possible spillover effects comparing students just above the cut-off who got tracked into the class of high scoring students to those just below who got tracked into the class of lower scoring students. Because they have 60 different schools with tracking, they have 60 different discontinuities in their dataset and instead of comparing students further out from either side of the cut-off (the further you get the more dissimilar students are) they compare the two students just to either side of the cut-off from each of the 60 schools. Since this is a top tier journal, they do a bunch of sensitivity analyses and model specifications to make sure their results are robust. They do additional analysis (via random surprise classroom visits, etc.) to get a handle on how contract vs civil service teachers differed in their behaviors and teaching.

- **Results:** Their results suggest that all students benefit from tracking, both those in the upper and lower parts of the distribution. Students in tracking schools scored 0.14 standard deviations higher than students in non-tracking schools (the effect increased to 0.18 standard deviations when controls were included in the model). They found that these gains persisted one year later, after the experimental tracking program was concluded. They also show that the results were similar for boys and girls (although girls got a bit of a larger boost from tracking on their math test results). They show differences in the effects of tracking were influenced by whether the student had a contract teacher or a civil service teacher, with all students (both initially low scoring and initially high scoring) benefiting if their teacher was a contract teacher and only initially high scoring students benefiting from tracking if their teacher was a civil service teacher (they provide additional analysis that suggests that this is because tracking induced civil service teachers to increase their effort when they were assigned to teach upper track students but not when they were assigned to teach lower track students while contract teachers exerted high effort no matter what types of students they were assigned to teach). Using the significant variation in student levels in non-tracked schools (classrooms are heterogeneous with students from across the full distribution, based on baseline testing), they also provide evidence of both direct and indirect peer effects. Their RDD results: despite the big gap in average peer achievement (with those assigned to lower level classes having on average lower scoring peers and vice versa), the marginal students' final test scores do not seem to be significantly affected by assignment to the bottom section; they speculate that this is the result of teachers assigned to the lower level class teaching to the top students within that group and so the marginal student does not suffer too much (i.e., there are no negative spillover effects).

Redding and Grissom (2021) Do Students in Gifted Programs Perform Better? Linking Gifted Program Participation to Achievement and Nonachievement Outcomes[17]

Summary: This study uses data from a nationally representative panel study and student-fixed effects models to evaluate the effect of receiving G&T services on achievement tests and teacher reported absences and student reported engagement. They find positive effects on both reading and math tests (smaller effect sizes than what Card and Guiliano found). But I'm a little wary of the robustness of their results because their results are so closely aligned with socioeconomic advantage (white and non-poor students are estimated to make bigger gains from G&T, at least in reading; Asian students do better in math). Student fixed effect techniques can control for selection and simultaneity bias only to the extent that unobservable factors related both to being assigned to G&T programming and subsequent achievement outcomes are time-invariant. This approach basically uses the individual student as their own comparison (comparing outcomes in the years they received G&T services to the outcomes in the years they did not). To the extent that student motivation, support, etc. remain unchanging, selection bias is controlled. The authors themselves caution that if unobserved factors like parents providing additional outside-of-school supports are more likely to occur during the years students are assigned to G&T then they would upwardly bias estimated program effects. They don't say this but differences in family resources could explain why they find larger benefits for socioeconomically advantaged students: the parents of socioeconomically disadvantaged students may tend to provide less outside of school support once their child was assigned to G&T (i.e., if resources are tight and they assume the extra programming would sufficiently cover their child's educational needs) while parents of socioeconomically advantaged students might tend to do the opposite (i.e., because they have the resources they may increase supports to ensure their child excels once identified as gifted). They also find differential program effects on students who are reported to move in and out of G&T programming and students who once they are reported to be in G&T are always reported to be receiving G&T services. They report that these two groups of students are similar on most of the observable measures available in the dataset. However, when they run their models separately on these two sub-samples, they find that it was the sample who *persisted in G&T once assigned* that

[17] https://journals.sagepub.com/doi/10.3102/01623737211008919

made the gains; for the students who switched out in at least one year, the estimated program effects were negative but not significant. This suggests there may be some unobservable factors that are at least biasing if not driving the estimated effects. For example, perhaps the students that moved in and out of G&T programming had lower levels of teacher and parent support and encouragement. Other concerns I have about this study relate to how G&T service status is measured: whether a child receives G&T programming is based on teacher answers to rather vague questions that changed a bit over time (there may be some measurement error). Even if their results are solid and not contaminated by bias, the fact that their estimated effects are quite small and accrue to socioeconomically advantaged students pose the policy question as to whether it's worth it to fund programs that produce such small effects and primarily for advantaged students whose parents can probably make up the difference if they aren't getting enough in regular classrooms and curricula.

- **Data, Sample and Method:** They use data from the nationally representative U.S.-based Early Childhood Longitudinal Study (2010-2011) Kindergarten Cohort (ECLS-K:2011) which tracks students from kindergarten (2011) through the 5th grade (n=18,170). The ECLS contains a lot of information about students, including information collected from their parents about their family life and a bunch of information collected from teachers about the students and their schools. They restrict the sample to public school students. Their analytic sample includes 37,980 student-year observations. Outcome variables include math and reading achievement test scores, teacher-reported student absences, student-reported engagement (do well in school, work hard in class, participate in class discussions, pay attention in class, listen carefully in class) and student mobility (whether student stayed or left the school within that year). The primary independent variable is whether the student received G&T services that year. This information is based on teacher report. Each year teachers are asked if the student received G&T instruction in math and/or reading. In year 3 an additional category was added that indicates participation in G&T programming in general. For students with IEPs, teachers are also asked if they receive G&T services as part of their plan. They use the information from all these questions to identify students participating in a G&T program. Their preferred statistical model is a **student fixed effect model**. This approach basically uses the individual student as their own comparison (comparing outcomes in the years they received G&T services to the outcomes in the years they did not). To the extent that student motivation, support, etc. remain unchanging, selection bias is controlled (i.e., in these student fixed effects models the time invariant variables drop out of the model). They estimate the effect of participating in G&T program on the change in the outcome (e.g., test score) from the previous year. Controls include a bunch of student (race, gender, SES, EL status, disability status, whether English is the primary language at home, parent's report of child's health), teacher (race, years of experience, indicators of whether they have a Master's degree, certification status) and school (size, % FRPL, locale) level variables. They look for differential effects across student groups (race, SES, etc.) by including interactions between these demographic variables and whether the student participated in G&T programming that year.

- **Results:** They find relatively small but positive and significant effects on reading test scores (students scored 0.065 standard deviations higher when they were receiving G&T services: the typical student who ever receives G&T services scores at the 78th rank in years when they don't get G&T and in the 80th when they do) and only a very small and marginally significant ($p=0.08$) on math test scores (0.019 standard deviations: the average student scores in the 76th percentile when they didn't receive G&T and in the 77th when they do). They look at differential effects by student race (everyone is compared to white students) and FRPL status (everyone is compared to lowest SES) and find only a handful of statistically significant results (on interaction terms): G&T participation has smaller effects on reading test scores for Black students (0.177 SDUs less than for white students), larger effects on math tests for Asian students (0.09 SDU higher than for white students) and the most affluent students benefit more from G&T compared to the least affluent but only in reading (0.099 SDUs more). They found little evidence that G&T participation impacted the non-achievement outcomes (student absences, engagement in school, or whether a student leaves or stays in a school). They run a number of different model specifications (drop students with gaps in reported G&T participation, drop cases with missing values/imputed, use only those who switched in and out of G&T, student and school fixed effects) and their initial results generally stand except the estimated effects on math test scores sometimes lose statistical significance.

- **Discussion:** I'm a little wary because their results are closely aligned with socioeconomic advantages (white and non-poor students make bigger gains from G&T; Asians students do better in math); might these be the results of advantages and not G&T program effects? Student fixed effects can control for selection and simultaneity bias only to the extent that unobservable student level factors related both to being assigned to G&T programming and subsequent achievement outcomes are time-invariant. The authors themselves caution that if unobserved factors like parents providing additional outside-of-school supports are more likely to occur during the years students are assigned to G&T than they would upwardly bias estimated program effects. They don't say this but differences in family resources could explain why they find larger benefits for socioeconomically advantaged students: the parents of socioeconomically disadvantaged students may tend to provide less outside of school support once their child was assigned to G&T (i.e., if resources are tight and they assume the extra programming would sufficiently cover their child's educational needs) while parents of socioeconomically advantaged students might tend to do the opposite (i.e., because they have the resources they may increase supports to ensure their child excels once identified as gifted). Another possibility is that the G&T programing received by students differs by race and poverty status. For example, if minority students are more likely to be assigned to less intensive G&T programming or if they are more likely to attend schools with fewer resources devoted to G&T programming (perhaps they receive add-on instruction within the regular classroom instead of more advanced curriculum in a separate class). Also, they report (footnote 6) that 60% of their sample consisted of students who once they were identified as receiving G&T education, continue to be so and 40% were reported by their teachers as participating in one year and not in at least one subsequent year. They report that these students are similar on observable variables available in the dataset (except that those who stayed in once in were more likely to be in poor, rural schools, located in the South). In footnote 9 they report that they ran their models separately on these two sub-samples and found that it was the sample who persisted in G&T once assigned that made the gains; for the students who switched out in at least one year the estimated program effects were negative but not significant. They also report (in footnote 10) that when they include prior student achievement as a control the estimated program effects (in both math and reading) are smaller. Taken together this sounds to me like there's unobservable things about the students could be at least biasing if not driving the estimated program effects. For example, perhaps the students that moved in and out of G&T programming had lower levels of teacher and parent support and encouragement. Another concern I have about this study relates to how G&T service status is measured: whether a child receives G&T programming is based on teacher answers to rather vague questions that changed a bit over time (there may be some measurement error). Even if there results are not biased, their estimated effects are quite small and accrue to socioeconomically advantaged students, which of course, raises the policy question: is it worth it to fund programs that produce such small effects and primarily for advantaged students whose parents can probably make up the difference if they aren't getting enough in regular classrooms and curricula?

Enriching Students Pays Off: Evidence from an Individualized Gifted and Talented Program in Secondary Education (Booij, Haan, & Plug, 2016)[18]

Summary: This study examines the effect of an enrichment type "pull-out" type G&T program (students get to trade regular classroom time to work on a self-designed independent project) offered at one prestigious secondary school in the Netherlands. It is included because of its statistical rigor and unlike the RDD studies above, which estimate program effects on marginal students (i.e., those just above the eligibility cut-off), this one uses RDD but explores the effect of G&T treatment on a group of exceptionally gifted students. In addition to focusing on one program at one school another advantage of this study is researchers had access to IQ test scores, standardized achievement test scores (exit exam from primary school) and a (presumably validated) test that measures motivation as well as supplement survey data on students' perceptions of the level of support they received from teachers and parents and their level of work effort, self-confidence, motivation, and academic self-esteem. This gives them the ability to control for selection and other bias beyond what most researchers have been able to do. Their estimates consistently show positive program effects on student achievement in the range of at least 0.30 standard deviations (larger for math and other subjects, smaller for reading). Based on analysis of their survey data they are able to rule out bias caused by spillover effects. They also show that the program did not spur students to work harder or increase their motivation or general self-esteem but that program participants did report an increase in academic self-esteem. This leads them to conclude that one of the mechanisms by which the G&T program works is that merely labeling students "gifted" raises their academic self-esteem and they rise to the occasion. The authors note that the students in this study are not your typical students and that the strong program effects may reflect that fact: they score high both on IQ tests and achievement test (students in this study were selected to participate based on their IQ test score cut-offs but only high achievers - based on their primary school exit achievement exam - are permitted into this school in the first place) and so they might be exceptionally exceptional in that they have both higher cognitive ability and stronger academic skills.

[18] https://www.econstor.eu/bitstream/10419/141516/1/dp9757.pdf

- **Data, sample, method**: This study examines the effect of an enrichment type "pull-out" type G&T program (students get to trade regular classroom time to work on a self-designed independent project) offered at **a prestigious secondary school in the Netherlands**. It is included because unlike the RDD studies above, which estimate program effects on marginal students (i.e., those just above the eligibility cut-off), this one uses RDD but explores the effect of G&T treatment on a group of **exceptionally gifted** students. (Dutch secondary education is tracked into three levels. The top level is further tracked into two types of schools and the school under study is among the most selective). Because all the students at this school are very high achievers, those who are then identified as "gifted" and eligible to participate in the G&T programs are exceptionally gifted students (even those just above the cut-off). Students at this school qualify for participation in the G&T program based on a standardized cognitive aptitude test. Students are tested during their first year and those who make the cut-off are eligible to participate for the next 6 years they are at the school. The cut-off is typically set as 1 standard deviation above the mean (but higher if G&T capacity is tight). The test is, however, only one factor the school considers for acceptance into the G&T program; while it is the main factor of determination, a committee makes the final determination (not all high scoring students get in; some students with lower are accepted). Because the cut-off is not strict, they **use a "fuzzy" regression discontinuity design (RDD).** Their sample includes 3,127 students, of which 785 students are assigned to the GT program. Their dataset includes student demographics (gender and age), primary education exit exam scores (CITO), GT program assignment status, scores on an intelligence test (IST) and a test that measures motivation (FES). The academic outcomes measures include grade retention, cumulative grade point averages (GPA) for math, languages, and other school subjects (all grades), and three indicators of choosing an advanced curriculum in the final two years (the number of exam subjects, the number of science subjects, and taking advanced math). They also had access to post-secondary data on university enrollment, field of study, whether the student switched majors, and the average starting salary that corresponds to field of study. The first stage in their two-stage RDD model estimates G&T program assignment predicted by a binary indicator for having an IST (intelligence test) score above the cut-off. The second stage estimates the effect of being assigned to the G&T program on academic outcomes controlling for gender, age (at the IST test), score of the exit exam at the end (CITO) or primary school and FES (motivation) test score. They also conducted surveys to gauge students' level of work effort, self-confidence, motivation, and academic self-esteem as well as they level of support they perceived receiving from teachers and parents.

- **Results:** Their estimates consistently show positive program effects on student achievement in the range of at least 0.30 standard deviations (i.e., the marginal student who is barely admitted to the GT program has a cumulative GPA at least 0.30 standard deviations higher than the group of students just below the cut-off). Specifically, their estimated effects show indicate the G&T program raises cumulative grade point averages in math by 0.38 SD and language scores by 0.30 SD (and up to 0.44 SD in other subjects). They also find that male students work more on math and science related independent projects, and female students work more on language related projects and that male students experience the largest gains in math grades, and female students in language grades. They also find that students assigned to the G&T program are more likely to follow a more science intensive curriculum (particularly girls), and tend to report stronger beliefs about their academic abilities. They find evidence that program effects persist into university, where G&T participants chose more challenging fields of study with, on average, higher wage returns. They also use survey data to try and understand how the program works. Based these results they conclude that the program did not encourage students to work harder, boost their general self-confidence, or raise their motivation to learn. The program did, however, improve the G&T program participants' academic esteem.
- **Discussion:** An advantage of this study – in addition to its statistical rigor - is that they had access to IQ test scores, standardized achievement test scores (exit exam from primary school) and a (presumably validated) test that measures motivation as well as supplement survey data on students' perceptions of the level of support they received from teachers and parents and their level of work effort, self-confidence, motivation, and academic self-esteem. This gives them the ability to control for selection and other bias beyond what most researchers have been able to do. First, they show that students just above and below the cut-off do not differ in pre-treatment test scores, providing confidence that the treatment and comparison groups are not significantly different in academic ability and that any program effect can be interpreted to be causal and not driven by selection effects. Another possible

limitation is related to the fact that their primary outcome - cumulative GPAs for each subject during the secondary school grades - may suffer from some measurement error (teachers may be upwardly biased in grading when they know a student has been assigned to the G&T program). They test for this possibility using a nationwide standardized test students take in their final year: they rerun their RDD models using the results of this externally validated standardized exam instead of cumulative GPAs (by subject) and find effect estimates that are as large, if not larger (i.e., the positive gains in standardized tests were larger than the positive gains in GPAs). The authors note that the size of their estimated program effects are comparable to what Card and Giuliano (2014, described above) find for high achievers. They also note the fact that Card and Giuliano found no positive program effects for students assigned to G&T programming based on their IQ test results while they do. They posit that this is because the gifted students in their study are comparable in that they were also high achievers (students in this study were selected to participate based on their IQ test score cut-offs but only high achievers - based on their primary school exit achievement exam - are permitted into this school in the first place). They also test to make sure their positive program results weren't driven by spillover effects - the just below cut-off comparison group being disappointed they weren't selected for G&T (if the students just below the cut-off are negatively impacted and their grades suffer the RDD results are biased upward). They find no decline in grades for students just below the cut-off. They also asked all students not assigned to the G&T program how disappointed they were about not be selected and found that over 80% said they were not disappointed (and that only 5 students said they were seriously disappointed). They also survey students to see if a chance in support from parents or teachers might explain their effects. If parents and teachers know that some of the children are gifted and assigned to the G&T program, they may treat these children differently. Students were asked six questions on whether they were helped, encouraged, or pushed by their parents and teachers. They find positive effects (i.e., students assigned to the G&T program reported more of this support than the students below the cut-off) but the differences were not statistically significant. Finally, their survey also asked students whether they think of themselves as a good learner and their regression results showed positive, significant, and substantial program effects on self-assessed measures of academic esteem. This leads them to conclude that one of the mechanisms by which the G&T program works is that merely labeling students "gifted" raises their academic self-esteem and they rise to the occasion.

Dobbie and Fryer (2011) Exam High Schools and Academic Achievement: Evidence from New York City[19]

Summary: I hesitate to even include this study… the only reason I do is it gets cited a few times by others. While they use the relatively robust RDD, the study has a couple of limitations (which may explain why it was never published), the most serious being that its comparison group is likely contaminated: they use administrative data from three of the 9 NYC "exam" schools (more rigorous curricula, higher achieving peers, more resources than typical public schools). Students who don't end up making the cut for one of the three exam schools under study may have in fact attended one of the other 6 exam schools or a private elite school with similarly rigorous standards or participated in the G&T program at a regular school (i.e., their below the cut-off comparison group is likely a terrible control and may explain why they find few positive effects). In addition, their data are more limited than other studies and so they are not able to do as much additional analysis to try and get a handle on the possibility of spillover effects or other endogenous biasing effects. Finally, they don't report on the extent of robustness checks they conducted.

- **Data, sample, method:** they use student level **data from NYC** to test whether enrollment in one of the city's three "exam" schools produces net benefits. Exam schools tend to have higher achieving peers, more rigorous instruction, and additional resources compared to regular public schools. Students compete to be enrolled into one of the three exam schools by taking the Specialized High Schools admissions test (SHSAT). The test is broken into a math and verbal section. The sample is restricted to NYC public school students in the 2002 through 2013 high school cohorts. **They employ a regression discontinuity design** to compare students who score just above the admissions cut-off to those who score just below.
- **Results:** Attending an exam school increases the rigor of high school courses taken and the probability that a student graduates with an advanced high school degree. Attending an exam

[19] https://www.nber.org/papers/w17286

school has little impact on Scholastic Aptitude Test scores, college enrollment, or college graduation.

- **Discussion:** While they use the relatively robust RDD, the study has a couple of limitations (which may explain why it was never published), the most serious being that its comparison group is likely contaminated: they use administrative data from three of the 9 NYC "exam" schools (more rigorous curricula, higher achieving peers, more resources than typical public schools). Students who don't end up making the cut for one of the three exam schools under study may have in fact attended one of the other 6 exam schools or a private elite school with similarly rigorous standards or participated in the G&T program at a regular school (i.e., their below the cut-off comparison group is likely a terrible control and may explain why they find few positive effects). In addition, their data are more limited than other studies and so they are not able to do as much additional analysis to try and get a handle on the possibility of spillover effects or other endogenous biasing effects. Finally, they don't report on the extent of robustness checks they conducted.

Adelson, McCoach, amd Gavin (2012) Examining the Effects of Gifted Programming in Mathematics and Reading Using the ECLS-K[20]

Summary: This study employs propensity score matching, which is generally less rigorous than RDD, but the researchers use a very rich dataset and a more thorough matching approach. Also, PSM evaluates program effects for all G&T participants, not just those just above the eligibility cut-off. Their sample comes from the nationally representative Early Childhood Longitudinal Study, Kindergarten Class of 1988-1989, which tracks students from kindergarten through to 5th grade and contains a ton of student, family, and school level information. To account for the fact that students are clustered in schools, they use hierarchical linear models (HLM) and to deal with non-random assignment they use propensity score matching to create comparison groups of not just students but schools as well. They maximized the use of this especially rich dataset and used up to 300 variables (that were both theoretically important and had a bivariate association with achievement or academic attitudes) to estimate the student level propensity scores and up to 82 variables (based on theory and whether they had a bivariate association with whether the school had a G&T program or the school's mean achievement scores) to estimate the school level propensity scores. They estimate G&T program effects at both the school and student levels. They find no effects at the school level – average reading and math scores were about the same regardless of whether a school offered G&T programming. They find no effects at the student level – average math and reading scores are the same for gifted students who attended a school with a gifted program and gifted students who attended a school w/o a gifted program. They also found no effects on students' reported attitudes about reading and math. There is of course still the possibility of selection bias because propensity score matching uses only what is observable (i.e., available in the data set). But they went further than other studies to limit selection effects. They matched students on 300 variables, including many often associated with endogeniety and selection effects that often go unmeasured in other studies. They also limit selection bias related to unobserved factors by comparing gifted students at schools with G&T programs to gifted students at schools that did not have G&T programs (since it wasn't even an option the comparison group contains both students who would have participated if they could have and

[20] https://journals.sagepub.com/doi/abs/10.1177/0016986211431487

those who would have not). Finally, selection is generally assumed to inflate estimated program effects and since they find none, it doesn't seem like selection is a big problem. The study is limited in that it does not test for heterogeneous program effects by student demographics (race, FRPL status, etc.)

- **Data, Sample, Method:** They use data from the nationally representative Early Childhood Longitudinal Study, Kindergarten Class of 1988-1989, which tracks students from kindergarten through to 5th grade and contains a rich set of student level, family level and school level variables. Teachers report whether students participated in gifted and talented programming separately for math and reading. They selected and analyzed reading and math samples separately. They selected only those students who remained in the same school through to 5th grade and who were consistently in or not in a gifted program (all or nothing). The reading sample included 5,630 students in 850 different schools and the math sample included 2,740 students in 720 schools. They used multiple imputation to deal with missing information. They checked to make sure their partial sample looked like the full nationally representative sample according to student and family demographics as well as school level demographics (% FRPL, % minority). They combined information from administrators (whether a school offers G&T programming or not; the number of PT and FT G&T teachers) and student level information collected from teachers as to whether they received G&T services to identify which schools provided a G&T program and which did not. They use propensity score matching to produce matched pairs of schools (those that provide G&T programs and those that do not) and students (those that participate in G&T and those that do not). They used up to 300 variables (that were both theoretically important and had a bivariate association with achievement or academic attitudes) to estimate the student level propensity scores and up to 82 variables (based on theory and whether they had a bivariate association with whether the school had a G&T program or the school's mean achievement scores) to estimate the school level propensity scores. Their outcome variables include achievement test scores in math and reading and academic attitude (based on survey questions asked of students in 3rd and 5th grade as to their perceptions of their grades, the difficulty of their schoolwork, and their interest and enjoyment in the subject). They test for G&T program effects at both the school and student level. At the student level instead of just comparing students who participated in G&T programming to those who did not they compare gifted students at schools with G&T programs to gifted students at schools that did not have G&T programs.

- **Results:** They find no effects at the school level – average reading and math scores were about the same regardless of whether a school offered G&T programming. They find no effects at the student level – average math and reading scores are the same for gifted students who attend a school with a gifted program and gifted students who attend a school w/o a gifted program. They found no effects on students' reported attitudes about reading and math either.
- **Discussion:** This appears to be a more rigorously designed PSM study than most (although I'm generally not a fan of this method so I don't see a lot of it). These researchers had access to a very rich data set with information about students, their families, and the schools they attend. They used up to 300 different variables to match students and up to 82 variables to match schools. Among the variables they used to match participating and non-participating students are a number of factors that are associated with endogeniety and selection bias effects but often go unmeasured in other studies (e.g., self-control, attention, cooperation, the level of their parents' participation in their education). They also do a better job of limiting selection bias related to unobserved motivation by comparing gifted students at schools with G&T programs to gifted students at schools that did not have G&T programs (since it wasn't even an option the comparison group contains both students who would have participated if they could have and those who would have not). That said, if there are unobserved factors that relate to school choice – if, say, rich parents remove their child from schools w/o G&T programs and move them to ones with G&T programs (there's research that shows this happens[21]) and if this means that more supported and encouraged students are attending the G&T schools leaving behind the less supported or encouraged students in the comparison schools then their results could still be biased (i.e., if rich parents who also have the means to provide outside of school supports and enrichment activities are more likely to remove their children from schools without G&T programs then those schools will

[21] https://www.jstor.org/stable/23646325?seq=1#metadata_info_tab_contents

contain more gifted but poor and presumably less supported students). This would inflate the estimated effects of G&T programs. Since they don't find any statistically significant effects if inflation is happening it's small. Finally, they confirm their results by looking for G&T program effects at both the school and student levels. The study is limited in that it does not test for heterogeneous program effects by student demographics (race, FRPL status, etc.)

Park, Lubinski and Benbow (2012) When Less is More: Effects of grade skipping on Adult STEM productivity among Mathematically Precocious Adolescents.[22]

Summary: This next study is included because it looks at the effects of acceleration (grade skipping is a cost-effective G&T type program…) and focuses on the exceptionally gifted students. Their sample is drawn from three cohorts of the Study of Mathematically Precocious Youth, a panel survey that has been tracking students for 40 years (3 cohorts include 1972-74, 1976-79, and 1980-83) and includes 3,467 students all in the top 1% or higher (based on results of SAT math tests) by age 13. They use a combination of exact (gender, number of grades previously skipped before identified as precocious by the study) and propensity matching (SAT scores, measures of subject interest, class standing, parent occupation and educational attainment, number of siblings, birth order) to generate a treatment and comparison group. They find that grade skippers were more likely to pursue advanced degrees, advanced degrees in STEM (unless they were female, in which case they were more likely to get a medical or law degree), and author peer reviewed articles, earned their degrees and authored peer reviewed articles at a younger age, have more citations and highly cited publications by age 50. A major limitation with any propensity score matching study is that matching is only on observed variables which leaves room for bias related to unobserved factors. Also, they have access to very few variables for matching (compared to a study described below) and so bias due to unobserved factors is likely even more of an issue here, meaning the differences they find could actually be due to these unobserved factors and not grade skipping.

- **Data, Sample, Method:** The type of G&T programming investigated here is acceleration (grade skipping). Their sample is drawn from three cohorts of the Study of Mathematically Precocious Youth, a panel survey that has been tracking students for 40 years (3 cohorts include 1972-74, 1976-79, and 1980-83) and includes 3,467 students all in the top 1% or higher (based on results of SAT math tests) by age 13. They use a combination of exact (gender, number of grades previously skipped before identified as precocious by the study) and propensity matching (SAT scores, measures of subject

[22] https://my.vanderbilt.edu/smpy/files/2013/02/Park-Lubinski-Benbow-2013.pdf

interest, class standing, parent occupation and educational attainment, number of siblings, birth order) to generate a treatment and comparison group. After matching grade skippers and non-skippers exactly on sex and number of previous grades skipped, matches were further improved by matching on these other covariates (SAT scores, measures of subject interest, class standing, parent occupation and educational attainment, number of siblings, birth order) by matching to the nearest in propensity score. Their analytic sample includes 363 grade skippers matched to 657 non-skippers. They compared the two groups straight up and then using logistic regression to control for the slight differences in covariates between the two groups.

- **Results:** Grade skippers were more likely to pursue advanced degrees, advanced degrees in STEM, and author peer reviewed articles, earned their degrees and authored peer reviewed articles at a younger age, have more citations and highly cited publications by age 50. They do find differences by gender: female grade skippers were actually less likely than non-skippers to get STEM PhDs, but they were more likely to than their matched controls to get PhDs in general; while female grade skippers were less likely to pursue STEM PhDs compared male grade skippers, female skippers tended to pursue medical degrees and law degrees (these outcomes mean they also had fewer STEM pubs and citations, of course).
- **Discussion:** A major limitation of any propensity score matching study is that matching is only on observed variables which leaves room for bias related to unobserved factors. Also, they have access to very few variables for matching (compared to a study described above) and so bias due to unobserved factors is likely an issue here, meaning the differences they find could be due to these unobserved factors and not grade skipping.

Bhatt, R. R. (2009). The impacts of gifted and talented education. Andrew Young School of Policy Studies Research Paper Series.23

Summary: This study was never published in a peer review journal, likely because of its unusual findings and weak instrumental variables….but, it gets cited fairly often so I include it here. Bhatt uses data from National Education Longitudinal Survey, a nationally representative, longitudinal study of 8th graders begun in 1988 that tracks students all the way through high school and includes a lot of information about students, their families and the schools they attend. Her analytic sample includes 5,265 8th graders attending 850 schools across the U.S. offering G&T programs. She examines the effect of G&T participation during the 8th grade on a number of outcome variables including scores on math and reading standardized tests, whether they took advanced placement classes in high school, enjoyed school, felt challenged, and took the college entrance exams. She employs instrumental variables regression techniques to try and control for selection bias. While Bhatt uses a rich dataset and was able to control for lots of other factors related to academic performance (student level: race, gender, average GPA from grades 6 and 7; family level: whether they get the newspaper, have encyclopedias at home, whether at least one parent works, parents' highest level of education, family SES; school-level: 8th grade attendance rate, student-teacher ratio, teacher salary, %FRPL, %remedial, % racial minority, urban-rural location, type of G&T admissions criteria used), her instrumental variables are weak and probably do not actually control for selection bias. This may explain why her estimated effects are almost three times larger (0.89 SD) than what the more rigorous studies above report (typically in the range of 0.30 SD). Additional evidence that her IVs might be invalid are the pattern of her results: it is generally assumed that the effect of unmeasured heterogeneity between participating and non-participating students will result in OLS estimates being biased upward (because the program participation variable is capturing both program effects and unmeasured stuff like greater motivation, family support, etc.) and so models that control for selection will thus produce smaller estimates of program effects. Bhatt finds the opposite, at least with math achievement scores. She suggests that maybe it is because lower ability students are often allowed to participate in G&T programs and her IV's capture this (parents push, teachers

[23] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1494334

adjust scores of below-cut-off students, etc.). Instead of positive selection bias (where estimates make the program look more effective than it is because OLS does not control for the fact that higher motivated students are assigned to G&T) Bhatt's posits that her OLS estimates suffered from negative selection bias (i.e., lower ability student's pulled subsequent test scores down). However, this occurs only with the math outcomes; the estimated gains in reading test scores are all smaller when using the IV model compared to those produced by the OLS model (indicating there was positive selection bias with the OLS model). Her argument would be stronger if she found evidence of negative selection bias in both cases. Another limitation of this study is that it does not examine whether the effects of G&T participation differ by student type (race/ethnicity, gender, FRPL status).

- **Data, Sample and Method:** Bhatt uses data from National Education Longitudinal Survey, a nationally representative, longitudinal study of 8th graders begun in 1988 that includes assessment scores in reading, social studies, mathematics, and science from the 8th, 10th, and 12th grades and high school and post-secondary transcripts (types of courses taken, grades) with additional data collected using surveys of students, parents and teachers (school environment, neighborhood environment, home life, support, attitudes, aspirations, extracurricular activities, etc.). Her analytic sample includes 5,265 8th graders attending 850 schools across the U.S. offering G&T programs. She examines the effect of G&T participation during the 8th grade on a number of outcome variables including scores on math and reading standardized tests for 8th, 10th and 12th grades, whether they took advanced placement classes in 10th grade, enjoyed school (8th grade), felt challenged (10th grade), and took the college entrance exams (PSAT, SAT) in the 10th or 12th grade. She employs **instrumental variables regression** techniques to try and control for selection bias. She employs two different 3-way interaction terms as her instruments: (1) the school uses past GPA to assign students to G&T program, (2) child's average GPA in 6th and 7th grades, and (3) percentage of remedial students in the child's school. The other IV she uses is the following 3-way interaction: (1) whether the school uses race as a criterion for admission into G&T (yes/no), (2) whether the student is a racial minority (yes/no) and (3) the % of students in the student's school who are racial minorities. The first stage uses these one of these 3-way interactions plus both the 2-way and the individual variable so that selection is off the 3-way variables (she's hoping that means they will be predictive of whether a student gets assigned to G&T program but not directly correlated with the academic outcomes she uses to evaluate the program effects) to predict whether the student is assigned to a G&T program. The second stage estimates the effect of being assigned to a G&T program. She shows both the base model results (OLS, which doesn't attempt to control selection bias) and IV 2SLS results. All models control for a lot of student, family, and school variables.

- **Results:** She finds that students who reported being in a G&T program in 8th grade have significantly higher standardized math scores (0.89 standard deviations) at the end of 8th grade (but no difference in ELA scores) compared to students who did not participate in G&T programs (she finds no significant differences in math scores in later grades); she also finds that G&T participating students are significantly more likely to take AP classes in 12th grade. She finds no other positive effects of G&T program participation (i.e., no significant differences between G&T participants and non-participants in their reports of enjoying school or feeling challenged, whether they agreed that it was important to their friends to get good grades, whether they knew schoolmates who dropped out, whether they took the SATs).
- **Discussion:** While Bhatt uses a rich dataset and was able to control for lots of other factors related to academic performance (student level: race, gender, average GPA from grades 6 and 7; family level: whether they get the newspaper, have encyclopedias at home, whether at least one parent works, parents' highest level of education, family SES; school-level: 8th grade attendance rate, student-teacher ratio, teacher salary, %FRPL, %remedial, % racial minority, urban-rural location, type of G&T admissions criteria used), her instrumental variables are weak and probably do not actually control for selection bias. This may explain why her estimated effects are larger than what the more rigorous studies above report (typically in the range of 0.30 SD). Recall that a strong IV is one that is highly correlated with program participation but not with subsequent academic achievement. Her 3-way interactions might be invalid if, for example, motivated parents of less-gifted students seek out schools in which their child would have a better chance of getting in. Or if highly motivated but-less gifted students knowing that

the school uses 6^{th} and 7^{th} grade GPA and that the competition in their school is high work harder to increase their GPA. However, even if her IVs are valid, they likely suffer from weak instrument bias. A test for the strength of the IVs is the F test in the first stage predicting participation in the G&T program: a rule of thumb is that the F statistic should be 10 or higher. Bhatt's F tests ranged from 2.3- 4.4. A weak instrument means the second stage estimate of the effect of participating in the G&T program will be imprecise and probably biased. Additional evidence that her IVs might be invalid as well as weak are the pattern of her results: it is generally assumed that the effect of unmeasured heterogeneity between participating and non-participating students will result in OLS estimates being biased upward (because the program participation variable is capturing both program effects and unmeasured stuff like greater motivation, support, etc.) and that IV models will produce smaller estimates of program effects (because they are separate out program effects from higher levels of motivation and support among program participants). Bhatt finds the opposite, at least with math achievement scores: the estimated program effect sizes are larger with the IV model compared to estimates produced using OLS. She suggests that maybe it is because lower ability students are often allowed to participate in G&T programs and her IV's capture this. Instead of positive selection bias (where estimates make the program look more effective than it is because OLS does not control for the fact that higher motivated students are assigned to G&T) Bhatt's posits that her OLS estimates suffered from negative selection bias (i.e., lower ability student's pulled subsequent test scores down). However, this occurs only with the math outcomes; the estimated gains in reading test scores are all smaller when using the IV model compared to those produced by the OLS model (indicating there was positive selection bias with the OLS model). Her argument would be stronger if she found evidence of negative selection bias in both cases. Another limitation: Bhatt does not examine whether the effects of G&T participation differ by student type (race/ethnicity, gender, FRPL status).

Does Sorting Students Improve Scores? An Analysis of Class (Collins and Gan, 2013) [24]

Summary: This study examines whether sorting students by ability (or G&T status) leads to academic gains. They use student-level **data from the Dallas Texas school district** including standardized test scores, a student's identification as gifted and/or special needs or EL and their demographics (race, gender and FRPL status). They had a classroom ID so they were able to link students to a particular class and use student level achievement test scores to develop a an index indicating how homogeneous (sorted) or heterogeneous (not sorted) a student's class was relative to the other same grade classes in the school (they do the same to measure sorting by G&T status). They use instrumental variables to try and isolate a causal effect of sorting. The estimated effects of sorting from the 2SLS IV model are positive and significant for both math and reading scores, and generally larger in magnitude than the OLS estimates, suggesting there was a downward bias caused by selection in the base model (i.e., OLS with a variable indicating whether the student attended a sorting school or not). These results hold across various specifications—for both level scores and score gains, and when outliers are excluded. They also ranked students according to their previous year testing score and estimated separate models for high and low scoring students. While the results suggest slightly larger effects for high scoring students, they still find large, positive, and significant results for the low scoring group. While they find positive effects for students in classes that are sorted (homogeneous) by ability, they do not find any significant effects for G&T students in schools where G&T students are sorted. Like Bhatt (described above) there IV results suggest that selection was causing downward bias on estimated program effects. Unlike Bhatt they find this with both math and reading outcomes. Their IV seems stronger and more plausibly valid than Bhatt's, although of course we can't know for sure. As discussed above there's no way to statistically assess whether the IV is exogenous and valid (i.e., whether it is both correlated to assignment to a tracked classroom but not correlated with subsequent academic achievement). This study is also not published in a peer-reviewed journal which may be because the robustness of results produced by IV models are tough to evaluate. Other limitations of this study are related to its investigation as to whether being in a homogenous G&T classroom improves achievement among G&T identified students

[24] https://www.nber.org/system/files/working_papers/w18848/w18848.pdf

(compared to those in unsorted classrooms). The authors point out that they had no information on what types of G&T programs the schools provide. Their finding of no effects by G&T sorting could be because G&T students in unsorted classes are pulled out of class for certain subjects or projects (if this positively impacts their 4^{th} grade test scores it will make any gains made by G&T students in sorted classes relatively smaller). They also did not explore whether there are differential effects by student gender, race or FRPL status.

- **Data, Sample and Method:** This study examines whether sorting students by ability (or G&T status) leads to academic gains. They use student-level **data from the Dallas Texas school district** including standardized test scores, a student's identification as gifted and/or special needs or EL and their demographics (race, gender and FRPL status). They had a classroom ID so they were able to link students to a particular class and use student level achievement test scores to develop a an index indicating how homogeneous (sorted) or heterogeneous (not sorted) a student's class was relative to the other same grade classes in the school. They construct a separate sort index using math and reading scores. They do the same with the gifted, EL and Special education status variables). Their sample includes all third grade students in the 2003-2004 school year who become fourth graders in 2004-2005, a total of 9,325 children from 135 different schools. They examine the impact of being in a sorted class on 4^{th} grade achievement test scores (math and reading) and on changes between scores between 3^{rd} and 4^{th} grade. To try and isolate the effect of sorting by test scores from sorting on unobserved student characteristics they use **instrumental variables.** Their IV is a measure of whether the school sorts students in the 5^{th} grade, the assumption being that if a school sorts students into (more or less) homogeneous classes in the 5^{th} grade they probably also sort 4^{th} graders (but that whether the school sorts in 5^{th} grade shouldn't affect a student's 4^{th} grade outcomes). The first stage model uses a school-level 5^{th} grade sorting indicator as a predictor of whether a student is in a sorted or not class in 4^{th} grade; the estimate from this first stage is entered into the second stage equation as a predictor in estimating the effect of being in a sorted classroom on math and reading scores on achievement tests taken at the end of the 4^{th} grade. Control variables include: student's 4^{th} grade math(reading) score, gender, race, EL, G&T and special education status; teacher's experience and the school's average teacher salary, the class size, the school's average math and reading scores, enrollment and enrollment-squared.

- **Results:** The estimated effects of sorting from the 2SLS IV model are positive and significant for both math and reading scores, and generally larger in magnitude than the OLS estimates, suggesting there was a downward bias caused by selection in the base model (OLS with a variable indicating whether the student attended a sorting school or not). These results hold across various specifications—for both level scores and score gains, and when outliers are excluded. They also ranked students according to their previous year testing score and estimated separate models for high and low scoring students. While the results suggest slightly larger effects for high scoring students, they still find large, positive, and significant results for the low scoring group. While they find positive effects for students in classes that are sorted (homogeneous) by ability, they do not find any significant effects for G&T students in schools where G&T students are sorted.
- **Discussion:** Like Bhatt, who also uses 2SLS IV methods, their results indicate that selection effects were producing a negative (downward) bias (their base model – OLS with an indicator variable measuring the degree of sorting in the child's 4th grade classroom – produced smaller positive estimated effects of sorting). Unlike Bhatt they find this pattern with both math and reading outcomes. As is the case with all IV models, it is hard to know for sure if the instrument is controlling selection effects and allowing researchers to isolate causal program effects. They provide evidence that their IV is at least moderately strong (they report correlations of 0.37 to 0.57 between 5th and 4th grade sorting indices, with sorting by G&T status the lowest and sorting by math scores the highest). However, as discussed above there's no way to statistically assess fully assess the quality of an IV (whether it is both correlated to assignment to a tracked classroom but not correlated with subsequent academic achievement). It is plausible like the authors say that their IV is not biased, but as with all IVs, this cannot be directly measured. It seems logical that the way 5th grade students are assigned to classrooms would have no impact on the academic performance of 4th graders (unless, say, schools that sort in 5th grade also provide extra help to 4th graders to prepare for their achievement tests; or more

motivated or supported students at the school know that their 4th grade test results will determine whether they get into a homogenously high scoring classroom and act upon that knowledge).

- **Other limitations:** The authors point out that they had no information on what types of G&T programs the schools provide. Their finding of no effects by G&T sorting could be because G&T students in unsorted classes are pulled out of class for certain subjects or projects (if this positively impacts their 4th grade test scores it will make any gains made by G&T students in sorted classes relatively smaller). They also did not explore whether there are differential effects by student gender, race or FRPL status.

Summary and Conclusions

Maine's Gifted and Talented (G&T) programs, and the subsequent funding that follows, appear to be unevenly distributed. Higher poverty SAUs are less likely to have approved G&T programs and to report students identified as G&T. This raises concerns about equitable opportunities to participate, if in fact G&T programs are an evidence-based intervention that should therefore be available to any student who would benefit. This leads to the more basic question of whether the costs of such programs are worth the investment, or whether Maine should consider following the precedent set by other New England states and reallocate these funds to other purposes.

The empirical evidence on the impacts of participation in G&T programs is decidedly mixed. In the absence of universal testing and random assignment, rigorous research on G&T program participation is hard to do–because of selection bias, confounding factors, simultaneity—and because there is so much variation on the type, quality and intensity of G&T programming. If there are net gains from G&T programs, they are more likely in the following circumstances:

- Socioeconomically disadvantaged students may benefit the most from G&T programs (Card and Guiliano); these benefits might come as much from indirect effects (more supportive classroom environment, classmate peers with stronger academic performance, higher teacher expectations) as they do from a more advanced curriculum. Yet in Maine, socioeconomically disadvantaged students are far less likely to participate. Universal screening may help to identify more students from disadvantaged backgrounds.
- More exceptionally gifted students—those outliers with the highest achievement—might benefit more than others identified (generally in the top 5%).

In conclusion, it is unclear whether the benefits of pull-out G&T programs are large or discernible enough in Maine to warrant the current level of investment. We recommend continued exploration of a personnel ratio in the EPS model to provide MTSS learning specialists who have the capacity to support any student with academic learning needs—at both ends of the spectrum—that are beyond the range of what can feasibly supported by the general classroom teacher through differentiated instruction.

Essential Programs and Services (EPS) Component Review: Small and Geographically Isolated School Adjustment

Background

The Essential Programs and Services (EPS) cost model provides an additional allocation to schools that are identified as small and geographically isolated. Such schools have less opportunity to achieve economies of scale by combining with nearby communities and may also have other additional costs inherent to geographic isolation. The form of the adjustment is a reduced student-to-teacher ratio for schools in lower size categories that meet the geographic isolation criteria, along with an additional per-pupil allocation amount for operation and maintenance of physical plant in island schools. Prior analyses of this adjustment were conducted in 2005, 2006, 2010 and 2018 as part of the ongoing review of components within the EPS funding formula.

Methods and Approach to Component Review

The additional allocation for schools qualifying as small and isolated increases both the state subsidy and the local required contribution. In this review we examine whether the adjustment is having its intended effect and whether SAUs are able to raise the additional funds locally.

We draw on a number of datasets to conduct this review. We obtained the list of schools qualifying for the small and isolated adjustment for the school year 2019-20 from the Maine DOE. From the Maine DOE we also obtained total EPS allocation, local required contribution, state contribution, mil rate (General Purpose Aid for Local Schools, FY2019-20) and local additional share raised (Budget Revenue Reports: Over/Under EPS Budget Report by SAU FY2019-20) as well as state property valuation data for FY2019-20. We obtained town-level median income data from the Maine Housing Authority which we then aggregated up to the district level. We used district level estimates of child poverty for SY2020 from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) as an additional measure in case school FRPL data are becoming less reliable. We then used these data to compare per pupil EPS allocations and state and local required contributions. We also compare property valuation and minimum receiver status, as well as other factors that indicate a district's ability to pay their local required contribution.

The latter analyses are relevant because property valuation in a given SAU directly impacts the amount of state subsidy they receive. The first step in allocating state subsidy is to determine the amount of funding that can be raised locally with a fixed mil rate expectation, typically around 7 to 8 mils. This method is intended to be equitable because it expects each property owner (residential or commercial) to pay an amount that is relative to the value of their property, based on the assumption that those with more valuable property have a greater ability to pay property tax. Once all property in a community has been taxed at the fixed statewide mile rate (which varies modestly from year to year), any remaining amount that must be raised to meet the total EPS allocation is provided through state subsidy. In most Maine communities the statewide mil expectation does not raise enough funds to cover the foundation amount determined by the EPS cost model, and the state share of school funding is substantial. Overall, state subsidies provide 55% of the total EPS funding model. However, some communities have high property valuation relative to the number of students that require an education, and the statewide mil rate would raise more funds than the EPS model requires. These communities instead are expected to raise 95% of the EPS foundation amount, and the remaining 5% is provided through state subsidy. These communities are termed "minimum receivers" and cover the cost of educating their resident pupils with lower mil rates than the statewide mil rate – sometimes substantially so (as low as 0.36 mils).

The approach taken in these analyses was to provide an overall description of the allocation and subsidy patterns in Maine's smallest school administrative units (SAUs). While state subsidy is determined at the town level and not on a per-pupil basis, our analyses rely on per-pupil amounts. This provides a scaled depiction of funding that allows more valid comparisons between SAUs, as otherwise the vast differences in student enrollments among Maine SAUs makes it difficult (if not impossible) to compare differences in their dollar amounts.

Analysis and Findings

In our analysis we focused on typical-cost public school districts. We exclude Maine Indian districts, schools in unorganized territories, 3 districts that did not have enrollment data and districts with zero attending students (i.e., those that do not operate schools and instead send their resident students to schools in other SAUs).

Of 191 public districts with attending students, 53 had at least one school that was designated as small and isolated in SY2020. The vast majority (50 districts) had one small and isolated school, and three districts had two small and isolated schools. See Appendix A for the list of geographically isolated small schools and the districts in which they are located.

Table 1. Description of SAUs with Geographically-Isolated Small Schools, Compared to Other Districts

	SAUs w/ small and isolated school(s) (n=53)	All other public SAUs (n=138)
Minimum receiver, % (n)	72% (38)	34% (47)
Avg. (median) per pupil Property valuation	$2,745,604 ($1,508,523)	$1,276,242 ($788,487)
Avg. (median, range) Adjusted local mil rate	5.62 (6.26, 0.36-8.28)	7.45 (8.28, 0.73-8.28)
Avg. (median) Per pupil EPS allocation	$12,073 ($11,921)	$11,650 ($11,597)
Avg. (median) Adjusted State Share Percentage	29.6% (21.8%)	44.1% (48.6%)
Avg. (median) Per pupil State subsidy	$3,629 ($2,660)	$5,169 ($5,826)
Avg. (median) Required local contribution per pupil	$8,444 ($9,099)	$6,471 ($5,949)

*SY2020. Sample excludes tribal districts and schools in unorganized territories.

Importantly, the finding that the total EPS allocation in FY2020 was on average $433 more per student for SAUs with small and isolated schools compared to all other districts ($12,073 versus $11,640, respectively). This likely is a reflection of additional funding directed to these units through the small and isolated school adjustment. The EPS adjustment can thus be seen as meeting its intent of ensuring that additional funds are made available to operate schools in these unique circumstances.

However, the additional funds that are allocated through the EPS formula to meet increased costs are disproportionately paid by local taxpayers and not through state subsidy. The SAUs with at least one small and isolated school are more than twice as likely to be a minimum receiver (72% compared to 34%). On average, the per pupil property valuation is higher among SAUs with at least one small and isolated schools ($2,745,604 vs $1,276,242) and therefore the local adjusted mil rate is lower (5.6 vs 7.5), as is the state share of the total allocation (29.6% vs 44.1%).

As described in the introduction, the proportionately higher property valuation in SAUs with small isolated schools has an impact on the amount of state subsidy they receive. The median per student state subsidy is $2,660 for SAUs with at least one small and isolated school, compared to $5,826—more than twice as much per pupil—among SAUs without any small and isolated schools.

The difference between the median per student local required contribution is $3,150, with SAUs with small and isolated schools needing to raise $9,099 per student compared to the $5,949 that has to be raised by SAUs without small and isolated schools. This is the flip side of the subsidy story and corroborates that communities receiving less state subsidy must raise more from local funds.

The finding that local property values are higher (when scaled per pupil) among districts with at least one small and isolated school does not necessarily reflect local ability and/or willingness to pay property taxes. Districts with small and isolated schools tend to have, on average, slightly higher child poverty rates and lower median incomes compared to other districts (see Table 2).

Approximately the same percentage of districts with and without small and isolated school(s) raised no additional funds beyond the local required share (9% vs 11%, respectively). Among the remaining districts that did raise optional additional local funds, those with at least one small and isolated school raised on average over twice as much in additional funds compared to other districts ($6,725 vs $3,007, respectively). There is a moderately strong positive correlation between the median income and the amount of additional funds raised locally per student ($r=0.470$, $p<0.01$). In other words, communities with higher incomes are more likely to budget additional education funding above and beyond the EPS foundation amount.

Table 2. Comparison of Income and Funds Raised for Education in SAUs with and without Small and Isolated Schools

	SAUs w/small and isolated school(s) (n=53)	All other public SAUs (n=138)
Avg rate (range) economically disadvantaged students (FRPL measure), 2018	51.0% (12%-100%)	46.9% (6%-100%)
Avg child poverty rate (range), SAIPE data	14.0% (5%-26%)	12.9% (2%-33%)
Avg median income, FY2020 (range)	$54,473 (24,697-77,239)	$61,384 (32,750-120,159)
% (#) that raised additional funds, above local required	91% (48)	89% (123)
Avg additional local raised, per pupil (median, range)	$6,725 ($4,540, $0-43,974)	$3,007 ($2,476, $0-12,412)

* Sample excludes tribal districts and schools in unorganized territories. Child poverty rate data come from SAIPE. Median income data was obtained from the Maine Housing Authority, with town level median income aggregated up to the district level. Additional local raised came from MDOE budget reports, 2019-20. https://www.maine.gov/doe/funding/reports/budget

Summary

The EPS model adjusts the total allocation for districts with small and isolated schools upwards, increasing the total allocation per student. This is an affirmation that the cost side of the funding formula is working as intended to provide these districts with additional funds to be able to operate their small and isolated schools. However, these districts are twice as likely to be minimum receivers, which means they must raise the additional dollars per student locally. SAUs with small and isolated schools need to raise $9,099 per student locally compared to the $5,949 that has to be raised on average by SAUs without small and isolated schools. These districts also have slightly higher rates of poverty and lower median incomes, which raises the concern as to whether they may struggle in terms of ability to pay. Analysis of additional optional funds raised locally in SY2020 demonstrates that many of these districts are able and willing to support education at a level over and above the required EPS foundation amount. This is encouraging, yet also raises questions about whether the current system for allocation of state subsidy is as equitable as possible for our rural communities.

In light of these analysis as well as similar themes raised in other component reviews, MEPRI recommends additional exploration of Maine's subsidy distribution system. Specifically, we wish to further examine the pros and cons of our methodology of using resident pupil counts as the scaling factor for comparing variables between SAUs. Other scaling factors (e.g. number of resident households contributing to local property taxes) may be more useful for evaluating whether Maine's system is equitable and fair to communities and individual residents.

Appendix A

Table 1: Schools Designated as Small and Isolated in SY2020

School	Grades	Enrollment	SAU
Adams School	k-8	51	Castine Public Schools
Airline Community School	Pk-8	43	Airline CSD
Albion Elementary School	Pk-6	109	RSU 49/MSAD 49
Alexander Elementary	k-8	40	Alexander Public Schools
Alton Elementary School	Pk-4	56	RSU 34
Andover Elementary School	Pk-4	34	Andover Public Schools
Bay Ridge Elementary	Pk-8	67	Cutler Public Schools
Beech Hill School	Pk-8	90	Otis Public Schools
Brooklin School	Pk-8	59	Brooklin Public Schools
Brooksville Elementary School	Pk-8	59	Brooksville Public Schools
Cape Cod Hill Elem School	Pk-5	171	RSU 09
Cave Hill School	Pk-8	83	RSU 24
Chebeague Island School	K-5	21	Chebeague Island Public Schools
Cliff Island School	K, 2, 3, 5	5	Portland Public Schools
Cranberry Isles School	1,2,4,5,6,8	10	Cranberry Isles Public Schools
Denmark Elementary School	k-4	85	RSU 72/MSAD 72
Dr Levesque Elementary School	Pk-6	137	RSU 33/MSAD 33
East Grand School	Pk-12	133	RSU 84/MSAD 14
East Range II CSD School	k-8	23	East Range CSD
Easton Elementary School	Pk-6	128	Easton Public Schools
Edgecomb Eddy School	Pk-6	104	Edgecomb Public Schools
Edna Drinkwater School	k-8	114	Northport Public Schools
Forest Hills Consolidated School	k-12	149	RSU 82/MSAD 12
Fort Street School	Pk-6	193	RSU 42/MSAD 42
Frenchboro Elementary School	4,7	3	Frenchboro Public Schools
Friendship Village School	k-6	83	RSU 40/MSAD 40
Georgetown Central School	Pk-6	46	Georgetown Public Schools
Greenville Consolidated School	k-12	192	Greenville Public Schools
Harmony Elementary	Pk-8	51	Harmony Public Schools
Hebron Station School	K-6	130	RSU 17/MSAD 17
Isle au Haut Rural School	K, 1, 3,4,6	6	Isle Au Haut Public Schools
Islesboro Central School	k-12	85	Islesboro Public Schools
Jonesboro Elementary School	Pk-8	55	Jonesboro Public Schools

School	Grades	Enrollment	SAU
Katahdin Elementary School	Pk-5	141	RSU 89
Katahdin Middle/High School	6-12	166	RSU 89
Lee/Winn School	Pk-4	84	RSU 30/MSAD 30
Leeds Central School	Pk-6	193	RSU 52/MSAD 52
Long Island Elementary School	k-5	12	Long Island Public Schools
Lubec Consolidated School	Pk-8	76	RSU 85/MSAD 19
Monhegan Island School	1,3,5,8	5	Monhegan Plt School Dept
Moscow Elementary	Pk-4	74	RSU 83/MSAD 13
Mt Jefferson Jr High School	5-8	82	RSU 30/MSAD 30
North Haven Community School	k-12	55	RSU 07/MSAD 07
Peaks Island School	Pk-5	40	Portland Public Schools
Penobscot Elementary School	Pk-8	69	Penobscot Public Schools
Phippsburg Elementary School	Pk-5	99	RSU 01 - LKRSU
Rangeley Lakes Regional School	Pk-12	209	RSU 78
Solon Elementary School	Pk-5	85	RSU 74/MSAD 74
Stratton Elementary School	Pk-8	88	Eustis Public Schools
Swans Island Elementary School	k-8	32	MSAD 76
Vinalhaven School	Pk-12	174	RSU 08/MSAD 08
Walker Memorial School	Pk-5	90	RSU 03/MSAD 03
Wesley Elementary School	1,3,4,6	7	Wesley Public Schools
Whiting Village School	Pk-8	32	Whiting Public Schools
Woodland Elementary School	Pk-6	138	Baileyville Public Schools
Woodstock School	k-5	69	RSU 44/MSAD 44

*List of schools obtained from Maine DOE finance team in January 2022. Enrollment and grade information obtained from the MDOE website.

Appendix B. Per-Pupil Data Elements for SAUs containing Small Isolated Schools (FY2020)

SAU	SAU enrollment	PP EPS allocation	PP state subsidy	PP required local contribution	PP additional local raised	FY20 Mil rate*	Child Poverty rate	Avg Median Income
Airline CSD	43	9348	3151	6197	4681	**4.74**	12.7	NA
Alexander Public Schools	40	11975	3947	8029	4148	8.28	15.5	47702
Andover Public Schools	34	10285	1142	9143	2143	8.28	20.0	50833
Baileyville Public Schools	336	10523	2660	7863	5289	8.28	19.9	NA
Brooklin Public Schools	59	11876	721	11154	9298	**2.76**	11.8	50000
Brooksville Public Schools	59	11150	897	10253	8561	**2.35**	15.7	72500
Castine Public Schools	51	10000	727	9273	7194	**2.23**	8.9	62500
Chebeague Island Public Schools	21	13887	1477	12410	12971	**3.22**	8.3	NA
Cranberry Isles Public Schools	10	14346	2517	11829	25338	**0.90**	15.8	NA
Cutler Public Schools	67	8282	2998	5285	2934	8.28	13.2	NA
East Range CSD	23	24861	9198	15663	0	**6.84**	23.1	NA
Easton Public Schools	243	11497	780	10717	7190	**7.31**	13.6	NA
Edgecomb Public Schools	104	11506	1337	10169	5727	**7.77**	15.4	63250
Eustis Public Schools	88	11802	975	10827	0	**4.38**	13.3	24697
Frenchboro Public Schools	3	13550	2959	10592	43974	**2.54**	14.3	NA
Georgetown Public Schools	46	12656	1178	11478	9337	**2.66**	13.4	77239
Greenville Public Schools	192	13615	2067	11548	7913	**6.08**	16.5	49394
Harmony Public Schools	51	13788	8835	4954	1333	8.28	7.4	34935
Isle Au Haut Public Schools	6	13380	777	12604	23745	**0.91**	NA	NA
Islesboro Public Schools	85	10277	1178	9099	16598	**1.99**	4.5	70573
Jonesboro Public Schools	55	10763	3250	7513	2429	8.28	15.5	NA

*Mil rates below 8.28 indicate the SAU is a minimum receiver.
**SAU has two small and isolated schools; all other SAUs have one small and isolated school.
NA = not available.

(Appendix B, Cont.) SAU	SAU enrollment	PP EPS allocation	PP state subsidy	PP required local contribution	PP additional local raised	FY20 Mil rate*	Child Poverty rate	Avg Median Income
Long Island Public Schools	12	9891	998	8892	7063	**1.44**	6.1	NA
Monhegan Plt School Dept	5	6764	785	5980	0	**0.36**	16.7	NA
MSAD 76	32	15549	2343	13206	12885	**3.99**	14.6	NA
Northport Public Schools	114	12108	822	11286	7029	**5.59**	8.7	70074
Otis Public Schools	90	10672	1391	9282	5457	**4.54**	13.8	NA
Penobscot Public Schools	69	11967	1506	10461	3803	**5.79**	14.4	56061
Portland Public Schools**	6,779	12558	2109	10449	3025	8.28	13.6	62178
RSU 01 - LKRSU	1,849	14952	6841	8110	2286	**6.66**	12.1	71022
RSU 03/MSAD 03	1,235	13800	8395	5405	1601	8.28	17.5	49581
RSU 07/MSAD 07	55	13525	855	12669	25921	**2.14**	8.7	NA
RSU 08/MSAD 08	174	14044	3407	10637	8499	**3.92**	14.1	59559
RSU 09	2,423	12763	8425	4338	0	**7.84**	15.0	52003
RSU 17/MSAD 17	3,428	10695	5250	5444	858	**7.71**	14.6	56334
RSU 24	846	12192	3006	9185	4271	**6.26**	17.4	52077
RSU 30/MSAD 30**	166	11566	7856	3711	2468	8.28	15.1	47773
RSU 33/MSAD 33	243	11183	6757	4427	0	8.28	15.2	NA
RSU 34	1,522	11356	7660	3696	1269	8.28	12.1	50990
RSU 40/MSAD 40	1,890	11921	5861	6060	2784	**8.07**	14.4	59935
RSU 42/MSAD 42	391	10270	6542	3728	1759	8.28	10.9	NA
RSU 44/MSAD 44	710	11294	1213	10081	4827	**4.61**	11.7	61421
RSU 49/MSAD 49	2,091	10722	7156	3565	1612	8.28	14.3	52128

*Mil rates below 8.28 (bold font) indicate the SAU is a minimum receiver.
**SAU has two small and isolated schools; all other SAUs have one small and isolated school.
NA = not available.

(Appendix B, Cont.) SAU	SAU enrollment	PP EPS allocation	PP state subsidy	PP required local contribution	PP additional local raised	FY20 Mil rate*	Child Poverty rate	Avg Median Income
RSU 52/MSAD 52	2,017	11117	7108	4009	1951	8.28	7.7	65124
RSU 72/MSAD 72	770	12937	5060	7877	3072	**6.16**	11.4	58375
RSU 74/MSAD 74	629	13436	7218	6219	3046	**7.57**	16.5	54047
RSU 78	209	12801	1080	11721	7950	**2.45**	10.0	57679
RSU 82/MSAD 12	149	12083	4743	7339	3517	8.28	10.5	40270
RSU 83/MSAD 13	181	12226	4965	7261	5427	**7.39**	16.7	36881
RSU 84/MSAD 14	133	13446	7275	6171	4540	**6.89**	17.1	NA
RSU 85/MSAD 19	76	11724	2094	9630	5589	**6.38**	25.9	40987
RSU 89**	307	12378	8501	3877	2762	**2.06**	23.5	39476
Wesley Public Schools	7	10556	1454	9103	13851	**4.00**	16.7	NA
Whiting Public Schools	32	8007	914	7094	6478	**5.37**	12.5	NA

*Mil rates below 8.28 indicate the SAU is a minimum receiver.
**SAU has two small and isolated schools; all other SAUs have one small and isolated school.
NA = not available.

SY2020. All financial data and student counts received directly from MDOE or from the MDOE website, including https://www.maine.gov/doe/funding/reports/budget . Per pupil calculations use responsible student counts. Enrollment counts are attending students. Child poverty rate data were obtained from SAIPE. Median income data were obtained through the Maine Housing Authority and aggregated up from the town level.