Analyzing the Effect of Funding on School Performance in DC Public Schools

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In this paper, we analyze the relationships between school funding and overall performance in D.C. public schools; specifically investigating if an increase in per-pupil expenditures is positively correlated with an increase in STAR score. Additionally, we examined if certain schools responded better to increased expenditure, and thus if funding was more efficient when targeted towards low income or "at-risk" students. After cleaning and merging various data sets pertaining to school finance, performance, and socioeconomic status, we calculated and plotted the change in per-pupil expenditure and the change in STAR score. Our final analysis found that there is not a significant relationship between the two variables and an increase in funding does not necessarily mean there will be subsequent increase in performance. Alternatively our analysis showed a negative correlation, seeing as schools with more funding and thus high per-pupil expenditures likely had lower STAR scores. This is in large part due to schools in low income areas historically under performing despite the fact that they are more likely to receive more federal funding.

Public schools | K-12 | Inequality | ...

Introduction

The COVID-19 pandemic has had a devastating impact on student performance. Following shutdowns at the onset of the pandemic, many schools nationwide faced severe staff shortages, declining enrollments, higher rates of misbehavior, and lost vital instructional time, all of which have had a profound impact on student performance. Earlier this year (October 2022), the National Assessment of Education Progress, also called the Nation's Report Card, released the results from their sampling of nearly 450,000 students in more than 10,000 schools, showing the significant impact the pandemic had on America's youth. Their testing found that only 26% of eighth graders and 36% of fourth graders were proficient in math, a significant drop off from the pre-pandemic statistics. While for reading, only 1 in 3 students were proficient and more than half of US states saw their average score decrease (1). Specifically in D.C., one of the worst-hit metropolitan areas, math scores dropped by over 10 points for both eighth and fourth graders while reading scores dropped by over 9 points.

These performance declines were most pronounced among low-income students. Many of these students faced challenges with remote learning due to a lack of reliable internet access and/or computers. The National Report Card reported that "only half of the fourth graders who were low performing in math said they had access to a computer at all times during the 2020-21 school year, compared with 80% of high performing students" (1). Additionally, without in-person school, many of these students no longer had access to necessary public services that could provide consistent meals, necessary therapy, etc. These factors have led to a widening achievement gap between high and low income students. When it comes to test scores, researchers from the Brooking Institute found that the pandemic significantly increased the disparity between low and high income schools by 20% in math and 15% in reading(2).

On a national level, the federal government has invested historic amounts of money into American public schools to ameliorate these learning dropoffs. In 2021, the government gave $123 billion to American schools to aid in academic recovery–which equates to around $2400 per student. However some experts like Denise Forte, the CEO of the Education Trust, believe that instead of this broad distribution of funding, we need to target resources to better assist students who have been "historically underserved" (1) .

On the Washington, D.C. level, City Council responded to these alarming trends with their fiscal year (FY) 2023 "Fair Shot" budget. According to Education Reform Now DC, the Council's budget takes effective steps towards fixing school funding inequity; investing in safe, stable, and positive learning environments for all students; and ensuring all educators receive

Significance Statement

The purpose of this study is to better understand the relationship between per-pupil expenditure and school performance, especially among low-income public schools in Washington, D.C. This is important because the D.C. Council FY 2023 budget includes an increase in targeted resources for schools with a high percentage of at-risk students. We want to understand if this was a smart decision and if increased funding will improve these school's overall performance.

superior preparation and support" (3). Supporters of increased funding could argue otherwise, seeing as the council failed to prohibit DCPS from making budget cuts, leading the majority of DC Public schools to have reduced FY 2023 budgets from FY 2022. However, the council did increase funding to "at-risk" students in order to bridge the performance discrepancies between low and high income students. By updating the Uniform Per student Funding Formula (UPSFF) –or the formula which is used to determine the annual operating funds for DCPS– to include weights for at-risk students, the budget can better accommodate schools serving a high percentage of low income students. The council hopes that these reforms will help all students, regardless of their background, "read on grade level, catch up on unfinished learning, and receive behavioral health support" (3). By providing targeted support to lower income schools as opposed to more comprehensive district-wide funding increases, the council believes their money can have a greater impact.

Our research will analyze if increased funding and subsequently increased expenditure has a positive impact on performance among D.C. schools. Furthermore, we will examine whether said financial increases have a disproportionate impact on high and low income schools. We hypothesize that an increase in per-pupil expenditure will have a positive impact in D.C., especially for schools serving a high percentage of "at-risk" students. In order to test this hypothesis, we will be collecting relevant pre-pandemic data on each D.C. public school's yearly expenditures and performance ranting. We will then calculate the percent changes in both of these variables in order to show a correlation through educational visualizations and regression models.

Related Work

Previous research has found evidence for the beneficial effects of increased funding on performance. Researchers from Northwestern University collected estimates from 31 different credible studies on the subject matter in order to examine the relationship between K-12 spending on test scores and educational attainment. Most notably, the researchers found that a "policy that increases per-pupil spending for four years will improve test scores 92 percent of the time, and educational attainment even more often." More specifically, they found that on average, a $1000 increase in per-pupil spending increases test scores by 0.044, high school graduation rate by 2.1% percentage points, and higher education attainment by 3.9 percentage points over a four year period(4) .

There is also research that shows the significant impact expenditure increases can have on low-income schools specifically. Researchers Lafortune, et al., studied the effect of school finance reforms on spending and achievement in low-income school districts using nationally representative samples from the National Assessment of Educational Progress. Their findings concluded that reform "increases the absolute and relative achievement of students in low-income districts." Their results also show significant long-term benefits, seeing as "given the existing estimates of the relationship between test scores and student's subsequent earnings. . . a $1 increase in funding will raise a low-income student's eventual earnings by more than $1 in present value" (5). These results imply that there is a positive benefit-cost ratio in regard to increasing funding to low-income schools.

Seeing as these financial reforms have proven to be constructive on a national level, we can now examine the impact of expenditure increases on the performance of DC public schools specifically. Our study will build on this previous research by investigating if these national-level results are consistent with a specific city's public school system. In order to do this, we will first need to collect publically available data on the finances, performance, and student makeup of the various DC public schools.

Data Source

We wanted to have three main datasets for each variable we were studying: School Financial data, School Performance data, and School Diversity data. To do this, we first compiled pairs of datasets from the years 2018-2019 and 2019-2020 via various online sources. More information about theses sources and the final dataframe can be found below:

Financial dataset .

NCES data:.

The National Center for Education Statistics, or NCES, has published each state's reported public school expenditure data from 1987-2019.

Edunomicslab data:.

Edunomicslab published another version of the NCES dataset which performs basic data cleaning. We decided to use their cleaned dataset only to gather financial data for the 2018-2019 school year, due to the fact that they are missing 2019-2020.

After combining the 2018-2019 from Edunomics and the 2019-2020 dataset from NCES, some of our relevant columns included:

- **Schoolid_stateassigned** - School's identifying number
- **Schoolname** - Full School Name
- **Distname** - School District
- **pp_total_raw_DC_1819** - total per-pupil expenditures (2018-2019)
- **enroll_raw_DC_1819** - total enrollment (2018-2019)
- **pp_total_raw_DC_1920** - total per-pupil expenditures (2019-2020)
- **enroll_raw_DC_1920** - total enrollment (2018-2019)

School performance dataset.

STAR data.

We gathered the 2018 and 2019 DC School Report Card and STAR Framework Data File to use as our school performance metric. Starting in FY 2017, the D.C. Office of the State Superintendent of Education (OSSE) annually releases the DC school Report Card for all public schools in the District, both within the DC Public Schools (DCPS) and public charter school systems.

STAR Score is a much more comprehensive evaluation of school performance than the standard test. STAR framework measures schools from five fields: Academic Achievement, Academic Growth, School Environment, English Language Proficiency, and Graduation Rate. Under these five secondary metrics, several third metrics like PARCC score, AP/BI, and Attendance are used to calculate the STAR Score.

After joining the two years together, relevant columns include:

- **School_code** - School's identifying number
- **Ward** - which ward the school is located within (8 possibilities)
- **STAR_Score_18** -Schools score out of 100 possible points (2018)
- **STAR_Rating_18** - School's score out of 5 (2018)
- **STAR_Score_19** -Schools score out of 100 possible points (2019)
- **STAR_Rating_19** - School's score out of 5 (2019)

Diversity dataset .

Diversity Data:. We gathered data on student backgrounds from the D.C. Policy Center's report Landscape of Diversity in D.C.'s Public Schools. The Center's excel file provides data on racial/ethnic and socioeconomic diversity scores for DCPS and public charter schools in FY 2018-2019. We ultimately decided that socioeconomic makeup of each school did not change enough to warrant compiling data from both FY 2018-2019 and 2019-2020.

This dataset includes relevant columns such as: School Code - School's identifying number Ward - which ward the school is located within (8 possibilities) Total Count of Students - enrollment At-Risk (Socioeconomic Diversity Score, 2018-19 (Majority group - Binary variable signifying if the majority of students are "at-Risk" or "Not at-risk"

- **School Code** - School's identifying number
- **Ward** - which ward the school is located within (8 possibilities)
- **Total Count of Students** - enrollment
- **At-Risk (%)** - percentage of enrolled students classified as "at-risk"
- **Socioeconomic Diversity Score, 2018-19 (%)** -School's score out of 50 possible points
- **Majority group** - Binary variable signifying if the majority of students are "at-Risk" or "Not at-risk"

Time window:.

In this research, data in FY18-19 and FY19-20 would be used. Because of Covid, some standard test are canceled in DC. Therefore, it is not mandatory for public schools to take the measurement of STAR Framework score. STAR Scores in FY20-21 and FY20-21 are not available. For this reason, only FY18-19 and FY19-20 would be researched.

Unit of analysis .

Unit of analysis in original data source are an individual public school in DC, which is the same as the final datset for analysis. Public school referring all school in DCPS system or charter school. In the final dataset there are 237 unique school.

Table 1. Correlation Matrix of important variables

Data Source	**Years**	**Observation Summary**	**Key Variables**
NCES data	2018-2019 2019-2020	Published each state's reported public school expenditure data	**Schoolid_stateassigned** **Schoolname** **Distname** **pp_total_raw_DC** **enroll_raw_DC**
STAR data	2018 2019	A much more comprehensive evaluation of school performance than the standard test	**School_code** **Ward** **STAR_Score** **STAR_Rating**
Diversity data	2018-2019	Student backgrounds from the D.C. Policy Center's report Landscape of Diversity in D.C.'s Public Schools	**School Code** **Total Count of Students** **At-Risk** **Socioeconomic Diversity Scor**

Method

Data Cleaning.

Before we began our analysis, we needed to clean the NCES and STAR datasets. In the methodology part of this report, a lot of effort was put towards extracting and cleaning the data, seeing as we are collecting 3 separate datasets with all different origins, formatting, and naming.

NCES.

We first collected the raw datasets directly from NCES website for years 2018-2019 and 2019-2020. After loading the datasets, we imported the "sweetviz" package, which quickly generates exploratory data analysis with shortcodes.

Then, we wrote a function, **nces_process**, that includes every step needed to preprocess our financial data. First, columns were split into different types: **finan_cols** which were financial variables pertaining to per-pupil expenditures, and **other_cols** which were school level and enrollment. One thing worth mentioning is the 2018-2019 data on whether schools provided free lunches or lunch subsidies. The data seems interesting, so the function checks and leaves this lunch-related column. The function then drops columns that have constant values except for the state and year columns. In its final step, the preprocess function converts all of the financial data to the numeric type.

After running the two years of data through this function it is successfully cleaned and we can now combine them. We merged horizontally based on the school id instead of concatenating.

We then evaluated differences in the **schtype_raw_DC_1819** and **schtype_raw_DC_1920** columns and found that there was a school type called NRD, that was only present in the 2018-2019 dataset. In order to remedy this, we converted the "NRD" values in the **schtype_raw_DC_1819** column to be na values.

From there we could merge the two columns into one in order to simplify our dataset. We then continued to drop useless columns that have duplicated metadata after merging.

In order to perform our later analysis, we added columns to this dataset that compared two years of financial data. We created the **cmp_numeric_data** function, which calculates the percent change between columns that ended in "_1819" and columns that ended in "_1920" by using the pandas pct_change function. We were then able to run the **pp_total_raw_DC**, **pp_site_raw_DC**, **pp_centshare_raw_DC**, **schoolstloc_raw_DC**, and **enroll_raw_DC** columns through the function and calculate the percentage change in per-pupil expenditures, percent share, etc..

STAR data.

Compared to financial data, STAR is rather simple. The metadata only contains the school id, name, and ward data. However, the NCES dataset already provides enough metadata so we decided to keep only the **School_Code**, **STAR_Score_18**, **STAR_Rating_18**, **STAR_rating_19**, and **STAR_rating_19**. We used the shared **School_Code** column to merge the two years' data. Finally, similar to the NCES datasets, we calculated the difference and change percentage between two years and added the results as new columns called **STAR_Score_inc** (which is the change in star rating), **STAR_Score_change** (percent change in STAR score), and **STAR_Rating_change** (percent change in star rating).

Diversity data.

The diversity data provides us with socioeconomic information about the students in DC public schools. Because we only gathered data from 2018-2019, we did not have to merge two datasets together to create our Diversity dataset. We did however, need to create a categorical variable called **risk_level** which classified schools into 5 levels depending on their percentage of at-risk students. Label 1 being 0-19%, 2 being 20-39%, 3 being 40-59%, 4 being 60-79%, and 5 being 80-100% of at-risk students.

Merge Strategy.

In order to merge the NCES, STAR, and Diversity datasets, we used the commonly shared state-assigned School_Code and schoolid_stateassigned columns. This merged dataset called all_df has over 50 columns before cleaning. We then ran a for loop to see which columns had the same values so we could spot possible duplicates, dropping columns we deemed repetitive. We then filtered down to some numeric data and retained columns we believed would be helpful for our later analysis.

Analysis of Missing School.

Because we used inner merge to combine the whole dataset, some schools were dropped from all_df. In 2018, there were 45 schools that do not have STAR scores and 6 schools that did not have financial data. In 2019, there were 40 schools that did not have STAR data and 10 schools that did not have financial data.

We found that charter schools were the most likely to be missing these datapoints. But there are also other factors that made a school more likely to be dropped due to missing data. The official explanation of school without STAR Score is it either didn't meet the minimum enrollment size requirement of out of operation in that time. Out of the 45 schools missing star score, 11 don't have enrollment data and the other schools have a lower average enrollment compared to the average enrollment in DC of 394. Therefore, we believe school un

Result

Visualization.

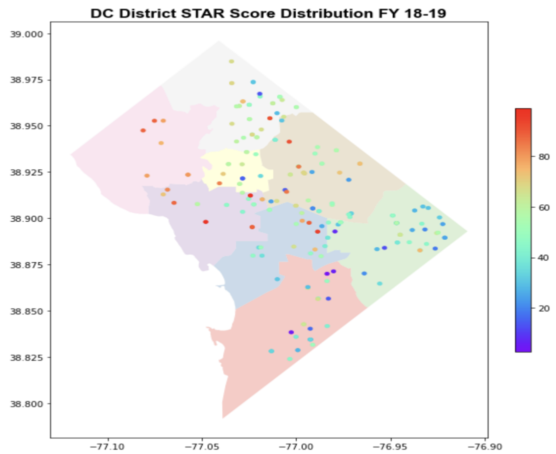

Fig. 1. Distribution of STAR Score in DC FY 18-19

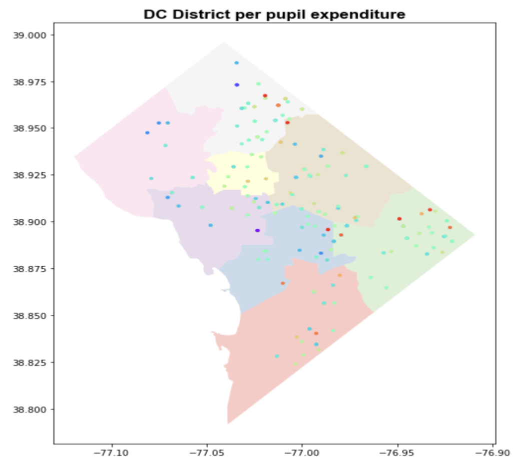

Fig. 2. Distribution of Expenditure in DC FY 18-19

Figure 1 shows the distribution of STAR Score in the DC area. From this figure, you can see that schools in wealthier communities like Georgetown and Foxhall village tend to have a higher STAR Score while schools in the downtown and East part of DC are underperforming. Showing that the quality of the school seems to align with the affluence of the community. Going forward, we would like to know whether this disparity in school performance is related to the disparity in school expenditure.

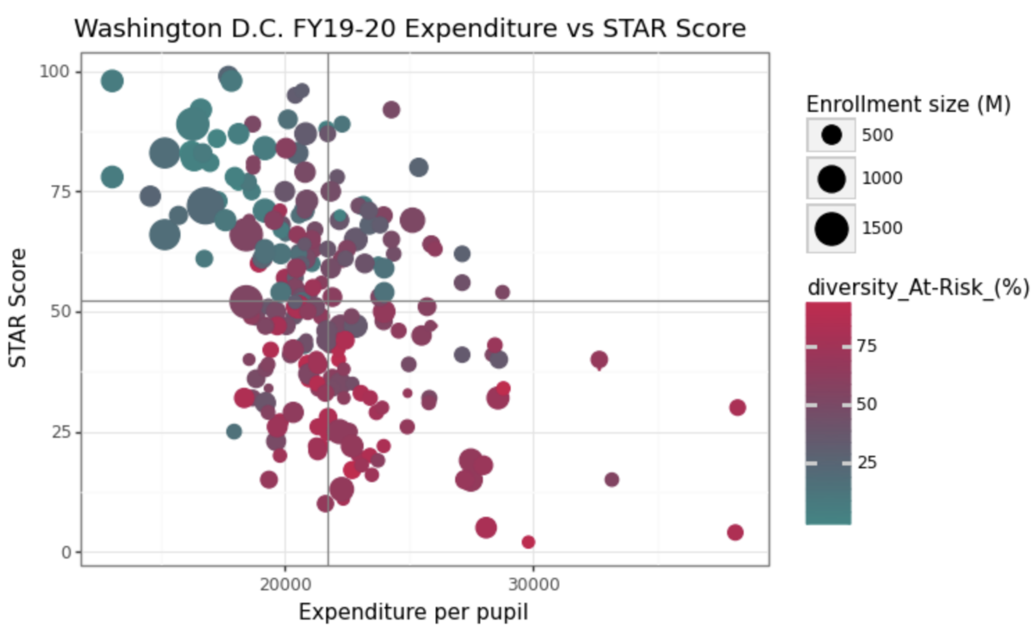

Fig. 3. FY18-19 STAR vs Expenditure

Figure 3 show the relationship between STAR Scores and Expenditure. It is clear that there is a negative correlation between expenditure and STAR Score. Schools with a higher percentage of "at-risk" students tend to receive more funding and have higher per-pupil expenditures while still having lower STAR Score. The STAR Score of most schools with a higher “at-risk” percentage are below the average score.

We would like to know if giving more expenditure to those underperforming school help them improve at a higher rate than their high income peers. So going forward, we will analyze the change rate of STAR Scores and expenditures.

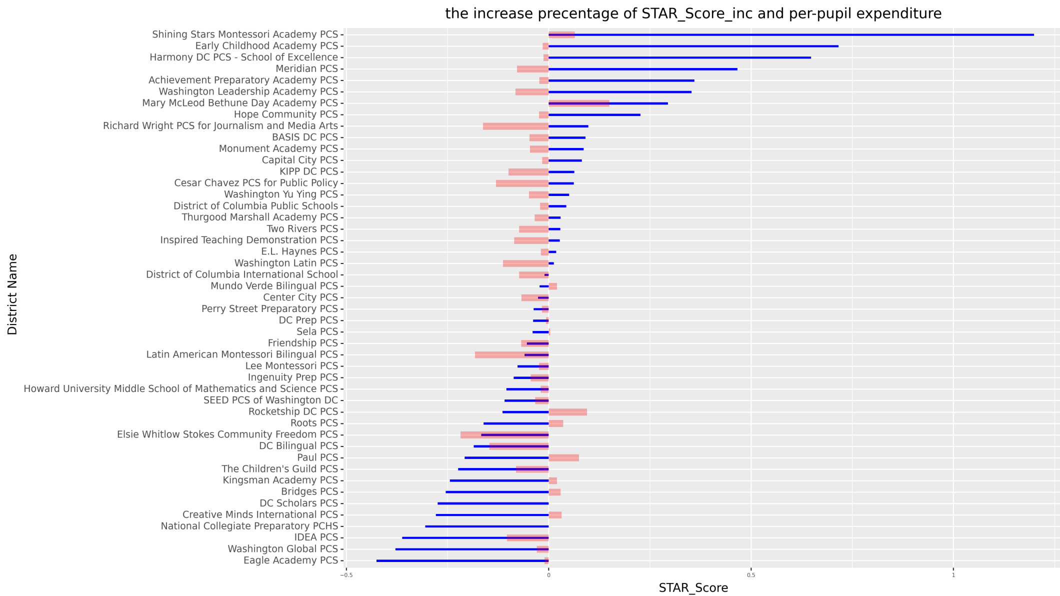

Fig. 4. Change rate of STAR and expenditure of every school district

Figure 4 compares the change rate for STAR score and per-pupil expenditure. School districts are sorted in descending order by STAR Score change rate. Looking at this visualization, there is not a clear pattern between the change rate of STAR Score and the change rate of expenditure. Meaning that only changing the per-pupil expenditure will likely not have an immediate effect on performance. One of the reasons can be the layback effect, where expenditure increases may take some time to actually take effect. It is also possible that money is not t being used correctly or efficiently.

Key Findings.

Our findings show that from FY 2019 to FY 2020, most schools who showed a change in per-pupil expenditures did not have a significant change in STAR scores, i.e. the schools' overall performances. Therefore our original hypothesis was incorrect, and per-pupil expenditure is not positively correlated with STAR scores.

Meanwhile, a comparison between the distribution of school level STAR scores and each school's per-pupil expenditure in these two fiscal years shows that under-performing schools, which are primarily located in Wards 7 and 8, were already receiving more funding even before the onset of the pandemic.

In order to show that these schools were given more funding due to the average student income, we conducted regression analysis on school level STAR Scores, per-pupil expenditures, the enrollment rate, and the percentage of "at-risk" students of each school in 2019. We found that on the school level,

- the STAR scores are negatively correlated with both per-pupil expenditures;
- it also negatively correlated with the school's enrollment;
- the per-pupil expenditure is positively correlated with the percentage of "at-risk" students.

Table 2. Correlation Matrix of important variables

Variable	Enrollment Size	Expenditure	At_Risk%	STAR Score
Enrollment Size	1	-0.26	-0.30	0.28
Expenditure	-0.26	1	0.39	-0.42
At_Risk%	-0.30	0.39	1	-0.68
STAR Score	0.28	-0.42	-0.68	1

These results shed light on the strains public-funded schools have been facing even before the COVID pandemic. The schools' lower STAR scores seems to connect to low enrollment and a high percentage of "at-risk" students. Additionally, most of these struggling schools are concentrated in wards 7 and 8 which are historically lower income.

We cannot be exactly sure why school performance is not increasing alongside increasing per-pupil expenditure and funding as previously expected. Further research led us to understand that this lack of a relationship may be related to the long-standing structural dilemma of funding DC public schools.

Discussion

A closer look and DC education funding.

DC's education funds are allocated based on a formula. The Uniform Per Student Funding Formula (UPSFF) is used to determine annual operating funding for the District's traditional and charter public schools... The UPSFF ensures that every District of Columbia public school student is funded at the same level, regardless of that student's choice of public school. The UPSFF also de-politicizes the funding process by providing a defined, stable, and predictable budgetary structure. Finally, the UPSFF, by linking funding to enrollment, creates competition in the education arena that encourages meaningful school improvement.(6)

However, a nonpolitical and objective approach to funding allocation does not guarantee overall educational equity. According to DC Fiscal Policy Institute's report of 2019 "Educational Equity Requires and Adequate School Budget," the approved education budgets continuously "fails to provide adequate resources" to meet the needs of the students in the public school system.(7) While the UPSFF may guarantee that all public schools get fair fundings proportionate to their enrollment, the total education budget "appears to be built largely around spending constraints" instead of schools' needs. In 2019, the DC's education budget had been "consistently below the recommended level in the DC Education Adequacy Study" for the past seven fiscal years and failed to cover the rising personnel costs in public school. The consequences of this funding shortage affected low-income, racially diverse areas the most, such as Wards 7 and 8. Many schools there were facing budget cuts of five percent or more, which would violate DC Code. Funding shortage may result in enrollment decline, which in turn would cause even lower funding for the next year according to the funding formula. Among the 19 schools that had deep budget cuts in 2019, 15 of them were in Wards 7 and 8, where the public schools serve a disproportionate share of Black and Latinx students and students from families with low incomes.

The COVID-pandemic makes the funding shortage problem even starker. In FY 2022, many schools relied on one-time federal relief funds, the Elementary and Secondary School Emergency Relief (ESSER) to navigate through the fiscal difficulties caused by the pandemic. According to a recent report, many schools are facing potential "fiscal cliffs" as the federal funds will be gone with the peak of pandemic. The DC Mayor has proposed a 5.9 percent increase (not inflation adjusted) to the UPSFF and a suite of funds to stabilize school budgets that may drop by five percent or more for FY 2023. Also, schools will have more discretion over how they use their funding. However, the new budget model may still fall short on addressing structural funding inadequacy and inequity.(8)

An even more fundamental and perennial problem behind the funding problem is the income segregation in DC schools. Three factors that contribute to the income segregation include attendance boundaries, the use of private schools, and migration to surrounding areas such as Maryland and Virginia. Attendance boundaries determine which schools a student can attend based on where they live, and which area people live is usually decided by income levels. If low-income families are concentrated in certain areas of the city, they may be more likely to attend schools with a high concentration of low-income students. This can create a cycle of poverty in which students from low-income families attend schools with fewer resources and lower academic achievement, hence more likely to fall into the "at-risk" category, making it more difficult for them to succeed.

The use of private schools and charter schools can also contribute to income segregation. Private schools and charter schools can have selective enrollment processes and admission criteria. This can make it difficult for low-income or "at-risk" students to access these schools and get the chance to get out of the cycle of poverty.

Additionally, migration to surrounding areas, such as Maryland and Virginia, which is know for high quality public education, can also worsen the fiscal situation of the low-performing public schools in DC and further drain the education funding resources of the District in general.

Limitations and further research.

Limitations of this research:

- The timeframe of our data is limited to a two-year span and prior research found that it took multiple years for increased expenditures to take effect.
- We focused on public funding for the District but did not include federal or private sources, which for some schools might be financially essential.
- The COVID pandemic may have brought significant changes to school's fiscal needs because of the need for remote teaching/learning. We can't capture these changes because of the lack of related data.

Things to address in future research:

- Lower enrollment could be a reasonable explanation for the shrinking total budget, but why is per-pupil spending also decreasing in D.C.?
- What is the families' role in supporting public education and how can families, schools, and governments put up joint efforts to address the problem of educational inequity?

1. Mervosh, Math scores fell in nearly every state, and reading dipped on national exam (https://www.nytimes.com/2022/10/24/us/math-reading-scores-pandemic.html) (year?).
2. M Kuhfeld, J Soland, K Lewis, Test score patterns across three covid-19-impacted school years. *EdWorkingPaper: 22-521* pp. 37–62 (2022).
3. J Hodge, Statement from education reform now dc on the fy23 budget (2022).
4. CK Jackson, C Mackevicius, The distribution of school spending impacts, (National Bureau of Economic Research), Technical report (2021).
5. J Lafortune, J Rothstein, DW Schanzenbach, School finance reform and the distribution of student achievement. *Am. Econ. Journal: Appl. Econ.* **10**, 1–26 (2018).
6. Uniform per student funding formula (https://www.focusdc.org/uniform-student-funding-formula.) (2020).
7. A Noth, Educational equity requires an adequate school budget, (2019).
8. Q Huddleston, New dc public schools budget model makes progress towards more transparency and flexibility (https://www.dcfpi.org/all/new-dc-public-schools-budget-model-makes-progress-towards-more-transparency-a (2022).