A Python-Driven Analysis of the Relationship between Local Authority spending in the UK and Year 4 Students' Results in the New Multiplication Test Check (MTC)

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1. Introduction

1.1 Education spending in the United Kingdom

It is not surprising that when funding per pupil in increased, student outcomes improve. An increase of £1000 in spending per pupil each year has been shown to increase test scores at the end of primary school by 0.3 standard deviations (Gibbons et al., 2017, p.1638). A student's knowledge of multiplication and fractions at primary school can be used to predict their ability in more complex concepts like algebra in secondary school (Seigler et al., 2012, p.693). Complex mathematics is used in all STEM subjects (science, technology, engineering and mathematics) so if we are to encourage more students to choose these subjects for further education we must make sure that from an early age we help students develop the mathematical skills that they need to be able to study these subjects with enjoyment. Furthermore, it has been well documented that jobs in STEM fields have significantly higher average salaries and adults with these STEM skills are more likely to find employment (Okrent and Burke, 2021, p.7). In light of the competition for funding across all government departments, it is essential that there is a wealth of up-to-date evidence confirming the correlation between increased spending in education and academic results so that current and future governments can be confident that money spent on education, particularly in early years, is a good investment for the future.

1.2 UK Multiplication Tables Check

In June 2020, the Department of Education (DoE) of the United Kingdom (UK) implemented the Multiplication Tables Check (MTC), a standardised test for all Year 4 students in the country. In the UK, year 4 students are generally aged 8 or 9. According to the UK Standards and Testing Agency, the purpose of the check is to evaluate fluency with multiplication tables and determine if a student needs extra support before starting secondary school in year 7 (age 11 or 12). Good recall of multiplication tables is important for more complex mathematics that students will encounter at secondary school. This includes operations with fractions, algebra, calculus and many other topics. Individual schools will have access to the information from the test, allowing them to identify the students that need support.

Given the importance of education spending, this paper aims to use the Python programming language to examine the relationship between education spending by local authorities in the UK and year 4 students' results in the new Mathematics Test Check (MTC). Specifically, the paper will explore the extent to which education spending is associated with student achievement in primary schools. It will focus specifically on the UK and the unique funding structure that is in place there, with a view to analysing its effectiveness and to provide meaningful insights that can inform policy and practice at both national and local level.

1.3 The Python Programming Language

Python is a common programming language known for its simplicity, and it's ability to be learned easily. It was first released in 1991 and has since become one of the most popular programming languages and is used extensively in the field of Data Science. Python is highly readability and has a vast community of developers constantly creating libraries and tools, which makes it a very powerful language for data analysis. Python was the chosen programming language for this paper due to its extensive set of libraries and tools, including NumPy, Pandas, SciPy, Matplotlib, and Seaborn, which made the process of preparing, analysing, and visualizing the data very straightforward. Its versatility and wide range of libraries make it an ideal language for working with large datasets, such as the ones used in this project. The code made use of the Pandas library for the preparation of the data and the Matplotlib and Seaborn libraries for the visualization of the data. By using Python, I was able to easily and efficiently analyse the data and present the results in a highly readable manner. Additionally, the code is reusable, which allows for future updates to the data, which changes on a yearly basis, to be analysed with the same code, ensuring the results can stay up-to-date.

2. Main Body

2.1 Background

2.1.1 UK School Funding

When analysing the correlation between school funding and the results in the MTC we must take into account how schools are funded in the UK, and how adjustments are made to compensate for geographical difference or performance data. The UK government allocates school funding on a per-pupil basis through the National Funding Formula (NFF). The NFF takes into account factors such as location (to account for higher staff costs), how many disadvantaged students there are (how many students at a school are eligible for free school meals), and the number of students that have low attainment as measured by the Early Years Foundation Stage Profile assessment (EYFSP)[1]. In 2020, 4.8% of the total core funding (£1.2 billion) was allocated to primary schools where students have low prior attainment, with a view to this money being used to improve attainment rates. A result of the NFF is that different areas in the country can attain markedly different amounts of funding. To put this into context, the local authority in Hackney, London, has spent, on average £7600 per pupil each year over the past 7 years, whereas, Kingston upon Hull has spent £3800 over the same period. There is even considerable difference within London itself where the difference in spending between the highest spending local authority and the lowest is £2900 per pupil. How, therefore, should we interpret the data knowing that some areas receive considerably more funding than others? Should we expect this to impact the correlation between funding and results in the MTC?

[1] The Early Years Foundation Stage Profile assessment is used to measure students' attainment before they enter primary school.

2.1.2 How the NFF Impacts Our Results

If the National Funding Formula (NFF) works correctly, we should expect to observe an equitable distribution of educational resources and opportunities across the country, irrespective of geographical location. That is to say, that we should *not* observe a drastic difference in test scores around the country that correlate with distribution of funds. We should find that a students' education is not disadvantaged because of their locale. It is helpful to imagine that areas receiving more funding through the NFF are not technically receiving extra money, rather getting the amount they need based on the parameters of the NFF. Therefore, if London local authorities have higher test scores, it shouldn't be ascribed to additional funding they receive. However, if students in London, for example, perform better in the MTC than their compatriots outside the capital, there are two possible interpretations. First, the NFF might be overestimating the funding needed per student in local authorities. Alternatively, there could be another factor unrelated to funding that results in better test scores in the MTC in London. As such, we will analyse data in a manner that considers these possibilities. We will create data sets that both include and exclude London data, in addition to evaluating London independently. This approach will allow us to see the influence of these factors on student performance. It will also allow us to verify if any correlation seen across the country as a whole is found when the smaller subsections are analysed.

2.2 Methodology

The aim of this investigation is to determine what the correlating factors are, in regard to spending, that affect primary school aged children learning of multiplication tables. The research will focus solely on the UK and will compare regional spending data with results in the MTC. The analysis will hopefully shed light on whether the NFF distributes funding effectively and if any correlation between spending and results is reflected in Nursery (pre-school) funding also.

2.2.1 Data Sources

All the data was freely available on the UK government website[2]. The two primary sets of data consisted of the MTC attainment data[3] and the spending data for local authorities and schools[4]. In both cases, the data was the most recent data available. Once it was downloaded, it was prepared. First, the MTC attainment data was prepared. After cleaning, the set consisted of the average mean score in the MTC of all pupils for each local authority. This meant removing much data related to gender, ethnicity and disadvantaged status as these were not within the score of the investigation. Secondly, the separate spending data consisted of figures going back to 2015. To be able to compare the data clearly, in each of the expenditure categories that we would be analysing the mean spending figure per pupil was calculated for the 7 financial years that were included in

[2] www.gov.uk
[3] explore-education-statistics.service.gov.uk/find-statistics/multiplication-tables-check-attainment/2021-22

[4] explore-education-statistics.service.gov.uk/find-statistics/la-and-school-expenditure/2021-22

the original data set. The spending data was already broken down into various expenditure categories. Three expenditure categories were chosen to compare to the MTC results: Total net expenditure; teaching staff expenditure; supply teaching staff. These categories were chosen because it was felt that they would be most likely to impact results in the MTC. The python code that was written to analyse the data makes further study of other categories extremely easy and will be reused for further study. To calculate the correlation between the MTC attainment and the different expenditure categories, a linear regression was performed and the r-value calculated. The p-value was also calculated to determine the level of statistical significance, with a p-value of less than 0.05 being considered statistically significant.

2.2.2 Preparing the Data Using Python

Python was chosen as the means for extracting and analysing the relationship between funding and MTC attainment. Python's extensive set of libraries and tools, including NumPy, Pandas, Matplotlib and Seaborn made the process of preparing, calculating and visualising the data very straightforward. The code made use of the Pandas library for the preparation of the data. To be able to reuse the code to analyse the different spending categories, some input prompts were placed at the beginning of the code. The prompts asked for the following information: Type of expenditure, e.g. supply teaching staff expenditure; whether to include, exclude or use just data from London; and finally whether to analyse expenditure from Nurseries or Primary schools. The original CSV files were loaded into pandas data frames, which could then be used to remove unnecessary columns and rows, calculate the mean expenditure for each chosen category and to merge the data frame containing the MTC scores with the data frame that included the spending information. The merged data frame consisted of the local authority name, their mean score in the MTC and the mean expenditure of the chosen category over the last 7 years. At this point, the code saved a copy of the merged data frame to a CSV file so that it can be read manually to check for anomalies. To calculate the linear regression, the stats.linregress() method was used. This method, from the SciPy library, calculated the slope and the intercept of the linear regression function, which would be used to visualise the correlation on a graph that would be generated, the r-value (Pearson correlation coefficient) as well as the p-value using Wald Test with t-distribution of the test statistic. The calculation of the Pearson correlation coefficient by python, which was done much faster than could have been done manually, greatly reduced the time needed to analyse the data and allowed for multiple data sets to be analysed.

2.2.3 Visualising the Data Using Python

Using a combination of the Matplotlib and Seaborn libraries, the code produced an easy-to-read scatter graph with the expenditure on the x-axis and MTC results on the y-axis. The function of the linear regression was placed on the same graph. Finally, to make the data more readable, the matplotlib.pyplot.annotate() method placed the r-value and the p-value onto the graph in a

separate text box. The resulting graph was then saved to a PNG file within the same directory. As with the calculation of the Pearson correlation coefficient, Python's ability to quickly and efficiently render these graphs saved a vast amount of time and allowed for more data to be explored. The Matplotlib library is a basic library for creating graphs that is very easy to use and flexible. It was chosen to create the scatter graphs including the MTC and spending data, onto which the previously calculated linear regression could be placed. It was also possible to annotate the graphs with the r and p values that had been generated with the aforementioned method, which resulted in better readability. Seaborn was chosen to style the data points on the graphs, specifically the colour of the scatter points and regression line, the background colour of the plot, the font size of the labels, and the style of the grid. The combination of the Matplotlib and Seaborn libraries allowed for greater flexibility and customization in creating the graphs, while also providing the ability to create more visually appealing and informative visualizations. It is worth noting that similar results could have been achieved by using the Matplotlib library exclusively. The motivation for using both libraries for the visualisation was to demonstrate the flexibility of the libraries and the Python programming language as a whole. In creating the graphs three separate libraries were used (Matplotlib, Seaborn and SciPy), yet the amount of code that was needed to generate them was minimal.

2.2.4 Strengths of the methodology

All data used in this test has been taken from a highly reputable source, is up-to-date and importantly is freely available for others to replicate or conduct further research on. Meanwhile, the use of python and it's associated libraries meant that the analysis could be done efficiently and accurately. The visualisations that were easily rendered by the python code are reader friendly, and any user can quickly create new graphs using different data. The inclusion of a number of different local authorities and the ability to exclude London from the data allowed for a more nuanced understanding of the relationship between the data, and means that we could check to see if any correlations that occurred in one part of the country were also found in another. The focus on specific expenditure categories allowed for a more targeted analysis of the impact of spending on MTC attainment.

2.2.5 Limitations of the Methodology

There are some limitations however to the methodology that could be rectified with further study. For example, the study only explores the relationship between spending in various categories and attainment in the MTC, which looks at primary year 4 students' ability to recall times tables up to twelve. This does not give a full picture of the relationship between funding and overall educational outcomes. The study does not explore other factors that might influence results in the MTC such as teacher quality, home situations of children and regional cultural factors. Finally, at the time of

writing, inflation in the UK is over 10%[5]. This paper does not consider the potential impact that above average inflation might have on school spending and student outcomes.

2.3 Results

The python code generated various results. *Table 1* shows the correlation between the chosen spending categories in primary and nursery schools and the results in the MTC together with the p-values.

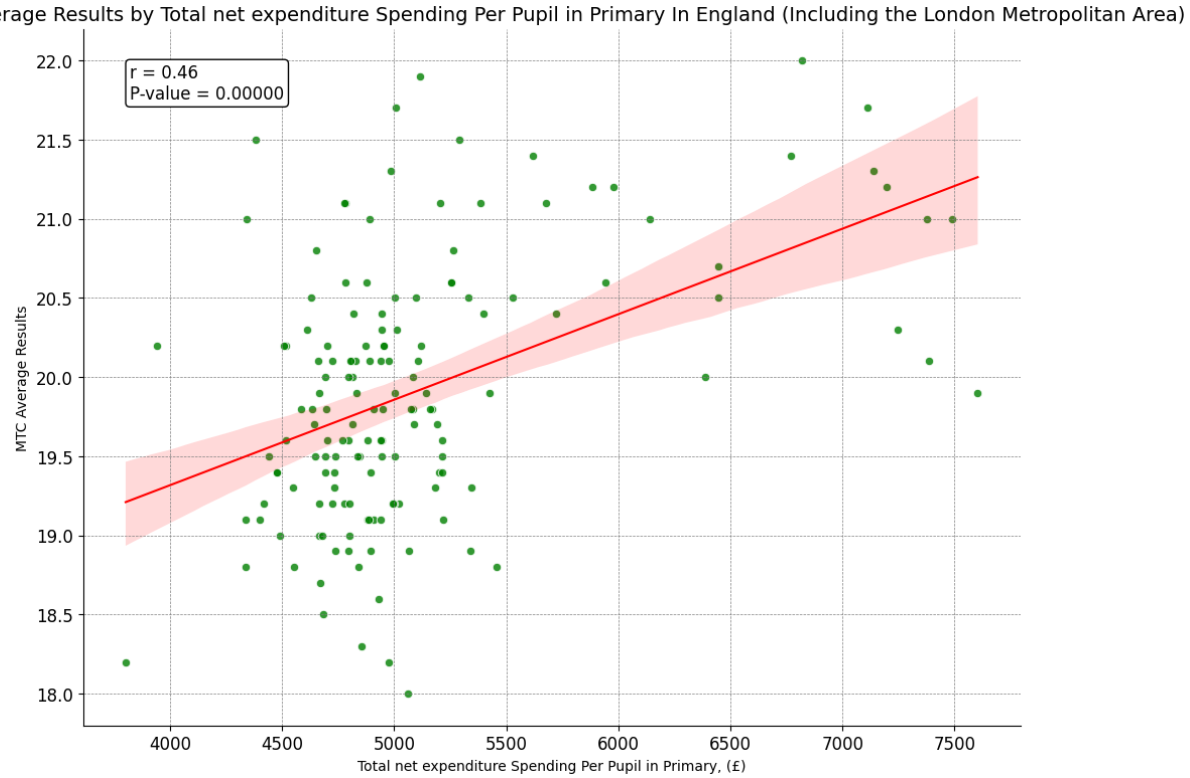
	Primary					
	UK Including London		UK Excluding London		London	
	r	P-value	r	P-value	r	P-value
Total Net Expenditure	0.46	0.00	0.06	0.51	-0.05	0.81
Teaching Staff	0.45	0.00	-0.02	0.80	-0.04	0.83
Supply Teaching Staff	-0.45	0.00	-0.29	0.00	-0.22	0.22

	Nursery					
	UK Including London		UK Excluding London		London	
	r	P-value	r	P-value	r	P-value
Total Net Expenditure	0.28	0.00	-0.07	0.52	0.07	0.73
Teaching Staff	0.33	0.00	0.20	0.07	-0.06	0.76
Supply Teaching Staff	-0.07	0.45	0.07	0.54	-0.16	0.45

Table 1: Correlation and p-values of expenditure categories with MTC results.

As the table shows, any correlation in Primary was echoed in Nursery to a weaker extent. This suggests that spending in primary school has a bigger impact on students' ability to learn multiplication tables than spending in nursery. This makes sense considering that in the UK, children don't formally start learning any calculation skills until they start primary school.

[5] https://www.ons.gov.uk/economy/inflationandpriceindices/bulletins/consumerpriceinflation/march2023#:~:text=a%20year%20earlier.-,The%20Consumer%20Prices%20Index%20(CPI)%20rose%20by%2010.1%25%20in,of%2011.1%25%20in%20October%202022.



2.3.1 Total Net Expenditure and Teaching Staff Expenditure to MTC Test Results

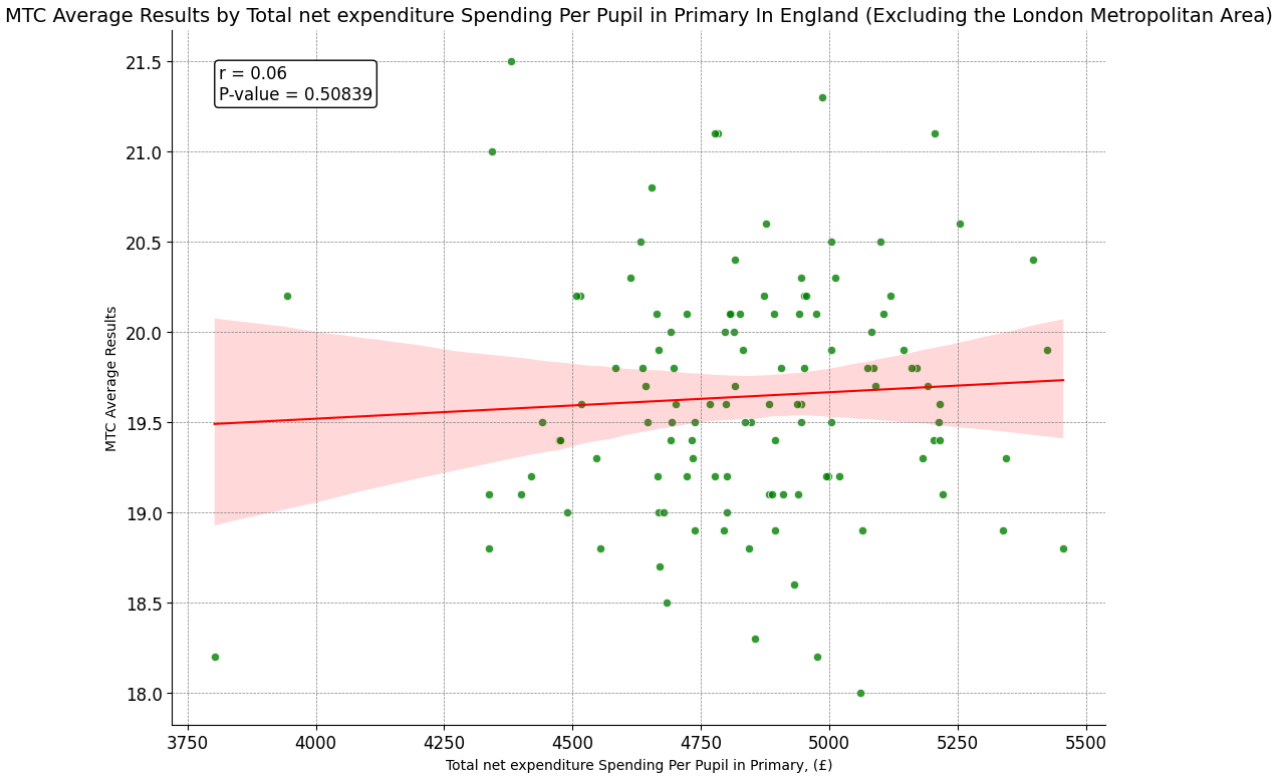
As highlighted before, the additional funding allocated to London Local Authorities via the NFF shouldn't influence the average scores at the MTC. This extra funding merely reflects the increased operational costs in London's metropolitan area, where teacher salaries and other school-related expenses borne by local authorities are typically higher than in other regions of the country. However as the graph above shows, when we look at the UK as whole, there is a statistically-significant positive correlation between net expenditure and MTC test results, albeit a moderate one of r=0.46. We see a similar statistically-significant correlation (r=0.45) between teaching staff expenditure and test results in the MTC. Firstly, we should determine if these correlations are the result of average test scores being higher in London.

	Mean MTC Score
UK including London	19.9
UK Excluding London	19.6
London	20.9

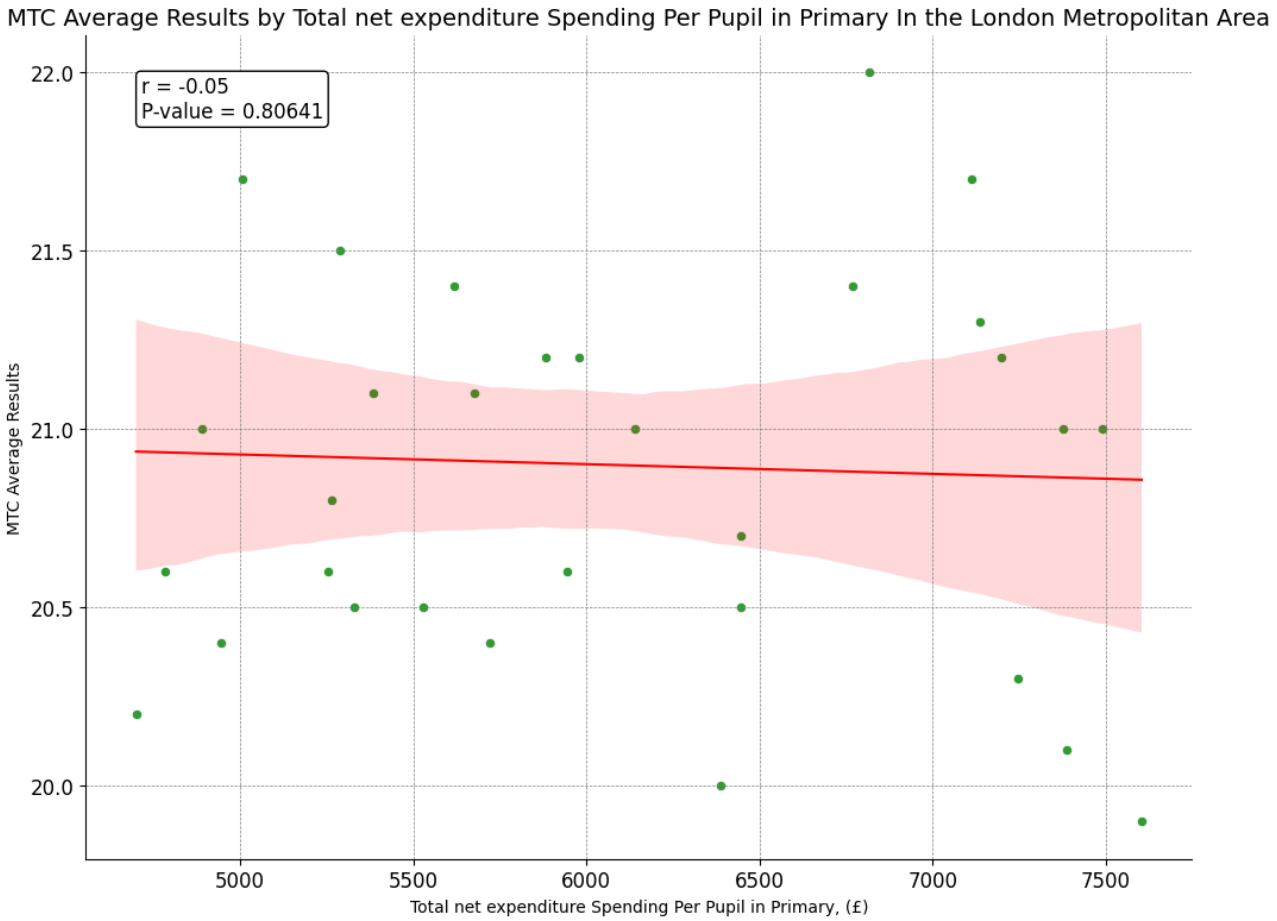
Table 2: Average MTC score by geographic region

Table 2 shows that students in London scored over 1 point (out of a total of 25) higher than their fellow students outside the nation's capital. Therefore, the correlation of 0.46 *is* attributable to the increased test scores and funding in London. Before any conclusions can be drawn, we should investigate if the difference in test scores can be attributed to the increased spending, or if another factor is at play. Using the data that we have produced, there is a way that this can be done. If it

were the case that schools in London get higher scores because they receive more money, we should expect to see similar correlations in the data that excludes London local authorities and the data which is exclusively from London local authorities. This is because within these areas of the country there are also, due to the NFF, vast differences in funding and in turn, expenditure. This as much as £2900 per pupil per year. The differences in spending are not as drastic as when London is included in the national data, and as such we should not see as strong a correlation as when London is included in the UK data as a whole. However, we would expect to see that the local authorities that receive more money through the funding formula in these areas are also getting higher results in the MTC. This is not the case.



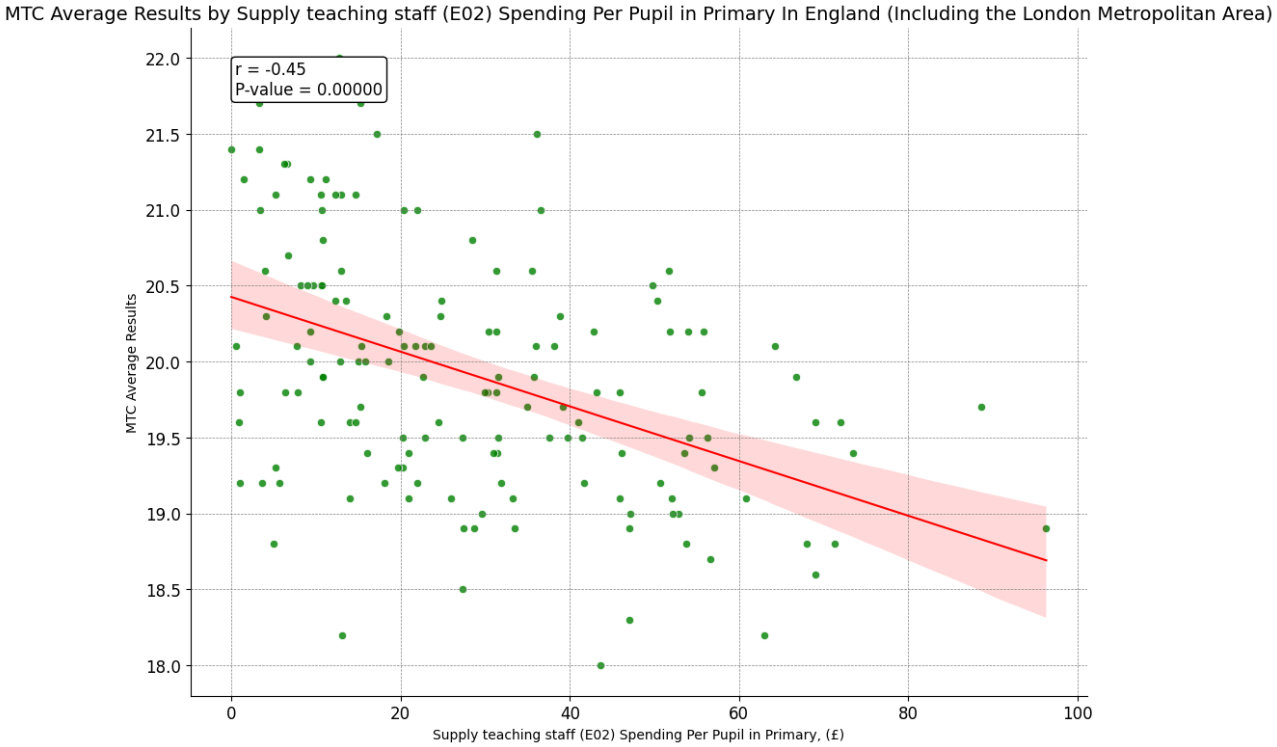
As table 1 and the graphs above show, total net expenditure and teaching staff expenditure were not shown to have any statistically significant positive correlation to MTC scores in the UK when London was excluded from the data. Here we observe that the Pearson correlation coefficient is only 0.06 with a p-value of 0.5. No statistically significant correlation is found when results and spending in London local authorities are compared either.



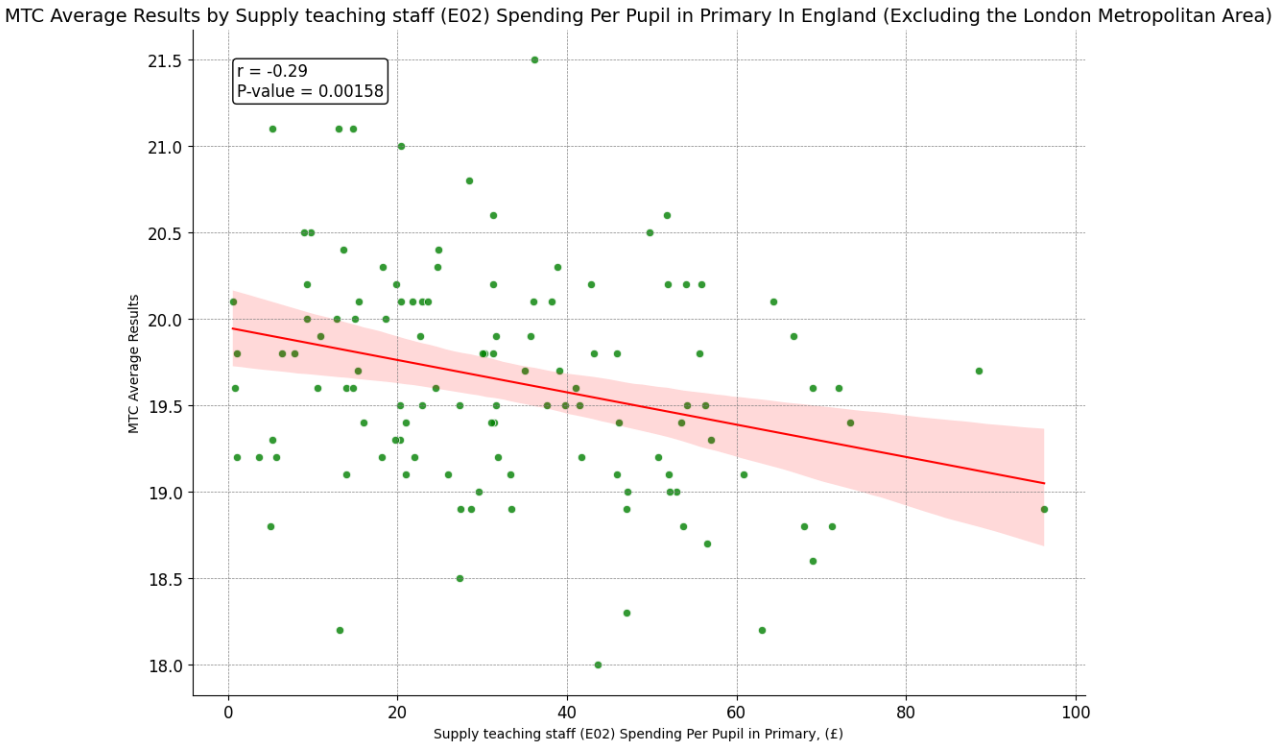
Therefore, I believe that there must be another factor that leads to students in London obtaining higher scores in the MTC, which should be investigated further. This finding could also be used to argue that the NFF is distributing funds evenly across the country.

2.3.2 Supply Teacher Spending to MTC Results.

When comparing the impacts of supply teacher spending on average scores in the MTC, there was a moderate, statistically-significant negative correlation (r=-0.45) in the UK with data from London included, as shown in the graph below.



However, unlike the Total net expenditure and teaching staff expenditure data, this correlation was also seen outside of London. The data in the UK excluding London showed a weak, statistically-significant negative correlation (r=-0.29) between supply teaching staff expenditure and MTC results.



Furthermore, in London there was a weak negative correlation (r=-0.22) but with an elevated p-value (p=0.22). This is probably due to the fact that there were fewer data included in the analysis, as there are fewer local authorities in London. The negative correlations suggest that

students get lower scores in the MTC if their school has had to spend more money on supply teachers. These findings shouldn't reflect negatively on supply teachers, but instead should highlight the importance of consistency in primary school education and how disruption can lead to worse outcomes for students. Furthermore, this supports work carried out by Hutchings et al. in 2006 that found that in schools where students receive higher GCSE[6] grades fewer supply teachers are used (Hutchings et al., 2006, p.v). Schools have to spend money on supply teachers to make up for shortfalls in their permanent staff who might be sick, on paternity or maternity leave or if they are simply unable to find a permanent teacher for the position. Regardless of the reason for the hiring of a supply teacher, the result for the student is disruption in their learning as a supply teacher, by the nature of the position, is not going to be able to provide, the important individualisation of teaching that can only come when a teacher knows a student well. This is particularly important when students are learning their multiplication tables.

3 Conclusion

3.1 Higher Scores in London

In summary, there were two key findings in the data we analysed. Firstly, that there is a factor that was not uncovered by this research, that leads to higher MTC results in London compared to the rest of the county. It could not be concluded that this was due to local authorities in London being allocated more through the NFF. In fact, when specific areas of the country were analysed this was not the case, no correlation was found. The same code, that was used to prepare the data for this paper, could easily be modified to explore what other factors might advantage students in London. This might include the number of disadvantaged students, gender or even cultural differences. This data can be found within the original CSV files. Policymakers may want to investigate further to understand what these factors are and consider ways to replicate them, where possible, in other parts of the country.

3.2 Supply Teacher Spending

Most importantly, I found that spending on supply teachers is negatively correlated with results in the MTC. This provides, hopefully, useful evidence to support the argument that local authorities and the UK government should prioritise teacher retention. According to recent research by the National Foundation for Educational Research (McLean et al., 2023, p. 20), 20% fewer teachers were recruited into the profession in 2022 than in the last year prior to the pandemic. The paper points to the falling competitiveness of pay and working conditions, citing that pay for teachers in the UK in 2021/22 was 12 per cent lower, when adjusted for inflation, than it was 10 years ago. Higher expenditure on supply teachers is a symptom of the problems that McLean et al. cite. Our findings suggest that increased disruption in a child's learning due to teacher shortages can lead to poor academic outcomes. Learning times tables is a skill that relies heavily on memory, and

[6] GCSE are a national exam that students take around the age of 16 in the UK.

teachers need to have a good understanding of their students' abilities and learning styles in order to provide effective support for them in mastering this foundational concept.

3.3 Potential Impact

The research has shown moderate and weak, statistically significant, correlations, whether positive or negative, between different expenditure categories and performance in the Multiplication Tables Check (MTC). However, as highlighted in the introduction, mastery of multiplication tables is essential for understanding many mathematical concepts that students will encounter in their future studies. Any small differences in a student's ability to perform these calculations in Year 4 can have far-reaching consequences for their future academic development. Therefore, I believe that moderate and even weak positive correlations should still be worthy of consideration. The UK Prime Minister, Rishi Sunak, has recently proposed that students should study maths until the age of 18, putting the UK more in line with other developed countries. It is therefore crucial that policymakers in the UK consider ways to support students and schools in promoting a love of maths and ensuring that children can engage with it effectively. The study of complex mathematics can be a rewarding and stimulating endeavour, but only if you have the prerequisite calculation skills needed to be able to do so. There may be a vast number of students in the UK and internationally that would have gone on to have enjoyed complex mathematics at secondary school and beyond if they had developed their ability to multiply further. As a result, they may have even improved their own economic prospects as adults. If schools and policymakers can find a way to discover these students and provide them with the extra support they need, there could be a significant boost to the UK economy as a result.

3.4 A word on python.

As discussed, further investigation of this topic using information in the same files could lead to significant insights into how money should be spent by authorities to help primary students to learn their times tables. By using the python coding language and its affiliated libraries this can be done easily and efficiently and allows for the results, as seen above, to be presented in a highly readable manner. This is tremendously beneficial for two reasons. Firstly, it is important that any findings, in the form of graphs or tables, can be presented in such a way that they can be understood easily by policymakers and the public as a whole. Python allows us to do this with very few lines of code. Secondly, the code is reusable and as such can stay up to date. Within a year, the financial figures and the MTC results will be updated. When this happens, the new dataset can be easily analysed using the same code.

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