Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

Sondre Børslien Krogh
Haider Slyngstad Billaud Qureshi

Does green spaces affect learning outcomes?

An empirical investigation into the effects of green spaces on national test results among fifth graders in Norway

Master's thesis in Economics
Supervisor: Doriane Mignon and Irmelin Slettemoen Helgesen
June 2023

NTNU
Norwegian University of
Science and Technology

Sondre Børslien Krogh
Haider Slyngstad Billaud Qureshi

Does green spaces affect learning outcomes?

An empirical investigation into the effects of green spaces on national test results among fifth graders in Norway

Master's thesis in Economics
Supervisor: Doriane Mignon and Irmelin Slettemoen Helgesen
June 2023

Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

NTNU
Norwegian University of
Science and Technology

Abstract

The purpose of this thesis was to analyze the existence of a link between the amount of green space around primary schools, and academic achievement among Norwegian fifth graders. The analysis was conducted using a novel panel data set consisting of test results from the national tests in math, English and reading, taken by Norwegian fifth graders, average forest, shrub and herbaceous vegetation land cover maps derived from the Copernicus Global Land Service, and a set of control variables controlling for geographic and socio-economics status. The data consists of around 5270 observations from 1503 schools spanning from the year 2015 to 2019.

Our main findings is identifying small, but statistically significant, positive associations between average percentage of forest cover within 2500 and 1000 meters of schools on math and English test scores. We find that a one percent increase in mean forest cover within 2500 meters of a school is associated with a 0.099 point increase in math scores, and a 0.097 point increase in English scores. Within 1000 meters, the same increase in mean forest cover is associated with a 0.098 point percent increase in math scores. We account for heterogeneity across schools and time by estimating a regression model with unit and time fixed effects, and calculate cluster robust standard errors. A big contribution of the thesis is also the construction of a novel data set which is used to do the first analysis of this kind on data from Norway.

The main limitations of our findings is a probable bias in the parameter estimates as a result of missing and dropped data, as well as a lack of rigorous sensitivity analysis.

Sammendrag

Formålet med denne masteroppgaven har vært å analysere om det eksisterer en sammenheng mellom mengden grøntarealer rundt norske barneskoler og femteklassingers prestasjoner på nasjonale prøver. Analysen ble gjennomført ved bruk av et nytt paneldatasett som inneholder informasjon om norske femteklassingers prestasjoner på nasjonale prøver i lesing, regning og engelsk, gjennomsnittlig dekke av skog, gress og buskas i områder rundt norske barneskoler, i tillegg til et sett med kontrollvariabler som kontrollerer for geografiske og sosioøkonomiske forhold.

Våre hovedfunn bekrefter en liten, men statistisk signifikant, positiv sammenheng mellom skogsdekke innenfor 2500 meter og 1000 meter fra skolene og prestasjonene i matematikk og engelsk. Vi fant at en én prosent økning i gjennomsnittlig skogsdekke innenfor 2500 meter fra en skole er assosiert med en økning på 0.099 poeng på matematikkprøven og en økning på 0.097 poeng på engelskprøven. Innenfor 1000 meter var en tilsvarende økning kun assosiert med en økning på 0.098 poeng på matematikkprøven. Vi tok hensyn til variasjoner mellom skoler og over tid ved å anvende en regresjonsmodell med faste effekter for enheter og tid, og vi beregnet klusterrobuste standardfeil. En viktig bidrag fra denne masteroppgaven har vært konstruksjonen av et nytt datasett, som vi brukte til å gjennomføre den første analysen av sitt slag med data fra Norge.

De viktigste begrensningene ved resultatene våre er sannsynligvis tilstedeværelsen av parameterestimater som ikke er helt presise på grunn av manglende og tapte data, samt fraværet av en streng sensitivitetsanalyse.

Preface

This master's thesis signifies the culmination of a long academic journey in the field of economics at NTNU in Trondheim. The process of working on this thesis has been time-consuming and challenging, but above all, immensely educational.

First and foremost, we would like to express our sincere gratitude to our supervisors, Irmelin Slettemoen Helgesen and Doriane Mignon. Their invaluable guidance and insightful perspectives have played a pivotal role in shaping this master's thesis. Their expertise and unwavering dedication have significantly contributed to the quality of our research and consistently kept us on track.

We are grateful to our fellow classmates for their active engagement, stimulating discussions, and collaborative efforts that enriched our academic journey. Their contributions greatly enhanced our learning experience.

Finally, we would like to express our thanks to Høyskoleparken for providing us with the green space that has contributed to our academic achievements in mysterious ways.
Tronheim den 15. juni 2023.

Contents

1 Introduction

"The challenge for Norwegian educational policy is that the country does not fully utilize the talent of its population."

– NOU 1988: 28, *"Med viten og vilje"*

The Hernes-commission that wrote the Norwegian Official Report in 1988 aptly named "with knowledge and will" that "The challenge for Norwegian educational policy is that the country does not fully utilize the talent of its population" (NOU 1988:28 Med viten og vilje., 1988). This statement remains still relevant today, demonstrating that certain issues still persist. While political willingness to bolster education in Norway is far from lacking, there are still barriers preventing the full utilization of the population's talent. These issues include disparities in educational achievement between urban and rural students, between genders, challenges related to immigration and internationally mediocre results and effective resource utilization (Finansdepartementet, 2021). Norway invests a significant amount of funds towards education, surpassing other OECD nations. However, the country's educational outcomes do not reflect the substantial investment made, only ranking slightly over international averages (PISA, 2019)(OECD, 2018).

This raises an important question: What are the underlying factors that could help us to better understand and improve student outcomes?

One such potential factor lies in the landscape surrounding our schools. The intersection of education and environment is a burgeoning area of interest. As urbanization increases worldwide, urban green spaces, including parks, forests, and other natural areas, are gaining attention in several disciplines like economics, psychology, public health, and education(UN, DESA, 2019). Besides improved air quality, noise reduction, and recreational opportunities, these green spaces are believed to enhance the overall quality of life and well-being of populations (EEA, 2020). As we will see in the literature section, some recent studies suggest a positive influence of green spaces on cognitive development and academic achievement among children and adolescents. This relationship is attributed to factors such as reduced stress levels, improved attention and concentration, increased physical activity, and enhanced social interactions(Matsuoka, 2010)(Wells, 2000).

Despite a growing body of literature on the importance of green spaces in urban planning and development, empirical evidence of their effects on academic achievement remains limited, especially in a Norwegian context. Understanding these effects could help us shape the future of educational and urban planning in Norway, which would ensure better utilization of public resources and contribute to long-term economic growth.

Since 1988, when the Hernes-commission published its report, the national education budget has seen a significant surge from an inflation-adjusted 42 billion kroner to an sizable

222 billion kroner in 2019(Storting Proposition No. 1, 1987–1988)(Storting Proposition No. 1, 2018–2019). This dramatic increase in the educational budget since the Hernes commission's report underscores the continuous commitment and political will to enhance education in Norway. The education system represents the primary formal investment in human capital(Becker, 2009). Therefore, it is reasonable to assert that the development of a nation's human capital is contingent upon the quality improvements within that system. Our welfare depends on our ability to acquire and apply knowledge. There is a correlation between the growth of knowledge and economic growth. However, the degree of closeness depends on how research and developments are organized (Hanushek & Woessmann, 2008).

In this master thesis, we aim to explore alternative and cost-effective factors in educational policy that could potentially lead to better outcomes. Specifically, we will investigate the impact of green spaces surrounding schools on students' academic achievement in reading, mathematics, and English. By analyzing satellite data and academic test results collected by the Norwegian Directorate for Education and Training (Udir) between 2015 and 2019, we will examine whether students attending schools with higher mean green areas within a certain radius demonstrate improved academic achievements compared to those in schools with limited greenery. This research question is particularly relevant for policymakers, educators, and urban planners, as it may provide valuable insights into the potential role of green spaces in promoting academic success and informing strategies for sustainable urban development.

1.1 Background and Context

The relationship between the natural environment and human well-being remains relatively unexplored. Green spaces have a range of enviormental benefits, but little is known in relation to educational outcomes in children. According to Dadvand et al., 2015, exposure to green spaces was found to positively influence cognitive development in primary schoolchildren. The study revealed improved working memory and reduced inattentiveness associated with greenness within and surrounding school boundaries. Research have suggested that exposure to green spaces may positively influence cognitive development and learning outcomes among children and adolescents. This relationship could be attributed to factors such as reduced stress levels, improved attention and concentration, increased physical activity, and enhanced social interactions. In Schertz and Berman, 2019, research has shown that interacting with natural environments has cognitive benefits. Exposure to natural stimuli, compared to urban stimuli, consistently improves working memory performance. The underlying mechanisms behind these effects are complex and require further investigation. The biophilia hypothesis suggests that our innate drive to connect with nature stems from the evolutionary adaptation of our ancestors to wild environments for survival (Wilson, 1984). While according to the stress reduction hypothesis, spending time in nature elicits a physiological response that reduces stress levels (Ulrich, 1983). Additionally, attention restoration theory proposes that nature has the ability to replenish cognitive resources, restoring concentration and attention (Kaplan, 1995). However, in order to substantiate or comprehend these mechanisms, it is necessary to identify and establish a tangible effect from green spaces.

If the positive effects of this relationship, as demonstrated in these studies such as Saenen et al., 2023, are thoroughly established, incorporating green spaces into educational settings could be a promising strategy to optimize educational policy. Further research, building upon the already existing literature, is needed to better understand the specific mechanisms underlying the cognitive benefits of green spaces and to determine the existence of a robust link between cognitive growth and green spaces.

In the context of Norway, this topic becomes particularly interesting when considering the differences environmental conditions in urban and rural areas. Given the amount of natural areas and low population density of the country, the opportunity for increased access to green spaces and their potential cognitive development benefits for children is interesting. Especially in rural areas where the access to nature is abundant. Somewhat paradoxically, it is the most urban regions of Norway that consistently yield the highest scores in national tests(Arnesen, 2021). Therefore, exploring how variations in green spaces affect educational outcomes can help us gain valuable insights that can inform evidence-based strategies for enhancing learning environments.

To try to establish a better understanding of the mechanisms and to determine if such an effect exists, we will analyze this using panel data methods, specifically a fixed effects model. By employing this approach, we aim to control for unobserved heterogeneity across schools and focus on the variations within each school over time. This will allow us to assess the potential impact of green areas on student achievement while accounting for other factors that may influence academic outcomes. Our primary research question is: "Does the amount of green spaces around schools affect the academic achievement of fifth-grade students in Norway on the national tests? If so, what types of green spaces have an impact, and what is their effect?"

To investigate this, we construct and utilize a novel data set that connects green spaces around schools in Norway with student achievement. Utilizing panel data methods, specifically a fixed effects model, we analyze this data.

While previous studies have explored this question to some extent(Matsuoka, 2010), our approach is unique as it extend the analysis to include data from Norway. No other study has utilized data from any of the Nordic countries, and it is possible that this novel data set may offer new insights into the link between green space and academic achievement.

We utilize satellite data from the Copernicus' Global Land Cover product(Buchhorn et al., 2020), and link this to national test result data for 5th graders(UDIR, n.d.-b). This provides data on green spaces surrounding schools, including parks, forests, and other natural areas, which will enable a more detailed understanding of the potential relationship between green spaces and academic achievement.

This study aims to contribute to the existing literature on the relationship between green spaces and academic achievement by examining it in the Norwegian context. The findings have the potential to inform educational and environmental policies, urban planning decisions, and resource allocation, thereby benefiting students' well-being and future prospects in Norway. Although the importance of green spaces in urban planning and development has been acknowledged(Miljødirektoratet, 2023), there is limited empirical evidence of their impact on academic achievement. From Norway more specifically, there is no research on this topic. Considering the substantial public investment in education and the long-term implications of academic success for individuals, it is important to understand how green spaces might enhance educational outcomes in Norwegian schools.

2 Research Question

In the following section we present our main research question together with the reasoning as for why we chose this question in particular. We also outline our hypothesis for what we expect our findings to be.

2.1 Main Research Question

As mentioned in the introduction, our main research question is going to be to figure out whether or not there is a connection between the amount of green space around schools in Norway, and academic achievement, as measured by achievement on the national tests among fifth graders. There are multiple reasons as to why we chose to narrow our scope to this specific question. The reason we chose to investigate schools in Norway is that since we are based in Norway, it is the situation we are the most familiar with and the most interested in. It also makes the process of acquiring the necessary data as easy as possible, which is an important aspect to consider, as this is what the whole thesis rests on. The choice of Norway is also interesting as it is a country that has a great range of different environments, providing ample variation in the green space data.

The test results from the national tests were chosen as a measure of achievement, as they are easily accessible and provide a standardized measure of student achievement that is comparable over time (NOU 2023: 1, 2023). We choose to look at the results from the fifth grade, as opposed to from the eight or ninth grade, because children in the fifth grade presumably spend more time outside, meaning that the possible effect of interaction with green space is heightened, thereby increasing the possibility of uncovering an effect. The time around the fifth grade is also a time of significant social, intellectual, and emotional growth for children (Eccles, 1999), meaning that if green spaces have an effect, it could be more visible here.

2.2 Hypothesis

We ground our hypothesis in the existing psychological literature connecting green spaces with cognitive processing. Here there are two main schools of thought: Attention restoration theory and the psycho-evolutionary theories.

Attention restoration theory (ART) theorises that mental fatigue, defined as when the capacity to focus or concentrate is lowered as a result of overuse, can be counteracted and reduced by contact with nature. Such fatigue will affect a students ability to take in new information and will lower their ability to perform on tests. (Matsuoka, 2010)

The psycho-evolutionary theories (PET's) states that the effect of natural settings on learning, rather than coming trough a reduction of fatigue, comes trough a result of stress reduction and trough a subconscious calming effect. Trough providing positive emotions and relaxation, an increased exposure to natural environments can lead to more learning and better performance during testing. (Matsuoka, 2010)

While these theories attribute the effect of natural environments on learning to slightly different processes, ART positing that it works trough cognitive processes, while the PET's concentrates on processes rooted in emotions, they both predict that an increase in exposure to natural environments can lead to better performance in a school setting. Based on this we hypothesise that in our analysis we will see that students at schools with more green space will perform better that students at schools with less green space, holding all other things equal.

3 Literature Review

In the following section, we review the relevant literature in the areas of economics, urban studies and psychology. While some of the studies do not specifically address academic achievement, they explore health-related facets. Similarly, certain studies are relevant to both academic achievement and health. The principal objective of this literature review is to get an overview of the existing result from previous research on the topic of green space and education. We review both papers directly investigating the green space - academic achievement link, as well as papers that underlie our hypothesized mechanisms rooted in psychology.

3.1 Green space - Academic Achievement Link

As the main topic of this thesis is the investigation of the link between green space and academic achievement, we begin by review the work directly looking at this question.

In a systematic review of the field, Browning and Rigolon, 2019 identified 13 peer-reviewed articles examining the relationship between academic outcomes, types of green spaces, and distances around schools. The review found that 64 percent of the 122 findings reported were non-significant, 8 percent were significant and negative, and 28 percent were significant and positive. The positive associations were primarily observed for greenness, tree cover, and green land cover at distances up to 2000 meters around schools. Additionally, end-of-semester grades and college preparatory exams demonstrated more positive associations compared to math or reading test scores. However, findings regarding writing test scores were mostly non-significant, and moderation effects of socioeconomic status, gender, and urbanization yielded mixed results. While the existing literature on green spaces and academic achievement is limited and shows mixed outcomes, there is sufficient evidence to warrant further research on this topic. The review highlights the need for future studies to consider potential confounding factors, moderation effects, and mechanistic pathways. Furthermore, the research is concentrated Europe and North America, and the current literature lacks studies conducted in Global South contexts. The review suggests that green spaces within and around schools may indeed have a positive influence on students' academic achievement. However, further research is necessary to establish a more robust understanding of the relationship between green spaces and academic achievement, as well as the most effective ways to leverage this connection for equitable and supportive learning environments. There is also little on the specific mechanism linked to this relationship.

The first study to consider the link between the effect of green space and academic achievement is Matsuoka, 2010, who finds several significant relationships between various green space and academic outcome variables using a constructed data set from 101 Michigan high schools. Green space in this study is measured by an array of more detailed and qualitative variables collected in person by the researcher. These include views of nature from each schools cafeteria and averaged classroom, ranked on a one to five scale ranging from *all built* at the bottom to all natural on the top, as well as the window area, the amount of *athletic field*, *parking lot* and landscaped area per student, number of trees per acre of landscaped area, percentage of landscaped area covered by shrubs and land cover, and percentage of landscaped area made up of mowed grass. School policy for length of lunch time and if the students are allowed to eat outdoors were also included. School socio-economic status, ethnicity, enrollment and building age was also controlled for. As measures for academic achievement, percentage of students that was awarded the Michigan merit award on the basis of their performance in the Michigan Educational Assessment Program test, graduation rates, and percentage of seniors that plan to attend four year college was used. Student behaviour as measured by rates of disorderly conduct and criminal activity among the students was also included. In their analysis a significant positive relationship is found between the degree of natural features in the view from the cafeteria window and all academic outcome variables. A negative relationship is also found between the amount of lawn, and some of the academic outcomes, suggesting that trees and shrubs are of importance.

Then, in the first study to use remote sensing techniques to get at the question Wu et al., 2014 uses data on academic achievement from 905 Massachusetts public schools collected over seven years (2006 to 2012) and includes the percentage of third graders that scored "Above Proficient" in English and Math. The data on green space comes in the from of NDVI values abstracted into circular buffers around each school with radii of 250m, 500m, 1000m, and 2000m, collected from MODIS. This data was collected at three different times for each year, in March, July, and October. In addition to this, a set of variables that control for know predictors of academic achievement, such as percentage of low income students, student/teacher ratio, and attendance was included. In their analysis the authors find a very significant link between surrounding greenness in March and academic achievement in both English and Math for all buffer distances, with coefficient estimates ranging from 0.19 to 0.42 and generally increasing with the size of the buffer. For the July data the link was less pronounced with a coefficient estimate range of -0.001 to 0.09, but still showed positive significant relationships for most of the buffer radii. The October data however showed slightly negative coefficient estimates ranging from 0 to -0.17 with significant results for all buffer sizes except for 250m. The authors hypothesise that this is because trees in the fall reflect more visible light, leading to lower NDVI scores. The main results of the paper also held up in a sensitivity analysis using only urban schools.

In the only experimental study looking into the green space - academic achievement link, Benfield et al., 2015 employs results from an introductory college composition class consisting of 567 undergraduates, where 134 students met in classrooms with window views looking directly at a concrete wall, while the remaining 433 students met in an otherwise identically classroom, but with views of an open grassy area containing trees. All though assignment into classroom type was not random, the two groups did not differ significantly differ on any demographic characteristics. The outcome variables used were a set of ratings from a survey that the students took at the beginning and end of the semester, ranking various aspects of the class (curriculum, importance of subject matter, enthusiasm of instructor, etc.) on a five point Likert-type scale (very low/poor to very very high/excellent), as well as grades on the midterm and final exam, and attendance. The authors find that being assigned a classroom with a natural view is associated with a significantly higher score on the rating of the quality of the curriculum, classroom resources, and the the course materials, as well as on end of term grades. These results provide relatively strong evidence that having visual access to green spaces can improve results and overall impressions in an educational setting, though weather the effect comes trough the students or the instructors is not identified.

Kweon et al., 2017 uses a land-use/land-cover map of Washington D.C. in combination with GIS shapefiles of school boundaries to calculate the percentage of each shcool's area that is made up of either buildings, paved surfaces, bare soil, grass and shrubs, or trees. This is then used in combination with test results for all D.C. schools ranging from grade 2 to 10, which reports the percentage of students who received Proficient or Advanced academic achievement scores in Mathematics and Reading in 2011. Using models that control for SES, enrollment, student/teacher ratio and ethnicity the authors finds significant positive relationships between percentage of tree cover and proficient or advanced placement in both math and reading. The simple use of a cross-sectional data with relatively few controls is however not very convincing in establishing a causal relationship.

In an ecological study, Beere and Kingham, 2017 examined the influence of green space access on academic achievement across various schools in New Zealand. The researchers used a data set comprising school decile ratings, representing socio-economic status (SES), the amount of green space surrounding the schools, and academic achievement based on national standards in mathematics, reading, and writing. The study used regression models to explore the relationship between green space and academic achievement, with control variables including gender, ethnicity, and SES. The green space access in relation to SES in New Zealand was found to differ from overseas studies, as low SES areas tended to have better access to green space. A statistically significant but weak negative association was found between green space and academic achievement. The researchers found that SES predictably had the most significant association with a school's achievement rates above the national standard. Interesting gender-based differences were noted, particularly in mathematics, where the gap between male and female students increased with

SES. The authors also examined the influence of green space on academic achievement by ethnicity, finding patterns of academic achievement for Māori and Pasifika students. SES was the most significant predictor of attainment for Māori students, whereas no linear or significant relationship was found for Pasifika students.

Browning et al., 2018 replicates Wu et al., 2014, investigating the relationship between vegetation around schools and student test scores, focusing on schools with less green cover and more disadvantaged students. The study used six years (2006-2012) of NDVI-derived greenness data to predict school-level math and reading achievement in 404 Chicago public schools. Their findings suggested that the greenness - academic achievement link could be either nonexistent or slightly negative in low-greenness, high-disadvantage contexts. They argued that these contexts might require a more nuanced modeling approach, distinguishing between tree cover and other kinds of green cover and considering potential moderating effects of poverty and race. They also emphasized the need to include "disadvantage" not only as a confounder but also as a moderator of the effects of green cover on academic achievement. They followed the "close replication" approach from experimental psychology, aiming to recreate the original study as closely as possible but with different participants. The initial replication yielded highly mixed results with some significant positive relationships between greenness and academic achievement, some negative, and some null. To address multicoliniarity, researchers simplified the race/ethnicity categories and introduced 'year' as a random effects variable. All models then showed near-zero but statistically significant negative relationships between greenness and achievement.

Sivarajah et al., 2018 used data on standardized achievement scores from third and sixth graders in 387 Toronto primary schools in combination with green space data on soft surface (grass and shrubs) and tree canopy from a Toronto city raster data set on urban tree canopy as well as data on tree species from a data set developed by the University of Toronto faculty of Forestry containing information on over 20000 trees to analyze the effect of green space on academic achievement, accounting for differences in socio-economic status. They find that the proportion of tree cover (as opposed to grass/shrubs) within a school's area to be a significant positive predictor on student achievement, with the effect being highest in schools with low socio-economic status.

Tallis et al., 2018 looked at 495 diverse elementary schools in California and the tree and shrub cover within 750 and 1000m of urban schools in combination with student test scores, whilst controlling for commonly established educational determinants such as socio-economic status, ethnicity, student teacher ratio, and gender ratio. Green space variables such as Normalized Difference Vegetation Index (NDVI) and agricultural area were also investigated for potential associations with student test performance. They found a significant, positive association between test scores and tree and shrub cover in urban schools, but no such association in rural schools or in five buffers close to urban schools (10, 50, 100, 100, 300, and 500m). Moreover, other green space variables - NDVI and agricultural area - showed no association with test performance for both rural and urban schools. Of all factors studied, minority representation had the largest effect on standardized test scores (8.1 percent difference), followed by tree and shrub cover around urban schools with an effect size of 2.9–3.0 percent at 750 and 1000m. Average tree-cover schools in urban settings demonstrated 4.2 percent better standardized test scores compared to low tree-cover urban schools.

Markevych et al., 2019 investigates the effects of green space on the academic achievement of adolescents from two German birth cohorts, GINIplus and LISA, with 1351 participants from Munich and 1078 from Wesel, aged 10 and 15. The cohorts were designed to investigate environmental and lifestyle factors, as well as genetic markers, in the development of allergic diseases but later included data on comorbidities, physical activity, diet, and mental health. Markevych et al. evaluated German and Maths grades from the latest school certificate. Green space was determined at both residential and school locations using the Normalized Difference Vegetation Index (NDVI) from MODIS, which represents vegetation levels on a scale of -1 to +1. Greenspace was also assessed based on tree cover density, along with proportions of agricultural land, forest, and urban green space within 500-meter and 1000-meter circular buffers around the residential and school addresses - this data was derived from the European Environmental Agency, and local land use data from the Bavarian Survey Office. The study used average greenspace variables for both home and school, weighted by the daily time typically spent at each location. Green space variables were both analyzed as continuous variables and categorized into tertiles to examine potential non-linear exposure-response relationships. Longitudinal associations between each greenspace variable and academic outcomes were assessed using logistic mixed-effects models, with person and school as random intercepts. The models were adjusted for potential confounders. Results found no associations between greenspace variables and grades in Wesel children, while several significant but inconsistent associations were observed in Munich children.

In a longitudinal study, Tuen Veronica Leung et al., 2019 investigated the influence of green spaces on academic achievement. Using a comprehensive data set from Massachusetts schools between 2006 and 2014, they employed the Normalized Difference Vegetation Index (NDVI) and land use data from the Massachusetts Geographic Information System (MassGIS) to quantify greenness. To measure academic achievement, they used the Composite Performance Index (CPI) and the percentage of students who scored "Proficient and Higher" (AP%) in English Language Arts (ELA) and Mathematics (MTH) from the Massachusetts Comprehensive Assessment System (MCAS). In their analysis, the researchers used Generalized Linear Mixed Models (GLMMs) to evaluate the association between surrounding greenness and academic achievement. They constructed 250-meter, 500-meter, 1000-meter, and 2000-meter circular buffers around each school to estimate students' exposure to greenness. They adjusted their analysis for sex, student-teacher ratio, financial status, language ability, and race and ethnicity. To verify the robustness of their results and assess if the greenness-academic achievement association varied by population characteristics, they carried out sensitivity and stratified analyses. Leung and her colleagues found a positive correlation between greenness and academic achievement after adjusting for potential confounding variables and spatial auto correlation . This suggests that an increase in greenness around schools can lead to an improvement in students' academic achievement. However, they noted that the impact's magnitude varied depending on other socio-demographic variables.

In Hodson and Sander, 2017 the authors examined the relationship between natural elements in urban landscapes and the academic achievement in standardised tested of third-grade students in the Twin Cities Metropolitan Area of Minnesota, USA, particularly 222 school attendance areas. They measured green space by calculating several environmental variables, including canopy cover, impervious surfaces, grass cover, shrub cover, and water bodies, using geo spatial data sources such as United States Geological Survey and National Land Cover Database 2011 . These variables were used to quantify the level of greenness and development intensity in each School Attendance Area (SAA). The researchers found through OLS - with adjustments for spatial auto correlation and heteroscedasticity being necessary - that greater exposure to green spaces was associated with improved academic achievement in reading and mathematics. More specifically they found a positive correlation was observed between impervious surfaces and reading performance. However, the relationships between grass, shrub, and water bodies and both mathematics and reading success were found to be statistically insignificant. On the other hand, a significant and positive correlation was found between tree cover and reading performance.

To summarize, the existing literature on the link between green spaces and academic achievement is varied. Some studies find positive relationships, some find negative relationship, and some find none at all. Different types of green space also seem to have different effects, with forest more often having a positive effect, while grass sometimes has a negative effect. The effect here is in general not clear, and and new research in the field will probably contribute with interesting results.

4 Data

In order to empirically investigate if there is any connection between green spaces around schools and academic achievement we use a novel data set containing three different type of greenness measures, test results from national standardized tests in Norway at the school level, and a set of control variables, from 2015 to 2019. This chapter describes this data set, and details its construction. It is divided into four main parts. Firstly the data is divided into three main parts: test results, green space, and controls. We describe the details of each of these and review their summary statistics. Then we describe the construction of the data set, and comment on a loss of data. A complete list of variables is included in the appendix.

4.1 Test results

4.1.1 About the Test Results Data

To measure how green space impacts children's learning we have chosen to use the test results from the Norwegian national tests for fifth graders. The Norwegian national tests are set of three tests testing student's competence in math, reading, and English. All three tests are administered to fifth and eight graders at the start of the school year. In the ninth grade, only math and reading tests are administered. The purpose of the tests are to give the primary schools knowledge about the their students basic skills in the respective subjects. (UDIR, n.d.-b)

In our data set we include scale points, school size and a uncertainty measure (a 95% confidence interval) for all fifth grades in Norway from 2015 to 2019, downloaded from the Norwegian directory of Educations website. (UDIR, n.d.-d) These tests exist not only to provide useful information for research but also to tailor further learning for the individual students.

The national tests were first implemented in Norway for the 4th and 10th grades in the spring of 2004. Following a period of trial and evaluation, the tests underwent refinement and changes. Since 2014, the scoring system for the national tests has been on a scale, which standardizes students' results such that a specific skill—for instance, mathematics—holds the same value regardless of the year the student took the test. A certain number of tasks in the test or one anchor text is repeated each year. By using the same anchor tasks or texts each year, it is possible to link the tests from one year to the next. This method allows comparisons of test scores for schools from year to year. All schools in Norway are obliged to have their students take the tests, making it a use full tool for assessing students' academic progress and maintaining a standardized education system throughout the country. (UDIR, 2022)

The average after the first implementation in 2014 was set to be 50 scale points with a standard deviation of 10. All test results were converted to this scale. Scale points are distributed over three mastery levels for the 5th-grade tests. The boundaries for mastery levels were set as close as possible to a certain percentiles of a normal distribution. (UDIR, 2022).

The calculation of scale points is grounded in Item Response Theory (IRT), which is a psychometric method for test design(Embretson & Reise, 2000). IRT allows one to convert raw test scores into a more interpretable scale that considers the difficulty of each item in the test. This standardized scoring system allows for consistency in the measurement of student performance over time and across different schools (citation needed), thus overcoming the limitations of using exam data and subject grades to measure academic achievement over time.

Exemptions from the National Test are given to students if they meet specific criteria, such as students who have special education needs or require specialized language instruction. These are the regulations outlined in the Education Act § 2-8 and the Private School Act § 2-7. The school is responsible for evaluating and determining which students should be granted exemptions. Around 4 to 6 percent of 5th grade students are usually exempted from national tests each year. (NOU 2023: 1, 2023)

Missing data in national test results sometimes occurs to protect the confidentiality and privacy of individual students. When results are based on a small number of students, data points are masked or suppressed to prevent identification. This ensures compliance with data protection regulations and maintains student privacy. (UDIR, n.d.-b)

4.1.2 Summary statistics

The summary statistics for the data on student outcomes are presented in Table 1. We can see that all three test types have similar means and standard deviations. The average school size is slightly over 37 students, with the largest school having 125 students and the smallest having 10 students.

We also inspect the distributions of our test scores. Figure 1 shows histograms for the three different test subjects. We see that all three seem to follow a normal distribution, with the English scores having spikes at three different values, and reading scores missing for two different values. We don't know what is causing this.

We also want to inspect how to the test results vary over time. To do this we compute similar histograms as above, but rater than showing frequency of the range of average test scores, we look at frequency for the range of the standard deviation of scale point

Table 1: Summary statistics for the test variables

Statistic	N	Mean	St. Dev.	Min	Max
English_Points	5,270	49.862	3.448	31	72
Reading_Points	5,270	49.746	3.314	38	64
Math_Points	5,270	49.884	3.661	33	64
English_Uncertainty	5,270	3.257	1.062	1.400	9.000
Reading_Uncertainty	5,270	3.188	1.029	1.400	8.300
Math_Uncertainty	5,270	3.161	0.996	1.400	7.800
English_School_Size	5,270	37.417	20.191	10	125
Reading_School_Size	5,270	37.409	20.205	10	123
Math_School_Size	5,270	37.752	20.275	10	124

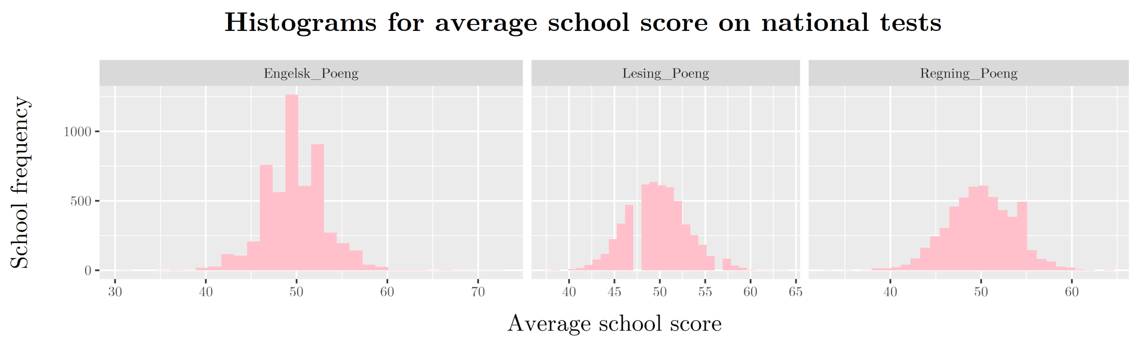


Figure 1: Histograms showing the distribution of scores for the three different subject types.

over time width-in the schools in out data set. As we see in Figure 2, all three subjects have distributions of unit grouped temporal standard deviations centered around about 2,5. This means that there is ample temporal variation in our dependent variables.

4.2 Data on Green spaces

4.2.1 About the data

Our green space data is derived from the Copernicus 100m land cover data set. (Buchhorn et al., 2020) This is a land cover classification map that covers the whole surface of the earth. Each pixel on the map corresponds to a 100 by 100 meter patch and trough statistical learning techniques, each pixel has been classified into one of 23 land cover classes. In addition to the main classification map, ten cover fraction maps are also available. In these maps, each pixel is assigned a value between 0 and 100, corresponding

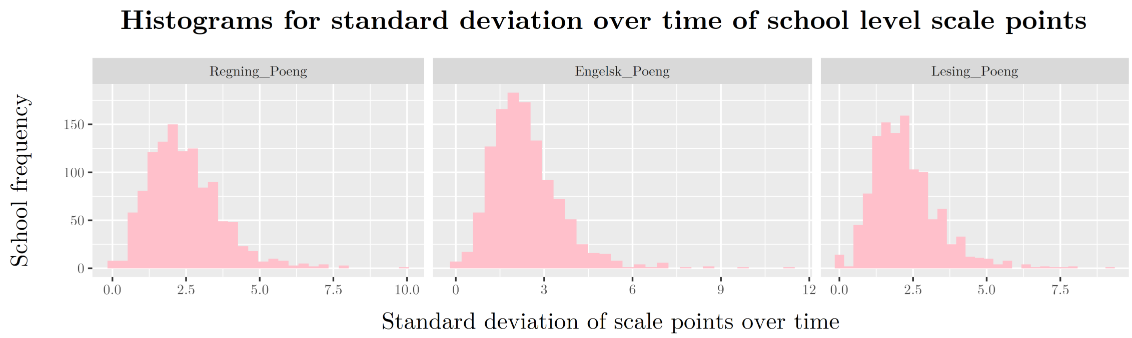


Figure 2: Histograms showing the distribution of temporal standard deviation of scores for the three different subject types.

to the percentage of that area that is covered by the land cover type in question. We use the forest, shrub, and herbaceous vegetation cover fraction map as our measures of green space. These measures are chosen because they cover the main type of green spaces that one might find in and around a typical Norwegian primary school, and because these are the types of green spaces that are common within the literature. This data is only available from 2015 to 2019, so this is what limits the temporal dimension of our data.

The Forests layers in this data set are characterized by high-density tree areas, typically requiring a minimum 30 percentage canopy cover by trees at least 5 meters tall. Herbaceous vegetation layer encompasses plants without persistent woody stems, commonly found in Norwegian grasslands. The Transitional Woodland/Shrub layer represent various stages of woodland development or degradation, often comprising bushy and herbaceous vegetation with scattered trees.

For each year the different type of cover fraction maps was loaded into QGIS, which is a program for working with geographical information. They were then combined with a GML file from GeoNorge containing the geographical positions for all Norwegian primary schools. Then using the buffer tool, five concentric circle-shaped MultiPolygon layers centered around each school were created, with radii of 100m, 500m, 1000m, 2500m and 5000m. Figure 3 shows an example of this. These radii were chosen because they allow for analysis of the effect of green space on academic achievement for different areas around each school, ranging from the area immediately around each school (100m), to the area visible from the school (2500m), to the area in which most of the school's students are likely to live (5000m). Then, using the zonal statistics tool, the mean and standard deviation of percentage of green space cover was calculated within each of the circles. This data was then exported and combined into a single file i R.

The different type of green space cover layers are visualized in Figure 4. The images consists of three distinct layers and one satellite imagery from SENTINEL 2, shown

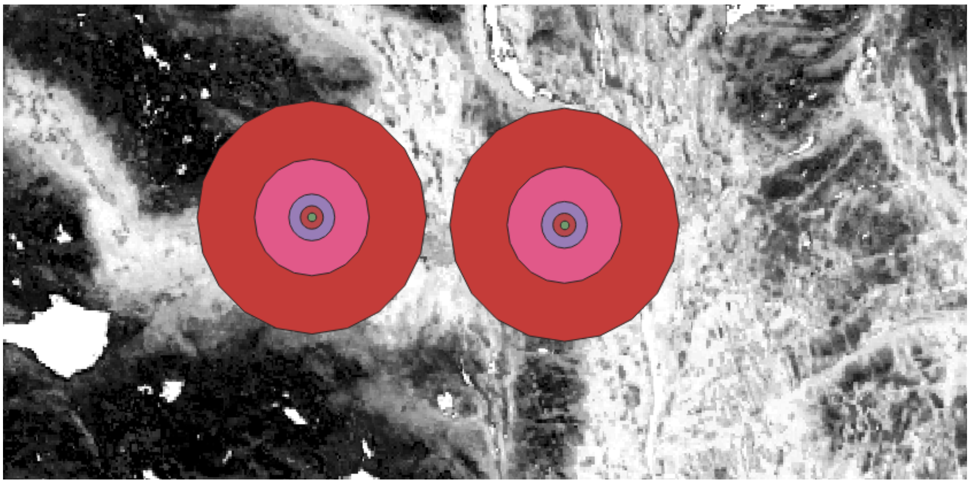
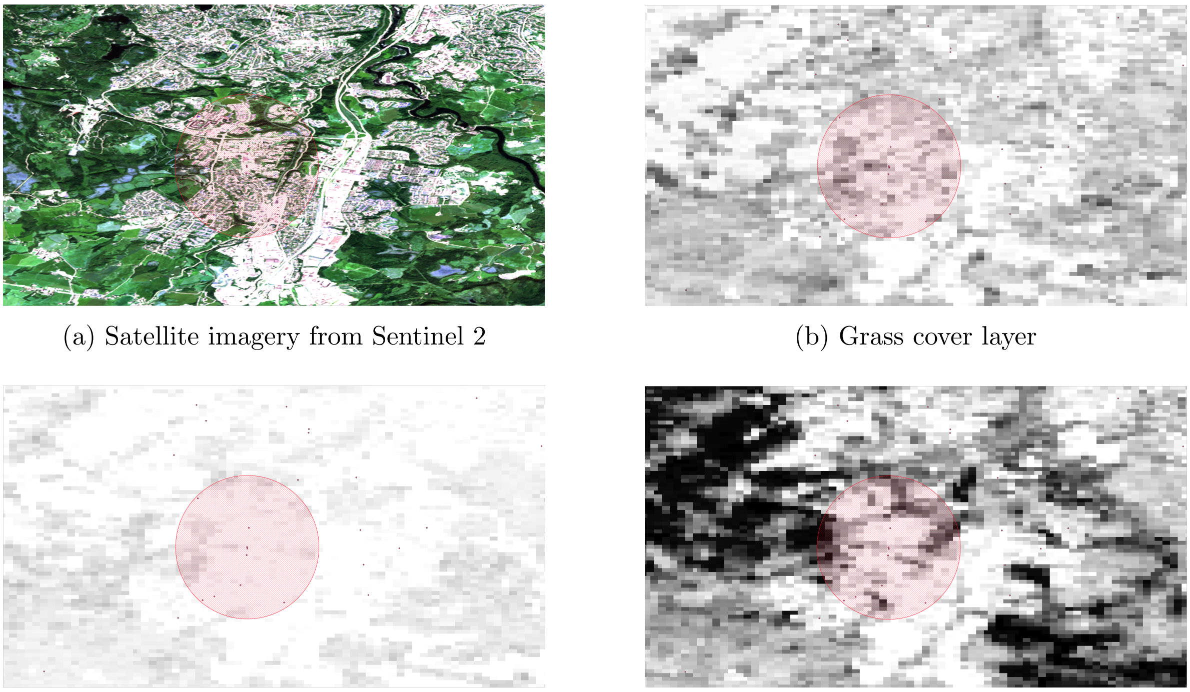


Figure 3: Two schools with corresponding multi-polygons over a herbaceous cover map. Darker shades indicate a higher percentage of herbaceous vegetation cover.

in QGIS. Each of the layers gives slightly different insights into the local environment. The maps are derived from satellite imagery from the Copernicus 100m land cover data set, with a pixel resolution of 100 by 100 meters. The top image, (a), shows satellite imagery from SENTINEL 2, which provides an unfiltered, raw visual of the school and its surrounding areas. This layer represents the baseline, against which the following layers can be compared. The second layer, (b), shows Grass cover. The color gradation signifies the extent of grass coverage. Darker shades indicate a greater amount of grass cover, which generally consists of herbaceous vegetation, a type of green space common in Norwegian grasslands and absent of persistent woody stems. The third layer, (c), maps the Shrub cover layer. Similar to the Grass cover layer, darker shades here denote a higher amount of shrub coverage. Transitional Woodland/Shrub typically consists of bushy and herbaceous vegetation with scattered trees. This layer represents various stages of woodland development or degradation. The fourth layer, (d), shows the Tree/Forest cover layer. The coloring scheme mirrors the previous two, with darker shades indicating a greater amount of tree/forest cover. Forest areas in this data set are characterized by high-density tree areas, requiring a minimum of 30 percentage canopy cover by trees at least 5 meters tall.

4.2.2 Summary statistics

We will now examine the summary statistics associated with our green space data. One of the main question of interest here is, as with the test score data, to determine how much time-variation is present, as this is an important prerequisite for meaningful results from the fixed effect model that will be employed in our analysis later on. Table 2 reports basic summary statistics for our green space variables. We can see that there is some difference between the different types of green spaces. Forest has the highest amount of



(a) Satellite imagery from Sentinel 2

(b) Grass cover layer

(c) Shrub cover layer

(d) Tree/Forest cover layer

Figure 4: Kattem skole in Trondheim with a 1000m buffer circle. The images show the distribution of different land covers. Darker shades indicate a greater amount of the respective cover (trees, shrubs, and grass).

average coverage and the largest standard deviation of coverage in all radii, followed by herbaceous vegetation, and then shrubs. For all cover types the mean cover is increasing with circle size, so an area around a school is likely to have a higher mean amount of green space cover when you increase the area around it that you are looking at. Also for all cover types there are schools for which there are no coverage for radii smaller than 2500 metres.

Next we turn to the distributions of our data as shown in Figure 5. Here all three types of green space seems to somewhat follow a Poisson distribution with increasing lambda value for the bigger areas. It is clear that we have a good amount of overall variation in all sizes.

Next, to asses if we have adequate variation in green space at the school level across time we can compute similar histograms where we can see the frequency of standard deviation in green space over time for the schools. These are displayed in Figure 6. As we can see all of our variables exhibit quite a lot of variance, with plenty of schools having a temporal standard deviations of well above 1. Some of the very high standard deviations observed are a result of some of the schools not having observations for all years. The reason for this is explained in section 4.4.

Table 2: Summary statistics for the green space variables.

Statistic	N	Mean	St. Dev.	Min	Max
shrub_Mean_100m	5,270	3.670	4.272	0.000	31.667
shrub_Mean_500m	5,270	4.737	3.571	0.000	26.262
shrub_Mean_1000m	5,270	5.006	3.240	0.000	19.840
shrub_Mean_2500m	5,270	5.284	2.920	0.000	17.580
shrub_Mean_5000m	5,270	5.576	2.865	0.395	19.945
herb_Mean_100m	5,270	14.273	12.691	0.000	65.600
herb_Mean_500m	5,270	14.844	9.155	0.000	59.968
herb_Mean_1000m	5,270	14.347	8.002	0.000	62.896
herb_Mean_2500m	5,270	13.972	7.458	0.027	66.628
herb_Mean_5000m	5,270	14.659	8.477	1.145	58.495
forest_Mean_100m	5,270	15.974	15.839	0.000	90.833
forest_Mean_500m	5,270	25.905	16.574	0.000	90.463
forest_Mean_1000m	5,270	30.144	16.573	0.000	85.905
forest_Mean_2500m	5,270	35.040	16.823	0.012	88.155
forest_Mean_5000m	5,270	37.392	16.849	0.097	83.631

4.2.3 Stylized example of change over time.

As a stylized example to illustrate how change might look we have looked at aerial images for one specific school. Hovden school was picked as it was one of the schools with a high degree of change in green space close to it. Table 3 presents the schools with the biggest changes in green space. Hovden school ranked among the top three schools with the highest negative changes in Forest mean 500, indicating substantial reduction in the forest cover near the school (- 11.17 percent change). Hovden School was particularly suitable for this example because we had access to high-resolution aerial photos and ground view images from Google Street View, allowing us to clearly observe the changes over time. The images presented in Figure 7 and 8 serve as visual evidence of the transformations in the green space surrounding the school. In Figure 9 we also present three maps showing the geographical distribution of green space change, defined as the difference in green space from the first period to the last, for each of the green space types, within 500m of each school aggregated at the municipality level.

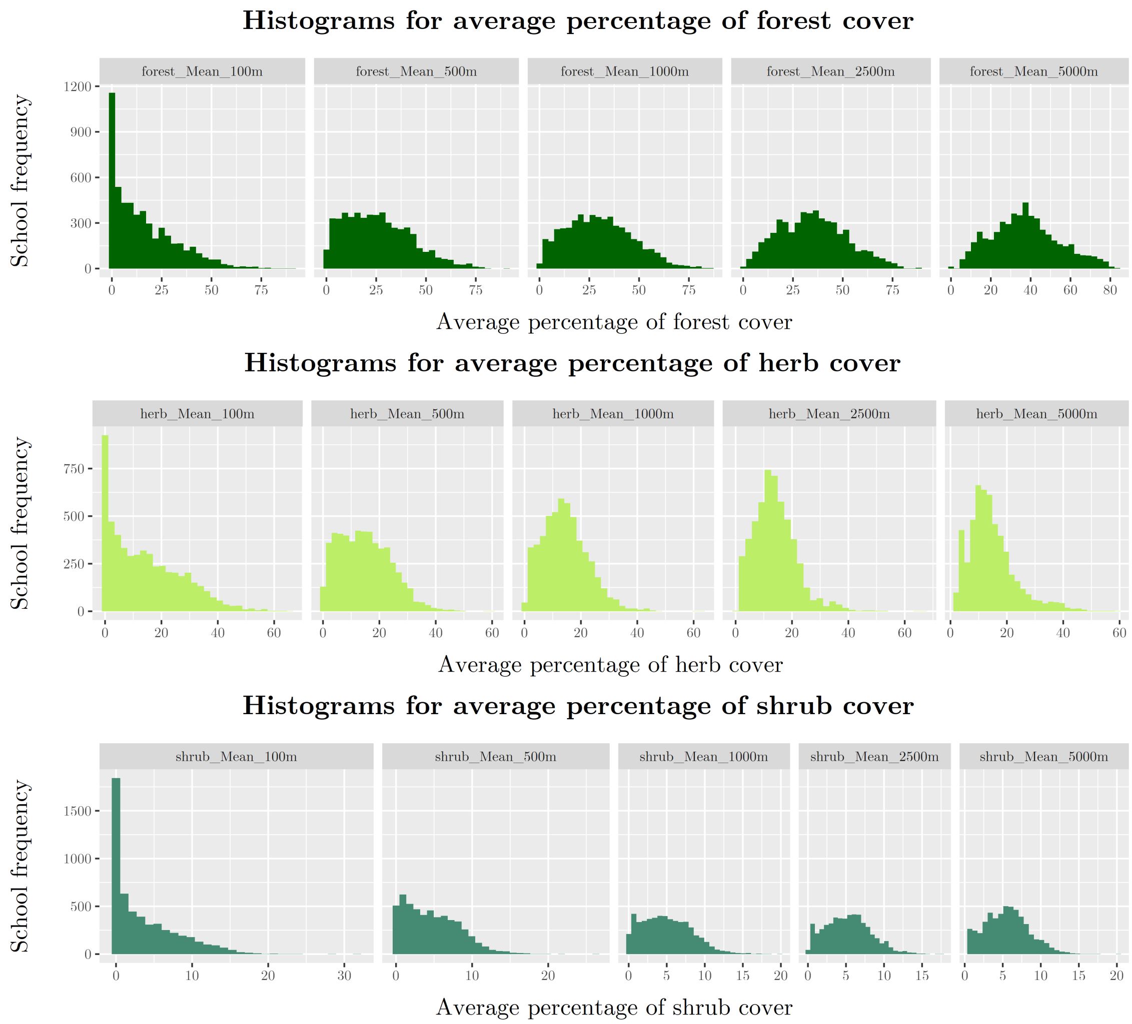


Figure 5

4.3 Data on controls

In this section we present the variables we use as controls in our analysis. Firstly, the details of each control is described, then the summary statistics for all the variables are presented and commented on.

4.3.1 Centrality

It is natural to assume that rural areas have a higher rate of green spaces, such as forests and untouched lands, than urban areas, and that an eventual effect of a change in green space is therefore also different. To control for this factor, we use measure of centrality as a control variable. Previous research has demonstrated a notable disparity in academic achievement between more centrally located regions and less centrally located areas in Norway. (Arnesen, 2021) To account for this, we utilize the Centrality Index developed by Statistics Norway (SSB). (SSB, 2020) The Centrality index is not frequently updated, and we therefore only have one observation of centrality per municipality, meaning that

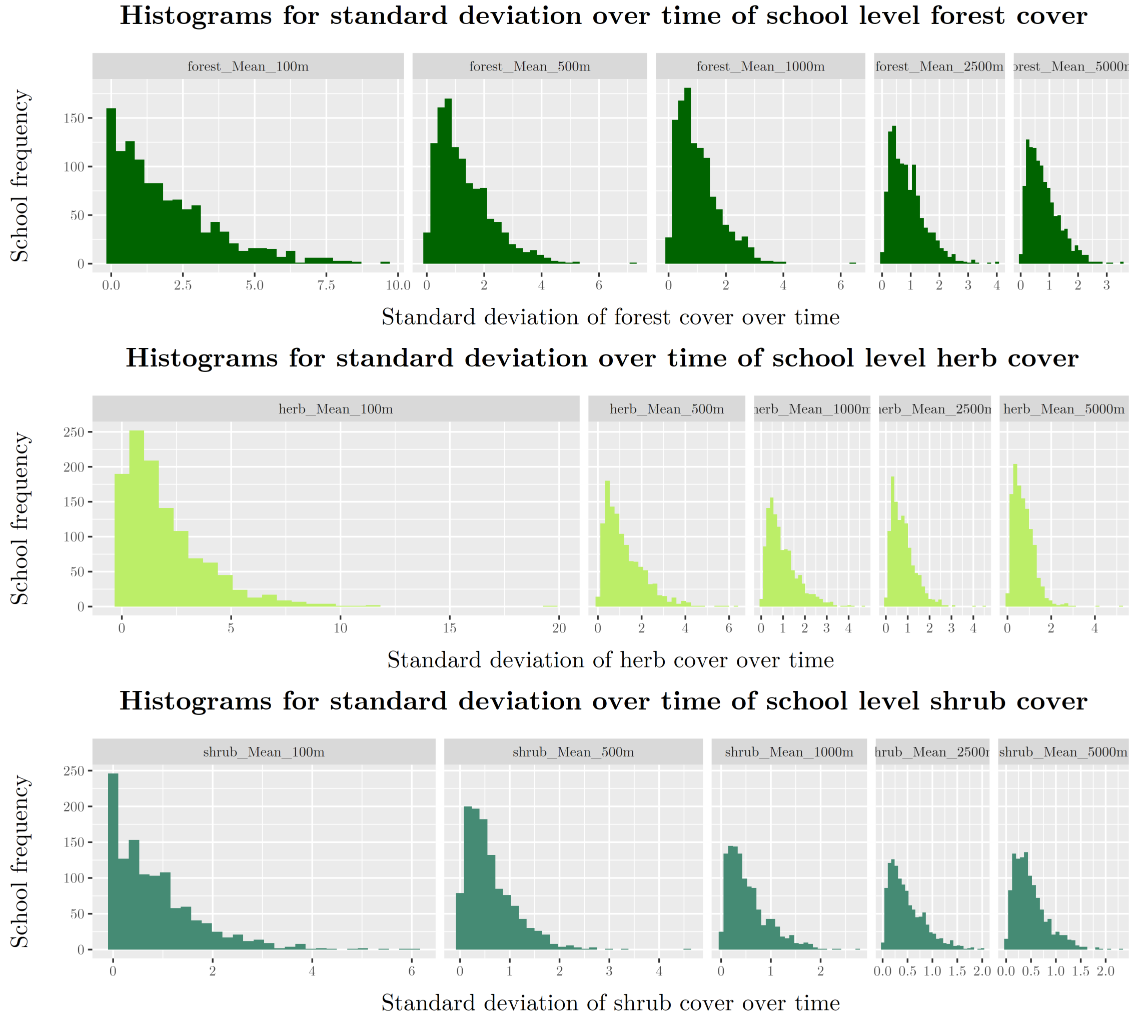


Figure 6

(a) 2015-19-08, Ortofoto 10, Owner: Geovekst

(b) 2019-08-06 , Ortofoto 10, Owner: Geovekst

Figure 7: These aerial photos illustrate the changes from 2015 to 2019. Along the main road we can clearly see trees that have been removed. Hovden School is the red dot. The images are screenshots from Norge i Bilder, Statens kartverk

each municipality has the same centrality each year. (Høydahl, 2020).

The centrality index assigns each municipality a value that represents its degree of cen-

(a) April 2010, Google Street View

(b) November 2018, Google Street View

Figure 8: Forest Cover Change in Hvdebygda. These images were taken approximately 300 meters away from Hovden School, with a sign serving as a constant reference point. The comparison highlights the noticeable differences in forest coverage between the two time periods. The images are screenshots from Google Street View.

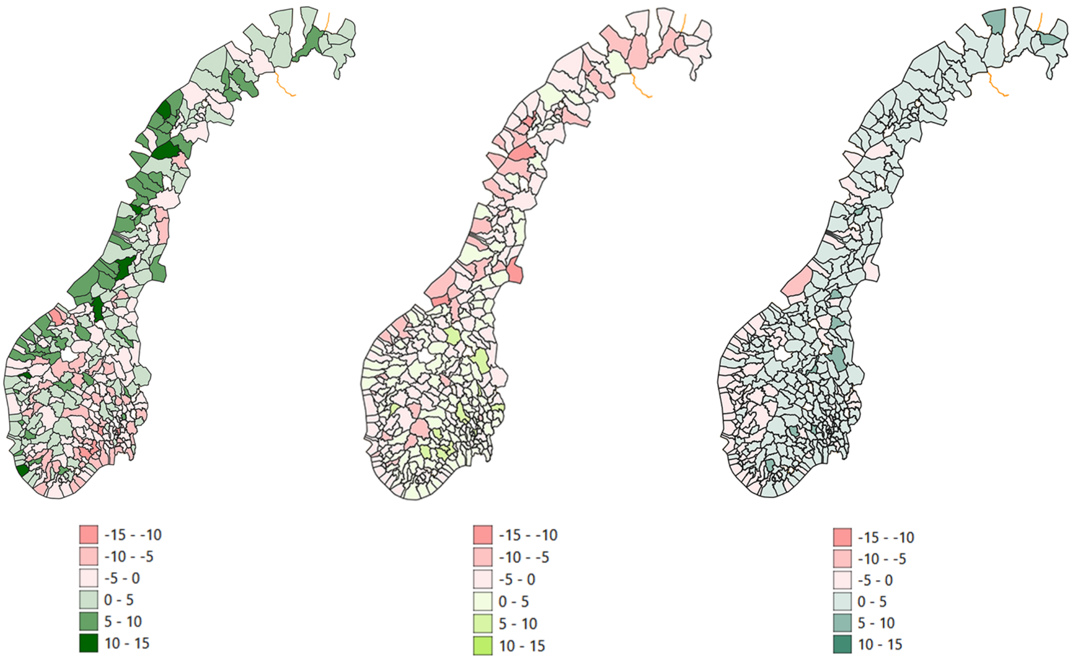


Figure 9: Maps showing change in green space around schools (500m) from 2015 to 2019 for all three types of green space, at the municipality level. Forest to the left. Herb in the middle. Shrub to the right.

trality based on multiple factors, including proximity to services and employment opportunities. When reintroduced in 2017, the Centrality Index established six classes of centrality with 6 being the least central, and 1 being the most central. The criteria for each class were set to ensure that the most populous cities, such as Stavanger, Bergen, and Trondheim, were not in the same class as Oslo. However, due to changes in municipal

Table 3: Top 5 Schools with Green Space Changes (500 meter radius)

Green Space Type	Change	School	Change %
	Top 5 Negative	Drangedal 10-Årige skole	-12.23
		Os skole	-11.73
		Hovden skule	-11.17
		Ormåsen barneskole	-11.15
		Bruhagen barneskole	-11.06
Forest	Top 5 Positive	Tustna barne- og ungdomsskole	13.45
		Gimsøy skole	12.27
		Ferkingstad skole	12.15
		Ogna skule	11.65
		Nord-Dønna montessoriskole	11.32
	Top 5 Negative	Rørvik skole	-12.46
		Baksalen skole	-11.78
		Sørli skole	-11.45
		Vadsø barne- og kulturskole Avd skole	-11.43
		Karrlagsund oppvekstsenter Avd skole	-11.25
Herbaceous Vegetation	Top 5 Positive	Røyse skole	12.5
		Midtneedsa oppvekstsenter Avd skule	9.44
		Vang skole	9.07
		Ingeberg skole	8.95
		Totenviken skole	8.85
	Top 5 Negative	Myking skule	-7.51
		Flekke skule	-6.82
		Dingemoen skule	-6.74
		Brekke skule	-6.61
		Eikefjord barne- og ungdomsskule	-6.25
Shrubs	Top 5 Positive	Grande skole	8.02
		Testmann Minne skole	7.61
		Bjerkelund skole	7.16
		Skavanger skole	6.28
		Lensvik skole	6.08

This table summarizes the 5 schools with the biggest positive and negative changes in green space types, including forest, herbaceous vegetation, and shrubs.

structures and other factors since 2017, adjustments have been made, but the principles underlying the original classification remain in place. The data used to calculate the Centrality Index has gone through several revisions, due to factors such as the municipality reform, updates to business data, and adjustments in the calculation of distances in the employment sub-index, among others. In our approach, we have simplified the classes into a dummy variable where municipalities with classifications of 1 or 2 are set to 1, and the rest of the municipalities are set to 0. Given our research objective, we are mostly separating between urban and rural municipalities. As such, the splitting into a 'highly central' versus 'less central' index still captures the essential variation in our data set, thereby preserving the core functionality of the Centrality Index for our study. (Høydahl, 2020)

In our analysis, this binary classification aids in better interpreting the regression results, allowing for a clearer, less ambiguous understanding of the impact of centrality on educational outcomes. However the reduction of a multi-tiered measure to a binary variable inevitably results in some loss of nuanced information about municipality centrality, particularly the gradations within the 'less central' category. It is also important to recognize this limitation when interpreting our findings. Bias could arise if municipalities within the 'less central' category have significant internal variability that is pertinent to our study.

4.3.2 Average Municipal Income

Motivated by the known correlation between socioeconomic factors and educational achievement (Albertsen, 2020), we attempt to control for this by including average income for each municipality for each year. The income data used in this study is downloaded from data set made by SSB on average monthly income, which provides income figures for every municipality, further broken down by residence, workplace, age, and gender. (SSB, n.d.)

We note that data regarding parental education levels or school-specific parental income—variables we initially sought to include in our analysis were not available for this study. Incorporating such variables could have provided a better understanding of the socioeconomic circumstances directly surrounding the students.

4.3.3 School size

School size refers to the total number of students in a school. Our data on school size comes from the same data set as the results on the national tests. It is not obvious what the effect of school size is on student outcomes. On the one hand, larger schools might have more resources that allows students to excel, but on the other hand, larger schools could be more crowded and competitive, thereby making it harder for students to develop. The size of the school is also likely correlated with the centrality of the municipality, as rural municipalities often have very small schools. Regardless of the effect, we still want to control for it. The summary statistics for the school sizes are reported in section 4.1.

4.3.4 Student Teacher Ratio

The student-teacher ratio refers to the number of teachers per school in comparison to the number of students. The student-teacher ratio at a school can influence the learning environment, and consequently, the academic results of students (Kirkebøen et al., 2017). Smaller student-teacher ratios can potentially allow for more personalized attention and instruction, and larger ratios could potentially limit the opportunities for individualized instruction. The student teacher ratio is reported for each school at every period, and is downloaded from UDIR. (UDIR, n.d.-c)

4.3.5 School Ownership Type

The variable of school ownership type refers to whether the school is public or private. Institutional differences can manifest in various ways, from the availability of resources to the structure of the curriculum, and these differences could potentially impact academic results. For example, public schools are typically larger and have more diversity, whereas private schools might offer a more specialized curriculum. (NOU 2023: 1, 2023) These structural changes and differences in school ownership could have implications for educational quality, student performance, and social development among the young population. The data on ownership type comes from the same data set as the national test results.

4.3.6 Summary Statistics for Controls

The basic overall summary statistics for our control variables are presented in Table 4. Here we see that in our time frame, an average of 3,5 % of schools are privately owned, and 38,8 % lie in central municipalities. The average student teacher ratio is 17,451 students per teacher, and the mean of the average municipal income is 44635,92 kr. One thing that stands out here is that there is a school in the data set with a student teacher ratio of 171,6. This seems very extreme, and upon further inspection we find four schools in the data set that at one period each has a student teacher ratio of over 100. The highest value for the student teacher ratio after below these four entries is 48,42. It seems likely that these four entries are the result of mistakes under data collection. Tough, with only four out of over 5000 observations, we don't see this as a major problem and decide to keep these observations.

4.4 Merging, Lost Data, and Unbalance

This section will outline the details of how the data used in our analysis was gathered, cleaned and merged, as well as discussing missing data and the resulting unbalance in the panel data set.

Table 4: Summary statistics for control variables

Statistic	N	Mean	St. Dev.	Min	Max
Ownership_Type	5,270	0.035	0.185	0	1
Central	5,270	0.388	0.487	0	1
Student_Teacher_Ratio	5,270	17.451	5.210	7.150	171.600
Average_Income	5,270	44,635.920	4,177.080	35,110	61,180

The merging process started with combining the green space data with the national tests data. In the GML file used to Geo-locate the schools there is data on 3058 primary schools. (GeoNorge, 2015) Using the schools organisational number, the green space data was merged with the test data which contains results from fifth grade students from 1745 schools. All of the schools from the test result data were able to be matched with their Geo-location. Next the municipality level data on centrality was merged in using each municipality's municipality number, only loosing one school in the process. Then school level student-teacher ratio is merged, also using the schools organisational numbers. Here we loose 2 schools, leaving us with 1742 schools. Finally municipality level average per capita income is merged using municipally numbers. Here we lose 239 schools, leaving us with a total of 1503 schools, each in theory with 5 years of observations each. The reason we lose this many schools here is because of mismatches is the data sets. We attempted to remedy this, but were unsuccessfully.

Then the data was converted to long format in anticipation of it being used to fit panel models later on. Since we have five years of observations for each school we now have 7515 rows of observations. When estimating the parameters of a regression model, any row that is not complete (i.e. has at least one data point missing) is dropped from the data set, so in order to compute summary statistics that is representative of the data that we are going to use to estimate our regression parameters, we drop any row that has missing data in any of the variables we are interested in, that being all the mean green space cover variables, the scale point variables, and all of the control variables. This removes slightly more rows than is removed in any of the individual regressions that will be ran later, as sometimes data is only missing for one of the subjects, while the others are still intact. Such a row would only be dropped in the regression where it would be needed, while the regressions that rely on the other subjects would still keep this row. Doing this removes 2245 observations, finally leaving us with a sample of 5270 observations over 1503 schools, meaning we have an average of 3.506 observations per school. Because some of the schools only lose of some of their observations, we have a unbalanced panel.

Figure 10 visualizes the extent of this. As we can see, most of the schools still have the observations from all five years, followed the loss of two, three and four observations per school beeing more or less equally common, and the loss of one observation is slightly more common than that. Out of the 8725 observations over the 1745 schools we started with, we end up dropping 3455 observations which is equal to 39.5 % .percent.

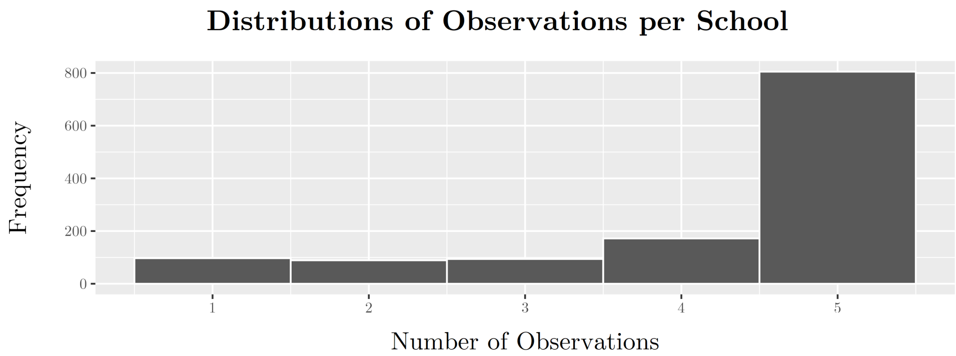


Figure 10: Distribution of number of years observed for the schools in out data

Obviously this amount of lost data is worrisome as it introduces a source of bias. If the reason a observation goes missing is systematic, the data set we use to do our analysis is not a representative sample of our subject matter. For example, some of our test result data is missing because the schools that produce them are so small that the reporting of these figures would poses a threat to the privacy of the students. If the size of a school influences how much of an effect green space has on academic achievement, our models might over- or underestimate the true effect. It is therefore important that we inspect our data and try to get a measure for how substantial the difference might be. One way we could do this is by comparing the means of the dropped and the remaining entries at the end of the merging process. The results of this is presented in Table 5. Here, the dropped data is all of the rows that are present in the data set which includes both green space variables, as well as test results data, i.e. the result of the first merge, but not present in the final data set. The mean for each variable is calculated in each group, and then the difference between these means are calculated as well as the difference expressed as a percentage. Then a independent t-test assuming equal variance is done, and the p-value is reported in the table. As we can see, there are significant differences for all variables except the test results. For the green space variables the differences are generally the highest for the small radii and fall as the radii increases. This positive difference probably reflect the fact that the small schools that have to censor their data generally lies in rural areas with higher levels of green spaces. This is also reflected in the differences of the class size variables. While these differences are concerning, it is not something we are able to remedy. Therefore we will just have to keep it in mind when interpreting the results of our analysis.

Table 5: Difference in means of dropped and kept variables.

Variable	Dropped	Final	Difference	% Difference	P-value
100m_Mean_shrub	4.89	3.67	1.22	33.29	0.00
500m_Mean_shrub	5.70	4.74	0.96	20.25	0.00
1000m_Mean_shrub	5.82	5.01	0.81	16.16	0.00
2500m_Mean_shrub	6.00	5.28	0.71	13.52	0.00
5000m_Mean_shrub	6.23	5.58	0.66	11.80	0.00
100m_Mean_herb	18.01	14.27	3.74	26.22	0.00
500m_Mean_herb	17.13	14.84	2.29	15.42	0.00
1000m_Mean_herb	16.26	14.35	1.91	13.30	0.00
2500m_Mean_herb	15.76	13.97	1.79	12.82	0.00
5000m_Mean_herb	16.56	14.66	1.90	12.97	0.00
100m_Mean_forest	20.71	15.97	4.74	29.68	0.00
500m_Mean_forest	29.65	25.90	3.74	14.45	0.00
1000m_Mean_forest	33.28	30.14	3.14	10.42	0.00
2500m_Mean_forest	37.05	35.04	2.02	5.75	0.00
5000m_Mean_forest	38.29	37.39	0.89	2.39	0.02
English_Points	49.72	49.86	-0.14	-0.28	0.11
Reading_Points	49.63	49.75	-0.12	-0.24	0.14
Math_Points	49.79	49.88	-0.09	-0.19	0.29
English_School_Size	36.48	37.42	-0.94	-2.51	0.05
Reading_School_Size	36.53	37.41	-0.88	-2.36	0.06
Math_School_Size	36.68	37.75	-1.07	-2.84	0.02

Finally, before moving on to our method and estimation strategy, we inspect the correlation within our data set. Figure 11 shows the correlation plot for all our dependent and independent variables. Some of the variables have correlation coefficients of close to one, but none of these are ever included in a regression model at the same time, so multicoliniarity issues are not relevant here. We can see that all three of our test result are highly correlated, as well as the class size. The same is true for some of the green space variables, but generally only within green space type. The shrub and herbaceous green space variables are strongly correlated to each other, while the forest green space type is only slightly correlated with shrub and herbaceous. In general, the green space variables are slightly negatively correlated with the rest of the variables.

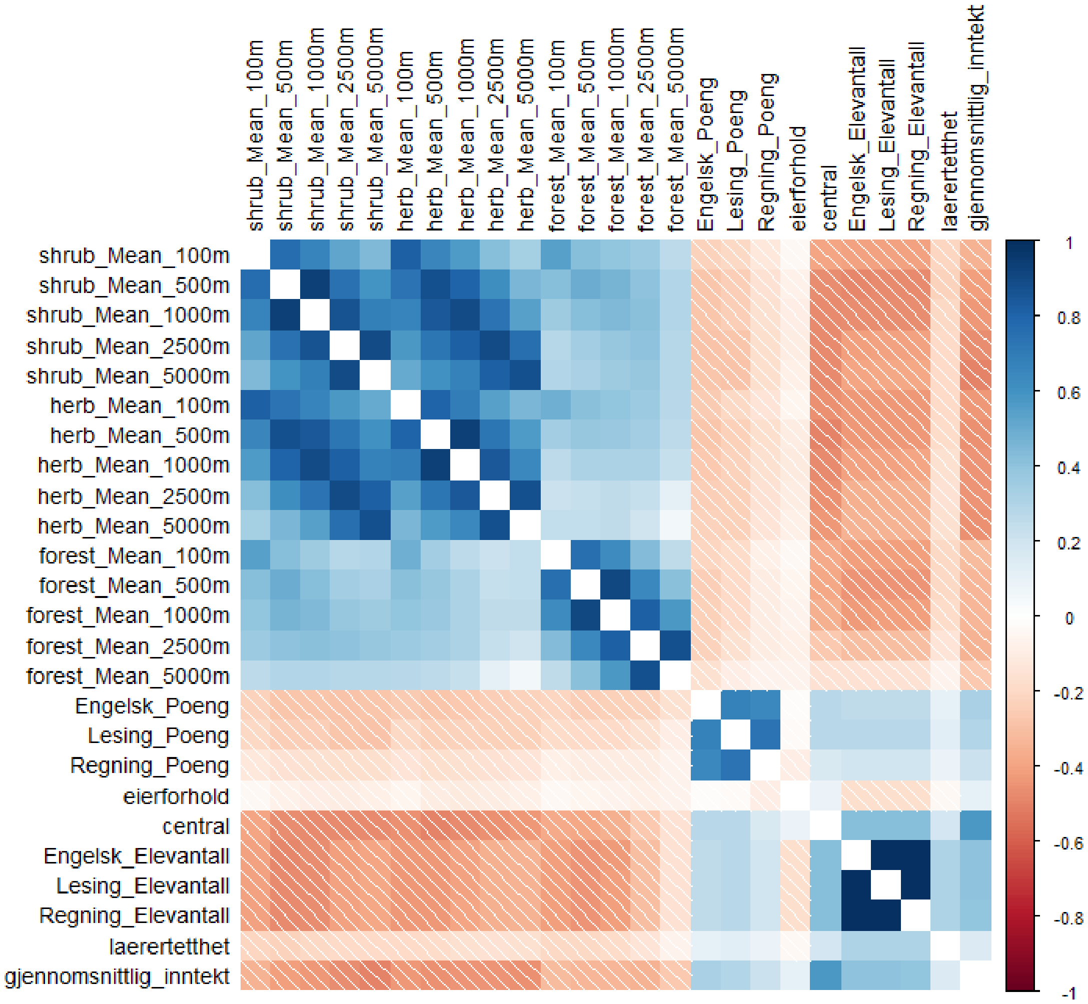


Figure 11: Correlation plot for all our dependent and independent variables.

5 Method and Estimation Strategy

In this section we outline our estimation strategy. First we explain the challenges that we face when we attempt to estimate the effect of green spaces on academic achievement, and then we outline and argue for the methods we employ to deal with these. The essence of our estimation strategy will be to run a series of fixed effects regressions for each possible combination the three subject types, the three green space types, and the five different radii, and to determine based on the results, weather or not there is evidence to support a link between green space and academic achievement among fifth grade students in Norway.

5.1 Regression, POLS, and bias

Our aim in this thesis is to determine if there exists a causal effect of green spaces on academic achievement for fifth graders in Norway. To do this we want to estimate the parameters in a linear regression model that assumes a relationship between our variables of interest. For a given subject and green space type, a basic version of this is expressed in equation (1).

$$Scale\_Points_{i,t,s} = \beta_0 + \beta_1 Green\_Space_{i,t,g,r} + \boldsymbol{\gamma}\boldsymbol{x}_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $Scale\_Points_{i,t,s}$ is the scale points scored a school i, at year t, in subject s, $Green\_Space_{i,t,g,r}$ is the average percentage green space cover type g, within a circle with radius r, around a school i, at year t, $\boldsymbol{x}_{i,t}$ is a vector containing our control variables, $\boldsymbol{\gamma}_{i,t}$ is a vector containing the parameters associated with the controls, and $\varepsilon_{i,t}$ is the error term. Using ordinary least squares on all $N \cdot T$ observations, we can determine the parameter values for β_0, β_1, and $\boldsymbol{\gamma}$ that minimizes the error of the residual, which is the difference between the values of $Scale\_Points$ predicted by the model, and the actual observed values. This is called the pooled OLS estimator, or the POLS estimator for short. Here we disregard the temporal structure of our data. Assuming that the error term is uncorrelated with our variable of interest $Green\_Space$, we can interpret the coefficient β_1 as the change in $Scale\_Points$ associated with a one unit change in $Green\_Space$. This is however an unrealistic assumption, and the result of such correlation is that the POLS estimator is biased. This is called omitted variables bias, and arises when important variables are left out of the model. (Wooldridge, 2016, p. 81) One can attempt to remedy this by including variables that one thinks might be relevant as controls. However, it is unlikely that all of the correlation between the independent variable of interest and the error term is able to be accounted for. This is a problem.

5.2 Fixed effects and clustered standard errors

To attempt to deal with this, we can exploit the fact that we have access to panel data. We begin by decomposing our error term into three parts:

$$\varepsilon_{i,t} = a_i + b_t + c_{i,t} \tag{2}$$

Here a_i is the part of the error that vary across units, but stay the same over time, b_t is the part of the error that is the same for all units, but vary over time, and $c_{i,t}$ is the idiosyncratic part of the error that vary across both units and time. By demeaning the variables in our model over their temporal and unitary dimensions we are able to remove a_i and b_t from our model. This is because these terms only vary over one dimension. So when demeaning over time, the unit specific error term that is constant over time will disappear, seeing as its mean will be the same as its value at each point in time. The same is true for the time specific error term when demeaning over units. This is the fixed effects estimator. (Wooldridge, 2016, p. 435)When demeaning over time we have unit fixed effects, and when demeaning over units, we have time fixed effects. When demeaning over both we have both unit and time fixed effects. Including time and unit fixed effects is our main strategy to reduce endogeneity in the regressors. After demeaning we estimate our parameters using POLS.

Seeing as we are looking at data that are clustered into schools, as well as looking at schools from all across Norway, we also worry that the residuals from our model might be heteroskedastic and auto-correlated. We know that if this is the case, the standard errors associated with our parameter estimates will be too low (Citation needed) and could lead us to faulty conclusions. To counteract this, we report standard errors clustered at the school level for all our regression results. (Verbeek, 2017, p. 398 - 399)

5.3 Specification of Econometric Model

We begin by estimating a POLS model with time fixed effects. We then estimate the main model using both time and unit fixed effects. This model is expressed in equation (3)

$$\begin{gathered} Scale\_Points_{i,t,s} = \beta_0 + \beta_1 Green\_Space_{i,t,r,g} + \beta_2 School\_Size_{i,t,s} + \\ \beta_3 Studen\_Teacher\_Ratio_{i,t} + \beta_4 Average\_Income_{i,t} + \sum_{j=1}^{5} \delta_j T_j + \sum_{k=1}^{N-1} \gamma_k U_k + \varepsilon_{i,t} \end{gathered} \tag{3}$$

where

$Scale\_Points_{i,t,s}$ = The scale points scored on the national test for subject s, at school i, at time t.

$Green\_Space_{i,t,r,g}$ = The average percentage of green space cover g, inside a circle with radius r, centered at school i, at time t.

$School\_Size_{i,t,s}$ = The number of students that took the national test at school i, at school i, at time t.

$Student\_Teacher\_Ratio_{i,t}$ = Student teacher ratio at school i, at time t.

$Average\_Income_{i,t}$ = Average income in the municipality that school i is located in at time t.

T_j = Dummy variable for time period. Equal to one when t = j

$\varepsilon_{i,t}$ = Error term for school i, at time t.

U_k = Dummy variable for unit (school). Equal to one when i = k. k ranges from 1 to N, where N is the number of units included in the data set used to fit the regression parameters. As discussed in the data chapter, this number varies because of missing data.

6 Results

In this section we present the results from the models presented in the chapter on empirical strategy. First we review the results from the baseline POLS model, which gives us a initial impression of the relationships within our data. Then we present the main results from the fixed effects model.

6.1 The POLS model

The results from the baseline POLS model with time fixed effects is summarized in Table 6. The full regression output for all POLS models can be found the appendix. These results provide a first look into into the relationship between green spaces and test results, and serves as a starting point for our analysis.

The POLS results shows three things. Firstly, the different subjects show different levels of significant relationships with the green space variables. Most affected is the English test scores, where all 15 of the green space variables show a highly significant relationship to the outcomes. Second most is the math test scores, where 8 out of the 15 variables show a significant relationship. Lastly, for the the reading scores, none of the green space variables show a significant relationship with the outcome. Secondly, all of the significant relationships are negative, with varying degrees of effect size, ranging from a one unit increase in average mean forest cover percentage around a school being associated with a 0.016 point decrease on the English national tests, to the same increase in average mean shrub cover percentage being associated with at 0.156 point decrease on the same test. Third and finally, we observe that herbaceous vegetation and shrubs have more significant relationships with test outcomes, both having 9, than forest, which only has 5.

We also note the direction, size, and significance of the controls. Class size show a significant, slight positive effect on outcomes in all models. As does municipality average income, though with a much smaller, barely positive effect. A school being privately owned only has a significant effect on the outcomes of the math test, with a negative effect of about 1.8 points. The student teacher ratio is only significant for the reading tests, with a slight increase in points associated with a higher student teacher ration. The centrality dummy is significant for English and reading, but not math, with central schools associated with about a half of a point increase in test scores.

Table 6: Summary of POLS Regression Results

Green Space Type	Radius	Math	English	Reading
Forest	100m	0.006	**-0.016*****	0.014
		(0.005)	(0.005)	(0.017)
	500m	0.0003	**-0.023*****	0.033
		(0.005)	(0.004)	(0.028)
	1000m	0.0001	**-0.022*****	0.046
		(0.005)	(0.005)	(0.036)
	2500m	-0.003	**-0.020*****	0.045
		(0.005)	(0.004)	(0.041)
	5000m	-0.002	**-0.015*****	0.003
		(0.005)	(0.004)	(0.046)
Herbaceous Vegetation	100m	-0.010	**-0.029*****	-0.007
		(0.007)	(0.006)	(0.016)
	500m	**-0.031*****	**-0.044*****	-0.001
		(0.009)	(0.008)	(0.033)
	1000m	**-0.033*****	**-0.045*****	-0.005
		(0.010)	(0.009)	(0.041)
	2500m	**-0.034*****	**-0.040*****	0.013
		(0.011)	(0.010)	(0.050)
	5000m	**-0.021****	**-0.024*****	0.036
		(0.009)	(0.008)	(0.051)
Shrubs	100m	-0.015	**-0.069*****	-0.007
		(0.018)	(0.017)	(0.034)
	500m	**-0.053****	**-0.118*****	-0.096
		(0.024)	(0.022)	(0.062)
	1000m	**-0.068****	**-0.133*****	-0.093
		(0.027)	(0.023)	(0.074)
	2500m	**-0.103*****	**-0.156*****	-0.060
		(0.028)	(0.025)	(0.084)
	5000m	**-0.090*****	**-0.136*****	-0.050
		(0.029)	(0.025)	(0.085)
Number of observations used		5399	5392	5378

Note: *p<0.1; **p<0.05; ***p<0.01

This table summarizes the parameter estimate of interest from 45 different POLS regression models. Each model estimates the effect of green space cover on test scores for one of the 45 different combinations of subject type, green space cover type, and radius around the school. Each model has time fixed effects and controls for class size, student-teacher ration, average monthly income at the municipality level, municipality centrality, and school ownership type. The standard errors are clustered at the school level. For detailed regression results, see the appendix.

6.2 The Fixed Effects model

The results from the model with unit and time fixed effects are presented in Table 7. As outlined in the previous chapter, these models likely provide more credible results.

The change from the POLS model is immediately apparent. Now we only have three significant variables. These are the parameter estimates of the change in mean forest cover percentage in circles with radii of 1000m and 2500m around each school, on test scores on the math test, as well as the the change in mean forest cover percentage in a circle with a radius of 2500m around each school, on the test scores on the English test. The estimates are all positive, with values of just under 0.1, meaning that a one percent increase in mean forest cover in a circle with a radius of 2500m around a school is associated with a increased score on the math test of 0.099 points, and on the English test of 0.097 points. A equal increase in a circle with a radius of 1000 is associated with a increased math score of 0.089 points. This drastic change in effect size from POLS to FE, suggest that there was heterogeneity at the unit level in the POLS model that was not being accounted for.

In addition to the three parameters that are significant at the 5 % level, we also see that forest cover within 5000m on English, herbaceous vegetation within 2500m on math and herbaceous vegetation within 5000m on reading are significant at a 10 % level. Again, forest has a slight positive effect, and herbaceous vegetation has a slight negative effect.

As for the control variables, it is now only the class size that has a significant effect, being slightly negative for all outcomes. The centrality and ownership type controls, are no longer included seeing as they have no variation over time.

Table 7: Summary of Fixed Effects Regression Results

Green Space Type	Radius	Math	English	Reading
Forest	100m	0.018	0.006	0.014
		(0.018)	(0.016)	(0.017)
	500m	0.0048	0.030	0.033
		(0.032)	(0.029)	(0.028)
	1000m	**0.089****	0.058	0.046
		(0.040)	(0.037)	(0.036)
	2500m	**0.099****	**0.097****	0.045
		(0.046)	(0.043)	(0.041)
	5000m	0.059	0.086*	0.003
		(0.052)	(0.047)	(0.046)
Herbaceous Vegetation	100m	-0.002	0.020	-0.007
		(0.016)	(0.015)	(0.016)
	500m	-0.016	0.029	-0.001
		(0.034)	(0.032)	(0.033)
	1000m	-0.048	-0.050	-0.005
		(0.043)	(0.040)	(0.041)
	2500m	-0.093*	0.077	0.013
		(0.051)	(0.050)	(0.050)
	5000m	-0.089	-0.094 *	0.036
		(0.056)	(0.055)	(0.051)
Shrubs	100m	-0.025	0.002	-0.007
		(0.037)	(0.033)	(0.034)
	500m	-0.032	0.064	-0.096
		(0.067)	(0.058)	(0.062)
	1000m	-0.084	-0.045	-0.093
		(0.076)	(0.072)	(0.074)
	2500m	-0.083	0.015	-0.060
		(0.088)	(0.082)	(0.084)
	5000m	-0.055	-0.040	-0.050
		(0.088)	(0.088)	(0.085)
Number of observations used		5339	5392	5378

Note: *p<0.1; **p<0.05; ***p<0.01

This table summarizes the parameter estimate of interest from 45 different fixed effects regression models. Each model estimates the effect of green space cover on test scores for one of the 45 different combinations of subject type, green space cover type, and radius around the school. Each model has unit and time fixed effects and controls for class size, student-teacher ration, average monthly income at the municipality level. The standard errors are clustered at the school level. For detailed regression results, see the appendix.

7 Discussion

In this sections we will discuss the results from our analysis. We start by looking at what our results means for our research question, then we discuss limitations of our work, followed by the implications for policy. Lastly we discuss suggestion for further work.

7.1 What Does The Results Say About Our Main Research Question?

We begin by discussing the implications of the results on our main research question, which is to determine whether or not green spaces around schools have an effect on the academic achievements of Norwegian fifth graders, as measured by their test results on the national tests. We also discuss the validity of our main hypothesis, rooted in environmental psychology, that this effect should be positive.

The results from the initial POLS model indicate that there is a statistically significant relationship between all of our measured green space variables and some of the subject test results, and that this relationship is negative in all cases. This goes against our main hypothesis that this effect should be positive. There are however reasons to be sceptical of these results. Despite doing our best to control for factors that are suspected to influence academic outcomes as well as local green space, such as school size, student teacher ratio, centrality, and municipal income level, it remains highly unlikely that the variation in our green space data can be considered exogenous. This means that the parameter estimates that we observe are most likely biased, and the effects we observe probably reflects some combination of omitted variables that affects both green space and academic achievement.

To deal with this, we estimate our model using fixed effects at the school level. We argue that this provides much more credible results, especially when combined with inference based on clustered standard errors. When doing this the results change dramatically. The significant effect of multiple variables suggests that the answer to our main questions is that, yes there is a connection between green space and academic achievement in as measured by scores on the national tests among Norwegian fifth graders. More specifically we find that for certain distances, forest cover has a positive effect on math and English scores, and herbaceous vegetation cover, also known as grass cover, has a slight negative effect on English scores. This partly confirms our hypothesis that green space should have a positive effect.

This leads us to discuss the potential mechanisms trough which the green space might be interacting with achievement. The fact that forest cover is positive, while herbaceous/grass cover is negative could support the hypothesis that it is the viewing of the natural elements that is the main mechanism leading to better performance, rather than interaction, as trees are more visible in the environment than grasslands. This would agree with the only experimental study in the literature, (Benfield et al., 2015) who finds increased ratings of, and grades in, a college composition class when exposed to views of natural environments.

The facts that it is only English and math that are the subjects affected and not reading is also interesting, as this might point towards specific types of skill sets or cognitive abilities being more affected by increased presence of green space. In this context, it's conceivable that the visual stimuli provided by forest cover may enhance attention and reduce stress, thereby improving performance in subjects that require higher levels of analytical thinking and problem-solving skills, like Math and English. Conversely, the lesser visual impact of grasslands may not stimulate the same cognitive response, potentially explaining the negative correlation observed. Furthermore, the specificity of the effects to English and Math, but not reading, might hint at the different cognitive processes these subjects entail. English and Math, which demand abstract reasoning and symbol manipulation, could benefit more from the mental restoration and stress reduction provided by green spaces. In contrast, reading, especially in one's native language, may rely more heavily on skills and knowledge that are less influenced by these environments, such as extensive vocabulary and cultural comprehension. This underscores the complexity of the green space-academic achievement relationship and highlights the need for further explorations into the specific mechanisms at play. In the end, our results only provide evidence for the existence of a green space - academic achievement link, but does not provide any insights into the mechanism driving these results

Our results agree with some of the existing literature. Like Hodson and Sander (2017) and Tallis et al. (2018), our results indicate a significant positive relationship between forest cover (akin to tree cover) and academic achievement. However, we found this effect only for Math and English, not Reading. Consistent with Matsuoka (2010) and Kweon et al. (2017), we found that the degree of natural features (forest cover) positively correlates with academic outcomes. Unlike Hodson and Sander (2017) and Tallis et al. (2018), we found that herbaceous vegetation (akin to grass/shrub cover) had a slight negative effect on English scores, albeit at the 10 % significance level.

7.2 Data Limitations

Our analysis encountered several limitations due to data constraints. While we did our best to construct a data set that that allows us to investigate our research question as best as possible, there are still some issues with it that limits our analysis and introduces sources of bias.

Firstly, the temporal dimension of the data, limited by availability, is relatively short, spanning only five years. While we show that even across this brief period, our variables of interest contain a decent amount of variation, this might still not be a long enough time period to adequately catch longer term changes in green space and test results. Secondly, we loose a significant amount of data, firstly because of the privacy related censoring that is done by UDIR, and secondly because of issues in our data merging process. This reduction of sample size probably introduces a source of bias into our results, especially considering the fact that the means of the kept and missing data are significantly different for a large number of our variables. The schools that are dropped are on average both greener, smaller, and lower performing, leading us to believe that the dropped schools are mostly small rural schools. Any difference in the relationship between green space and academic achievement in these schools from the kept schools will skew our final results. Thirdly, there are many variables that are know to influence academic achievement, such as parental income and educational level, and ethnicity (SSB, 2019), that most likely also varies with green space, that we were not able to include in our data set. Also for some of our control variables like centrality and school ownership type, we were not able to get data for each year, and thus they were not able to be used in our unit fixed effects model. Access to more detailed control variables for all years would help improve the analysis and provide more credible results.

There is also some limitations associated with our green space data. Firstly of all, there is some uncertainty included in the data set. While the methods used to classify the land cover maps are very sophisticated, they are not 100% accurate. In their guidance manual, the creators of the Copernicus data set gives an accuracy estimate of 80% (Buchhorn et al., 2020). The processes used to make this data set, is very complicated, so we have no choice but to trust that their data is as accurate as possible. Even so, the spacial resolution of the data is only 100 by 100 meters. While this is a relatively high resolution in comparison to other data available, it still might not be sensitive enough to pick up on finer nuances in green space variability. Another thing our data is unable to pick up on is the change in green space over the year. In our data set the green space of an area is determined based on an entire year of data. How this is done in slightly unclear to us. Other studies like Wu et al. (2014), are able to pick up on changing forest cover over the seasons, and find that the link between green space and academic performance

7.3 Methodological Limitations

While we attempt to counteract endogeneity and bias as best we can trough our use of time and unit fixed effects, though beneficial in reducing regressors' endogeneity, this method only captures all unobserved time-stable and time-varying factors shared among all units. There's a potential for bias from unobserved variables that fluctuate across both time and individual units. There is also the assumed structure of the models residuals, justifying clustering the standard errors at the unit level which might not be correct, thus leading to faulty inference.

As a result of the construction of our data set taking longer than first anticipated, we have had to limit our ambition in terms of modeling sophistication. We could have spent more time exploring alternative model specifications, potentially improving our results by incorporating logarithmic and/or quadratic terms, as well as including interactions in the model. Applying more complicated models such as generalized mixed models or multilevel models, which we have seen used in the literature could potentially have yielded more credible results, however we have not had the time to fully understand how these models would work in our setting.

Our analysis could also have benefited from a more rigours sensitivity analysis. While not mentioned in the text, we did make our analysis more robust by expanding out green space data from initially only containing forest cover data, to also including herbaceous vegetation and shrub cover maps. To further strengthen our results we could have used other types of green space data as well. Two examples are the global NDVI, and European high resolution forest cover maps. (Service, n.d.-a) (Service, n.d.-b). The NDVI map could provide access to a lot more data, with maps updated on a frequent basis, while the high resolution forest cover map could provide access to maps with very high resolutions (10 x 10 meters), but only at a few time points. We could also have extended our analysis to national test results from eight and ninth graders, as well as used other markers for academic achievement such as exam and end of year grades, as well as UDIR's statistics on how much each school contributes to their students basic skills in reading, math, and English. (UDIR, n.d.-a) (UDIR, n.d.-e). We could also have looked more for additional control variables, to investigate how the addition of these would influence our results.

7.4 Policy implications

As we have mentioned, we have identified a positive association between forest coverage within 1000m and 2500m radii around schools, and student test scores in Mathematics and English, while herbaceous vegetation and shrubs exhibited a negative correlation within the same radii. Potential policy implications suggest an increase or preservation of forest coverage proximate to schools could potentially augment student performance, but additional educational strategies may be necessary to enhance English and reading scores.

A possibility to increase educational outcomes for a relatively cheap price has obvious utility for policy makers bot regional and national. A budgetary comparison between implementing green spaces and traditional educational spending revealed costs for planting a tree can vary from 20 to over 14,000 NOK, whereas a full-time teaching position in 2021 costs an approximated 790,000 Kroner(Johnsrud, 2023) (**faktisk**). This raises questions about the cost-effectiveness of green spaces to improve educational outcomes

As we do find positive association between forest coverage, and some previous literature points also towards this, it could be wise for policy makers to look at the possible added value that trees and green spaces might add to educational environment. But future research is needed.

7.5 Suggestions for Further Work

As we mentioned above in the section on our methodological limitations, there is plenty of potential extension of our analysis incorporating more data on green space, academic achievement, and control variables. Seeing as data is fairly easy to get a hold of, and the tools needed to process them is not too hard to learn, there are a lot of opportunity to strengthen our understanding of this very interesting field.
While we were able to show some associations within our data, we were not able to get at what mechanism are at play. An obvious future research question is to expand on this, and try to isolate how green space translates to improved academic ability. Is it the mere viewing of green spaces that is important or is direct interaction and activity within these spaces needed. Does the green space work trough cognitive or emotional channels? More evidence to determine a causal link is also necessary. While perhaps a bit too grand in scope, a randomized experiment would of course be ideal, however experiments that not randomized or study designs exploiting any potential natural experiments could also be very useful.

8 Conclusion

This thesis has analyzed the existence of a link between the amount of green space around primary schools, and academic achievement among Norwegian fifth graders. The analysis was conducted using a novel panel data set consisting of test results from the national tests in math, English and reading taken by Norwegian fifth graders, average forest, shrub and herbaceous vegetation land cover maps derived from the Copernicus Global Land Service, and a set of control variables controlling for geographic and socio-economics status. The data consisted of around 5270 observations from 1503 schools spanning from 2015 to 2019.

Our main findings is identifying small, but statistically significant, positive associations between average percentage of forest cover within 2500 and 1000 meters of schools on math and English test scores. We find that a one percent increase in mean forest cover within 2500 meters of a school is associated with a 0.099 point increase in math scores, and a 0.097 point increase in English scores. Within 1000 meters, the same increase is mean forest cover is associated with a 0.098 point percent increase in math scores. We account for heterogeneity across schools and time by estimating a regression model with unit and time fixed effects, and calculate cluster robust standard errors. A big contribution of the thesis is also the construction of a novel data set which is used to do the first analysis of its kind on data from Norway.

The main limitations of our findings is a probable bias in the parameter estimates as a result of missing and dropped data, as well as a lack of rigorous sensitivity analysis.
We find that

References

Albertsen, D. (2020). Forskjellene består i resultatene fra nasjonale prøver. https://www.ssb.no/utdanning/artikler-og-publikasjoner/forskjellene-bestar-i-resultatene-fra-nasjonale-prover

Arnesen. (2021). Elever i sentrale kommuner skårer høyest på nasjonale prøver. *Statistisk sentralbyrå (SSB)*. https://www.ssb.no/utdanning/grunnskoler/statistikk/nasjonale-prover/artikler/elever-i-sentrale-kommuner-skarer-hoyest-pa-nasjonale-prover

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Beere, P., & Kingham, S. (2017). Assessing the relationship between greenspace and academic achievement in urban new zealand primary schools. *New Zealand Geographer*, *73*(3), 155–165. https://doi.org/https://doi.org/10.1111/nzg.12155

Benfield, J. A., Rainbolt, G. N., Bell, P. A., & Donovan, G. H. (2015). Classrooms with nature views: Evidence of differing student perceptions and behaviors. *Environment and Behavior*, *47*(2), 140–157. https://doi.org/10.1177/0013916513499583

Browning, M. H., Kuo, M., Sachdeva, S., Lee, K., & Westphal, L. (2018). Greenness and school-wide test scores are not always positively associated – a replication of "linking student performance in massachusetts elementary schools with the 'greenness' of school surroundings using remote sensing". *Landscape and Urban Planning*, *178*, 69–72. https://doi.org/https://doi.org/10.1016/j.landurbplan.2018.05.007

Browning, M. H., & Rigolon, A. (2019). School green space and its impact on academic performance: A systematic literature review. *International Journal of Environmental Research and Public Health*, *16*(3), 429. https://doi.org/10.3390/ijerph16030429

Buchhorn, M., Smets, B., Bertels, L., Roo, B. D., Lesiv, M., Tsendbazar, N.-E., Herold, M., & Fritz, S. (2020). Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. https://doi.org/10.5281/zenodo.3939050

Dadvand, P., Nieuwenhuijsen, M. J., Esnaola, M., Forns, J., Basagaña, X., Alvarez-Pedrerol, M., Rivas, I., López-Vicente, M., De Castro Pascual, M., Su, J., Jerrett, M., Querol, X., & Sunyer, J. (2015). Green spaces and cognitive development in primary schoolchildren. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(26), 7937–7942. https://doi.org/10.1073/pnas.1503402112

Eccles, J. S. (1999). The development of children ages 6 to 14. *The Future of Children*, *9*(2), 30–44. Retrieved June 14, 2023, from http://www.jstor.org/stable/1602703

EEA, E. E. A. (2020). *Healthy environment, healthy lives: How the environment influences health and well-being in europe* (No. 21/2019). European Environment Agency. https://www.eea.europa.eu/publications/healthy-environment-healthy-lives

Embretson, S. E., & Reise, S. P. (2000). *Item response theory for psychologists*. Lawrence Erlbaum Associates Publishers.

Finansdepartementet. (2021). *Perspektivmeldingen 2021*. Oslo.

GeoNorge. (2015). Kartkatalogen. *kartkatalog.geonorge.no*. Retrieved June 15, 2023, from https://kartkatalog.geonorge.no/metadata/grunnskoler/db4b872f-264d-434c-9574-57232f1e90d2

Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of economic literature*, *46*(3), 607–668.

Hodson, C. B., & Sander, H. A. (2017). Green urban landscapes and school-level academic performance. *Landscape and Urban Planning*, *160*, 16–27. https://doi.org/https://doi.org/10.1016/j.landurbplan.2016.11.011

Høydahl, E. (2020). Sentralitetsindeksen: Oppdatering med 2020-kommuner [. Publisert 27. februar 2020]. *NOTATER / DOCUMENTS*, (4).

Johnsrud, H. (2023). Email correspondence regarding the cost of planting trees [Prosjektleder Oslotrær - Plan].

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework [Green Psychology]. *Journal of Environmental Psychology*, *15*(3), 169–182. https://doi.org/https://doi.org/10.1016/0272-4944(95)90001-2

Kirkebøen, L. J., Kotsadam, A., Raaum, O., Andresen, S., & Rogstad, J. (2017). *Effekter av satsing på økt lærertetthet på ungdomstrinnet* (tech. rep. No. 2017/39). Rapporter. https://www.ssb.no/utdanning/artikler-og-publikasjoner/_attachment/332335?_ts=16044ba4410

Kweon, B.-S., Ellis, C., Lee, J., & Jacobs, K. (2017). The link between school environments and student academic performance. *Urban Forestry Urban Greening*, *23*. https://doi.org/10.1016/j.ufug.2017.02.002

Markevych, I., Feng, X., Astell-Burt, T., Standl, M., Sugiri, D., Schikowski, T., Koletzko, S., Herberth, G., Bauer, C.-P., von Berg, A., Berdel, D., & Heinrich, J. (2019). Residential and school greenspace and academic performance: Evidence from the giniplus and lisa longitudinal studies of german adolescents. *Environmental Pollution*, *245*, 71–76. https://doi.org/https://doi.org/10.1016/j.envpol.2018.10.053

Matsuoka, R. H. (2010). Student performance and high school landscapes: Examining the links. *Landscape and Urban Planning*, *97*(4), 273–282. https://doi.org/https://doi.org/10.1016/j.landurbplan.2010.06.011

Miljødirektoratet. (2023). Veileder: By- og tettstedsnær grønnstruktur i arealplanlegging [14.07.2020]. https://www.miljodirektoratet.no/ansvarsomrader/overvakingarealplanlegging / arealplanlegging / miljohensyn - i - arealplanlegging / friluftsliv / gronnstruktur-i-arealplanlegging/

NOU 1988:28 Med viten og vilje. (1988). *Innstilling fra universitets- og høyskoleutvalget oppnevnt ved kongelig resolusjon av 22. juli 1987 : Avgitt til kultur- og vitenskapsdepartementet 9. september 1988*. Forvaltningstjenestene Statens Trykningskontor.

NOU 2023: 1. (2023). *NOU 2023: 1 Kvalitetsvurdering og kvalitetsutvikling i skolen – Et kunnskapsgrunnlag* [Utredning fra et utvalg oppnevnt ved kongelig resolusjon 1. april 2022. Avgitt til Kunnskapsdepartementet 31. januar 2023.]. Departementenes sikkerhets- og serviceorganisasjon.

OECD. (2018). *Education at a glance 2018: Oecd indicators*. https://doi.org/10.1787/eag-2018-en

PISA. (2019). *Pisa 2018 results: Combined executive summaries (volume i, ii & iii)*. OECD Publishing. http://www.oecd.org/termsandconditions

Saenen, N. D., Nawrot, T. S., Hautekiet, P., et al. (2023). Residential green space improves cognitive performances in primary schoolchildren independent of traffic-related air pollution exposure. *Environmental Health*, *22*(33). https://doi.org/10.1186/s12940-023-00982-z

Schertz, K. E., & Berman, M. G. (2019). Understanding nature and its cognitive benefits. *Current Directions in Psychological Science*, *28*(5), 496–502. https://doi.org/10.1177/0963721419854100

Service, C. G. L. (n.d.-a). Normalized difference vegetation index — copernicus global land service. *land.copernicus.eu*. https://land.copernicus.eu/global/products/NDVI

Service, C. G. L. (n.d.-b). Status maps — copernicus land monitoring service. *land.copernicus.eu*. Retrieved June 15, 2023, from https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density/status-maps

Sivarajah, S., Smith, S., & Thomas, S. (2018). Tree cover and species composition effects on academic performance of primary school students. *PLOS ONE*, *13*, e0193254. https://doi.org/10.1371/journal.pone.0193254

SSB. (n.d.). 12852: Kommunefordelt månedslønn, etter bosted, arbeidssted, alder og kjønn (k) 2015 - 2022. statistikkbanken. *SSB*. https://www.ssb.no/statbank/table/12852/

SSB. (2019). Nasjonale prøver: Foreldrenes utdanning spiller stor rolle. *ssb.no*. Retrieved June 15, 2023, from https://www.ssb.no/utdanning/artikler-og-publikasjoner/foreldrenes-utdanning-avgjorende

SSB. (2020). Sentralitetsindeksen - oppdatering med 2020-kommuner. *ssb.no*. https://www.ssb.no/befolkning/artikler-og-publikasjoner/sentralitetsindeksen.oppdatering-med-2020-kommuner

Storting Proposition No. 1. (2018–2019). For budsjettåret 2019 under kunnskapsdepartementet [proposal to the parliament (proposal for parliamentary resolution)] [Retrieved from https://www.regjeringen.no/contentassets/70b764ab133b4703929bdd51d0a51fc2/nn-no/pdfs/prp201820190001_kddddpdfs.pdf].

Storting Proposition No. 1. (1987–1988). *The state budget including social security for the budget term 1988* [Retrieved from https://www.stortinget.no/no/Saker-og-publikasjoner/Stortingsforhandlinger/Lesevisning/?p=1987-88&paid=1&wid=a&psid=DIVL763&pgid=a_0045].

Tallis, H., Bratman, G. N., Samhouri, J. F., & Fargione, J. (2018). Are california elementary school test scores more strongly associated with urban trees than poverty? *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.02074

Tuen Veronica Leung, W., Yee Tiffany Tam, T., Pan, W.-C., Wu, C.-D., Candice Lung, S.-C., & Spengler, J. D. (2019). How is environmental greenness related to students' academic performance in english and mathematics? *Landscape and Urban Planning*, *181*, 118–124. https://doi.org/https://doi.org/10.1016/j.landurbplan.2018.09.021

UDIR. (n.d.-a). Grunnskolekarakterer. *www.udir.no*. Retrieved June 15, 2023, from https://www.udir.no/tall-og-forskning/statistikk/statistikk-grunnskole/grunnskolekarakterer/

UDIR. (n.d.-b). Information about the national tests [Accessed: 2023-05-04].

UDIR. (n.d.-c). Lærertetthet i grunnskolen. *www.udir.no*. Retrieved June 15, 2023, from https://www.udir.no/tall-og-forskning/statistikk/statistikk-grunnskole/tall-for-larertetthet-i-grunnskolen/

UDIR. (n.d.-d). Nasjonale prøver 5. trinn – resultater. *www.udir.no*. https://www.udir.no/tall-og-forskning/statistikk/statistikk-grunnskole/nasjonale-prover-5.-trinn/

UDIR. (n.d.-e). Skolebidrag barnetrinnet. *www.udir.no*. Retrieved June 15, 2023, from https://www.udir.no/tall-og-forskning/statistikk/statistikk-grunnskole/skolebidrag-barnetrinnet/

UDIR. (2022). Tekniske krav til prøvene. *Utdanningsdirektoratet (Udir)*. https://www.udir.no/eksamen-og-prover/prover/rammeverk-for-nasjonale-prover2/tekniske-krav-til-provene/#maling-av-utvikling-over-tid-og-ankerprover

Ulrich, R. S. (1983). Aesthetic and affective response to natural environment. In I. Altman & J. F. Wohlwill (Eds.), *Behavior and the natural environment*. Springer. https://doi.org/10.1007/978-1-4613-3539-9_4

UN, DESA. (2019). *World urbanization prospects: The 2018 revision*. United Nations, Department Of Economic; Social Affairs. Population Division. https://population.un.org/wup/publications/Files/WUP2018-Report.pdf

Verbeek, M. (2017). *A guide to modern econometrics* (5th ed.). John Wiley Sons, Inc.

Wells, N. M. (2000). At home with nature: Effects of “greenness” on children’s cognitive functioning. *Environment and behavior*, *32*(6), 775–795.

Wilson, E. O. (1984). *Biophilia*. Harvard University Press. https://doi.org/10.2307/j.ctvk12s6h

Wooldridge, J. M. (2016). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning. Retrieved June 15, 2023, from https://books.google.no/books/about/Introductory_Econometrics_A_Modern_Appro.html?id=_9qpCgAAQBAJ&redir_esc=y

Wu, C.-D., McNeely, E., Cedeño-Laurent, J. G., Pan, W.-C., Adamkiewicz, G., Dominici, F., Lung, S.-C. C., Su, H.-J., & Spengler, J. D. (2014). Linking student performance in massachusetts elementary schools with the “greenness” of school surroundings using remote sensing. *PLOS ONE*, *9*(10), 1–9. https://doi.org/10.1371/journal.pone.0108548

9 Appendix

9.1 Regression output from POLS models

Table 8: Pooled with time fixed effects for Forest Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	0.006				
	(0.005)				
Forest_Mean_500m		0.0003			
		(0.005)			
Forest_Mean_1000m			0.0001		
			(0.005)		
Forest_Mean_2500m				−0.003	
				(0.005)	
Forest_Mean_5000m					−0.002
					(0.005)
Math_Class_Size	0.018***	0.017***	0.017***	0.016***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.019*	0.018	0.017	0.017	0.017
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Average_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.295	0.262	0.260	0.255	0.262
	(0.183)	(0.182)	(0.182)	(0.182)	(0.182)
eierforholdPrivat	−1.815***	−1.843***	−1.845***	−1.872***	−1.857***
	(0.562)	(0.558)	(0.558)	(0.558)	(0.557)
Constant	42.196***	42.424***	42.437***	42.711***	42.641***
	(0.915)	(0.935)	(0.951)	(0.981)	(0.976)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.071	0.071	0.071	0.071	0.071
Adjusted R^2	0.070	0.070	0.070	0.070	0.070
F Statistic (df = 6; 5392)	69.147***	68.641***	68.639***	68.822***	68.750***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 9: Pooled with time fixed effects for Shrub Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	−0.015				
	(0.018)				
Shrub_Mean_500m		−0.053**			
		(0.024)			
Shrub_Mean_1000m			−0.068**		
			(0.027)		
Shrub_Mean_2500m				−0.103***	
				(0.028)	
Shrub_Mean_5000m					−0.090***
					(0.029)
Math_Class_Size	0.016***	0.014***	0.013***	0.013***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.016	0.015	0.015	0.015	0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Average_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.233	0.169	0.153	0.114	0.144
	(0.186)	(0.186)	(0.186)	(0.186)	(0.187)
eierforholdPrivat	−1.867***	−1.948***	−1.990***	−2.023***	−1.955***
	(0.556)	(0.558)	(0.560)	(0.562)	(0.562)
Constant	42.639***	43.155***	43.363***	43.933***	43.897***
	(0.897)	(0.920)	(0.926)	(0.930)	(0.939)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.071	0.073	0.073	0.076	0.074
Adjusted R^2	0.070	0.072	0.072	0.074	0.073
F Statistic (df = 6; 5392)	68.895***	70.470***	71.153***	73.398***	72.109***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 10: Pooled with time fixed effects for Herb Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	−0.010				
	(0.007)				
Herb_Mean_500m		−0.031***			
		(0.009)			
Herb_Mean_1000m			−0.033***		
			(0.010)		
Herb_Mean_2500m				−0.034***	
				(0.011)	
Herb_Mean_5000m					−0.021**
					(0.009)
Math_Class_Size	0.015***	0.013***	0.014***	0.015***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.016	0.015	0.016	0.016	0.016
	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)
Average_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.205	0.109	0.122	0.133	0.182
	(0.186)	(0.186)	(0.186)	(0.185)	(0.186)
eierforholdPrivat	−1.895***	−2.013***	−2.009***	−1.976***	−1.918***
	(0.556)	(0.559)	(0.560)	(0.560)	(0.559)
Constant	42.932***	43.705***	43.692***	43.688***	43.356***
	(0.934)	(0.945)	(0.939)	(0.935)	(0.938)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.072	0.075	0.075	0.075	0.073
Adjusted R^2	0.071	0.074	0.074	0.074	0.072
F Statistic (df = 6; 5392)	69.446***	72.732***	72.527***	72.419***	70.474***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 11: Pooled with time fixed effects for Forest English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	-0.016^{***}				
	(0.005)				
Forest_Mean_500m		-0.023^{***}			
		(0.004)			
Forest_Mean_1000m			-0.022^{***}		
			(0.005)		
Forest_Mean_2500m				-0.020^{***}	
				(0.004)	
Forest_Mean_5000m					-0.015^{***}
					(0.004)
English_Class_Size	0.015^{***}	0.013^{***}	0.013^{***}	0.016^{***}	0.018^{***}
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Student_Teacher_Ratio	0.014	0.013	0.014	0.015	0.017^{*}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Average_Income	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.584^{***}	0.540^{***}	0.583^{***}	0.656^{***}	0.697^{***}
	(0.169)	(0.168)	(0.166)	(0.166)	(0.167)
eierforholdPrivat	-0.604	-0.699	-0.711	-0.689	-0.587
	(0.888)	(0.891)	(0.891)	(0.897)	(0.896)
Constant	41.038^{***}	41.610^{***}	41.757^{***}	42.057^{***}	41.620^{***}
	(0.946)	(0.957)	(0.973)	(1.006)	(1.012)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.134	0.138	0.138	0.137	0.134
Adjusted R^2	0.133	0.137	0.137	0.136	0.133
F Statistic (df = 6; 5385)	138.384^{***}	143.957^{***}	143.115^{***}	142.936^{***}	139.241^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 12: Pooled with time fixed effects for Shrub English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	-0.069^{***}				
	(0.017)				
Shrub_Mean_500m		-0.118^{***}			
		(0.022)			
Shrub_Mean_1000m			-0.133^{***}		
			(0.023)		
Shrub_Mean_2500m				-0.156^{***}	
				(0.025)	
Shrub_Mean_5000m					-0.136^{***}
					(0.025)
English_Class_Size	0.015^{***}	0.012^{***}	0.012^{***}	0.014^{***}	0.016^{***}
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Student_Teacher_Ratio	0.013	0.012	0.014	0.013	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Average_Income	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.569^{***}	0.482^{***}	0.476^{***}	0.466^{***}	0.510^{***}
	(0.171)	(0.172)	(0.173)	(0.172)	(0.173)
eierforholdPrivat	−0.604	−0.740	−0.793	−0.781	−0.676
	(0.891)	(0.898)	(0.899)	(0.902)	(0.899)
Constant	41.199^{***}	41.922^{***}	42.131^{***}	42.598^{***}	42.542^{***}
	(0.919)	(0.924)	(0.915)	(0.964)	(1.001)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.135	0.139	0.140	0.141	0.138
Adjusted R^2	0.134	0.138	0.139	0.140	0.137
F Statistic (df = 6; 5385)	139.715^{***}	145.022^{***}	145.547^{***}	147.139^{***}	143.376^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Pooled with time fixed effects for Herb English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	-0.026^{***}				
	(0.006)				
Herb_Mean_500m		-0.044^{***}			
		(0.008)			
Herb_Mean_1000m			-0.045^{***}		
			(0.009)		
Herb_Mean_2500m				-0.040^{***}	
				(0.010)	
Herb_Mean_5000m					-0.024^{***}
					(0.008)
English_Class_Size	0.015^{***}	0.014^{***}	0.015^{***}	0.017^{***}	0.018^{***}
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Student_Teacher_Ratio	0.014	0.015^{*}	0.016^{*}	0.016^{*}	0.016^{*}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Average_Income	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.538^{***}	0.470^{***}	0.501^{***}	0.540^{***}	0.596^{***}
	(0.170)	(0.172)	(0.173)	(0.172)	(0.173)
eierforholdPrivat	-0.642	-0.750	-0.732	-0.665	-0.597
	(0.893)	(0.901)	(0.901)	(0.899)	(0.896)
Constant	41.656^{***}	42.140^{***}	42.014^{***}	41.782^{***}	41.390^{***}
	(0.948)	(0.961)	(0.939)	(0.980)	(1.004)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.136	0.138	0.137	0.135	0.132
Adjusted R^2	0.135	0.137	0.136	0.134	0.131
F Statistic (df = 6; 5385)	140.806^{***}	143.856^{***}	142.098^{***}	139.592^{***}	136.302^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 14: Pooled with time fixed effects for Forest Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	−0.007				
	(0.004)				
Forest_Mean_500m		−0.006			
		(0.004)			
Forest_Mean_1000m			−0.007		
			(0.004)		
Forest_Mean_2500m				−0.007	
				(0.004)	
Forest_Mean_5000m					−0.001
					(0.004)
Reading_Class_Size	0.023***	0.023***	0.022***	0.023***	0.024***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.021**	0.021**	0.021**	0.021**	0.022***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
skr central	0.717***	0.721***	0.726***	0.749***	0.760***
	(0.163)	(0.162)	(0.162)	(0.162)	(0.162)
eierforholdPrivat	−0.524	−0.538	−0.554	−0.549	−0.496
	(0.390)	(0.396)	(0.396)	(0.396)	(0.394)
Constant	42.303***	42.353***	42.475***	42.592***	42.116***
	(0.757)	(0.785)	(0.800)	(0.816)	(0.804)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.130	0.130	0.130	0.130	0.129
Adjusted R^2	0.129	0.129	0.129	0.129	0.128
F Statistic (df = 6; 5371)	133.569***	133.449***	133.764***	133.810***	132.696***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 15: Pooled with time fixed effects for Shrub Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	-0.034^{**}				
	(0.016)				
Shrub_Mean_500m		-0.060^{***}			
		(0.021)			
Shrub_Mean_1000m			-0.078^{***}		
			(0.024)		
Shrub_Mean_2500m				-0.130^{***}	
				(0.026)	
Shrub_Mean_5000m					-0.139^{***}
					(0.026)
Reading_Class_Size	0.022^{***}	0.021^{***}	0.020^{***}	0.020^{***}	0.021^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.020^{**}	0.019^{**}	0.020^{**}	0.019^{**}	0.017^{**}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.700^{***}	0.656^{***}	0.636^{***}	0.575^{***}	0.579^{***}
	(0.165)	(0.165)	(0.164)	(0.163)	(0.164)
eierforholdPrivat	-0.536	-0.605	-0.651	-0.709^{*}	-0.653^{*}
	(0.392)	(0.394)	(0.397)	(0.396)	(0.392)
Constant	42.453^{***}	42.818^{***}	43.063^{***}	43.901^{***}	44.280^{***}
	(0.752)	(0.772)	(0.777)	(0.771)	(0.771)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.131	0.132	0.133	0.138	0.139
Adjusted R^2	0.130	0.131	0.132	0.137	0.138
F Statistic (df = 6; 5371)	134.433^{***}	135.895^{***}	137.158^{***}	143.123^{***}	144.269^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 16: Pooled with time fixed effects for Herb Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	-0.007				
	(0.006)				
Herb_Mean_500m		-0.018^{**}			
		(0.008)			
Herb_Mean_1000m			-0.022^{**}		
			(0.009)		
Herb_Mean_2500m				-0.032^{***}	
				(0.010)	
Herb_Mean_5000m					-0.030^{***}
					(0.008)
Reading_Class_Size	0.023^{***}	0.022^{***}	0.022^{***}	0.022^{***}	0.022^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Student_Teacher_Ratio	0.021^{**}	0.021^{***}	0.021^{***}	0.021^{***}	0.020^{**}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
central	0.722^{***}	0.670^{***}	0.670^{***}	0.640^{***}	0.648^{***}
	(0.165)	(0.165)	(0.164)	(0.163)	(0.164)
eierforholdPrivat	-0.523	-0.587	-0.592	-0.608	-0.589
	(0.393)	(0.394)	(0.395)	(0.393)	(0.391)
Constant	42.354^{***}	42.763^{***}	42.825^{***}	43.185^{***}	43.318^{***}
	(0.784)	(0.794)	(0.787)	(0.781)	(0.777)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.130	0.131	0.131	0.133	0.133
Adjusted R^2	0.129	0.130	0.130	0.132	0.132
F Statistic (df = 6; 5371)	133.178^{***}	134.611^{***}	134.858^{***}	137.144^{***}	137.757^{***}
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

9.2 Regression output from Fixed Effect models

Table 17: Group and Time Fixed Effects Forest Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	0.018				
	(0.018)				
Forest_Mean_500m		0.048			
		(0.032)			
Forest_Mean_1000m			0.089**		
			(0.040)		
Forest_Mean_2500m				0.099**	
				(0.046)	
Forest_Mean_5000m					0.059
					(0.052)
Math_Class_Size	−0.026***	−0.026***	−0.026***	−0.026***	−0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	−0.003	−0.003	−0.003	−0.003	−0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	−0.00005	−0.00003	−0.00002	−0.00002	−0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.004	0.005	0.006	0.005	0.004
Adjusted R^2	-0.308	-0.308	-0.307	-0.307	-0.308
F Statistic (df = 4; 4108)	4.451***	4.960***	5.831***	5.560***	4.549***
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 18: Group and Time Fixed Effects Shrub Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	−0.025				
	(0.037)				
Shrub_Mean_500m		−0.032			
		(0.067)			
Shrub_Mean_1000m			−0.084		
			(0.076)		
Shrub_Mean_2500m				−0.083	
				(0.088)	
Shrub_Mean_5000m					−0.055
					(0.088)
Math_Class_Size	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	−0.003	−0.003	−0.003	−0.003	−0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	−0.0001	−0.00005	−0.00005	−0.00004	−0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.004	0.004	0.004	0.004	0.004
Adjusted R^2	-0.309	-0.309	-0.308	-0.308	-0.309
F Statistic (df = 4; 4108)	4.277^{***}	4.229^{***}	4.529^{***}	4.426^{***}	4.265^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

Table 19: Group and Time Fixed Effects Herb Math with Clustered standard errors

	Dependent variable:				
	Math_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	−0.002				
	(0.016)				
Herb_Mean_500m		−0.016			
		(0.034)			
Herb_Mean_1000m			−0.048		
			(0.043)		
Herb_Mean_2500m				-0.093^{*}	
				(0.051)	
Herb_Mean_5000m					−0.089
					(0.056)
Math_Class_Size	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	−0.003	−0.003	−0.003	−0.003	−0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Average_Income	−0.00005	−0.00004	−0.00003	−0.00001	−0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,399	5,399	5,399	5,399	5,399
R^2	0.004	0.004	0.004	0.005	0.005
Adjusted R^2	-0.309	-0.309	-0.308	-0.307	-0.308
F Statistic (df = 4; 4108)	4.160^{***}	4.227^{***}	4.585^{***}	5.147^{***}	4.904^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 20: Group and Time Fixed Effects Forest English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	0.006				
	(0.016)				
Forest_Mean_500m		0.030			
		(0.029)			
Forest_Mean_1000m			0.058		
			(0.037)		
Forest_Mean_2500m				0.097**	
				(0.043)	
Forest_Mean_5000m					0.086*
					(0.047)
English_Class_Size	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Student_Teacher_Ratio	0.011	0.011	0.011	0.011	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	−0.0002*	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.003	0.004	0.004	0.005	0.004
Adjusted R^2	-0.307	-0.306	-0.306	-0.305	-0.306
F Statistic (df = 4; 4111)	3.588***	3.889***	4.368***	5.051***	4.491***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 21: Group and Time Fixed Effects Shrub English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	−0.002				
	(0.033)				
Shrub_Mean_500m		−0.064			
		(0.058)			
Shrub_Mean_1000m			−0.045		
			(0.072)		
Shrub_Mean_2500m				−0.015	
				(0.082)	
Shrub_Mean_5000m					−0.040
					(0.088)
English_Class_Size	-0.020^{***}	-0.020^{***}	-0.020^{***}	-0.020^{***}	-0.020^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Student_Teacher_Ratio	0.011	0.011	0.011	0.011	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	-0.0002^{*}	-0.0002^{*}	-0.0002^{*}	-0.0002^{*}	-0.0002^{*}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.003	0.004	0.004	0.003	0.004
Adjusted R^2	-0.307	-0.306	-0.307	-0.307	-0.307
F Statistic (df = 4; 4111)	3.553^{***}	3.892^{***}	3.669^{***}	3.562^{***}	3.615^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 22: Group and Time Fixed Effects Herb English with Clustered standard errors

	Dependent variable:				
	English_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	−0.020				
	(0.015)				
Herb_Mean_500m		−0.029			
		(0.032)			
Herb_Mean_1000m			−0.050		
			(0.040)		
Herb_Mean_2500m				−0.077	
				(0.050)	
Herb_Mean_5000m					−0.094*
					(0.055)
English_Class_Size	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Student_Teacher_Ratio	0.011	0.011	0.011	0.011	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,392	5,392	5,392	5,392	5,392
R^2	0.004	0.004	0.004	0.004	0.004
Adjusted R^2	-0.306	-0.307	-0.306	-0.306	-0.306
F Statistic (df = 4; 4111)	3.991***	3.821***	4.054***	4.286***	4.460***
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 23: Group and Time Fixed Effects Forest Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Forest_Mean_100m	0.014				
	(0.017)				
Forest_Mean_500m		0.033			
		(0.028)			
Forest_Mean_1000m			0.046		
			(0.036)		
Forest_Mean_2500m				0.045	
				(0.041)	
Forest_Mean_5000m					0.003
					(0.046)
Reading_Class_Size	−0.013**	−0.013**	−0.013**	−0.013**	−0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	0.009	0.009	0.009	0.009	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.002	0.002	0.002	0.002	0.001
Adjusted R^2	-0.311	-0.310	-0.310	-0.310	-0.311
F Statistic (df = 4; 4096)	1.726	1.948*	2.049*	1.848	1.500
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 24: Group and Time Fixed Effects Shrub Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Shrub_Mean_100m	−0.007				
	(0.034)				
Shrub_Mean_500m		−0.096			
		(0.062)			
Shrub_Mean_1000m			−0.093		
			(0.074)		
Shrub_Mean_2500m				−0.060	
				(0.084)	
Shrub_Mean_5000m					−0.050
					(0.085)
Reading_Class_Size	−0.013**	−0.013**	−0.013**	−0.013**	−0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	0.009	0.009	0.009	0.009	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.001	0.002	0.002	0.002	0.002
Adjusted R^2	-0.311	-0.310	-0.310	-0.311	-0.311
F Statistic (df = 4; 4096)	1.512	2.314*	2.048*	1.672	1.609
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 25: Group and Time Fixed Effects Herb Reading with Clustered standard errors

	Dependent variable:				
	Reading_Points				
	(1)	(2)	(3)	(4)	(5)
Herb_Mean_100m	−0.007				
	(0.016)				
Herb_Mean_500m		−0.001			
		(0.033)			
Herb_Mean_1000m			−0.005		
			(0.041)		
Herb_Mean_2500m				0.013	
				(0.050)	
Herb_Mean_5000m					0.036
					(0.051)
Reading_Class_Size	−0.013**	−0.013**	−0.013**	−0.013**	−0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Student_Teacher_Ratio	0.009	0.009	0.009	0.009	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average_Income	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,378	5,378	5,378	5,378	5,378
R^2	0.002	0.001	0.001	0.001	0.002
Adjusted R^2	-0.311	-0.311	-0.311	-0.311	-0.311
F Statistic (df = 4; 4096)	1.549	1.499	1.503	1.521	1.644
Note:			*p<0.1; **p<0.05; ***p<0.01		

9.3 List of Variables

Table 26: List of all variables in data set with description

Variable	Description
Id	Number identifying each school. Introduced when converting the data to long format.
Wave	Number identifying which year the row contains data from.
Municipality number	Municipality number. A unique number identifying each municipality.
Organisational number	Organisational number. A unique number identifying each school.
Ownership_Type	Ownership type. Lists weather the school is privately of publicly owned.
Region_number	Region number. A unique number associated with each region.
Region	Region.
Municipality_name	Municipality name.
School_ name	School name.
Forest_Mean_100	The mean of forest cover data inside a circle with of radius 100m surrounding each school.
Forest_Mean_500	The mean of forest cover data inside a circle with of radius 500m surrounding each school.
Forest_Mean_1000	The mean of forest cover data inside a circle with of radius 1000m surrounding each school.
Forest_Mean_2500	The mean of forest cover data inside a circle with of radius 2500m surrounding each school.
Forest_Mean_5000	The mean of forest cover data inside a circle with of radius 5000m surrounding each school.
Forest_StDev_100	The standard deviation of forest cover data inside a circle with of radius 100m surrounding each school.
Forest_StDev_500	The standard deviation of forest cover data inside a circle with of radius 500m surrounding each school.
Forest_StDev_1000	The standard deviation of forest cover data inside a circle with of radius 1000m surrounding each school.
Forest_StDev_2500	The standard deviation of forest cover data inside a circle with of radius 2500m surrounding each school.

Table 26: continued from previous page

Forest_StDev_5000	The standard deviation of forest cover data inside a circle with of radius 5000m surrounding each school.
Herb_Mean_100	The mean of herb cover data inside a circle with of radius 100m surrounding each school.
Herb_Mean_500	The mean of herb cover data inside a circle with of radius 500m surrounding each school.
Herb_Mean_1000	The mean of herb cover data inside a circle with of radius 1000m surrounding each school.
Herb_Mean_2500	The mean of herb cover data inside a circle with of radius 2500m surrounding each school.
Herb_Mean_5000	The mean of herb cover data inside a circle with of radius 5000m surrounding each school.
Herb_StDev_100	The standard deviation of herb cover data inside a circle with of radius 100m surrounding each school.
Herb_StDev_500	The standard deviation of herb cover data inside a circle with of radius 500m surrounding each school.
Herb_StDev_1000	The standard deviation of herb cover data inside a circle with of radius 1000m surrounding each school.
Herb_StDev_2500	The standard deviation of herb cover data inside a circle with of radius 2500m surrounding each school.
Herb_StDev_5000	The standard deviation of herb cover data inside a circle with of radius 2500m surrounding each school.
Shrub_Mean_100	The mean of shrub cover data inside a circle with of radius 100m surrounding each school.
Shrub_Mean_500	The mean of shrub cover data inside a circle with of radius 500m surrounding each school.
Shrub_Mean_1000	The mean of shrub cover data inside a circle with of radius 1000m surrounding each school.
Shrub_Mean_2500	The mean of shrub cover data inside a circle with of radius 2500m surrounding each school.
Shrub_Mean_5000	The mean of shrub cover data inside a circle with of radius 5000m surrounding each school.
Shrub_StDev_100	The standard deviation of shrub cover data inside a circle with of radius 100m surrounding each school.
Shrub_StDev_500	The standard deviation of shrub cover data inside a circle with of radius 500m surrounding each school.

Shrub_StDev_1000	The standard deviation of shrub cover data inside a circle with of radius 1000m surrounding each school.
Shrub_StDev_2500	The standard deviation of shrub cover data inside a circle with of radius 2500m surrounding each school.
Shrub_StDev_5000	The standard deviation of shrub cover data inside a circle with of radius 2500m surrounding each school.
English_Points	Scale points scored in the English national test averaged at the school level per year.
English_Uncertainty	Uncertainty measure for the English scale points based on the number of students in each school. Adding and subtracting the uncertainty measure to/from the scale points yields two numbers defining a 95 percent confidence interval for the scale points for each school at each year.
English_School_Size	The number of students per school per year that took the English national test.
Reading_Points	Scale points scored in the Reading national test averaged at the school level per year.
Reading_Uncertainty	Uncertainty measure for the reading scale points based on the number of students in each school. Adding and subtracting the uncertainty measure to/from the scale points yields two numbers defining a 95 percent confidence interval for the scale points for each school at each year.
Reading_School_Size	The number of students per school per year that took the reading national test.
Math_Points	Scale points scored in the Math national test averaged at the school level per year.
Math_Uncertainty	Uncertainty measure for the math scale points based on the number of students in each school. Adding and subtracting the uncertainty measure to/from the scale points yields two numbers defining a 95 percent confidence interval for the scale points for each school at each year.
Math_School_Size	The number of students per school per year that took the math national test.

Table 26: continued from previous page

Central	Dummy variable for centrality based on the centrality measure developed by SSB. Equal to one if the municipality falls in to the top two out for six centrality grades. Equal to zero otherwise.
Student_Teacher_Ratio	Teacher student ration for each school at each year.
Average_Income	Average income in each municipality at each year.

NTNU
Norwegian University of
Science and Technology