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How Acoustics in California High Performance Schools Relate to Student Achievement

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HOW ACOUSTICS IN CALIFORNIA HIGH PERFORMANCE SCHOOLS RELATE TO STUDENT ACHIEVEMENT

By

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HOW ACOUSTICS IN CALIFORNIA HIGH PERFORMANCE SCHOOLS RELATE TO STUDENT ACHIEVEMENT

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This research project seeks to determine if students attending K-12 schools meeting a minimum standard of high performance classroom conditions in the state of California do evidence higher scholastic achievement, based on publically available results on state-wide standardized tests. In three phases, a subset of 200+ schools applying for grants dedicated to building high performance schools over the past decade was correlated with an existing database of achievement scores for all public schools in California. The criteria utilized to specify high performance classrooms was provided by the California High Performance Initiative (HPI) Grant program. Academic achievement was evaluated on a school-level by the Academic Performance Index (API) score, which aggregates individual student scores on California standardized tests.

In the first phase, API scores for schools meeting the HPI construction criteria were compared with scores for normal schools that did not meet such a standard, on a yearly interval from 2008 to 2013. Results show no significant difference between normal and high performance schools, however a general trend may be seen indicating greater improvements in API scores for high performance schools over normal ones.

In the second phase, API scores for a subset of high performance schools undergoing HPI modifications were compared across time, before and after completion of construction. A significant relationship was found, $p<0.05$ between API performance and construction conditions; schools within the post-modernization condition exhibited lower API performance than they did within the pre-modernization condition.

In the third and final phase, API results for the 2012-2013 academic year were analyzed across classroom acoustic conditions. Schools were categorized has exhibiting none, minimum, and improved levels of acoustic criteria for their classrooms. No significant relationship was found in relation to API performance. A general negative trend in performance was observed as acoustic conditions improved.

While significant relationships were found between varying types of as-built conditions and standardized test performance, many of these findings are just as inconsistent as previous research. However, a general overall trend indicating that schools that meet high performance criteria exhibit improved academic performance on standardized tests was found. It is likely that academic performance in this study is due to a multitude of factors beyond the built environment and the level of performance must be described in greater detail in order to exhibit any further meaningful trends, despite the added statistical power of a larger dataset. More developed statistical methods to account for these variables is suggested for future work.

Acknowledgements

This project has been a long time in completion, and a fantastic experience throughout the process. I have enjoyed the opportunity to craft a research program from data collection through analysis and I consider this a valuable lesson for my future endeavors in architectural acoustics.

I would like to thank my employer, Veneklasen Associates, which saw fit to invest time and money in my personal and professional development. I'd like to thank my associates, who worked overtime so that I could devote my focus to this research. In particular, I would like to thank John Loverde, and Dr. Mahabir Atwal, who have given me the freedom to pursue this project, and the support to see it to conclusion.

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Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

1.1. Introduction to Work

The economic and environmental impact of high performance schools has been the subject of numerous studies of the last 20 years. However, research regarding the impact of so called green schools on the performance of students is not as extensive (National Research Council 2007). Results from previous studies do seem to indicate a promising general trend of better student achievement with better-built environments. These studies often rely on conclusions drawn from surveys or indirect measures, or focus on single indoor environmental factors such as acoustics (Baker and Bernstein 2012). Recent government emphasis on funding grounded in academic improvement and green building construction indicate that research with a new experimental design is worth being pursued.

Student performance has traditionally been analyzed on a national level by standardized testing. The California Standardized Testing and Results (STAR) program was one example. Each year until its replacement in 2013, the STAR program administered grade-specific statewide tests across a range of subjects including: English/Language Arts, Math, History/Social Studies, and Science. Student test results were then used to calculate a single-number metric called the yearly Academic Performance Index (API), indicating overall school performance (California Department of Education 2003). This metric was chosen for the current research because it defines a relatively current, nationally accepted standard for school-wide academic achievement.

Furthermore, both STAR scores and API composite scores for all California public schools are publicly available and reported yearly at the state, county, district, and school levels, as well as across different demographic groups.

In 2006, voters in California approved a plan to set aside $100 million for supplemental HPI grants to allow state school districts to build classroom buildings with high performance attributes. The attributes were assessed by a High Performance Rating Criteria (HPRC), which was modelled after criteria set forth by the California Collaborative for High Performance Schools (CHPS). The criteria on indoor environmental quality included assessments of the buildings' thermal, air quality, lighting and acoustic conditions, among other items. The HPRC was similar to the popular LEED rating system, in that schools were required to meet all prerequisites in the assorted categories of the HPRC in order to be eligible for HPI grant money. Therefore, HPI grant approval delineated a minimum standard of indoor environmental quality for high performance schools.

Previous studies have focused on singular characteristics of the built environment such as indoor air quality, thermal comfort, light, or acoustics (Smejde et al 1997, Schoer and Shaffran 1973, Heschong Mahone Group 1999, Ronsse 2011.) Other studies focusing on overall impact have been limited to smaller sample sizes (Bruick 2009, LaBuhn 2010), use subjective evidence (Issa et. al 2011) or are similar iterations of the same experimental design (Cash 1993, Earthman et. al 1995). This study aims to investigate a larger sample of school data than previous research, while utilizing standardized, direct measures to evaluate both building condition and student performance. The study will not attempt to determine any individual contribution of individual classroom qualities other

than acoustics. The benefit of this is to help verify previous conclusions with more a more robust sample size and nationally accepted criteria, while attempting to verify if acoustics as a subcategory of building performance is distinguishable from the overall effect.

The goal of this paper is to determine the impact of a high performance indoor environment on student achievement as measured by standardized test results over time and building condition. A subset of 200+ schools applying for HPI Grants over the past decade was correlated with an existing API database of school achievement scores for all public schools in California between 2008 and 2013. Additionally, specific acoustical metrics pertaining to each school were correlated with the same API database. The main question involved with the analyses are whether or not a significant relationship exists between building conditions and student achievement when using government specified criteria over a larger than sample size than those utilized in previous studies.

1.2. Outline of Thesis

This study examines the effect of a high performance built environment on student achievement. Publically available data on school-wide academic performance and school construction conditions was compiled and organized. Statistical analysis was performed and the results are evaluated to help understand the relationship between the physical classroom environment and standardized test scores. Chapter 2 discusses previous research pertinent to this study and explains how this study was developed. Chapter 3 presents the methodology, including metric selection for building conditions and student achievement, collection of the dataset, and the statistical analyses used in the

study. Chapter 4 presents and discusses the results for the three sets of analyses performed. Chapter 5 summarizes the results and suggests ideas for future work.

Chapter 2: Literature Review

This chapter discusses previous research that led to the motivation for and application to this research. Previous research is separated into subsections involving (1) attributes of high performance schools, (2) the High Performance Incentive Grant (HPIG) and criteria to evaluate high performance schools, and (3) the Academic Performance Index (API) and criteria to evaluate student achievement. Finally, the application of the previous studies to this study will be discussed.

2.1 Building Attributes of High Performance Schools

While it is generally accepted that the quality of the built environment has an effect on occupant heath and productivity, the complexity of interactions between people and environments means that it is difficult to establish direct cause-and-effect relationships between specific building attributes and human outcomes. Research summaries produced by the McGraw-Hill Research Foundation and National Clearinghouse for Educational Facilities (NCEF) list acoustics, indoor air quality (IAQ), lighting, and thermal comfort, among others, as specific qualities that are of particular importance in schools. (Baker and Bernstein 2012, Schneider 2002). The focus of this review includes the aforementioned building qualities as general knowledge. However the focus of the statistical analysis will be on the comprehensive effect.

2.1.1 Acoustics

Acoustics in classrooms has historically been evaluated by two factors: background noise level (BNL) and reverberation time (RT). Both have been shown to

have a significant effect on speech intelligibility, or how well speech can be understood by a listener. BNL is the noise level in a furnished, typically unoccupied space measured in decibels (dB). A high BNL can affect students' ability to hear, absorb and retain information. Sato and Bradley (2008) performed speech recognition tests in 41 classrooms of elementary students between 6 and 11 years old. They found that for a teacher voice level of approximately 60 dBA, the occupied BNL should be 40 dBA maximum for good speech intelligibility. RT is the time it takes for sound to decay 60 dB after termination, measured in seconds. Similar to BNL, a high RT is thought to hinder student's ability to understand speech. RT was first quantified by Wallace Clement Sabine (Mehta, Johnson and Rocafort 1998).

Studies focusing on the direct impact of acoustic parameters on student achievement have found that internal and external environmental noise has a direct impact on student achievement. Shield and Dockrell (2008) compared external and classroom noise levels with assessment scores on standardized tests of children aged 7 and 11. They found that external noise sources in the form of road traffic and aircraft noise had a negative effect on children's test scores, however the subject most affected differed by school. The A-weighted Lmax was further found to have the most significant correlation, implying the importance of individual noise events. For internal noise, the background noise level was found to have the most significant negative correlation (Shield and Dockrell 2008).

Similarly, Ronsse (2011) measured RT's and unoccupied BNL levels in 125 elementary school classrooms. They found a significant, negative correlation between high unoccupied BNL's and student achievement scores in language, and reading

comprehension for 1 of 2 school district tested when controlling for the effects of poverty rates. Ronsse also studied the effect of RT's on student achievement, but found that they were not significantly correlated with achievement test results (Ronsse 2011). She concluded that a wider range of RT's was needed to properly determine the relationship.

Klatte, Lachmann, and Meis (2010) studied the combined effect of background sounds and RT on speech perception and listening comprehension tasks for 108 children and 94 adults. Participants were asked to perform word-to picture matching and execution of complex oral instructions while subject to varying combinations of BNL and RT conditions. Three different background noise conditions were presented: silence, background speech and classroom noise without speech. Two different RT conditions were utilized: a "favorable" condition with RT=0.47 seconds and an "unfavorable" condition with RT=1.1 seconds. They found that classroom noise resulted in reliable disruption of speech perception for children, while background speech exhibited a strong, significant effect on listening comprehension with children. RT was found to have no effect under silence, but a significant adverse effect when coupled with all types of background noise. (Klatte et. al 2010).

2.1.2 Indoor Air Quality

IAQ as measured by the amount of pollutants and volatile organic compounds (VOC's) is often linked to student performance through absenteeism; poor indoor air quality makes students sick, and therefore unable to attend school. Health symptoms often related to low ventilation include headaches, dizziness, tiredness, and upper airway irritation (throat, nose, eyes). Smedje and Norback (1997) examined the number of reported asthmatic and sick building symptoms in 39 schools before and after installation

of a new ventilation system. They found that schools with new ventilation systems exhibited an increase in air exchange rate (outdoor air flow) and a decrease in reported symptoms.

Studies have also shown a correlation between poor ventilation as measured by carbon dioxide levels and performance. Higher levels of carbon dioxide proved to affect performance on concentration, logic, reasoning and typing tests. Myhrvold, Olsen and Lauridsen (1996) measured carbon dioxide concentrations and administered concentration tests and a health symptoms questionnaire for approximately 800 students in 35 schools, before and after rehabilitation of the ventilation systems. They found that in classrooms with high carbon dioxide levels, student scores on concentration tests were low, with statistically significant results.

2.1.3 Lighting

Research on classroom lighting tends to focus on the amount of natural light or daylight in a space. Heschong Mahone (1999, 2002) analyzed student performance data from three elementary school districts as compared to the amount of daylight provided by the classroom environment measured on a 0 to 5 scale. They found that students in classrooms with the most daylight had a greater improvement in standardized math and reading tests over the course of one year than students in windowless classrooms (20-26%).

Studies focusing on other lighting variables such as illuminance, luminance, and color characteristics have narrowed what may be considered optimal lighting for learning. Hathaway (1995) studied student dental health, attendance, and academic achievement under four different artificial light sources over a two-year period. Students exposed to

full spectrum fluorescent lamps with ultraviolet supplement exhibited better achievement scores on the administered standardized Canadian Test of Basic Skills than those under other lights (Hathaway). Similarly, proper levels of correlated color temperature (CCT) and illuminance in a dynamic lighting system have been shown to have a positive effect on student performance in concentration tests (Sleeger et. al 2013).

2.1.4 Thermal Comfort

The majority of studies addressing thermal comfort categorize the attribute into thermal comfort, humidity and air velocity. Schneider summarizes some of the previous research regarding the topic including Harner (1974), and McGuffey (1979, 1982). These researchers found that the optimum temperature band for classrooms is between sixty-eight to seventy-four degrees Fahrenheit. Similarly, they also conclude that students perform better at mental tasks in rooms between forty and seventy percent humidity. Temperature and humidity levels outside of these ranges has been found to adversely affect learning environments (McGuffey 1979, 1982). Much like IAQ, studies regarding thermal comfort do not provide evidence of a direct relationship between the attribute student achievement outcomes, instead focusing on indirect relationships such as absenteeism or self-reporting questionnaires of thermal discomfort (Amasuomo and Amasuomo, 2016).

2.1.5 High Performance Schools and Student Achievement

Existing research on the relative overall benefit of high performance school buildings tends to focus on smaller sample sizes and survey based evidence. General trends seem to indicate that there is a relationship between some type of better performing building condition and student achievement, however significant differences

have not appeared, possibly due to indirect relationships, non-robust sample sizes, or both.

Cash (1993) analyzed a sample of 47 small, rural, public Virginia high schools based on building conditions and student behavior as well as achievement scores. Building criteria was assessed using a survey of existing conditions focusing on objective building observations, as well as cosmetic conditions. Acoustical performance was assessed in two ways. Exterior noise conditions as well as the type of ceiling installed within classrooms: open deck, acoustical tiles installed in at least three-fourths of classrooms, or acoustical tiles installed within all classrooms. Differing acoustical conditions accounted for no more than two points of difference in the mean scale score for achievement (Cash 1993). However, student achievement in general was found to be higher in buildings with higher quality ratings.

Earthman (1995) conducted a similar study of high schools in North Dakota, comparing student achievement and behavior across 29 building conditions, determined by survey. Results were inconclusive as to an overall effect of building condition on achievement. In fact, student achievement scores were higher in substandard building conditions in categories widely considered important to student learning: building age, air conditioning and noise (Earthman 1995). This indicates that it has been difficult to find statistical significance with this experimental setup.

Neilson and Zimmerman (2011) performed a statistical analysis of a school district in New Haven, Connecticut, which planned to completely rebuild or renovate 37 of 42 schools in a six-year period. Construction focused on heating and air conditioning, but also included renovations to classroom facilities and technology. While improvement

in student achievement was documented, the specific building factors that led such gains was not analyzed beyond a general, subjective survey of school principals.

Bruick (2009), and LaBuhn (2010) conducted research regarding the relationship between green school buildings as certified by LEED and student achievement. The sample size of high performance schools for each study were 2 and 4 schools respectively. Neither found a significant relationship between green building construction and student achievement. In fact, LaBhun (2010) found that the 4 LEED certified schools were often outperformed by at least one non-LEED school in its comparison group. Bruick did find that a survey of 182 teachers indicated an overall satisfaction and preference for green schools and better building conditions.

The contradiction between subjective occupant responses and relationships borne out in studies is not a singular problem. In 2011, Issa, Rankin, Atatalla and Christian performed a case study in which a sample of green and energy-retrofitted Toronto schools was found to have lower absenteeism rates and higher student performance when compared with conventional schools. The results were not statistically significant however, and could not be generalized. Further, a survey of occupant satisfaction with acoustics actually decreased within high performance schools. She indicates that these concerns are justified, since LEED did not take into account the quality of acoustics in its assessments at the time of study (Issa et. al 2011).

There appears to be a disconnect between subjective occupant response to high performance buildings and how beneficial those structures may be as a direct influence on student achievement. The benefit analysis of green school construction is of particular importance because of the high initial cost associated with these endeavors. School

districts with limited funds may be hesitant to pursue high performance attributes when there is a lack of statistical evidence supporting green building benefits.

2.2 High Performance Incentive Grant: Criteria for High Performance Schools

Definition of green buildings, schools in particular, is important in order to delineate between those schools that qualify as high performing and those that are considered traditionally adequate. There are many programs that certify levels of sustainable design, and qualification in these programs is not mutually exclusive with qualification for a HPI grant.

The HPRC was chosen for this study because it focuses on the construction conditions for school projects in particular, and is publicly accessible by request from the California Division of the State Architect (DSA).

2.2.1 History

In 1999, CHPS was formed with the mission of facilitating the design, construction, and operation of high performance schools. In particular, CHPS hoped to: increase performance, reduce operation costs, and reduce the schools impact on the environment (Bucaneg 2008). Subsequently, it developed recommended high performance criteria to accomplish these goals and provide a basis for defining high performance schools.

In 2007, Proposition 1D, California Assembly Bill 127 was approved, providing $100 million in supplemental incentive grants to promote the use of high performance attributes in new construction and modernization projects for K-12 schools. In particular, the HPI Grant program focuses on 5 attributes: site, water, energy, materials, and indoor environmental quality. According to the bill, high performance attributes include using

designs and materials that promote energy and water efficiency, utilize recycled materials and those that emit a minimum of toxic substances, and emphasize natural lighting, indoor air quality, and acoustics conducive to the process of teaching and learning (HPI).

In order to ascertain the level of high performance attributes in each project, the HPRC was created. The HPRC was based on CHPS criteria for the years 2002, 2006, and 2009 with slight modifications. In 2011, changes were approved adding credits and amending sections to reflect changes in the CHPS 2009 criteria and 2008 California Energy Code requirements. Incentive amounts were significantly increased from 4% to 6.52% and a HPI Base Incentive Grant was made available

Also in 2011, Tom Torlakson, State Superintendent of Public Instruction, implemented the Schools of the Future (SOTF) initiative, focusing on state school facility program reform, and the design of high performance, green schools. The SOTF committee produced a report advising eight policy areas: educational impact of design, school site selection and community impact, modernization, funding and governance, high efficiency schools, renewable energy, grid neutral schools and financing of high performance schools. The initiative led to the proposal of this paper by PreFast, a designer of high performance, pre-fabricated classrooms and schools.

In 2015, Senate Bill 869 chapter 39, Statues of 2014 removed the power of the State Allocation Board to approve HPI Grants, effectively ending the program. All remaining funds were transferred to new construction and modernization programs.

2.2.2 High Performance Rating Criteria

2.2.2.1 Overview

The HPRC was assessed in the form of a rating scorecard: each of the 5 attributes emphasized by the program was assigned its own section and subsections with more detailed criteria. Applications were submitted under the categories of new construction, additions to a site, or modernization. The HPI grant was not a standalone grant, and was considered additional funding. Each HPI application was submitted during an overall drawing plan review process that was performed by the DSA and received a score that directly correlated with the amount of funding a project receives.

Each HPRC attribute contained subcategories with a designated number of points that could be earned upon completion. An example of the acoustics subcategory may be seen in Figure _. In order to be HPI approved, each new application was required to meet all the prerequisite requirements in all HPRC categories. They then selected the other credits they wish to pursue. A minimum of 27 HPRC points was required to qualify for a new project grant. Additions and modernization projects were only required to meet the prerequisites for the categories within the scope of construction; then, the district selected the credits they wished to pursue. A minimum of 20 HPRC points was required to qualify for an addition or modernization grant.

For the purposes of this study, each school was either considered approved or unapproved for the HPI. The purpose is only to delineate between those projects that are required to meet a high performance standard and those that do not. It is assumed that schools that have not applied for the HPI grant do not meet the same construction

standard. For the purposes of this study, schools that applied for the grant are referenced as High Performance, while schools that did not are referenced as Normal.

2.2.2.2 Acoustics

A portion of this study specifically focuses on the Acoustic subcategory pertaining to Indoor Environmental Quality. The intention is to concentrate on one of the factors that align with previous research and will have the most direct impact on school occupants.

The HPRC acoustics subcategory for acoustics was based upon the American National Standard Acoustical Performance Criteria, or ANSI S12.60. In the 2002 version, projects applying for HPI certification "must have a maximum (unoccupied) noise level of 45 dBA, with a maximum (unoccupied) reverberation time of 0.6 seconds. Extra points were available if the maximum (unoccupied) noise level was reduced to 40 dBA (1 point) or 35 dBA (2 points). In the 2006 version the number of HPI points awarded for improved acoustical performance was increased from two to three. No changes were implemented in the acoustics subcategory for CHPS 2009 and 2011 modifications.

2.3 Academic Performance Index: Criteria for Student Achievement

Standardized testing is the principle measure of learning outcomes in the United States today. Student achievement on standardized tests is directly tied to funding for schools and school districts and the data is publicly available. While there are questions regarding the validity of tests controlled by commercial publishers, there is value in such a large dataset: the possible application of statistical results to a larger population. The California Academic Performance Index (API) is a publicly available measure for evaluating student achievement on a school level, and may be further sorted by

socioeconomic factors. The combination of student outcomes with specific, school-related, variables make the API an excellent factor for evaluating student achievement in tandem with the HPRC.

2.3.1 History

The Public Schools Accountability Act of 1999 was approved in order to provide a comprehensive accountability system to hold each of the states' K-12 public schools accountable for the academic progress and achievement of its pupils (California State Legislature). This system, in conjunction with the Governor's Performance Award Program (GPAP) was created to provide state funding awards to schools that show adequate improvement. (Tobias 2004).

2.3.2 Academic Performance Index

2.3.2.1 Overview

The API is a comprehensive accountability system that monitors the achievement of all the state's public schools, including charter schools, and local educational agencies (LEAs) that serve students in kindergarten through grade twelve (API). The API is based on improvement model: the assessment results from one year are compared to assessment results from the prior year to measure improvement. Results are summarized from student achievement scores on the California Standardized Testing and Results Program (STAR) and California High School Exit Examination (CAHSEE). STAR administers grade-specific tests in English/Language Arts, Math, History, Science and Writing topic areas.

The intent of the API is to compare school achievement results from one year to the next, rather than track individual student progress. Schools that meet state

participation and growth criteria may be eligible for awards or financial funding. Schools that do not meet growth targets may be identified for state intervention programs to improve performance.

2.3.2.2 Scoring

The API score is a single number, ranging from a low of 200 to a high of 1000. The API score is calculated by converting students' performance on state-wide assessments into points on the API scale. The calculation is performed for schools, LEA's and each student group with 11 or more valid scores at each particular school. The formula accounts for the number of valid student scores weighted by both performance level and subject.

The state has set an API score of 800 as the target score for all schools to meet. Schools that do not meet the target score are required to meet annual growth targets until that goal is achieved. The growth target is generally calculated as five percent of the difference between the school's API and the state target of 800. Schools that meet or exceed the target score are expected to annually maintain or improve a score above the target.

The annual API reporting cycle includes a Base and a Growth API. The Base API begins the reporting cycle and is calculated using assessment results of the previous year. Since testing is conducted in the spring, the Base API will be released the following spring. The Growth API is calculated using the same indicators as the Base API, but uses student achievement scores from the current year, released in the fall of the same year. For example, 2011 Base API will be released in spring 2011 using results from spring 2010 testing. The 2011 Growth API will be released in fall 2011, using results from

spring 2011. The academic improvement, released in the Growth API Report, is the delta between the 2011 Base API and 2011 Growth API. Since API success is measured by the improvement in score from year to year, the comparison of performance in non-adjacent years is not possible.

Over the history of the API, different API indicators have been used as standardized tests are modernized or subject weighting in the API calculation changes. Therefore, only single API scores in the same base and growth year are compared. In order to maintain student achievement comparability across multiple years and different reporting cycles, this study will only use the difference in API scores from the same year (Difference API) and averages over time.

2.3.2.3 School Demographics and Similar Schools Lists

Demographic information pertaining to each school is also included in each API report. In addition to the school type (traditional, charter, small) and grade range (K-5, 6-8, 9-12), the number of students by race, socioeconomic status, English proficiency and disability are also reported. Based on these and other demographic descriptors, California has created a Schools Characteristic Index (SCI). The purpose of the SCI is to group schools that face similar educational opportunities and challenges. Every year, each school is compared with a different List of 100 Similar Schools chosen for their similarity in SCI.

A school's SCI is calculated in a multiple linear regression using eight general characteristic indicators. The regression uses API values as the dependent variable and eliminates characteristic independent variables in a stepwise regression so the maximum

possible set of predictors is included. The total SCI score is the sum of two SCI component scores multiplied by a weighting factor.

In order to capture all of the variation in school performance that may be attributed to the set of indicators, the California Department of Education has used the Floating comparison band method (API). In this method, schools are divided into grade level categories rank ordered according to SCI values. A comparison group for each school is formed by locating that school at the median of its own group. The 50 schools immediately above and below are then chosen as the comparison group.

While the use of the SCI and list of similar schools for the state of California emphasizes a school's comparative ranking, this study uses the Similar Schools lists as a tool for selecting a representative sample of both HPI and non-HPI approved schools.

Chapter 3: Methodology

The purpose of this study was to evaluate the comprehensive impact of high performance construction, as well as classroom acoustic conditions on student achievement. Data for school building conditions and student achievement were mined from publicly available databases via the California Division of the State Architect and California Department of Education. Building performance was assessed using the California HPRC as developed by the HPIG Initiative, while student achievement was evaluated on a school-wide level through a yearly API score calculated by the state.

A list of all schools applying for the HPIG from program inception in 2007 to the year 2013 was provided by the California Division of the State Architect upon email request. HPRC scorecards for 244 schools obtaining grant approval were analyzed for type of high performance construction and classroom acoustic conditions. Further demographic information including construction completion date was culled from the DSA's online project tracking database.

API scores and demographic information for all California schools from 1999 to 2013, were obtained from the California Department of Education website. Yearly Base, Growth, and Difference API scores for all schools in the High Performance sample set was then extracted. Additionally, a sample set of schools meeting Normal construction conditions was selected using the state provided demographic and socioeconomic data. The API scores for these schools were obtained as well.

This thesis investigates the compiled data by four distinct statistical analyses. The first analysis (Phase 1) compares the API data of High Performance schools with those that are Normal by year. Phase 2 examines the comparative change in consecutive, yearly API scores between High Performance and Normal Schools. The third analysis (Phase 3) analyzes API scores of HPI schools before and after completion of High Performance construction. For the final analysis, Phase 4 studies the impact of improved classroom acoustic conditions on API scores by year.

No analysis was conducted on subject-specific standardized test results nor specific building attributes beyond acoustics. No attempt was made to account for correlations between acoustics and other indoor environmental conditions. The intent of this study is to focus on the overall relationship between High Performance school construction conditions and student achievement in a sample that is much larger than what typically feasible for studies focusing on specific building conditions and subjects. Analysis of the acoustics specific data is intended as a preliminary evaluation of the feasibility of separating particular indoor environmental variables from the overall effect.

3.1 Experimental Methods

This section reviews the methodology used in the data collection and analysis processes, and is separated into four subsections: (1) HPI data provided by DSA, (2) HPI acoustic data, (3) API data provided by CDE, and (4) statistical procedures used for the analysis of data.

3.1.1 Collection High Performance Construction Data provided by DSA

In this section, the methodology for the collection of data provided by DSA is discussed. In February 2013, an email request was submitted to the California Division of

Division of the State Architect
CALIFORNIA DEPARTMENT OF GENERAL SERVICES

Headquarters Office
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Sacramento, CA 95811 | F 916.445.3521
www.dgs.ca.gov/dsa

February 25, 2013

Jan Leeman
126 Waverley Street
Palo Alto, CA 94301

Re: ***PRA Records Production***

Dear Mr. Jan Leeman,

You recently requested for the production of records under the Public Records Act (Govt. Code Section 6250 et seq.) regarding the High Performance Index Scorecards outlined in your February 12, 2013 letter to the Department of General Services, Division of the State Architect ("DGS-DSA"):

> "HPI scorecards-An electronic table (preferred) or photocopy of HPI scorecards for construction projects that have been approved for HPBIG grants from the inception of the program until January 1, 2013. If an electronic table is provided, the table should contain the "HPI Point Claimed" and "DSA-HPI Points Verified" columns from the scorecard for each category of points (e.g. SSl.0 Code Compliance, SS1.1 Environmentally Sensitive land, etc.)."

DSA staff has conducted a good faith search and has identified the enclosed records that are responsive to your request.

If you have any questions, please feel free to contact me at (916) 327-5410.

Sincerely yours,

Kristy Lac
Public Records Officer

Enclosures

Sacramento Regional Office
1102 Q Street, Suite 5200
Sacramento, CA 95811
T 916.445.8730

Oakland Regional Office
1515 Clay Street, Suite 1201
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Los Angeles Regional Office
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Los Angeles, CA 90012
T 213.897.3995

San Diego Regional Office
10920 Via Frontera, Suite 300
San Diego, CA 92127
T 858.674.5400

Fig. 3.1. DSA response to HPI scorecard data request

the State Architect, requesting all HPI Scorecards from the inception of the program until January 1, 2013. "HPI Point Claimed" and "DSA-HPI Points Verified" for each category of points were to be specifically included. Individual HPI scorecards for 244 school construction projects were subsequently provided by the DSA in .pdf format. The response from the DSA is shown in Figure 3.1 below.

A second request was submitted to the California Office of Public School Construction (OPSC) for data on all projects approved for HPIG grants from program inception to January 2013. The data included: county name, school district name, school name, OPSC project number, status of HPIG grant, dollar amount of HPIG grant, and HPI application score. However, the data received from this request was not submitted to the University.

In this study, descriptive data for the 244 projects referenced by the HPI scorecards was obtained through the Project Status eTracker module located on the California DGS website (https://www.apps2.dgs.ca.gov/DSA/Tracker/ProjectStatus.aspx). The eTracker module provides access to government information on school and public building construction projects in DSA. A specific DSA application number referenced on each HPI scorecard was entered into the eTracker database, producing relevant project data. Information from the HPI scorecards and DSA website was then compiled into a summary database using Microsoft Excel. A description of the database categories is shown in Table 3.1. An example HPI scorecard and application summary page from the website may be seen in Figure 3.2 and Figure 3.3.

Table 3.1. *Research Summary Database Categories and Definitions.*

Category	Definition
School Name	Name of the School
Project Name	Name of construction projects assigned by the DSA.
DSA Application Number	Project identification number assigned by the DSA
CDS Code	School identification number assigned by the California Department of Education
School Type	School categorization based on grades taught: Elementary School, Middle School, High School
Construction Type	Project categorization based on purpose of construction: New, Addition, Modernization
Construction Scope	Type of school buildings included in construction: Classroom, Administration, Gymnasium, Multipurpose, Library, Food Services
Field Review Start	Date of initial DSA field review of construction project
Field Review Finish	Date of final DSA field review of construction project.
Date of 90-Day Letter	Date indicating the initiation of project closing. Letter issued by DSA for: • DSA District Structural Engineer determines the project is essentially complete • DSA received a final verified report from the Project Inspector and/or design professional in charge of the project • The project becomes occupied. • Construction stops for one year or more
DSA Project Certification Status	• Closeout with Certification (#1) • Certificate of Compliance without Receipt of All Documents (#2) • Closeout without Certification – Exceptions or Unpaid Fees (#3) • Closeout without Certification – Safety Related Deficiencies (#4) • Resolution of Certification: Project no longer exists (#5) • Resolution of Certification: Project no longer used for school purposes (#6) • Cancelled • Void
School SCI score for the year 2012	School Characteristics Index, calculated by California Department of Education. Composite, single number rating evaluating demographic characteristics for a school. Schools with similar SCI's face similar educational challenges and opportunities

# of Students Eligible for Free Lunch Program in 2005	# of students eligible per school for Free Lunch program in the year 2005
# of Students Eligible for Free Lunch Program in 2013	# of students eligible per school for Free Lunch program in the year 2013
Base API (1999-2013)	Base API scores for each school over 14 distinct API reporting cycles
Growth API (1999-2013)	Growth API scores for each school over 14 distinct API reporting cycles
Difference API (1999-2013)	Difference API scores for each school over 14 distinct API reporting cycles
Acoustics Score (via HPI Scorecard)	Number of HPI points, verified by the DSA, in the Acoustics subcategory of HPI scorecard for each school

DSA High Performance Incentive (HPI) 2006 Scorecard and Guidelines

Date of Scorecard:			1/28/09				DSA Application Number	04-109775			
CHPS SECTION		PREREQUISITES (MANDATORY)	**2006 CRITERIA SUMMARY**: FOR DETAILED EXPLANATION SEE "CHPS BEST PRACTICES MANUAL VOLUME 3 - CRITERIA," 2006 EDITION (available at http://www.chps.net/manual/index.htm)	Max Possible HPI Points Rating	POINTS Claimed	DSA VERIFICATION	**DSA - DOCUMENTS NEEDED FOR REVIEW.** VIA SEPARATE SUBMITTAL, IDENTIFY EACH CATEGORY & ASSOCIATED PREREQUISITE OR CREDIT--SUCH AS--SSP1.1, OR EEC4.1. THEN, PROVIDE SPECIFIC INFORMATION OR SUPPORTING DOCUMENTATION DESCRIBED IN THIS COLUMN	PLANS	SPECS	DISTRICT LETTER OR SUPPORTING DOCUMENTS	SITE VERIFICATION--See Note 3
SUSTAINABLE SITES (2 prerequisites; 14 possible points)											
1. Site Selection (6)											
SS1.0	Code Compliance	√	Comply with all requirements of Title 5 and CA Education Code and Public Resource Code sections specified.	X	X	X	**OPSC to Verify**				
SS1.1	Environmentally Sensitive Land		No development on sites that are: prime agricultural land, in flood zone, habitat for endangered species, near a wetland or considered parkland.	1	1	1	State Parcel # and how far above (elevation) the 100 -Year Flood plain or submit PDF file of FEMA website map.				
SS1.2	Greenfields		Do not develop on greenfields.	1	1	1	State prior use of land:(e.g. farmland)				
SS1.3	Central Location		Create centrally located sites within which 50% of students are located within minimum distances of the school.	1	1	1	State percentage of Elem, Middle and HS students within prescribed distance.			√	
SS1.4	Joint-Use of Facilities		Design at least one space for "joint-use" and provide specified security measures	1	0	0	List the groups and contact information of Joint-use facilities. Identify facilities and/or spaces.	√		√	
SS1.5	Joint-Use of Parks		Share park or recreation space.	1	0	0	List the groups and contact information of Joint-use parks.	√		√	
SS1.6	Reduced Footprint		Reduce the building footprint.	1	1	1	Provide floor area ratio (FAR) calculation	√			
2. Transportation (3)											
SS2.1	Public Transportation		Locate near public transportation.	1	1	1	Identify transit system(s) and provide website link(s)				
SS2.2	Bicycles		Provide bike racks & bike lanes for a percentage of the school population.	1	0	0	Cite CSI Section. List number and type of racks, and provide bike lane and sidewalk infomation.	√	√		√
SS2.3	Minimize Parking		Minimize parking lot & create preferred parking for carpools.	1	0	0	List number of classrooms by school level. List number of carpool spaces and total number of parking spaces on the plans.	√			√
3. Stormwater Management (2)											
SS3.0	Construction Site Runoff Control	√	Control erosion & sedimentation to reduce negative impacts on water & air quality. Must incorporate minimum US EPA's National Pollutant Discharge Elimination System (NPDES) Part 2.	X	X	X	Cite CSI Section or Provide date and file/id number of SWPPP with State Water Resources Control Board or regional affiliate.				
SS3.1	Limit Stormwater Runoff		Minimize runoff.	1	0	0	Cite CSI Section if applicable. Calculate existing and post-development imperviousness in %. State methods to reduce runoff.	√	√	√	
SS3.2	Treat Stormwater Runoff		Treat runoff.	1	0	0	Cite CSI Section. Identify Best Management Practices (BMP) systems to mitigate stormwater runoff	√	√	√	√

Fig. 3.2. Page 1 of HPI Scorecard with DSA application number 04-109775


Application Summary

Office ID: 02 | Application #: 107553 | File #: 34-39

Project Name: Natomas Creekside Learning Center (natomas Unified Sd)

Project Scope: Construction of 1-2 CR bldgs, Admin/library bldg., M:/Gym bldg, Ped walkway, 7 outdoor eating pavillions (inc #2), 1-Site work (incr#1)

Address: 3200 N. Park Dr

City: Sacramento | Zip: 95821

PTN #: 75283-29 | OPSC #: | # Of Incr: 2

Project Type: SCHOOL (K-12) | Project Class: Class 1 | Special Type: NA

Estimated Amt: $50,000,000.00 | Contracted Amt: $70,203,948.00 | Change Order Amt: $4,141,782.63

Adj Est.Date#1: | Adj Est.Amt#1: | Final Project Cost: $0.00

Adj Est.Date#2: | Adj Est.Amt#2: | Received Date: 9/13/2005

Appr. Date: | Appr. Ext. Date: | Closed Date: 8/9/2010

Incomplete Submittal | Complete Submittal Received Date: 11/3/2005

SB 575
New Campus | Modernization

	Auto Fire Detection	Sprinkler System
Required		
Included In Plan		

Required review services
Access Compliance | Fire & Life Safety | HPS
Structural Safety | Field Review | CGS Review

Special review type
Class.S Reduction | Concurrent Review | Incremental Review
Over the Counter

Energy Efficiency
The Plan meet Title 24 Energy Requirements
Project's new construction exceeds Title 24 by 25.97 %
Project's modernization exceeds Title 24 by 0 %

Climate Zone: 12 | Project's Sq.footage: 202606 | EPR Approved Date: 10/11/2007
HPI: | HPI Points: | HPI Hours:
Energy Notes: The score for the High Performance Grant is 30 points. With plug load removed

Client's Notes: 8/2/06 - Shade structures removed from the scope of this application at backcheck for inc. 2. - WVW. The HPS score is 30 points. Site named ; Re-exam fee paid 7/15/10 (KU)

Fig. 3.3. Screenshot of the application summary page of DSA project number 04-109775

Minimum criteria for HPI construction projects was implemented for analysis. First, all projects included new construction, addition, or modernization of at least one classroom building indicated by the Construction Scope. Second, all projects in the dataset were fully completed at the time of data collection as indicated by the Field Review Finish date provided by the DSA. Lastly, each project was given a DSA Certification number of 1, 2 or 3. Further criteria were implemented for each of the four statistical analyses. 77 schools met the minimum criteria out of the initial set of 244.

3.1.2 Collection of HPI Acoustic Data provided by DSA

For the purposes of this thesis, it was determined that the Acoustics subsection of the HPI scorecard contained three tiers of acoustic performance for classrooms. The minimum or prerequisite acoustical performance for HPI school classrooms is a maximum unoccupied BNL of 45 dBA, and a maximum unoccupied RT of 0.6 seconds. All schools certified as High Performance by DSA are required to meet this standard. In order to exhibit improved acoustical performance, HPI classrooms must exhibit a maximum unoccupied BNL of 40 dBA or a maximum unoccupied BNL of 35 dBA. The maximum unoccupied classroom RT is constant at 0.6 seconds. An example acoustics subsection of a school meeting only the prerequisite criteria is shown in Figure 3.4

DSA High Performance Incentive (HPI) 2006 Scorecard

Date of Scorecard:			1/28/09				
CHPS SECTION		PREREQUISITES (MANDATORY)	**2006 CRITERIA SUMMARY**: FOR DETAILED EXPLANATION SEE "CHPS BEST PRACTICES MANUAL VOLUME 3 - CRITERIA," 2006 EDITION (available at http://www.chps.net/manual/index.htm)	Max Possible HPI Points Rating	POINTS Claimed	DSA VERIFICATION	F
3. Acoustics (3)							
EQ3.0	Minimum Acoustical Performance	√	Classrooms must have a maximum (unoccupied) noise level of 45dbA, with maximum (unoccupied) reverberation times of 0.6 sec.	X	X	X	C r
EQ3.1	Improved Acoustical Performance		Classrooms must have a maximum (unoccupied) noise level of 40dbA or 35 dbA, with maximum (unoccupied) reverberation times of 0.6 sec.	3	0	0	C r
4. Thermal Comfort (2)							

Fig. 3.4. Acoustics Subsection of HPI Scorecard with DSA application number 04-109775

The number of HPI points awarded by DSA has varied through different iterations of the scorecard. However, the standards for BNL and RT have remained constant for all HPI Scorecards. For this thesis, HPI schools that were only verified by DSA for the Prerequisite category were labeled as Minimum. Schools that were awarded any number of DSA verified points for improved acoustical performance were labeled as Improved. The standardized acoustics score for all 78 HPI schools was then added to the database.

3.1.3 Collection of API Data provided by CDE

The methodology for the collection of school demographic and student achievement data is discussed in this section. API data for all California schools by year is publicly available for download via the California Department of Education website (http://www.cde.ca.gov/ta/ac/ap/. Base API scores, Growth API scores and demographic information may be obtained in online report format for a specific school in a specific

year, or in .txt database format for every school in the state of California in a specific year.

The DSA project names were cross-referenced with Google Maps (https://www.google.com/maps) to confirm school identity. In 31 cases, the DSA project name and school name were identical. The school name was then entered into the CDE database search function, providing: school CDS code, demographic data, and Base or Growth API scores (separate reports) for a particular reporting cycle. This information was added to the research database for all 77 schools. A description of database categories may be seen in Table 3.1 of the previous section. The CDE search function, online report links, and an example online Base API report are shown in Figure 3.5, Figure 3.6, and Figure 3.7.

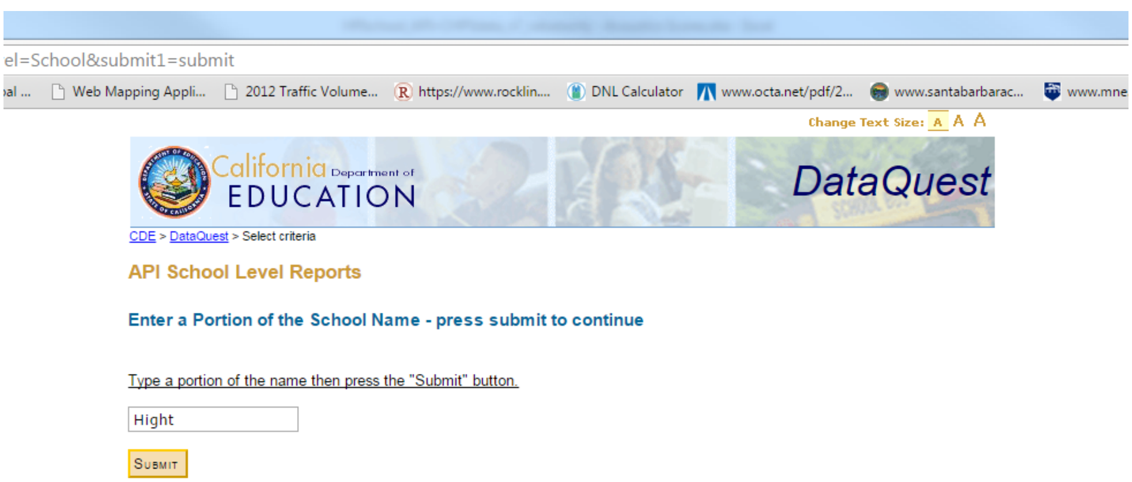


Fig. 3.5. Screenshot of the CDE database search function by school name

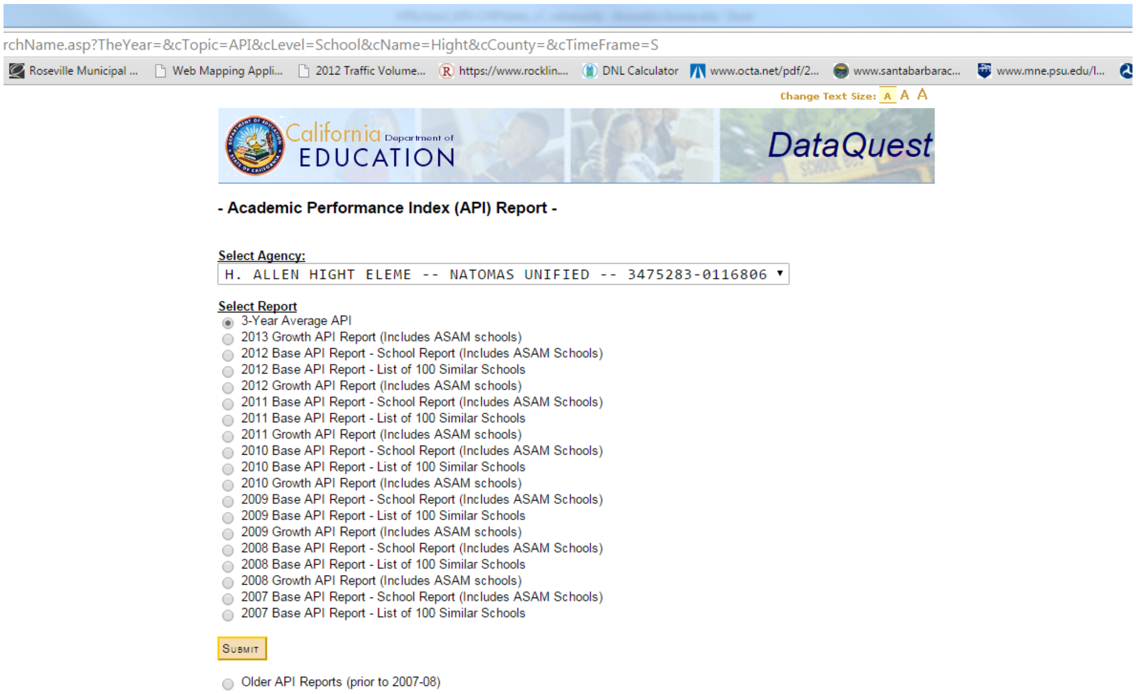
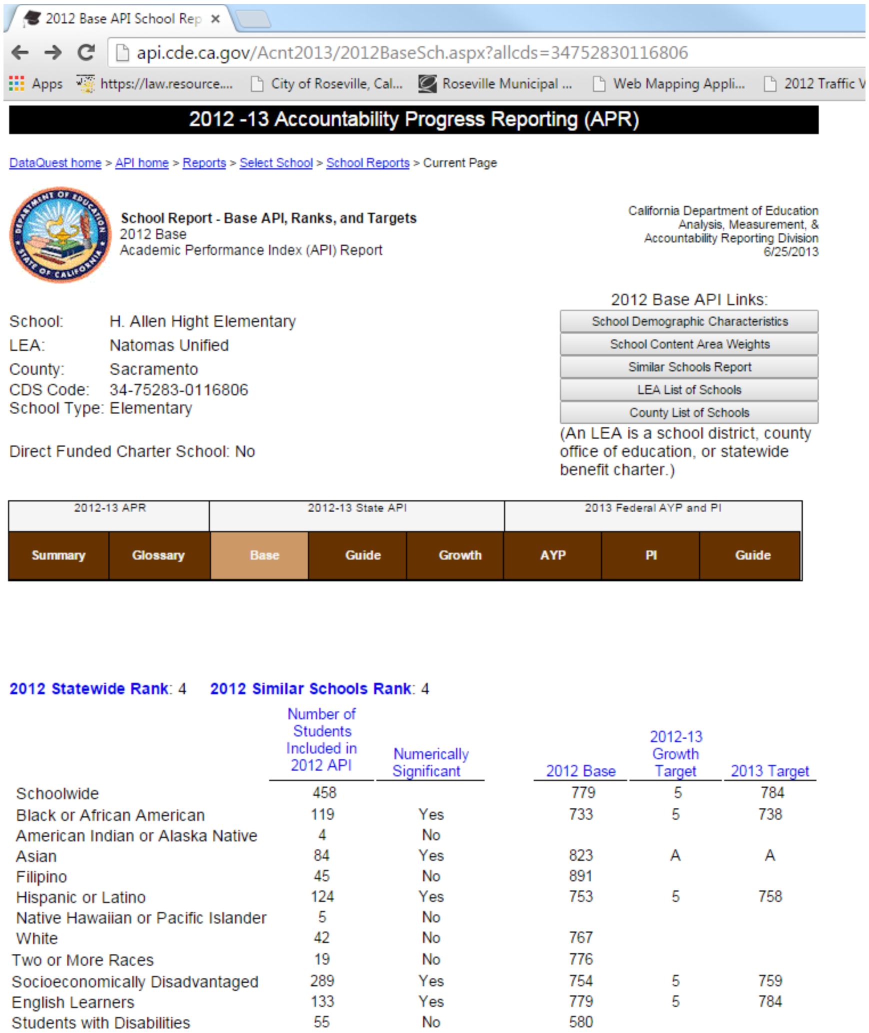


Fig. 3.6. Screenshot of online API reports for a school, organized by year.



	Number of Students Included in 2012 API	Numerically Significant	2012 Base	2012-13 Growth Target	2013 Target
Schoolwide	458		779	5	784
Black or African American	119	Yes	733	5	738
American Indian or Alaska Native	4	No			
Asian	84	Yes	823	A	A
Filipino	45	No	891		
Hispanic or Latino	124	Yes	753	5	758
Native Hawaiian or Pacific Islander	5	No			
White	42	No	767		
Two or More Races	19	No	776		
Socioeconomically Disadvantaged	289	Yes	754	5	759
English Learners	133	Yes	779	5	784
Students with Disabilities	55	No	580		

Fig. 3.7. Screenshot of 2012 Base API Report

For the yearly Base API report, a list of 100 Similar Schools is compiled by the CDE specifically for the reported school for that year. The Similar Schools Report include county, school district, and school name, as well as CDS Code, and Base API for that year. The lists are available via a link in the online report. The Similar Schools Report for 2005 and 2013 were obtained for all 77 HPI schools. An example report may be seen in Figure 3.7 below

2011 Base API School Rep × Google Maps ×

api.cde.ca.gov/Acnt2012/2011BaseSchSS.aspx?allcds=34752830116806

Apps https://law.resource.... City of Roseville, Cal... Roseville Municipal ... Web Mapping Appli... 2012 Traffic Volume... ht

00 Similar Schools

isted alphabetically by county, school district, and school name.

DS Code	County	School District	School	2011 Base API
1-10017-0109835	Alameda	Alameda County Office of Educa	FAME Public Charter	777
1-61192-6001051	Alameda	Hayward Unified	Lorin A. Eden Elementary	749
1-61259-0115618	Alameda	Oakland Unified	Greenleaf Elementary	822
7-61648-6003578	Contra Costa	Antioch Unified	Belshaw Elementary	790
7-61796-6004956	Contra Costa	West Contra Costa Unified	Shannon Elementary	747
9-61903-6005573	El Dorado	Lake Tahoe Unified	Tahoe Valley Elementary	808
0-73965-6006662	Fresno	Central Unified	Houghton-Kearney Elementary	788
0-62117-6005912	Fresno	Clovis Unified	Tarpey Elementary	817
0-62166-6006332	Fresno	Fresno Unified	Kratt Elementary	801
0-62166-6006431	Fresno	Fresno Unified	Powers-Ginsburg Elementary	795
0-62166-0111633	Fresno	Fresno Unified	Valley Arts and Science Academy (VASA)	667
0-62265-0106815	Fresno	Kings Canyon Joint Unified	Thomas Law Reed Elementary	810
0-62265-6006878	Fresno	Kings Canyon Joint Unified	Washington Elementary	796
0-75408-6007090	Fresno	Riverdale Joint Unified	Fipps Primary	850
5-10157-1530492	Kern	Kern County Office of Educatio	Valley Oaks Charter	748
5-63362-6009948	Kern	Panama-Buena Vista Union	Panama Elementary	785
6-63974-6118590	Kings	Lemoore Union Elementary	Cinnamon Elementary	777
9-64485-6012975	Los Angeles	East Whittier City Elementary	Ceres Elementary	881
9-64568-6013817	Los Angeles	Glendale Unified	John Muir Elementary	823
9-64642-6108542	Los Angeles	Keppel Union Elementary	Pearblossom Elementary	802
9-64725-6015143	Los Angeles	Long Beach Unified	Birney Elementary	809
9-64725-6015374	Los Angeles	Long Beach Unified	Holmes Elementary	797
9-64725-6015382	Los Angeles	Long Beach Unified	Hudson K-8	779
9-64725-6118269	Los Angeles	Long Beach Unified	New City	623
9-64733-0122622	Los Angeles	Los Angeles Unified	Aspire Firestone Academy	815
9-64733-6016109	Los Angeles	Los Angeles Unified	Broad Avenue Elementary	757
9-64733-6016372	Los Angeles	Los Angeles Unified	Carthay Center Elementary	786
9-64733-6016406	Los Angeles	Los Angeles Unified	Catskill Avenue Elementary	807
9-64733-6017644	Los Angeles	Los Angeles Unified	Hubbard Street Elementary	792
9-64733-6018725	Los Angeles	Los Angeles Unified	Plainview Avenue Elementary	782
9-64733-6018857	Los Angeles	Los Angeles Unified	Reseda Elementary	831
9-64733-6019046	Los Angeles	Los Angeles Unified	San Pascual Avenue Elementary	756

Fig. 3.8. Screenshot of 2012 Similar Schools Report for an example HPI school

The .txt database of Growth and API reports of all California schools for the years 1999-2013 were downloaded from the CDE website. Referencing the CDE identification code for the 78 HPI schools, the following data was extracted and compiled in the research database: Base API, Growth API, Difference API, school SCI for the year 2012, and the number of students eligible for the Free Lunch program in the years 2005 and 2013

3.1.4 Statistical Analysis

In order to create a balanced dataset, 77 additional schools meeting Normal conditions were added to the set of 77 HPI schools. For each HPI school, the yearly lists of 100 Similar Schools from 2005 and 2013 were analyzed and ranked based upon the number of student participants in the Free or Reduced-Price Lunch programs. The similar school whose two-year average of participating students most closely matched that of the comparative HPI school was then selected. A check was performed to ensure that the chosen school had not applied for an HPI Grant. If the school had submitted an application, the next closest school was chosen. Finally, Base, Growth, and Difference API data for the 77 similar Non-HPI (Normal) schools was extracted and compiled in the research database. A total of 154 schools were included in the database for statistical analysis (77 HPI schools, 77 Normal school).

The data collected from the study was analyzed using a number of statistical methods in Microsoft Excel and SPSS. Performance data was collected in the form of API and HPI Acoustic scores. Performance data was analyzed across school construction as well as across time. School construction was categorized as High Performance or Normal, while time was categorized as Pre-Modification (Pre-Mod) and Post-Modification (Post-Mod). Base, Growth, and Difference API scores are considered the dependent variables while school construction and time are considered the independent variables.

For many cases, the data exhibited features that required non-parametric tests. Data may be considered suitable for parametric test if they meet the following conditions: data is measured at an interval or ratio level, data sets have equal variances, and that data

yields a normal distribution. Equal variances across data sets, or homogeneity of variance, may be found by using Levene's test. Normal distribution in a data set was determined by using the Kolmogorov-Smirnov, or K-S, test (Field and Hole, 2003). Parametric, robust parametric and non-parametric tests were implemented so that all possible results from the statistical analysis may be presented and discussed.

3.1.4.1. Standard Error of the Mean

Standard error of the mean (SE) is a standard deviation of the sample means and used to represent how accurate a sample can be. As SE increases, so does the variability of the sample means. SE is reported in the form of error bars in results graphs in the next chapter. SE is found by equation 3.1:

$$\mathrm{SE} = \frac{\mathrm{s}}{\sqrt{\mathrm{N}}} \qquad (3.1)$$

where *s* is the sample standard deviation and *N* is the sample size (Field and Hole, 2003).

3.1.4.2. Phase 1 Tests

In Phase 1, average Base, Growth, and Difference API scores were compared across Building Construction. The analysis was conducted for five annual API report periods: 2008-2009, 2009-2010, 2010-2011, 2011-2012, and 2012-2013. Some schools were not open for all five academic reporting cycles, or were found to have missing data for various years. If a school was found to have missing API data in all three API scoring categories for a particular year, then that school and its partner matched via comparison of the Free Lunch Program were excluded from the statistical analysis.

An independent-samples *t*-test was used to compare each dependent variable across the building condition variable. The relationship was analyzed over five annual

API reporting periods. The independent measures *t*-test is used to compare the means of two experimental conditions in which different participants are assigned to each condition (Field 2013). An example is the relationship between Difference API scores across High Performance and Normal conditions. Any significant relationships were reported using this statistic. The independent measures *t*-test reported the *t* value with the degrees of freedom, or df. The final report for these tests are reported with the respective significance in the following format: *t*(df)=____, where df is degrees of freedom as reported by SPSS. The effect size, *d*, was found by equation 3.2:

$$d = \frac{\mathrm{M1}-\mathrm{M2}}{s1} \tag{3.2}$$

where M1 is the mean of the control group, M2 is the mean of the comparison group and *s* is the standard deviation of the control group

Some data was found to have not-normal distributions which meant that the parametric test above may not be accurate for these cases because of possible inaccurate *p* values. Therefore, a robust method of testing for each *t-test* was performed in SPSS by bootstrapping using 1000 samples. The results of the independent samples *t*-test using 1000 bootstrap samples was reported in the same manner described in the paragraph above.

A non-parametric test, the Wilcoxon rank-sum test was also performed to compare each dependent variable across the building condition variable. The relationship was analyzed over five annual API reporting periods. An example is the relationship between Difference API scores across High Performance and Normal conditions. Each

Wilcoxon rank-sum test statistic, W, was reported along significance. The effect size, r is found using equation 3.3:

$$r = \frac{Z}{\sqrt{N}} \qquad (3.3)$$

where Z is the z-score produced by SPSS and N is the total number of observations compared (Field and Hole 2003).

3.1.4.3. Phase 2 Tests

For Phase 2, average Difference API scores for High Performance schools were compared before and after completion of construction. A DSA Field Review Start date of August 2007 was used to delineate the Pre-Mod condition and a DSA Field Review finish date of August 2011 was used to delineate the Post-Mod condition. Previously existing High Performance schools that initiated and completed construction within the criteria were included in the analysis. API data for the 2008-2009, 2009-2010, and 2010-2011 report periods in between the two conditions were excluded from analysis.

A paired samples *t*-test was used to compare each dependent variable across the time variable. For example, The Difference API score was analyzed across the Pre-Mod and Post mod condition. The paired samples *t*-test is used to compare the means of two experimental conditions and the same participants took part in both conditions of the experiment (Field 2013). Any significant relationships were reported using this statistic. The paired samples *t*-test reported the *t* value with the degrees of freedom, or df. The final report for these tests are reported with the respective significance in the following format: *t*(df)=____, where df is degrees of freedom as reported by SPSS. The effect size, *d*, was found by equation 3.2 above.

Some data was found to have not-normal distributions which meant that the parametric test above may not be accurate for these cases because of possible inaccurate *p* values. Therefore, a robust method of testing for each *t-test* was performed in SPSS by bootstrapping using 1000 samples. The results of the independent samples *t*-test using 1000 bootstrap samples was reported in the same manner described in Section 3.1.4.3 above.

A non-parametric test, the Wilcoxon signed-rank test was also performed to compare each dependent variable across the time variable. An example is the relationship between Difference API scores across Pre-Mod and Post-Mod conditions. Each Wilcoxon signed-rank test statistic, T, was reported along significance. The effect size, r is found by using equation 3.3.

3.1.4.4. Phase 3 Tests

In Phase 3, average Base, Growth and Difference API scores were analyzed across HPI Acoustics categories. The list of HPI schools was sorted by School Type and ranked by 2012 SCI score. High Performance schools meeting the Improved Acoustics criteria were matched with a corresponding set of schools meeting the Minimum Acoustics criteria by comparing SCI score. The list of schools in the Improved Acoustics category was also correlated with a corresponding similar school in the Normal building construction category as described in Section 3.1.3. These schools were labeled as the None (acoustics) category. Analysis was conducted for the 2012-2013 API report period.

A one-way ANOVA was used to compare each dependent variable across the Acoustics variable. An example for this is the relationship between Difference API scores across None, Minimum, and Improved Acoustics conditions. Each one-way ANOVA test

statistic was reported with significance in the following format: F(df_M, df_R) were df_M is the degrees of freedom for the effect of the model, and df_R is the degrees of freedom for the residuals of the model. The effect size, r, was found by using a complex version of effect size, ω, and was found by taking the square root of equation 3.4:

$$\omega^2 = \frac{MS_M - MS_R}{MS_M + ((n-1) * MS_R)} \qquad (3.4)$$

where MS_M is the mean sum of squares, MS_R is the mean squared error, and n is the sample size.

Some data was found to have not-normal distributions which meant that the parametric tests above may not be accurate for these cases because of possible inaccurate *p* values. Therefore Brown-Forsythe and Welch robust tests of the equality of means were performed and reported.

Specific, planned, contrasts were performed in which the Normal condition was compared against the Minimum and Improved Conditions, and the Minimum condition was compared against the Improved Condition. Any significant relationships were reported using the *t*-statistic. The *t*-test reported the *t* value with the degrees of freedom, or df. The final report for these tests are reported with the respective significance in the following format: *t*(df)=____, where df is degrees of freedom as reported by SPSS. The effect size, *r*, was found by taking the square root of equation 3.5:

$$r^2 = \frac{t^2}{t^2 + df} \qquad (3.5)$$

Where *t* is the reported test value and *df* is the degrees of freedom.

3.1.4.5. Statistical Power Analysis

Since planned comparisons were used, a power analysis was not implemented to determine the probability of each result presenting a genuine effect.

Chapter 4: Results and Discussion

This chapter presents the results from analysis of High Performance Incentive Scorecards and Academic Performance Index scores over a five year period. HPI performance and API results were reported and analyzed using the statistical analysis methodology previously discussed.

4.1 Overall Demographic Results

There were 154 total schools in the dataset: 58 elementary schools, 18 middle schools, and 78 high schools**.** There were 77 HPI schools and 77 Normal schools. Of the 77 HPI schools, 11 were characterized as having Improved acoustical performance and 66 qualified for Minimum acoustical performance. All 77 Normal schools were assumed to have no extra acoustical performance.

Base, Growth, and Difference API scores for 154 schools were compiled in a project database using Microsoft Excel. For each statistical analysis, specific criteria were implemented to ensure a balanced design. API results for specific analyses are included in the following sections.

4.2 Phase 1 Results

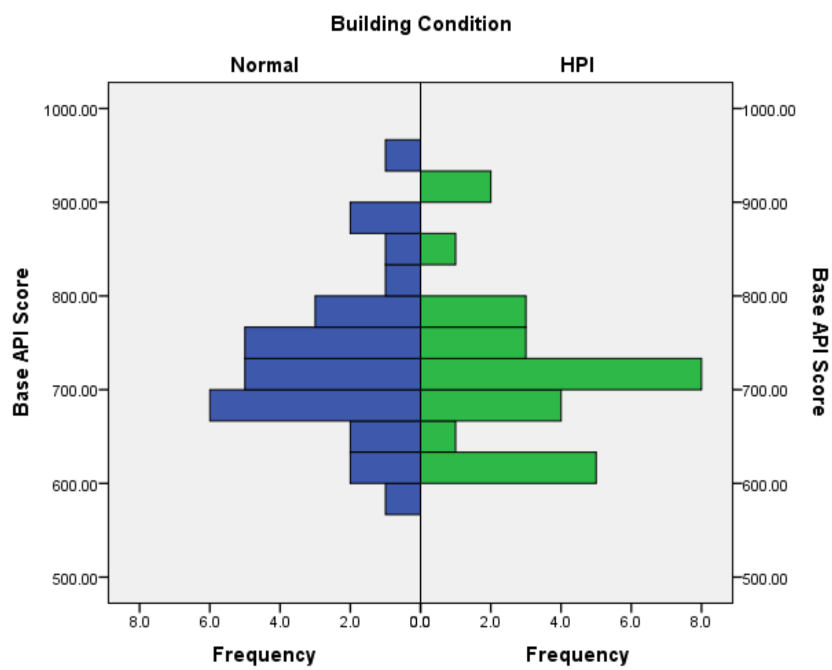
Academic Performance was measured in terms of Base, Growth, and Difference API scores for each school during five consecutive Academic Reporting Cycles from the year 2008 to the year 2013. Statistical analyses using SPSS were conducted as described earlier in Section 3.1.4. some results exhibited a non-normal distribution, as concluded by a Kolmogorov-Smirnov test. Therefore, bootstrapping was performed for the

independent-measures *t*-test. Wilcoxon rank-sum tests were used to further analyze the relationships between each school condition (Normal, High Performance).

Additionally, results for the non-bootstrapped, independent-measures *t*-tests are also reported to further strengthen the results even though it is a parametric test.

4.2.1 2008-2009 Demographic Results

96 schools out of 154 schools in the total dataset were excluded from analysis as described in Section 3.1.4.2. Base, Growth, and Difference API scores for the 2008-2009 academic year were analyzed for 58 schools (29 High Performance, 29 Normal). For the Normal category, there were 29 valid cases for Base, Growth, and Difference API respectively. For the High Performance category, there were 27, 29, and 27 valid cases for the Base, Growth, and Difference API respectively. Base, Growth, and Difference API scores for each building condition may be seen in Figures 4.1, 4.2, and 4.3



<u>Fig. 4.1.</u> Histogram of Base API Scores in 2008-2009 for Normal and HPI Schools.

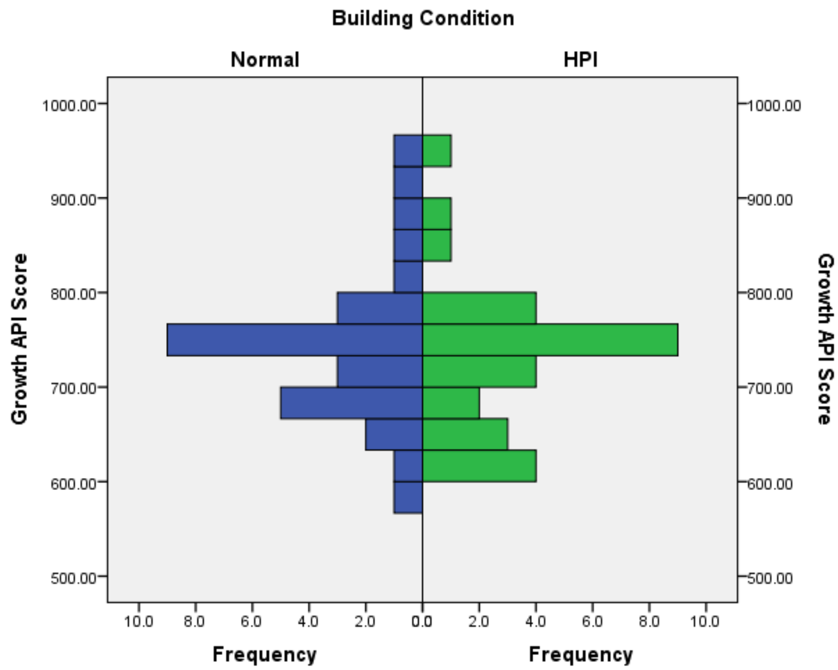


Fig. 4.2. Histogram of Growth API Scores in 2008-2009 for Normal and HPI Schools.

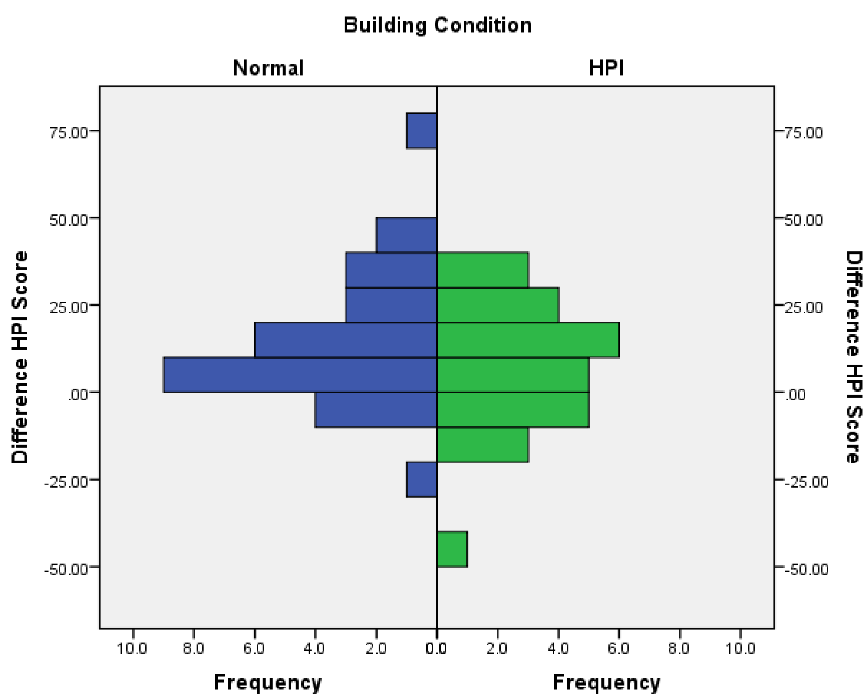


Fig. 4.3. Histogram of Difference API Scores in 2008-2009 for Normal and HPI Schools.

4.2.2 2008-2009 Academic Performance Index (API) Results across High Performance conditions

This section discusses the API performance results across the Building Construction condition for the 2008-2009 yearly API reporting cycle. The mean API performance results for each Scoring Category across Normal and HPI conditions are shown in Figures 4.4, 4.5, and 4.6. A trend can initially be seen that Normal schools performed better than High Performance schools for all scoring categories. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report.

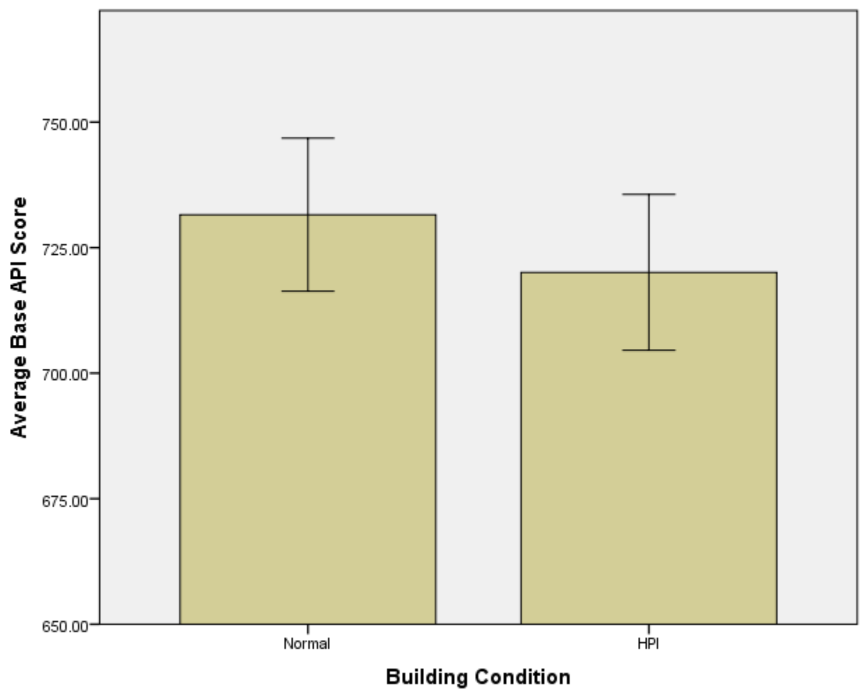


Fig. 4.4. Average Base API in 2008-2009 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

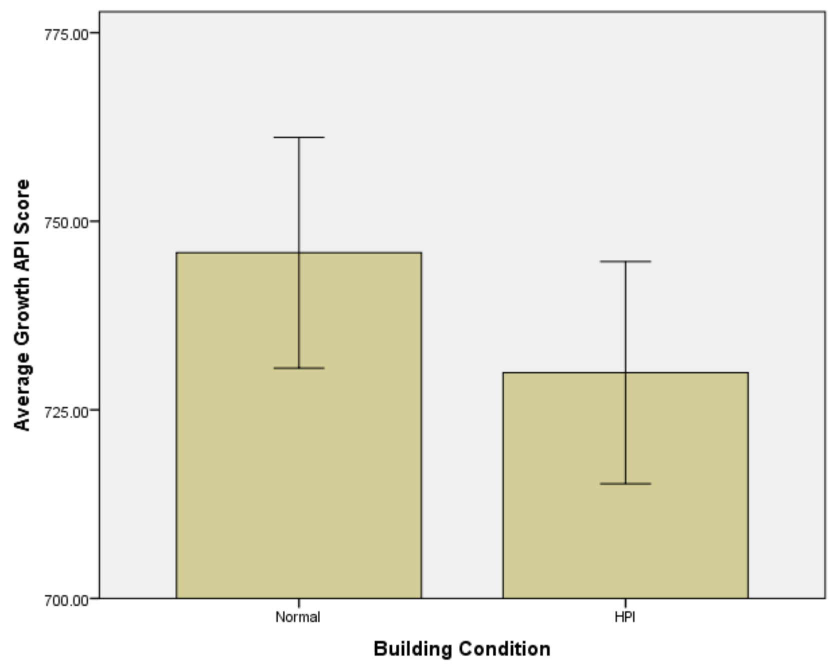


Fig. 4.5. Average Growth API in 2008-2009 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

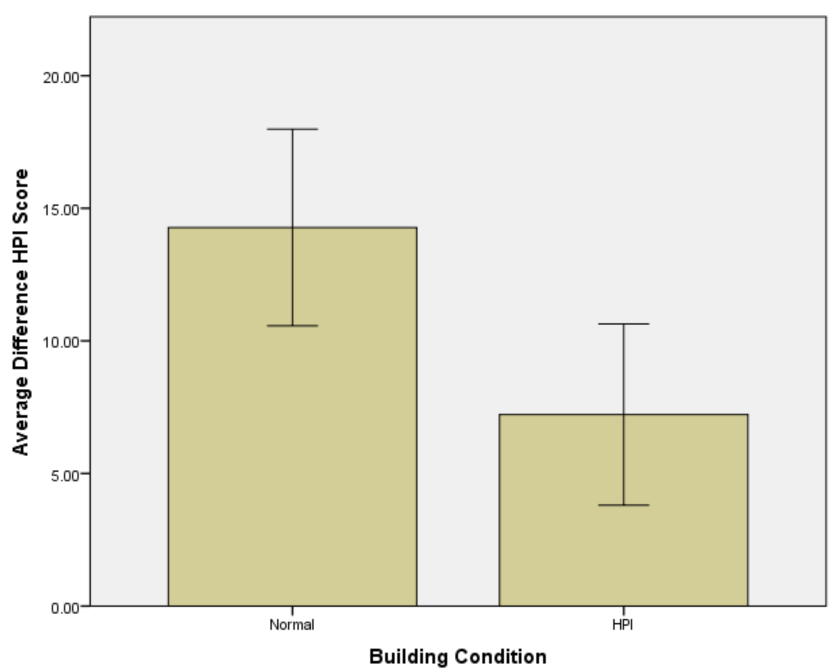


Fig. 4.6. Average Difference API in 2008-2009 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

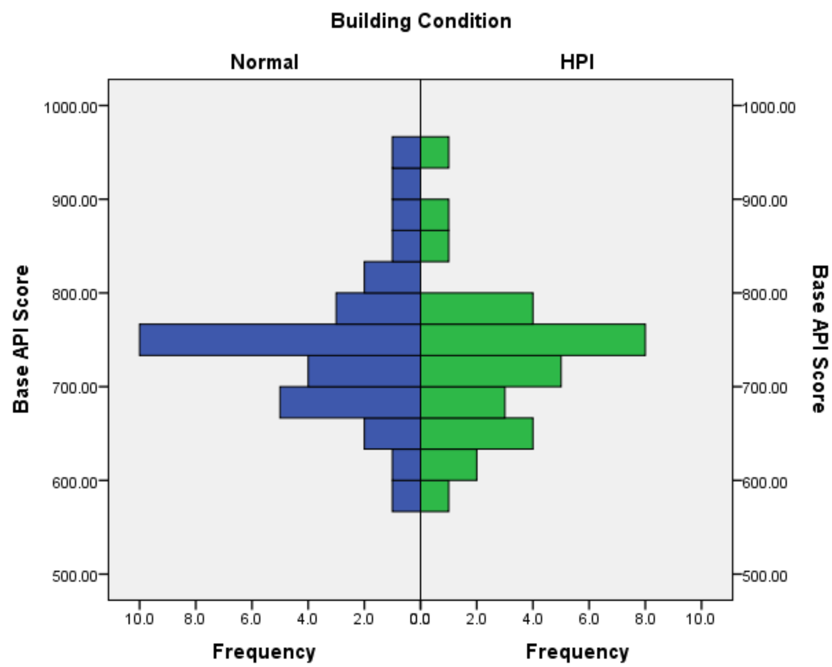
Levene's Test for homoscedasticity was performed. For all API categories, the assumption of equal variances is fulfilled. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each building performance condition. The test showed a significant, non-normal distribution in Growth API Scores for the Normal school condition D(29)=0.171, p=.030 as well as in Difference API scores for the Normal school condition D(29)=0.186, p=.012. Therefore, an independent measures *t*-test using 1000 bootstrap samples as well as a Wilcoxon rank-sum test were deemed appropriate and used to further analyze the relationships. All statistical tests found no significant relationship across school conditions and represent small effect sizes. Test results, including mean difference, standard error, bootstrapped confidence interval, significance, and effect size are reported in Appendix A.

Additionally, an independent-measures *t*-test without bootstrapping was still used to further strengthen the results even though it is a parametric test. Further results of the independent-measures *t*-test, including mean, standard error, confidence interval, significance, and effect size are reported in Appendix A

4.2.3 2009-2010 Demographic Results

88 schools out of 154 schools in the total dataset were excluded from analysis as described in Section 3.1.4.2. Base, Growth, and Difference API scores for the 2009-2010 academic year were analyzed for 66 schools (33 High Performance, 33 Normal). For the Normal category, there were 32, 33, and 32 valid cases for Base, Growth, and Difference API respectively. For the High Performance category, there were 30, 33, and 30 valid cases for the Base, Growth, and Difference API respectively. Base, Growth, and

Difference API scores for each building condition may be seen in Figures 4.7, 4.8, and 4.9



<u>Fig. 4.7.</u> Histogram of Base API Scores in 2009-2010 for Normal and HPI Schools.

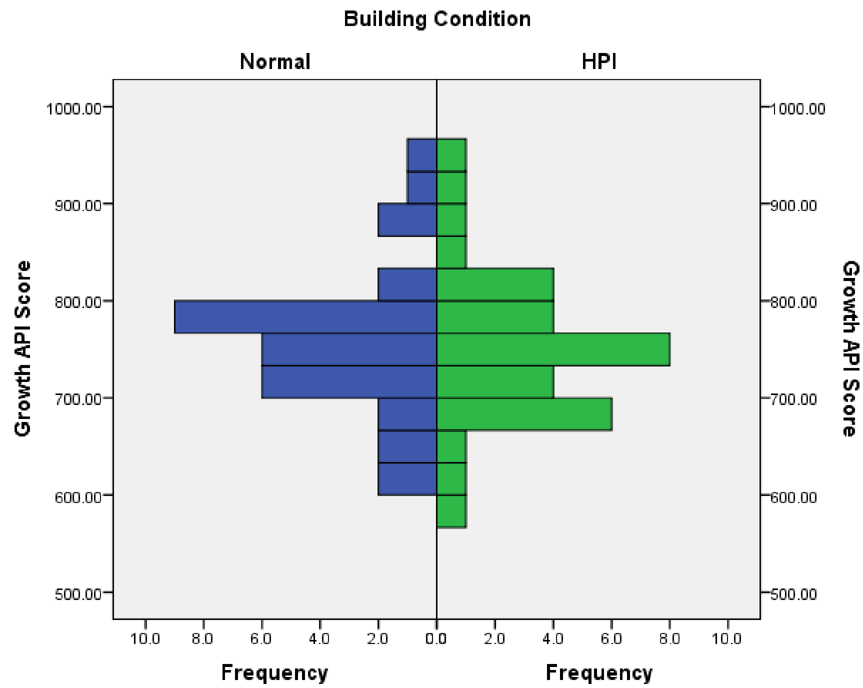


Fig. 4.8. Histogram of Growth API Scores in 2009-2010 for Normal and HPI Schools.

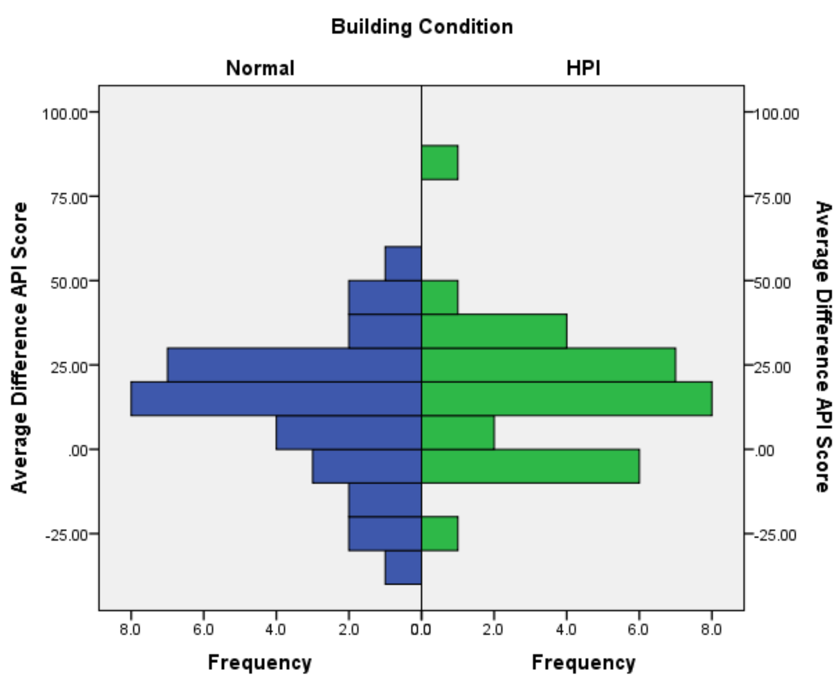


Fig. 4.9. Histogram of Difference API Scores in 2009-2010 for Normal and HPI Schools.

4.2.4 2009-2010 Academic Performance Index (API) Results across High Performance conditions

This section discusses the API performance results across the High Performance construction condition for the 2009-2010 yearly API reporting cycle. The API performance results for each Scoring Category across both performance conditions are shown in Figures 4.10, 4.11, and 4.12. A trend can initially be seen that Normal schools performed better than High Performance schools for Base and Growth API scoring categories. However, High Performance schools exhibited a higher Difference API than Normal schools. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report.

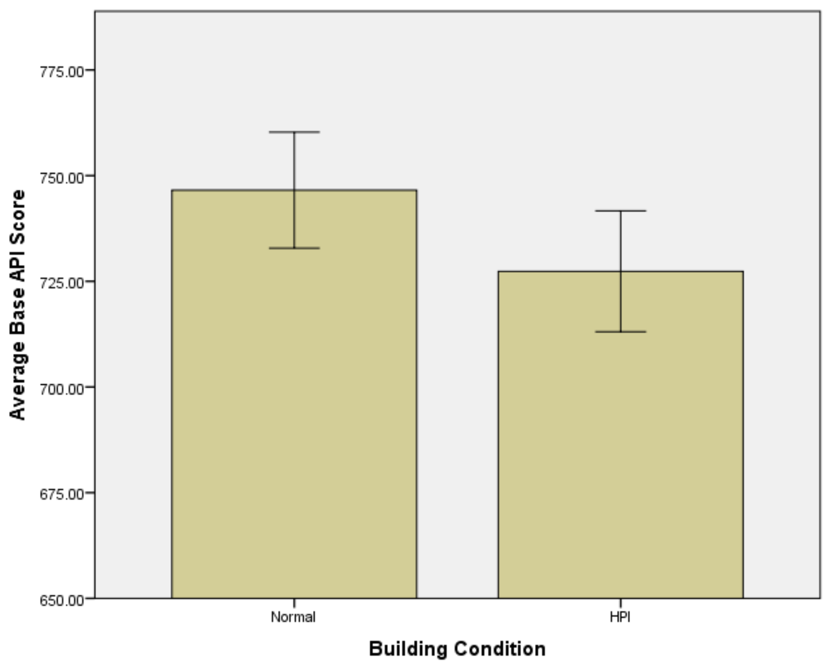
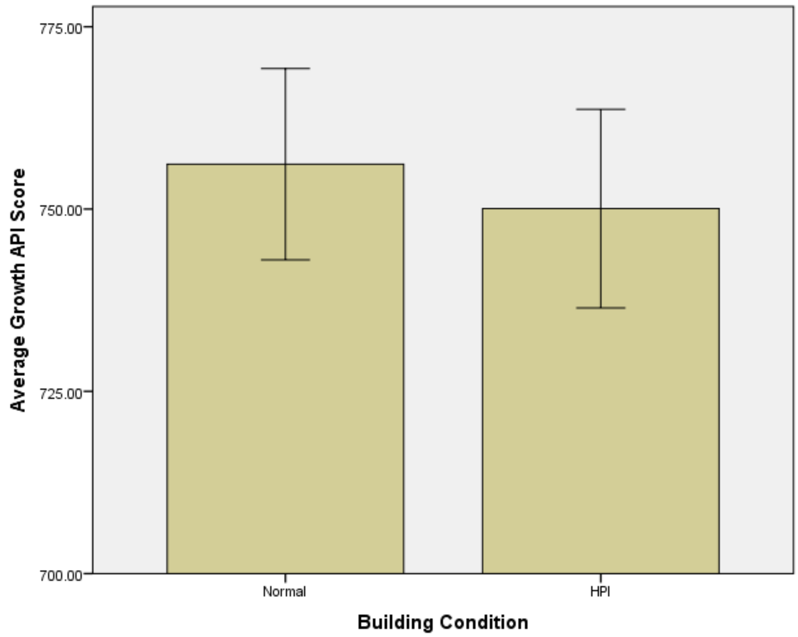
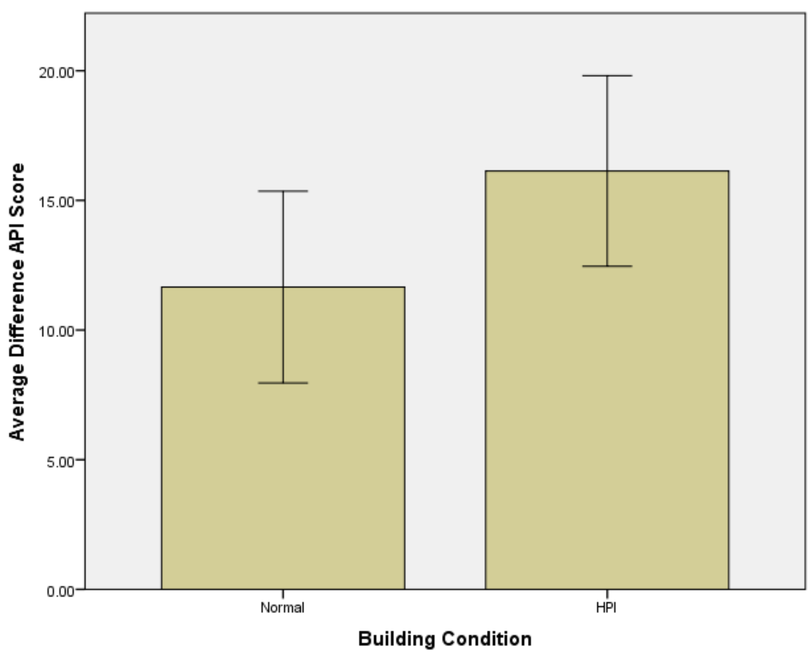


Fig. 4.10. Average Base API in 2009-2010 for Normal and HPI Schools. Error Bars represent the standard error of the mean.



<u>Fig. 4.11.</u> Average Growth API in 2009-2010 for Normal and HPI Schools. Error Bars represent the standard error of the mean.



<u>Fig. 4.12.</u> Average Growth API in 2009-2010 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

Levene's Test for homoscedasticity was performed. For all API categories, the assumption of equal variances is fulfilled. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each building performance condition. The test showed a significant, non-normal distribution in Base API Scores for the Normal school condition $D(32)=0.172$, $p=.017$. Therefore, an independent measures *t*-test using 1000 bootstrap samples as well as a Wilcoxon rank-sum test were deemed appropriate and used to further analyze the relationships. All statistical tests found no significant relationship across school conditions and represent small effect sizes. Test results, including mean difference, standard error, bootstrapped confidence interval, significance, and effect size are reported in Appendix A.

Additionally, an independent-measures *t*-test without bootstrapping was still used to further strengthen the results even though it is a parametric test. Further results of the independent-measures *t*-test, including mean difference, standard error, confidence interval, and significance, and effect size are reported in Appendix A.

4.2.5 2010-2011 Demographic Results

42 schools out of 154 schools in the total dataset were excluded from analysis as described in Section 3.1.4.2. Base, Growth, and Difference API scores for the 2010-2011 academic year were analyzed for 112 schools (56 High Performance, 56 Normal). For the Normal category, there were 56 valid cases for Base, Growth, and Difference API respectively. For the High Performance category, there were 33, 56, and 33 valid cases for the Base, Growth, and Difference API respectively. Base, Growth, and Difference API scores for each building condition may be seen in Figures 4.13, 4.14, and 4.15.

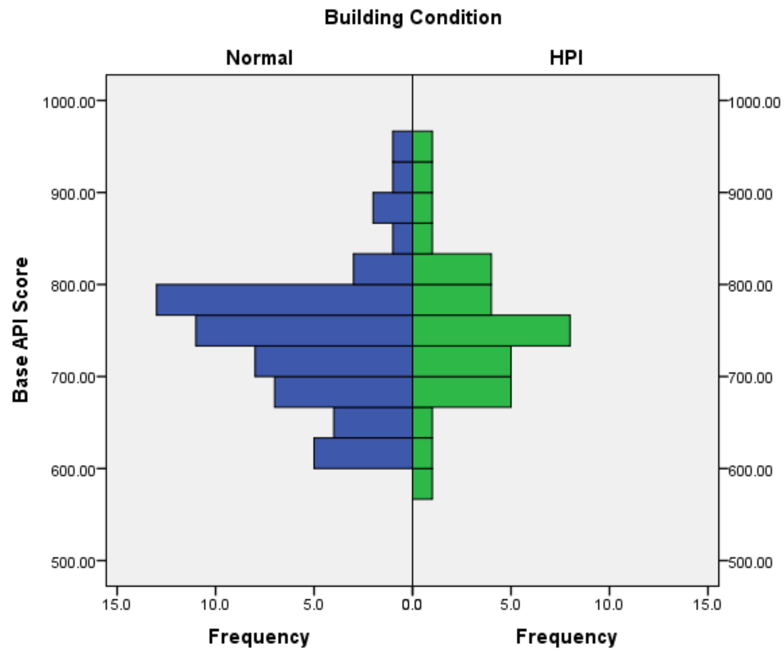


Fig. 4.13. Histogram of Base API Scores in 2010-2011 for Normal and HPI Schools.

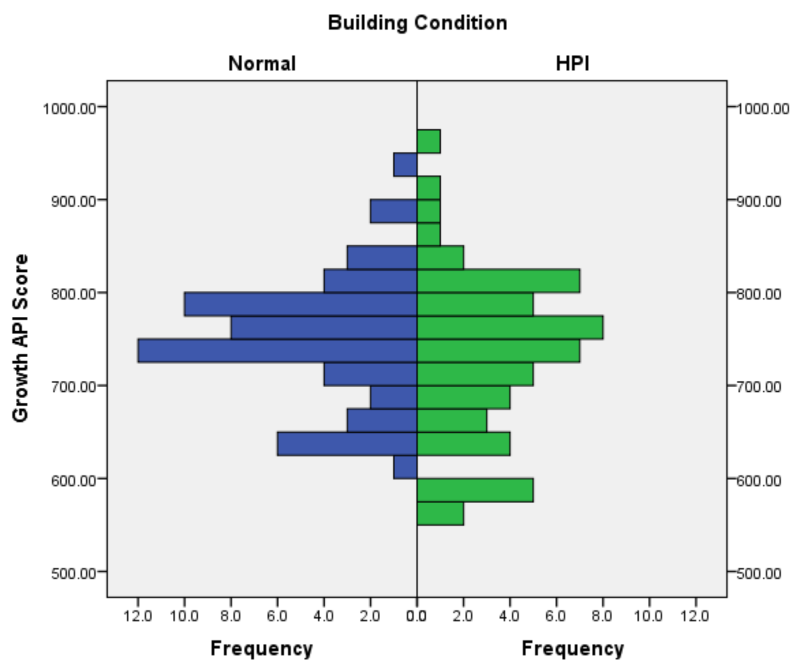


Fig. 4.14. Histogram of Growth API Scores in 2010-2011 for Normal and HPI Schools.

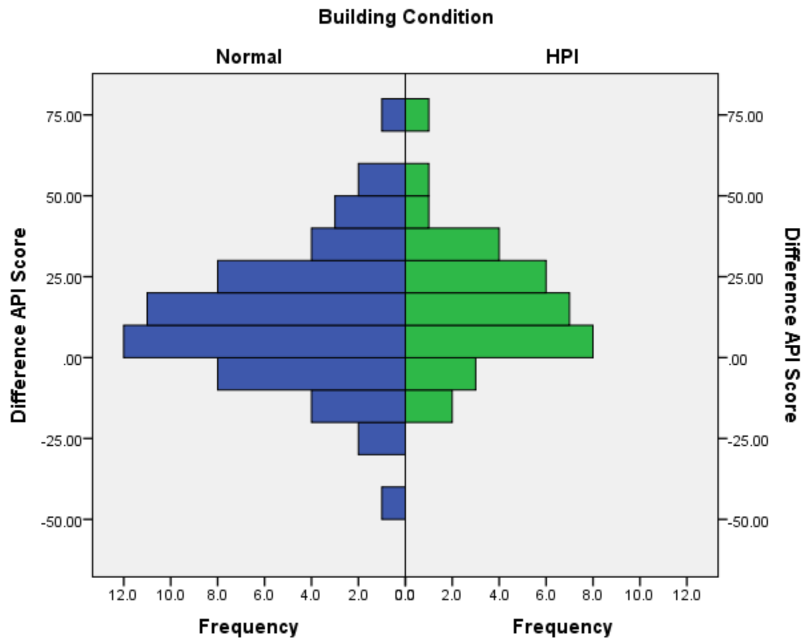


Fig. 4.15. Histogram of Difference API Scores in 2010-2011 for Normal and HPI Schools.

4.2.6 2010-2011 Academic Performance Index (API) Results across High Performance conditions

This section discusses the API performance results across the High Performance construction condition for the 2010-2011 yearly API reporting cycle. The API performance results for each Scoring Category across both performance conditions are shown in Figures 4.16, 4.17, and 4.18. Normal schools performed better than High Performance schools for the Growth API scoring category. However, High Performance schools exhibited a higher Base and Difference API than Normal schools. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report.

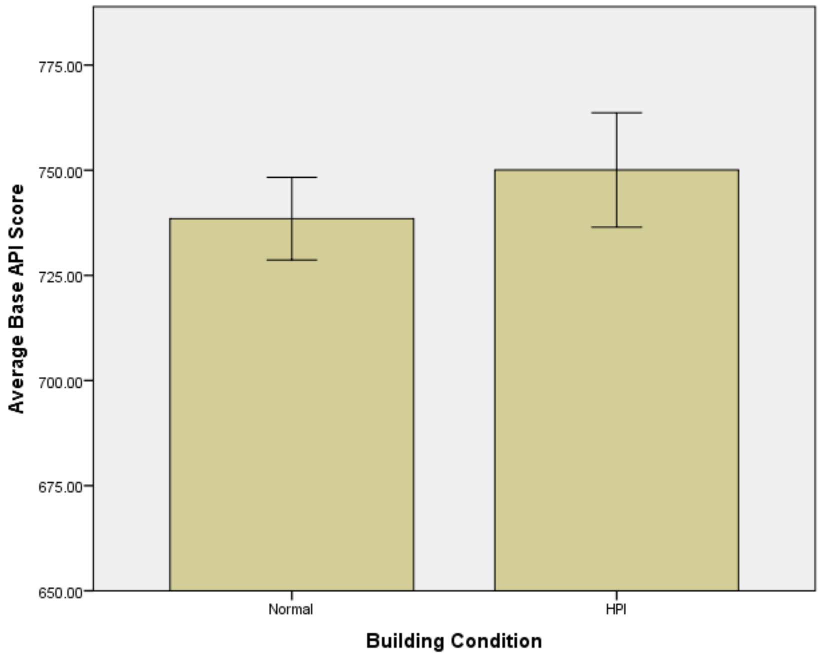


Fig. 4.16. Average Base API in 2010-2011 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

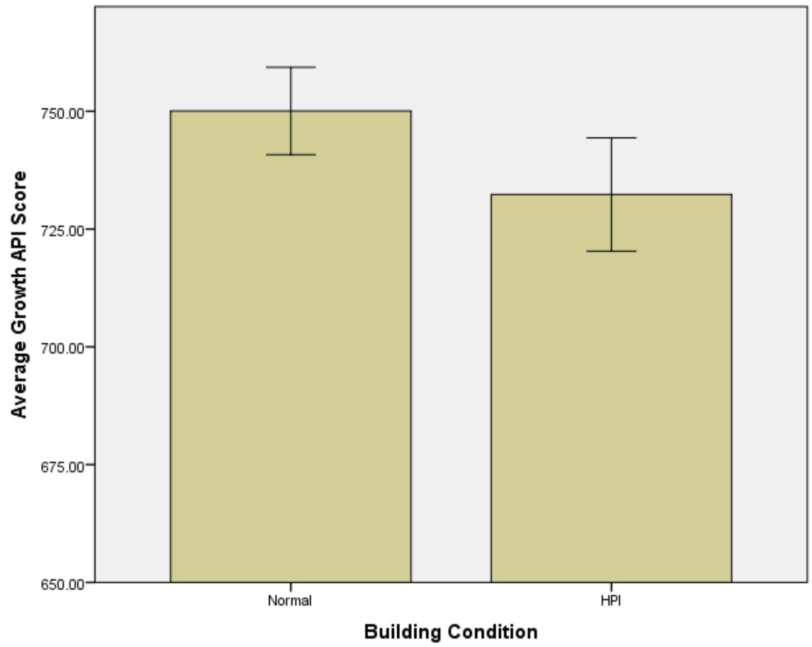


Fig. 4.17. Average Growth API in 2010-2011 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

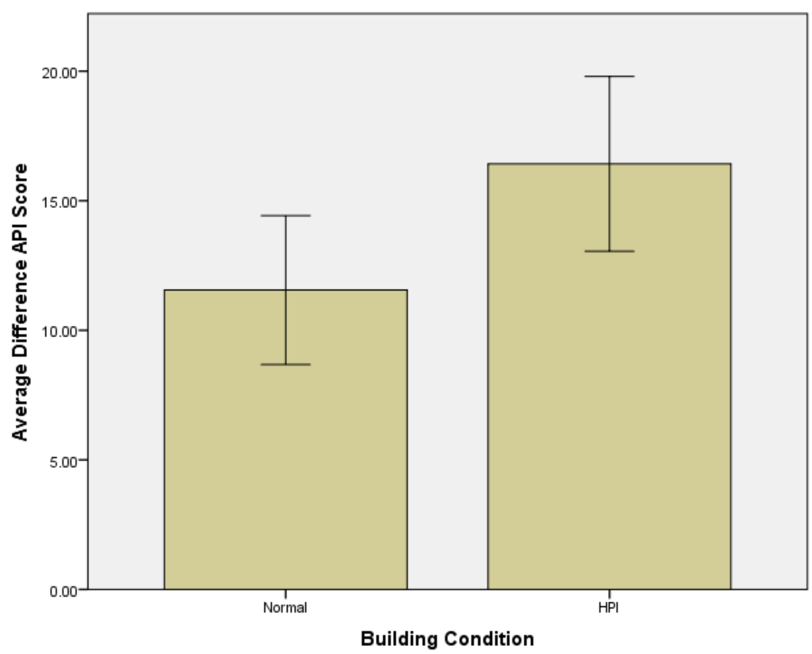


Fig. 4.18. Average Difference API in 2010-2011 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

Levene's Test for homoscedasticity was performed. For all API categories, the assumption of equal variances is fulfilled. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each building performance condition. The test showed a normal distribution for all API scoring Categories. Therefore, an independent measures *t*-test was deemed appropriate and used to further analyze the relationships. All statistical tests found no significant relationship across school conditions and represent small to medium effect sizes. Further results of the independent-measures *t*-test, including mean, standard error, confidence interval, significance and effect size are reported in Appendix A.

4.2.7 2011-2012 Demographic Results

14 schools out of 154 schools in the total dataset were excluded from analysis as described in Section 3.1.4.2. Base, Growth, and Difference API scores for the 2011-2012 academic year were analyzed for 140 schools (70 High Performance, 70 Normal). For the Normal category, there were 69, 70, and 70 valid cases for Base, Growth, and Difference API respectively. For the High Performance category, there were 56, 70, and 56 valid cases for the Base, Growth, and Difference API respectively. Base, Growth, and Difference API scores for each building condition may be seen in Figures 4.19, 4.20, and 4.21.

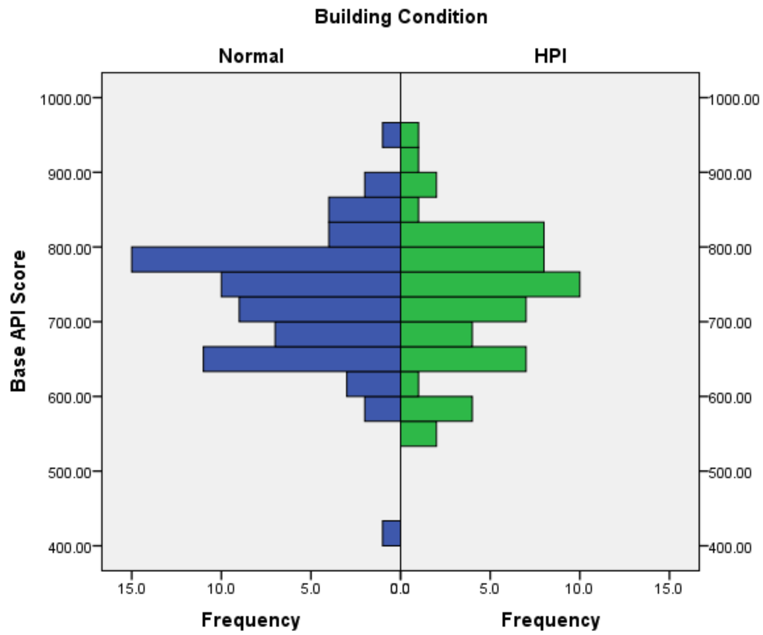


Fig. 4.19. Histogram of Base API Scores in 2011-2012 for Normal and HPI Schools.

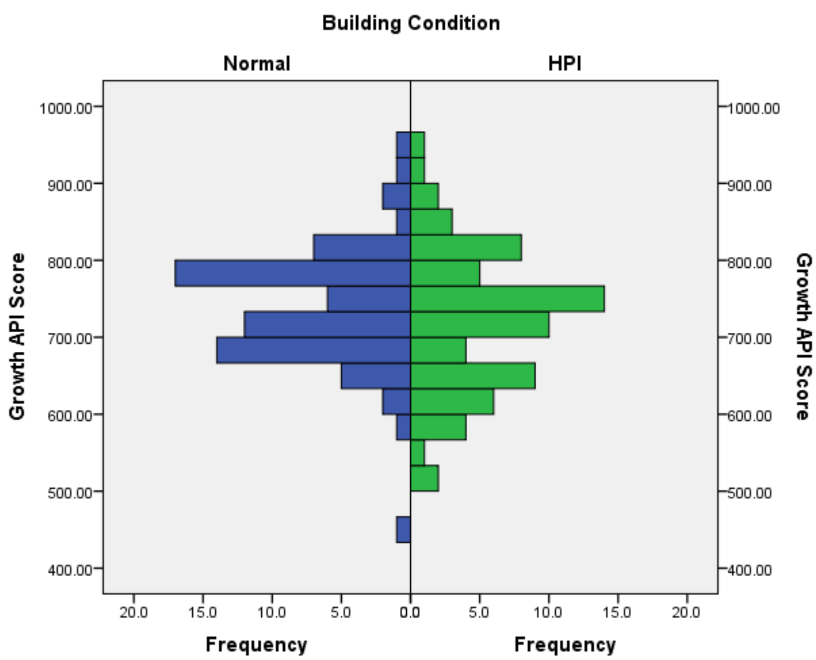


Fig. 4.20. Histogram of Growth API Scores in 2011-2012 for Normal and HPI Schools.

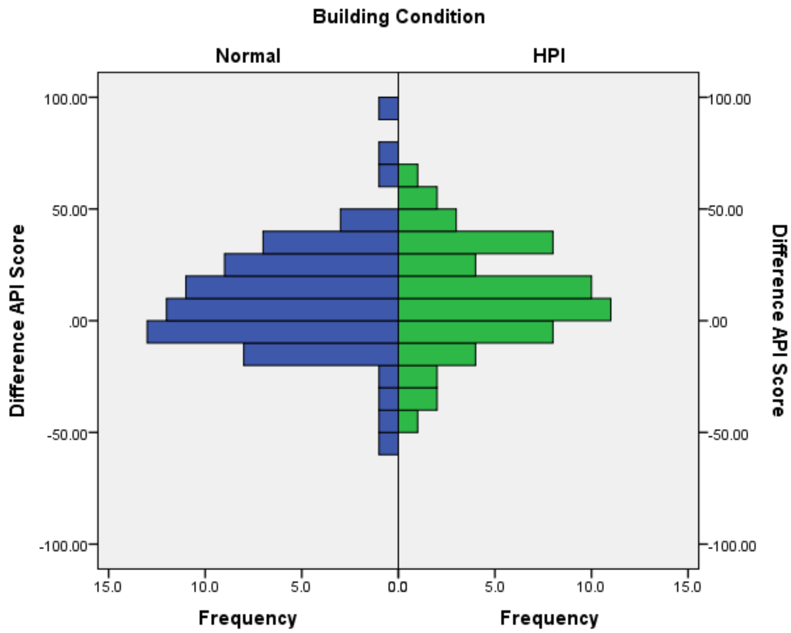
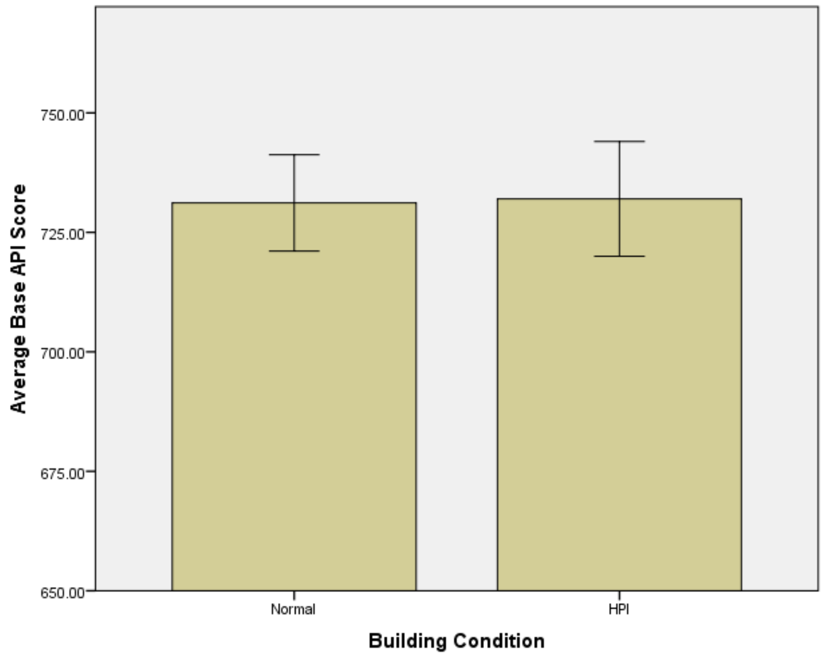


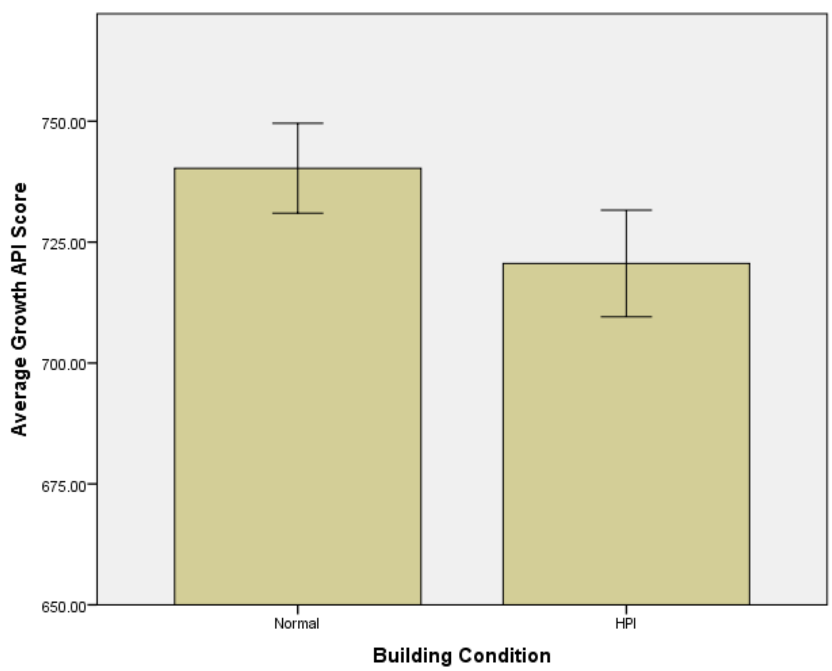
Fig. 4.21. Histogram of Difference API Scores in 2011-2012 for Normal and HPI Schools.

4.2.8 2011-2012 Academic Performance Index (API) Results across High Performance conditions

This section discusses the API performance results across the High Performance construction condition for the 2011-2012 yearly API reporting cycle. The API performance results for each Scoring Category across both performance conditions are shown in Figures 4.22, 4.23, and 4.24. Normal schools performed better than High Performance schools for the Growth API scoring category. However, High Performance schools exhibited a higher Base and Difference API than Normal schools. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report.



<u>Fig. 4.22.</u> Average Base API in 2011-2012 for Normal and HPI Schools. Error Bars represent the standard error of the mean.



<u>Fig. 4.23.</u> Average Growth API in 2011-2012 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

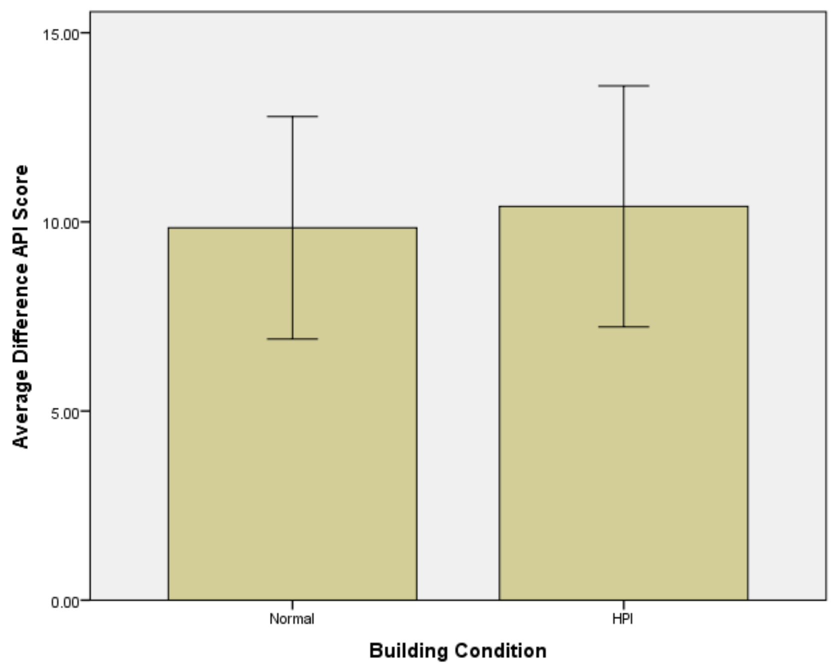


Fig. 4.24. Average Difference API in 2011-2012 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

Levene's Test for homoscedasticity was performed. The assumption of equal variances is fulfilled across all scoring categories. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each building performance condition. The test showed a normal distribution for all API scoring Categories. However, Figures 4.13, 4.14, and 4.15 report histograms for Normal schools which show the presence of outliers that may bias the analysis. Therefore, an independent measures *t*-test using 1000 bootstrap samples as well as a Wilcoxon rank-sum test were deemed appropriate and used to further analyze the relationships. All statistical tests found no significant relationship across school conditions and represent small effect sizes. Test results, including mean difference, standard error, bootstrapped confidence interval, significance, and effect size are reported in Appendix A.

Additionally, an independent-measures *t*-test without bootstrapping was still used to further strengthen the results even though it is a parametric test. Further results of the independent-measures *t*-test, including mean difference, standard error, confidence interval, significance and effect size are reported in Appendix A.

4.2.9 2012-2013 Demographic Results

14 schools out of 154 schools in the total dataset were excluded from analysis as described in Section 3.1.4.2. Base, Growth, and Difference API scores for the 2012-2013 academic year were analyzed for 140 schools (70 High Performance, 70 Normal). For the Normal category, there were 70, 69, and 69 valid cases for Base, Growth, and Difference API respectively. For the HPI category, there were 70 valid cases for all API scoring categories. Base, Growth, and Difference API scores for each building condition may be seen in Figures 4.25, 4.26, and 4.27.

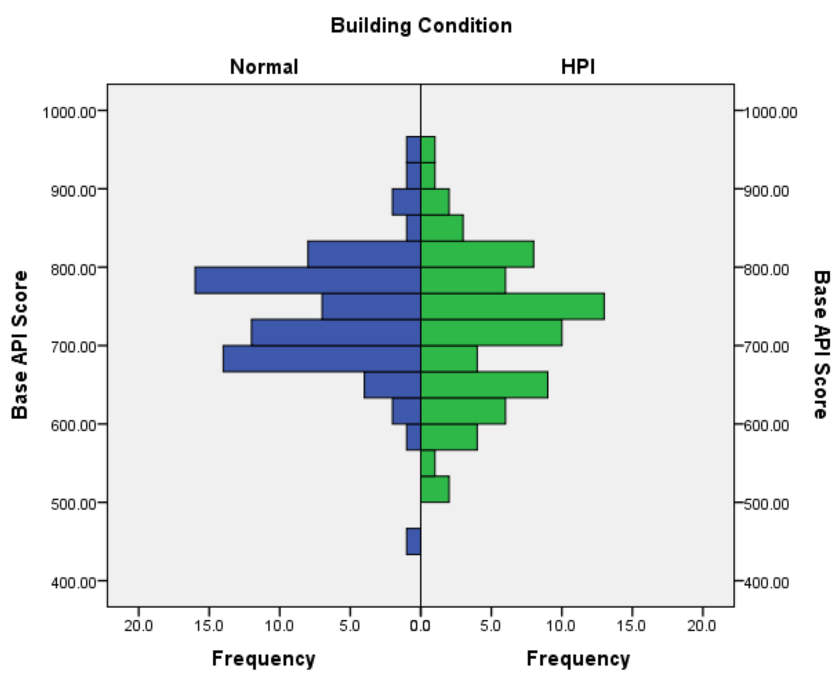
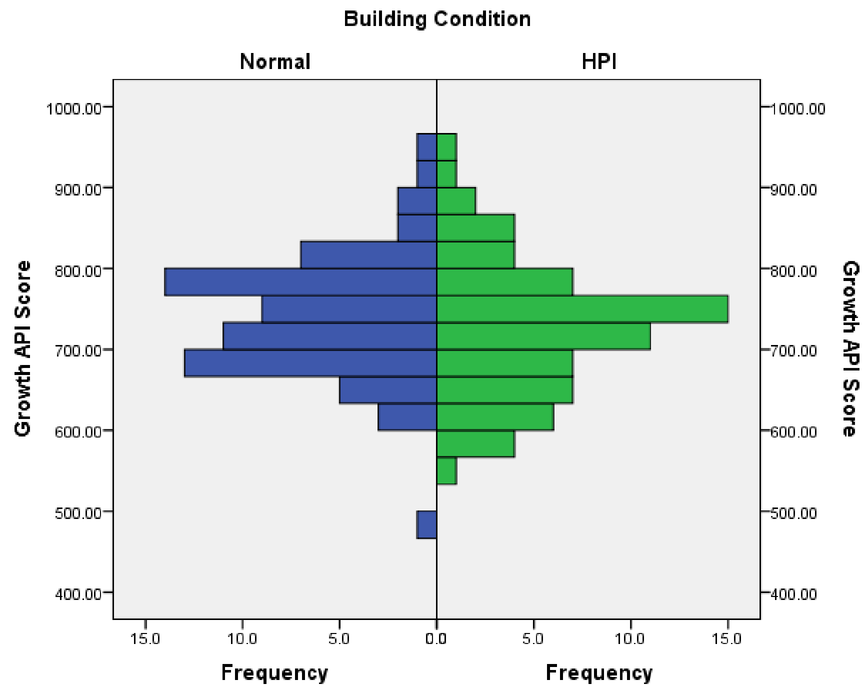
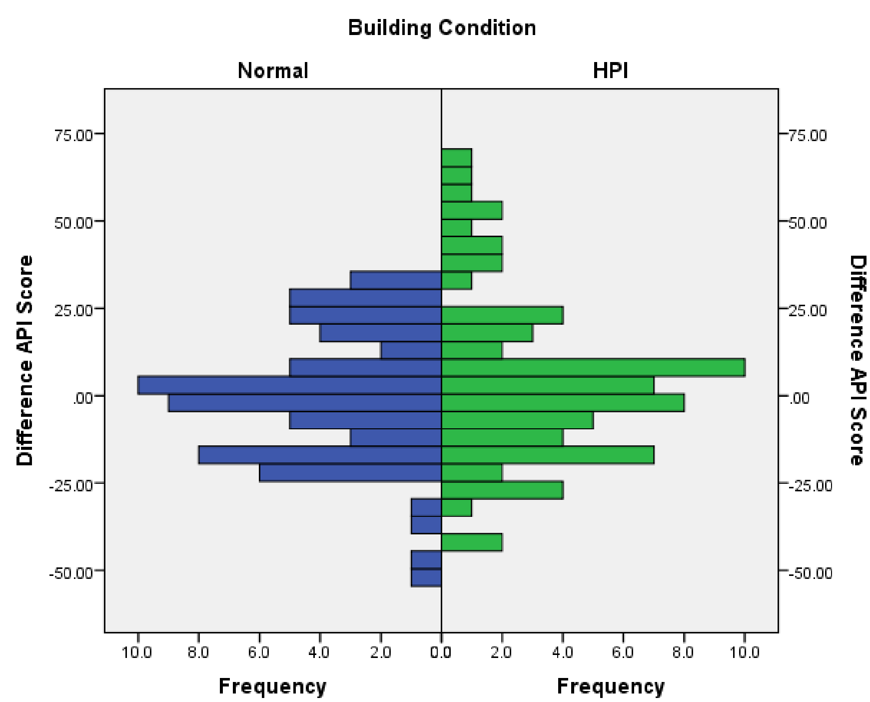


Fig. 4.25. Histogram of Base API Scores in 2012-2013 for Normal and HPI Schools.



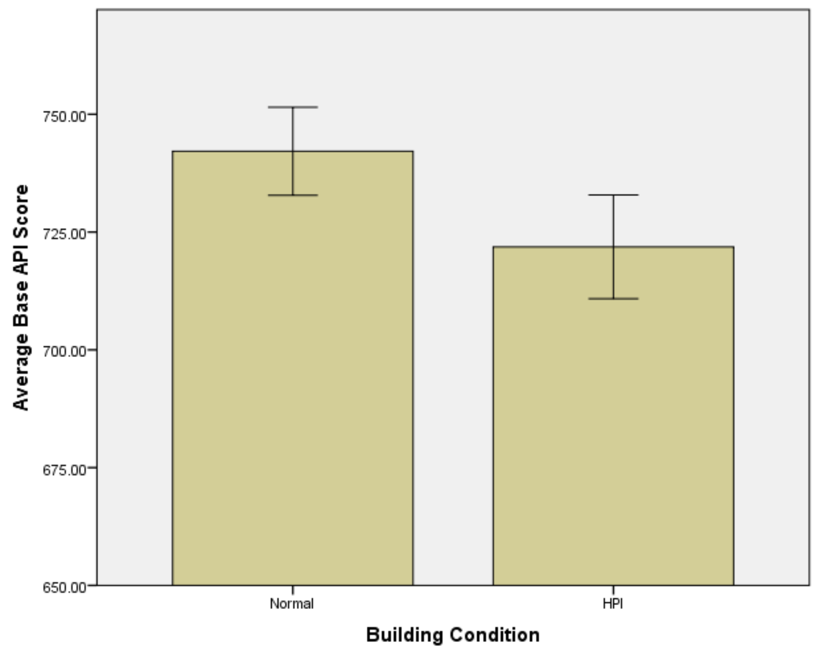
<u>Fig. 4.26.</u> Histogram of Growth API Scores in 2012-2013 for Normal and HPI Schools.



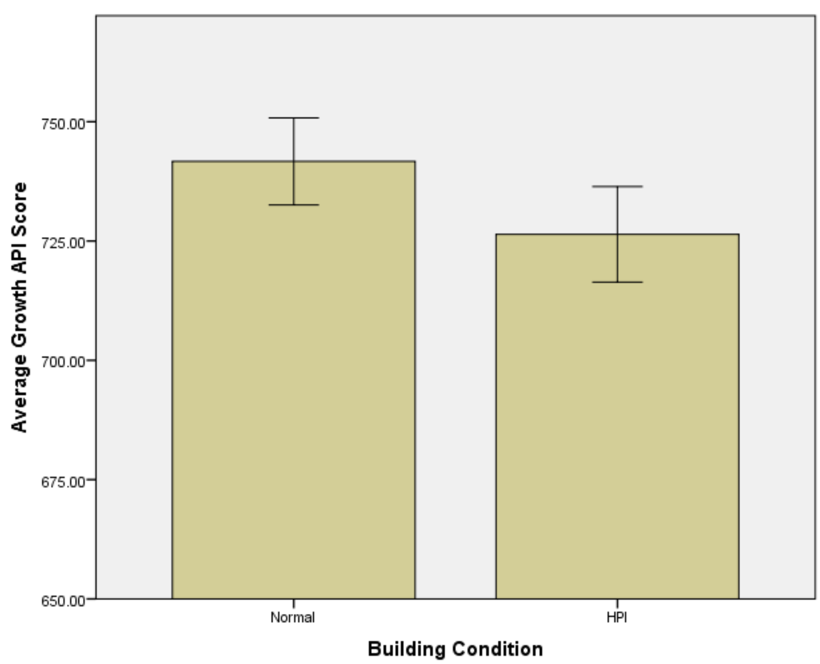
<u>Fig. 4.27.</u> Histogram of Difference API Scores in 2012-2013 for Normal and HPI Schools.

4.2.10 2012-2013 Academic Performance Index (API) Results across High Performance conditions

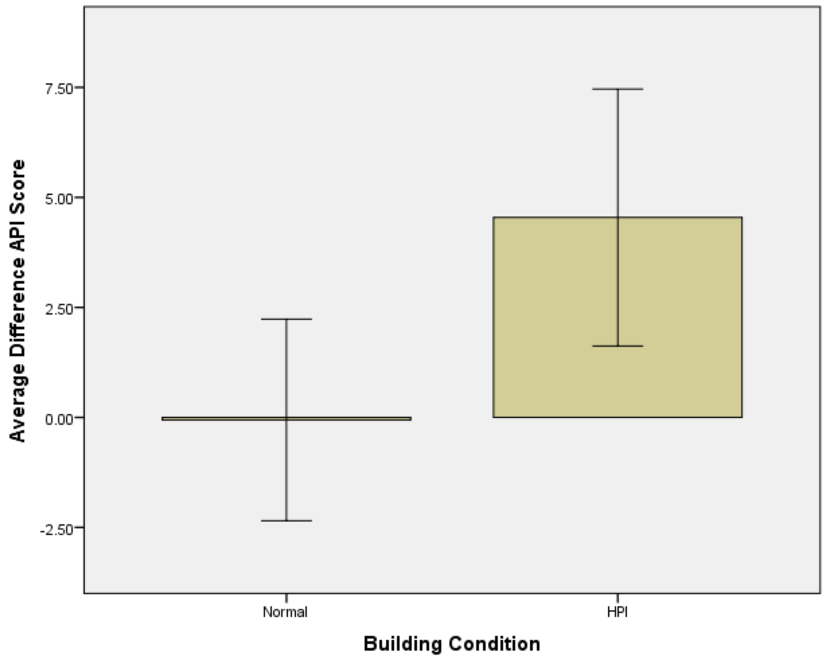
This section discusses the API performance results across the High Performance construction condition for the 2012-2013 yearly API reporting cycle. The API performance results for each Scoring Category across both performance conditions are shown in Figures 4.28, 4.29, and 4.30. Normal schools performed better than High Performance schools for Base and Growth API scoring categories. However, High Performance schools performed better than Normal schools for the Difference API. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report. It is of note that the trend of High Performance schools exhibiting a higher average Difference API than Normal schools has been consistent over five yearly report periods. While the difference is not significant, it may indicate some relationship between High Performance construction and achievement.



<u>Fig. 4.28.</u> Average Base API in 2012-2013 for Normal and HPI Schools. Error Bars represent the standard error of the mean.



<u>Fig. 4.29.</u> Average Growth API in 2012-2013 for Normal and HPI Schools. Error Bars represent the standard error of the mean.



<u>Fig. 4.30.</u> Average Difference API in 2012-2013 for Normal and HPI Schools. Error Bars represent the standard error of the mean.

Levene's Test for homoscedasticity was performed. The assumption of equal variances is fulfilled across all scoring categories. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each building performance condition. The test showed a significant, non-normal distribution in Difference API Scores for the High Performance school condition D(69)=0.128, p<.01. Therefore, an independent measures *t*-test using 1000 bootstrap samples as well as a Wilcoxon rank-sum test were deemed appropriate and used to further analyze the relationships. All statistical tests found no significant relationship across school conditions and represent small effect sizes. Test results, including mean difference, standard error, bootstrapped confidence interval, significance, and effect size are reported in Appendix A.

Additionally, an independent-measures *t*-test without bootstrapping was still used to further strengthen the results even though it is a parametric test. Further results of the independent-measures *t*-test, including mean difference, standard error, confidence interval, significance and effect size are reported in Appendix A.

4.3 Phase 2 Results

Academic Performance was measured in terms of Difference API scores for a subset of HPI schools that were determined to have construction dates between August 2007 and August 2011. The time period before construction began was labeled Pre-Mod while the time after construction completed was labeled Post-Mod. Statistical analyses using SPSS were conducted as described earlier in Section 3.1.4. Results exhibited in a non-normal distribution, as concluded by a Kolmogorov-Smirnov test. Therefore, a paired-samples *t*-test using 1000 bootstrap samples as well as a Wilcoxon signed-rank test were deemed appropriate and used to further analyze the relationships

Additionally, results for the non-bootstrapped, paired-samples *t*-test is also reported to further strengthen the results even though it is a parametric test.

4.3.1 Demographic Results

There were 15 total existing schools characterized as having completed High Performance additions or modifications by the Fall 2011 academic year: 4 elementary schools, 2 middle school, and 9 high schools. The earliest construction start date was August 26, 2007 and the latest construction completion date was August 31, 2011 as determined by the DSA Field Review dates. All 15 schools showed valid Difference API scores for the Pre-Mod and Post-Mod conditions. Difference API score results may be seen in Figure 4.31.

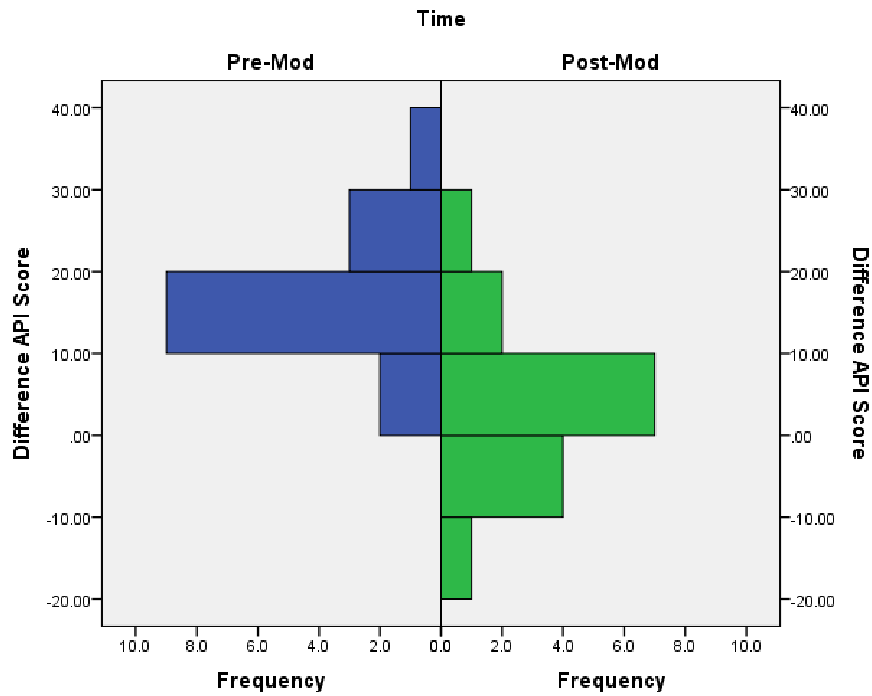


Fig. 4.31. Histogram of Difference API scores in High Performance schools before construction (Pre-Mod) and after construction (Post-Mod) conditions.

4.3.2 Difference API Results in High Performance Schools across Time

This section discusses the API performance results across the time condition for HPI schools. The Difference API results across both Pre-Mod and Post-Mod conditions are shown in Figure 4.32. High Performance schools exhibited better Difference API results for the Pre-Mod condition. The standard error of the mean bars do not overlap, suggesting that there is a significant relationship.

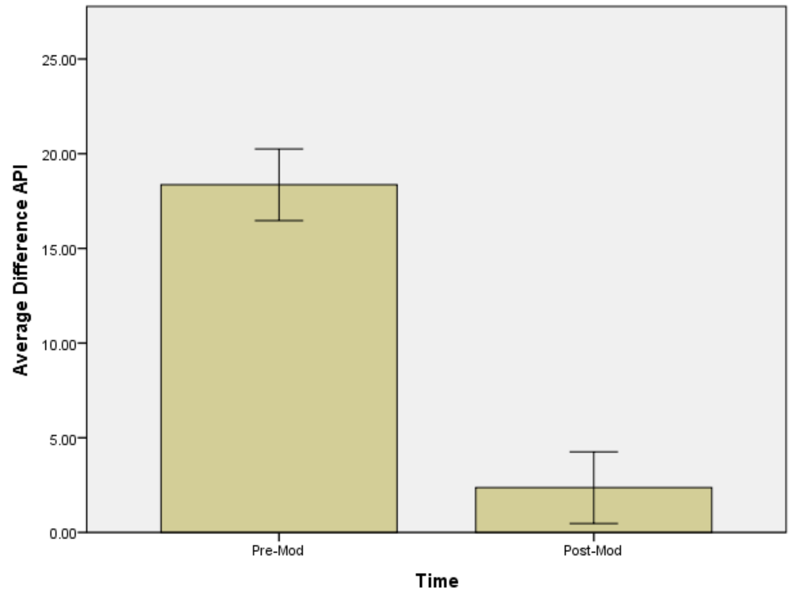


Fig. 4.32. Average Difference API scores for High Performance Schools before HPI Construction and after HPI Construction. Error bars represent standard error of the mean.

The change in Difference API scores over time was analyzed using a paired-samples *t*-test. On average, schools exhibited a higher Difference API before undergoing HPI construction (M=18.4, SE=2.2), than after construction was completed (M=2.37, SE=2.5). This difference, 16.0, 95%CI[9.34, 24.3], was significant $t(14)=4.22$, $p=.001$ and represented a large effect size, $d=1.67$. Similarly, a Wilcoxon signed-rank test found that Difference API scores were significantly higher Pre-Modification than Post-Modification, T=5, $p=.002$, $r=-.81$.

4.3.3 Difference API Results in All Schools across Time

The average Difference API scores for all 154 schools including both HPI and Normal were also graphed over time. The results are shown in Figure 4.33, where the x-axis is time and the y-axis is the Average Difference API score over the entire dataset.

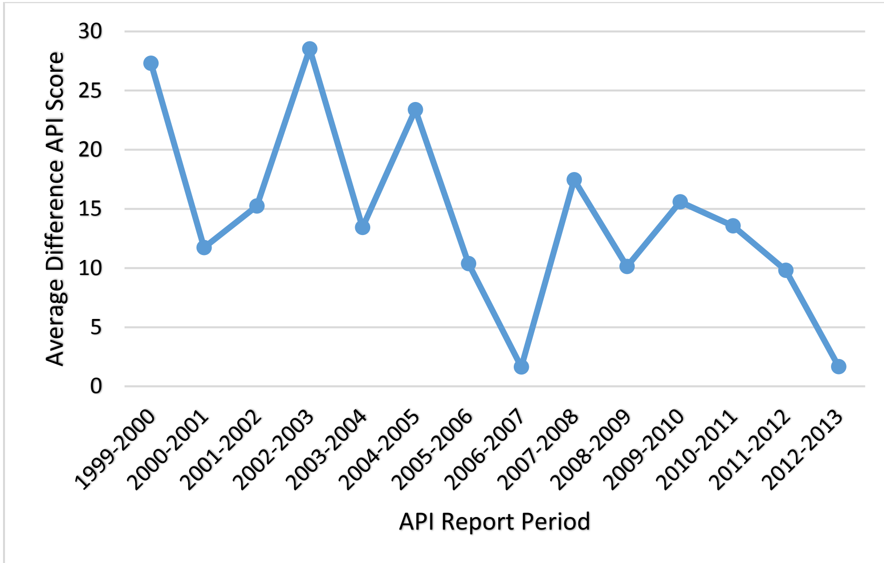


Fig. 4.33. Average Difference API scores for all schools over time.

For all schools in the dataset, a trend can be seen showing a decrease in Difference API scores over time. Furthermore, Difference API scores before 2007 are higher on average than scores after 2007. The years 2007-2010 that were excluded from analysis also show higher average Difference API scores than the years 2011-2013, which were included. The data indicates that the significant difference between Pre-Mod and Post-Mod conditions in the previous analysis may not be indicative of the actual effect of High Performance construction on API scores.

4.4 Phase 3 Results

Academic Performance was measured in terms of Base, Growth, and Difference API scores for each school for the 2012-2013 API report cycle. Statistical analyses using SPSS were conducted as described earlier in Section 3.1.4. Some results exhibited a non-

normal distribution, as concluded by a Kolmogorov-Smirnov test. Therefore, Brown-Forsythe and Welch robust tests of the equality of means were performed.

4.4.1 Acoustic Conditions Demographics Results

33 total schools were analyzed in Phase 3: 12 elementary schools, 3 middle schools and 18 high schools. For the 2012-2013 academic year, 11 schools were characterized as having Improved acoustics conditions. Of the 66 schools having Minimum acoustics conditions, 11 were chosen based on SCI ranking as described in Section 3.1.4.4. A final set of 11 schools meeting None acoustics conditions were chosen from the set of 77 Normal schools based on number of participants in the Free Lunch program as described in Section 3.1.3. Base, Growth, and Difference API score results for the 33 schools in all three acoustic conditions are shown in Figures 4.34, Figure 4.35, and Figure 4.36 below.

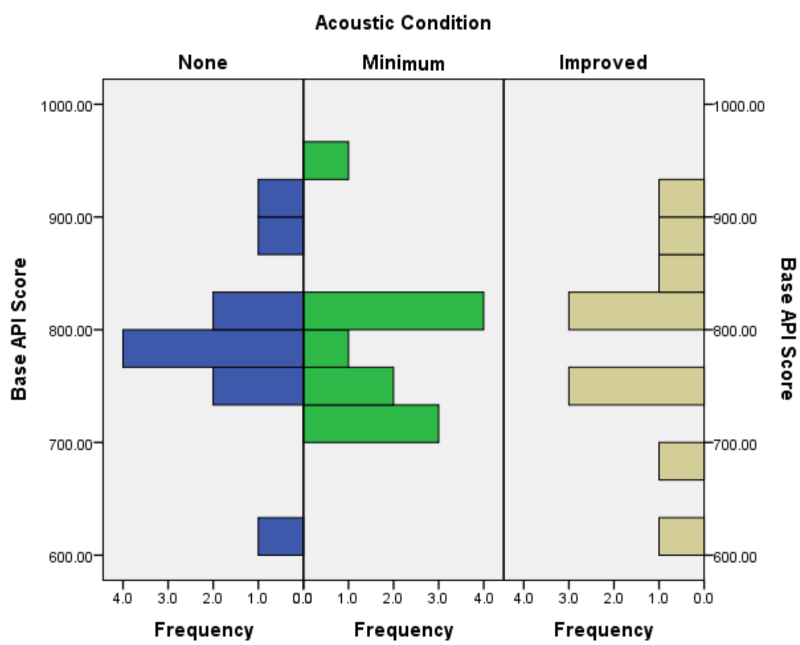


Fig. 4.34. Histogram of Base API Scores in 2012-2013 for None, Minimum, and Improved Acoustic Conditions.

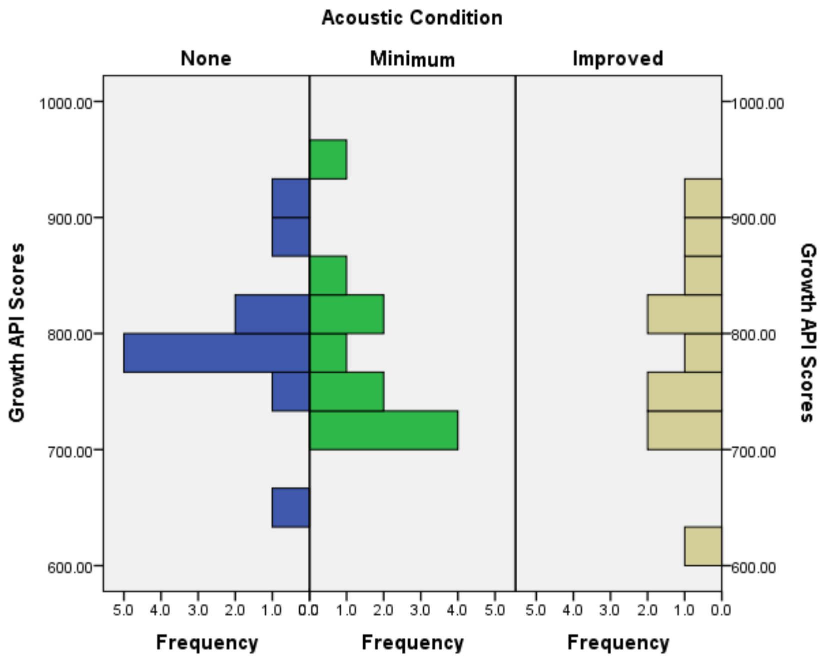


Fig. 4.35. Histogram of Growth API Scores in 2012-2013 for None, Minimum, and Improved Acoustic Conditions.

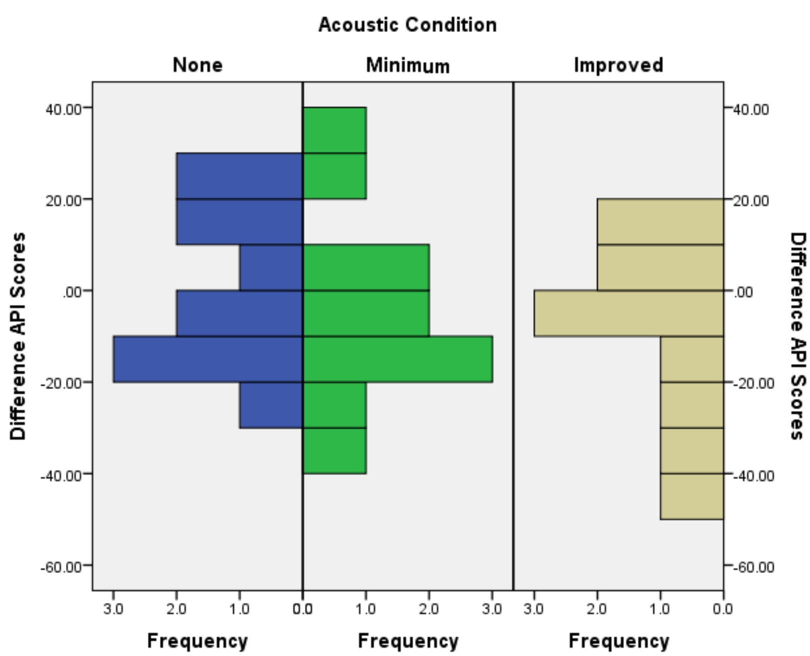


Fig. 4.36. Histogram of Difference API Scores in 2012-2013 for None, Minimum, and Improved Acoustic Conditions.

4.4.2 2012-2013 Academic Performance Index (API) Results across Acoustic conditions

This section discusses the API performance results across the Acoustic building condition for the 2012-2013 yearly API reporting cycle. The average API performance results for each Scoring Category across both performance conditions are shown in Figures 4.37, 4.38, and 4.39. Schools with None, Minimum and Improved acoustics showed approximately equal Base API and Growth API scores. A trend may be seen in Difference API indicating decreasing scores moving from None to Minimum to Improved Acoustic categories. The standard error of the mean bars overlap, suggesting that there are no significant relationships to report.

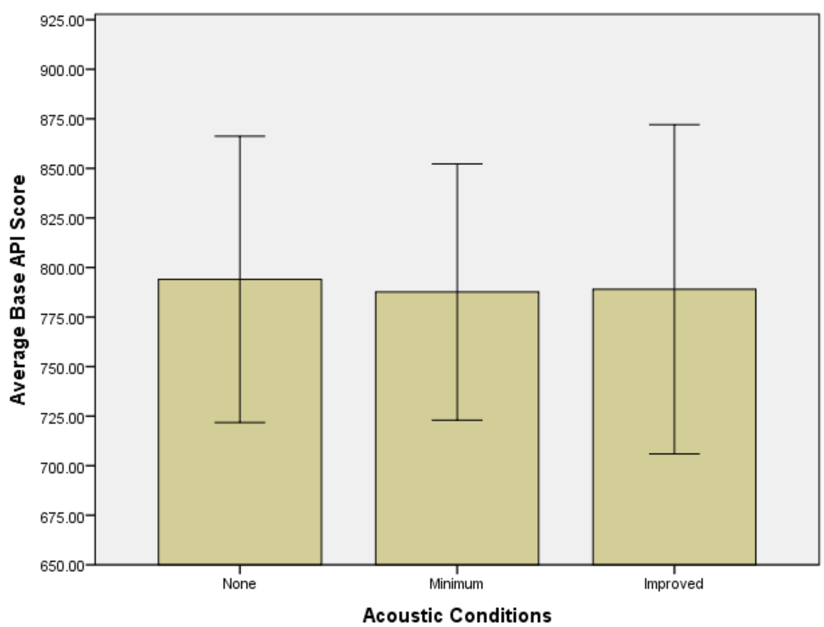


Fig. 4.37. Average Base API scores for None, Minimum, and Improved Acoustic Conditions. Error bars represent standard error of the mean.

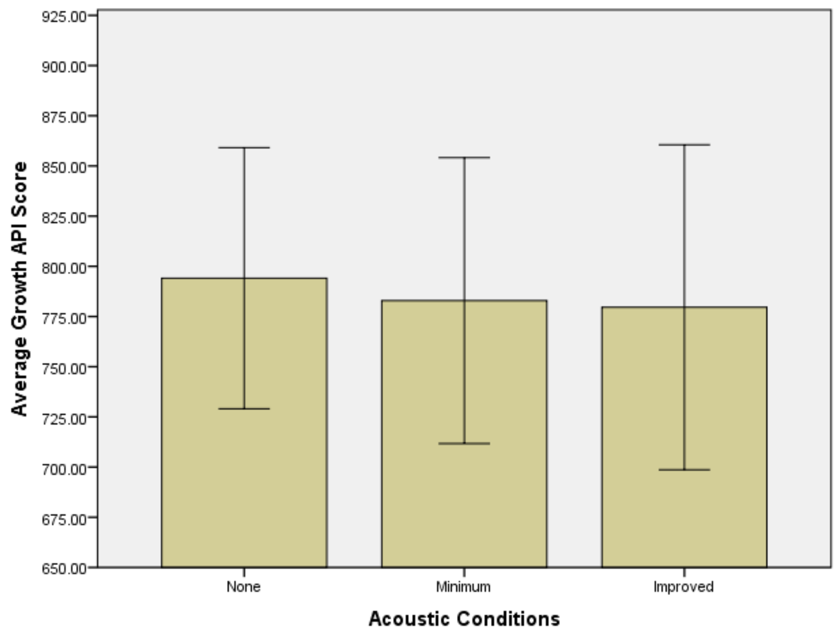


Fig. 4.38. Average Growth API scores for None, Minimum, and Improved Acoustic Conditions. Error bars represent standard error of the mean.

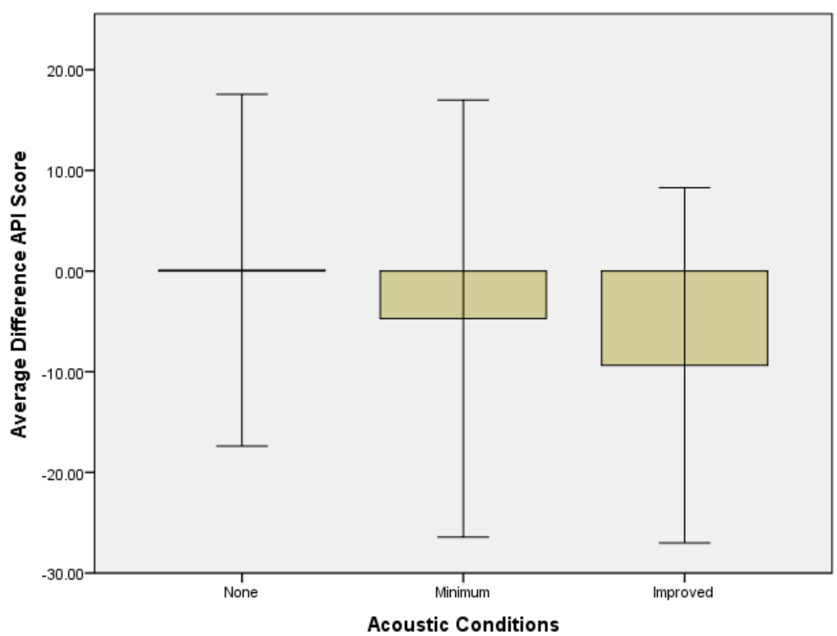


Fig. 4.39. Average Difference API scores for None, Minimum, and Improved Acoustic Conditions. Error bars represent standard error of the mean.

Levene's Test for homoscedasticity was performed. The assumption of equal variances is fulfilled across all scoring categories. A Kolmogorov-Smirnov test was also run on the API results for Base, Growth, and Difference scores across each Acoustic condition. The test showed a significant, non-normal distribution in Growth API Scores for the None condition D(11)=0.258, p=.04. Therefore Brown-Forsythe and Welch robust tests of the equality of means were deemed appropriate and used to further analyze the relationships. Results are reported in Appendix A

All statistical tests found no significant relationship across school conditions and represent small to medium effect sizes. The one-way ANOVA and planned comparison test results including the value of the test statistic, significance, and effect size are reported in Appendix A.

Chapter 5: Conclusions

This study examined the comprehensive effect of high performance construction on student achievement in California schools. This work mined publically available databases for Academic Performance Index (API) scores and High Performance Incentive (HPI) Grant projects. Student achievement as measured by API scores on a schoolwide level was extracted for the years 1999-2013. High Performance building conditions were evaluated based on results from HPI application scorecards and data from the California Division of the State Architect (DSA). Specific data relating to the acoustic conditions in school classrooms was taken from the Acoustics subsection of the HPI scorecard. One hundred and fifty-four California schools were determined to meet research criteria and were analyzed using three separate statistical methods.

In Phase 1, API results for the years 2008 through 2013 were analyzed across overall building conditions, comparing schools categorized as high performance against schools that were considered normal. In Phase 2, API results for a subset of high performance schools were analyzed across time, comparing student achievement before and after the completion of high performance construction. In Phase 3, API results for the 2012-2013 year were analyzed across classroom acoustic conditions, comparing schools with meeting none, minimum, and improved levels of criteria.

Results found no significant difference in API scores between normal and high performance schools, although there was a general trend worth reporting. A significant difference in Difference API scores, $p<0.05$, was found before and after completion of

high performance construction for both parametric and non-parametric statistical analysis. No significant relationship was found in relation to acoustic conditions.

5.1 Phase 1

Cash (1993) found a trend of improved student achievement in buildings with higher quality ratings, for building conditions. Earthman's (1995) study revealed no a similar trend but no significant results. The criteria that these studies used to evaluate school condition were based on surveys provided by school personnel or assessors. Categories varied from cosmetic to structural, and lacked quantitative performance factors to measure attributes such as daylight, or acoustics. The purpose of utilizing the HPRC in this study was to standardize building criteria and focus specifically on constructed attributes of classrooms, on an objective, scaled, rating.

Issa et al found lower absenteeism rates and higher student performance in green and energy-retrofitted Toronto schools when compared with conventional schools (2011). One major difference between those studies and this thesis is the scale. The previous study compared 10 conventional, 20 energy retrofitted, and three green schools, while this study compared 77 high performance schools with 77 conventional schools. Issa theorized that small sample size could be a reason for the lack of statistical significance. This study attempted to address that issue.

For API performance across all scoring categories, there were no significant differences between Normal and High Performance schools. However, a trend may be seen showing that High Performance schools exhibited greater Difference API scores than Normal schools. Typically, difference API scores are used to evaluate school improvement. Therefore it is noteworthy that High Performance schools began to show

greater improvement than Normal schools approximately two years after the HPIG program inception, even if the differences were not statistically significant.

5.2 Phase 2

Nielson found that test scores for a Connecticut school district showed a significant increase after major construction projects were undertaken (2011). However, the study does not make a distinction on whether or not tests results were affected through the built environment or general motivation factors that go hand in hand with new construction. Similarly, in Phase 2, no attempt was made to delineate between direct effects of the built environment and other factors known to affect academic achievement. Furthermore, the study does not look at student achievement by subject.

For Difference API scores, a significant, negative difference, $p<0.05$ was found for High Performance schools between Pre-Mod and Post-Mod conditions for both parametric and non-parametric test. This is trend is not consistent with Nielson's findings. Average Difference API scores were graphed for Normal and High Performance schools in the data set from 1999-2013. Downward trends may be seen beginning in the 2004-2005 and 2009-2010 school years. Furthermore, average Difference API scores before 2007 are approximately 5 API points higher than after 2007. This suggests that other factors beyond the built environment have an effect on achievement results measured in this manner.

Another factor that could have influence on the results for Phase 2 is the fact that by definition, modifications are not comprehensive. The criteria for an acceptable modified school was simply that construction occurred within at least one classroom building. This may be considered a minimum standard: high school students often switch

classrooms and buildings between classes and including buildings that did not undergo modernization for any level of school may artificially influence the intended relationship

5.3 Phase 3

Ronsse found that higher background noise levels (BNL) had a significant, negative effect on student performance in language arts subject areas in Omaha, Nebraska (2011). Klatte also found that higher noise levels also had a significant negative effect on speech intelligibility and listening comprehension (2010) in simulated classrooms. While reverberation time was found to have no significant effect on its own, it did increase disruption caused by background sounds. Similar to Phase 2, this thesis does not attempt to delineate between specific test subjects, but instead focuses on schoolwide achievement.

For the year 2012-2013, no significant differences were exhibited between schools with varying levels of acoustic treatment within classrooms. A negative trend in Difference API score was observed as acoustic conditions improved. This trend was unexpected given previous research. For the 2011-2012 academic year, the trend was reversed, as schools categorized as Minimum or Improved exhibited higher Difference API scores than schools categorized as None. Interestingly, Minimum schools had the highest average Difference API.

Similar to Phase 2, Phase 3 results exhibit trends that suggest API data does not hold up well to analysis of specific school or test characteristics. This is reasonable considering that the API itself is calculated from multiple factors. Research into history of the API shows that significant changes to both the California standardized tests and the

API calculations occur frequently. This could make it difficult to isolate the particular contribution of building attributes.

A further issue could arise with the implementation of acoustic criteria within the CHPS program. The acoustic criteria itself is only checked during design; there is no post-construction commissioning to determine whether or not classrooms actually meet specified criteria for background noise level and reverberation time.

5.4 Future Research

This thesis found that there is no significant difference in API achievement scores between Normal and High Performance schools. There is, however, a general trend indicating that High Performance schools have a positive effect on API improvement. A significant difference in API scores was found in high performance schools when comparing achievement before and after construction. This difference was negative and not supportive of previous research. No significant difference was found between schools with differing levels of classroom acoustics. No apparent trend was recognizable. Cash (1993) and Earthman (1995) did study the effect of building condition on student behavior. The research suggests that subjectively, school occupants (students and teachers) respond better to higher quality building conditions. Further research into student behavior rather than academic performance could be an approach that still resonates with policy makers, while providing a more consistent pattern.

General academic achievement data was used in this study, but it will be interesting to see what effect, if any, the same analyses would uncover in results of specific standardized tests, which may be broken down by subject. Previous research indicated that differences in BNL and RT had a greater effect on reading and listening

comprehension tasks, such as those required for English/Language Arts subjects (Ronsse 2011, Klatte 2010). Data for standardized tests at a school level is publicly available and could be analyzed in much the same way as API data for this study. Similarly, young children appear to be affected more readily by learning conditions. This could be due to their less developed levels of concentration as opposed to students in middle school or high school. Defining a sample by school type (elementary, middle, or high school) while maintaining a statistically robust sample size may produce more significant results.

Although a significant, negative difference in API scores was found in high performance schools before and after construction, it should be noted that the Difference API exhibits a high level of variability from year to year. It may be worthwhile to compare the performance of both Normal and High Performance schools in consecutive years in future tests. Furthermore, more stringent criteria may be used to delineate high performance schools. In this case, one classroom building undergoing construction may not be indicative of the whole effect. Perhaps only schools undergoing complete modernization would be a more accurate sample.

For future research involving acoustic attributes of the built environment, it is recommended that in addition to looking at statistical significance, it may be useful to ascertain the definition of a “significant” improvement in academic achievement. For instance, the California Department of education provides yearly Growth targets. Perhaps this could be used as a further variable for looking at the real world impact of the Difference API, rather than the statistical impact in the academic sense.

Further, a more in depth analysis should be performed to review the interaction between multiple aspects of the High Performance scorecard. The results of this study suggest that

it is difficult to isolate a single variable effect from the HPIG scorecard. It may be wise to perform a more in-depth analysis of the comprehensive effect of all indoor environmental variables and their interactions.

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Appendix A: Statistical Analyses Results

Table A.1 *Results of t-tests and Descriptive Statistics for 2008-2009 Base API, Growth API, and Difference API by Building Performance Condition*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	720.07	80.63	27	731.55	82.07	29	11.48	21.76	.53	54	.14	-32.16, 55.11
Growth API	729.93	79.31	29	745.83	82.32	29	15.90	21.23	.75	56	.19	-26.63, 58.42
Difference API	7.22	17.76	27	14.28	19.95	29	7.05	5.06	1.39	54	.25	-3.09, 17.2

* $p < .05$

Table A.2 *Results of t-tests and Descriptive Statistics for 2008-2009 Base API, Growth API, and Difference API by Building Performance Condition using 1000 bootstrap samples*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	720.07	80.63	27	731.55	82.07	29	11.48	21.48	.53	54		-32.15, 53.89
Growth API	727.30	81.22	27	745.83	82.32	29	18.53	21.48	.85	54		-24.12, 60.38
Difference API	7.22	17.76	27	14.28	19.95	29	7.05	5.03	1.39	54		-2.25, 17.16

Note: 95% CI for Mean Difference using 1000 bootstrap samples

* $p < .05$

Table A.3 *Results of Wilcoxon rank-sum tests for Difference between 2008-2009 mean API scores across Building Performance Condition*

Null Hypothesis	N	W	SE	*r*
The distribution of Base API is the same across categories of building performance condition	56	742	60.98	-.06
The distribution of Growth API is the same across categories of building performance condition	58	795	64.29	-.12
The distribution of Difference API is the same across categories of building performance condition		90.95	60.95	-1.16

* $p < .05$

Table A.4 Results of t-tests and Descriptive Statistics for 2009-2010 Base API, Growth API, and Difference API by Building Performance Condition

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	727.37	78.4	30	746.56	77.58	32	19.20	19.82	.97	60	.25	-20.44, 58.84
Growth API	750.06	78.25	33	756.15	75.4	33	6.09	18.92	.32	64	.04	-31.70, 43.88
Difference API	16.13	20.14	30	11.66	20.91	32	-4.48	5.22	-.86	60	-.21	-14.91, 5.95

* p < .05

Table A.5 *Results of t-tests and Descriptive Statistics for 2009-2010 Base API, Growth API, and Difference API by Building Performance Condition using 1000 bootstrap samples*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	727.37	78.4	30	746.56	77.58	32	19.20	20.02	.97	60	.25	-20.44, 58.84
Growth API	743.5	78.56	30	758.21	75.65	32	14.72	19.59	.75	60	.19	-24.46, 53.90
Difference API	16.13	20.91	30	11.66	20.14	32	-4.48	5.25	-.86	60	-.22	-14.92, 5.96

Note: 95% CI for Mean Difference using 1000 bootstrap samples

* p < .05

Table A.6 *Results of Wilcoxon rank-sum tests for Difference between 2009-2010 mean API scores across Building Performance Condition*

Null Hypothesis	N	W	SE	*r*
The distribution of Base API is the same across categories of building performance condition	62	857.5	70.98	-.16
The distribution of Growth API is the same across categories of building performance condition	66	1,077	77.97	-.05
The distribution of Difference API is the same across categories of building performance condition	62	989.5	70.95	.08

* p < .05

Table A.7 *Results of t-tests and Descriptive Statistics for 2010-2011 Base API, Growth API, and Difference API by Building Performance Condition*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	750.06	78.16	33	738.5	73.55	56	-11.56	16.52	-.7	87		-44.39, 21.28
Growth API	732.34	89.96	56	750.05	69.39	56	17.71	15.18	1.17	110		-12.37, 47.8
Difference API	16.42	19.38	33	11.55	21.5	56	-4.87	4.55	-1.07	87		-13.92, 4.18

* p < .05

Table A.8 *Results of t-tests and Descriptive Statistics for 2011-2012 Base API, Growth API, and Difference API by Building Performance Condition*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	732.02	89.85	56	731.16	83.76	69	-.86	15.56	-.06	123	-.01	-31.67, 29.95
Growth API	720.6	92.28	70	740.27	77.74	70	19.67	14.42	1.36	138	.25	-8.84, 48.19
Difference API	10.41	23.83	56	9.84	24.6	70	-.57	4.35	-.13	124	-.02	-9.18, 8.01

* p < .05

Table A.9 *Results of t-tests and Descriptive Statistics for 2011-2012 Base API, Growth API, and Difference API by Building Performance Condition using 1000 bootstrap samples*

Outcome	Group						Mean Difference	SE	T	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	732.02	89.85	56	731.16	83.76	69	-.86	15.32	-.06	123	-.01	-28.97, 30.38
Growth API	742.43	82.61	56	741.35	77.78	69	-1.08	14.04	-.08	123	-.01	-27.38, 25.81
Difference API	10.41	23.83	56	10.19	24.61	69	-.22	4.35	-.05	123	-.01	-8.54, 8.08

Note: 95% CI for Mean Difference using 1000 bootstrap samples

* p < .05

Table A.10 *Results of Wilcoxon rank-sum tests for Difference between 2011-2012 mean API scores across Building Performance Condition*

Null Hypothesis	N	W	SE	*r*
The distribution of Base API is the same across categories of building performance condition	125	3,553	201.41	.01
The distribution of Growth API is the same across categories of building performance condition	140	4,602	239.94	-.12
The distribution of Difference API is the same across categories of building performance condition	126	3,636	203.65	.03

* p < .05

Table A.11 *Results of t-tests and Descriptive Statistics for 2012-2013 Base API, Growth API, and Difference API by Building Performance Condition*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	721.86	92.13	70	742.16	78.29	70	20.3	14.45	1.41	138	.26	-8.27, 48.87
Growth API	726.4	83.87	70	741.68	75.63	69	15.28	13.55	1.13	137	.20	-11.52, 42.08
Difference API	4.54	24.42	70	-.06	19.04	69	-4.6	3.72	-1.24	137	.20	-11.94, 2.74

* p < .05

Table A.12 *Results of t-tests and Descriptive Statistics for 2012-2013 Base API, Growth API, and Difference API by Building Performance Condition using 1000 bootstrap samples*

Outcome	Group						Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	High Performance			Normal								
	M	SD	N	M	SD	N						
Base API	721.86	92.13	70	741.74	78.78	69	19.88	14.54	1.37	137	.25	-8.80, 49.63
Growth API	726.4	83.87	70	741.68	75.63	69	15.28	13.55	1.13	137	.20	-13.25, 42.75
Difference API	4.54	24.42	70	-.06	19.04	69	-4.6	3.72	-1.24	137	.20	-11.48, 2.57

Note: 95% CI for Mean Difference using 1000 bootstrap samples

* p < .05

Table A.13 *Results of Wilcoxon Rank-Sum tests for Difference between 2012-2013 mean API scores across Building Performance Condition*

Null Hypothesis	N	W	SE	*r*
The distribution of Base API is the same across categories of building performance condition	140	4,602	239.94	-.12
The distribution of Growth API is the same across categories of building performance condition	139	4,604	237.37	-.11
The distribution of Difference API is the same across categories of building performance condition	139	5,065	237.32	.16

* p < .05

Table A.14 *Results of t-tests and Descriptive Statistics for Base API, Growth API, and Difference API by Construction Condition*

Outcome	Group					Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	Post-Mod		Pre-Mod								
	M	SD	M	SD	N						
Difference API	18.36	8.7	2.37	9.56	15	15.99	3.79	4.22**	14	1.67	7.87, 24.11

* p < .05

** p < .001

Table A.15 *Results of t-tests and Descriptive Statistics for Base API, Growth API, and Difference API by Construction Condition using 1000 bootstrap samples*

Outcome	Group					Mean Difference	SE	t	df	*d*	95% CI for Mean Difference
	Post-Mod		Pre-Mod								
	M	SD	M	SD	N						
Difference API	18.36	8.7	2.37	9.56	15	15.99	3.79	4.22**	14	1.67	9.33, 24.34

Note: 95% CI for Mean Difference using 1000 bootstrap samples

* p < .05

** p < .001

Table A.16 *Results of Wilcoxon signed-rank tests for Difference between mean API scores across Building Performance Condition*

Null Hypothesis	N	T	SE	*r*
The median of differences between Difference API Pre-Mod and Difference API Post-Mod equals 0	15	5**	17.61	-.81

* p < .05

Table A.17 *One-Way Analysis of Variance (ANOVA) of Base API Scores by Acoustic Condition*

	df	Sum of Squares	Mean Square	F	*p*
Between Groups	2	246.97	123.49	.02	.98
Within Groups	30	162984.15	5432.82		
Total	32	163231.5			

* p < .05

Table A.18 *One-Way Analysis of Variance (ANOVA) of Growth API Scores by Acoustic Condition*

	df	Sum of Squares	Mean Square	F	*p*
Between Groups	2	1263.82	631.91	.12	.89
Within Groups	30	158472.4	5282.41		
Total	32	159736.2			

* p < .05

Table A.19 *One-Way Analysis of Variance (ANOVA) of Difference API Scores by Acoustic Condition*

	df	Sum of Squares	Mean Square	F	*p*
Between Groups	2	491.70	245.85	.68	.52
Within Groups	30	10881.64	362.72		
Total	32	11373.33			

* p < .05

Table A.20 *Results of Welch's F-test for API Scores across Acoustic Condition*

	F	df	*p*
Base API	.02	2	.98
Growth API	.12	2	.88
Difference API	.77	2	.48

* p < .05

Table A.21 *Results of Brown-Forsythe F-test for API Scores across Acoustic Condition*

	F	df	*p*
Base API	.02	2	.98
Growth API	.12	2	.89
Difference API	.68	2	.52

* p < .05