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Associations Between Teacher Interactional Quality and Student Achievement: a Classroom-Level Analysis of Randomized and Non-Randomized Teacher Assignments in the Measure of Effective Teaching Project

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ASSOCIATIONS BETWEEN TEACHER INTERACTIONAL QUALITY AND STUDENT ACHIEVEMENT: A CLASSROOM-LEVEL ANALYSIS OF RANDOMIZED AND NON-RANDOMIZED TEACHER ASSIGNMENTS IN THE MEASURE OF EFFECTIVE TEACHING PROJECT

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ABSTRACT

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The powerful role teachers have on students' learning and academic performance has been well established in the empirical literature. However, researchers have not been successful in explaining what exactly it is about teachers that foster students' academic success in the classroom. The premise of this dissertation was that teachers who provide affirming, supportive, and organized interactions, also known as teacher interactional quality, have beneficial effects on students' academic achievement. This dissertation used the largest education dataset of United States students, known as the Measures of Effective Teaching (MET), to examine the association of teacher interactional quality on classroom achievement. The MET dataset incorporated random assignment in the placement of teachers to classrooms of students and collected multiple measures of teacher quality. This investigation contributed to the existing body of research on teacher quality by examining the associations between teacher interactional quality in fourth and fifth grade classrooms and achievement outcomes. In addition, the distribution of teacher interactional quality across classrooms with different percentages of free or reduced lunch receipt was examined. Findings indicated that teacher interactional quality and free or reduced lunch percentage were associated with English/language art classroom achievement outcomes when teachers went about their everyday practices in the classroom and when teachers were randomized to classrooms of students. Teacher interactional quality was associated with math classroom achievement outcomes only during the business-as-usual year when teachers went about their usual teaching practices in the classroom. Furthermore, teacher interactional quality impact on English/language art classroom achievement outcomes changed based on the proportion of free or reduced lunch in the classroom during the business-as-usual year but not during the year when teachers were randomly assigned to classrooms of students. Recommendations are derived for conducting longitudinal follow-ups with students who have been exposed to certain levels of interactional quality, examining the experiences of students from different socioeconomic backgrounds and ethnicities, and pursuing the distinction between classrooms with and without typical random assignment of teachers. Teacher preparation programs have the ability to identify desirable teacher dispositions and positive interactional styles early on in the program through multiple observations and reflective opportunities. If preparation programs are able to better identify teacher qualities that have an impact on student learning, this information can be used to attract, prepare, support, and retain teachers who are skilled in their interactions and emotionally attuned to the needs of students. This information can be used as a foundation for states and districts as they develop mentoring, coaching, professional development, and teacher evaluation systems for strengthening the recruitment and retention of high quality teachers.

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CHAPTER I

INTRODUCTION

The powerful role teachers have on students' learning and academic performance has been well established in the literature. However, researchers have not been successful in identifying what exactly it is about teachers that determines students' level of academic success. A teacher's experience, educational attainment level, and salary are not consistently predictive of students' academic outcomes, and when there have been significant findings with these factors, the effects have been small (Croninger, Rice, Rathbun, & Nishio, 2007; Hanushek, Kain, & Rivkin, 1999; Hanushek & Rivkin, 2006; Jackson, Rockoff, & Staiger, 2014; Jepsen & Rivkin, 2009; Kane, Rockoff, & Staiger, 2008; Murnane & Steele, 2007;). Therefore, the intention of this dissertation was to examine the influence on classroom achievement of teachers who effectively support a student's social and academic development during interactions with students. This dissertation used a unique dataset known as the Measures of Effective Teaching (MET) to examine the influential impact of teacher-student interactions on achievement outcomes.

In recognition of the effects of teachers on children, United States federal initiatives such as No Child Left Behind and Race to the Top have mandated the appointment of effective teachers in every classroom. As a result of these efforts and other educational and political movements, there has been an increased demand for teacher performance evaluations in the classroom, especially with regard to instructional strategies and curriculum alignment with state and national standards. With teachers across the country striving to promote students' education and also wishing to demonstrate their effectiveness to others through performance evaluations, it is incumbent on researchers to document the skills and characteristics of high quality teaching.

In this dissertation, the quality of teachers was presumed to be their interactional effectiveness with students. Using the teaching through interactions (TTI) theoretical framework of Hamre et al. (2013), this dissertation examined the extent to which a tripartite composite of interactional quality was associated with students' academic achievement outcomes. Over the past two decades, Bridget Hamre and Robert Pianta have identified the complex social systems of the classroom, along with the added complexity of teacher-student interactions. The framework focused on the broad interactional domains of emotional support, classroom organization, and instructional support. These three domains were articulated in a theoretical model as exerting their influences through students' engagement in school (Deci & Ryan, 2000), expectations about ability and success (Eccles & Wigfield, 2002), productive social skills (Mashburn et al., 2008), and behavioral or disciplinary problems (Crosnoe, Johnson, & Elder, 2004). The direct and indirect effect of high-quality interactions are proposed to foster students' academic achievement throughout preschool through sixth grade (Cameron, Connor, & Morrison, 2005; Hamre & Pianta, 2005; Kane & Staiger, 2012; National Institute on Child Health and Development, 2005; Pianta, Belsky, Vandergrift, Houts, & Morrison, 2008; Reyes, Brackett, Rivers, White, & Salovey, 2012).

Teacher-Student Interactions

Research has long shown the powerful effects adults have on children's developmental trajectories. Parents and other caregivers who create an emotionally supportive, predictable, consistent, and safe environment fulfill children's impetus for self-reliant exploration of the environment (Ainsworth, 1979; Bowlby, 1969). Young children who receive such responsive and sensitive care develop a sense of security with their caregivers. Gradually, children who have developed security with familiar caregivers gain a productive template for the give-and-take of relationships.

A caring teacher expresses affection in several ways that resemble gestures from a responsive parent (Birch & Ladd, 1998; Hafen et al., 2014). Such a teacher greets students warmly, gets to know them as individuals, and meets students' unique needs. Yet the purpose of schooling, the transitions that students make as they progress through the grades, and the number of children in a classroom affect how a skilled and nurturing teacher interacts at school. Recognizing the complexity of the classroom environment, Hamre and Pianta (2001) introduced a lens through which to study a teacher's interactions with students. The TTI framework includes teacher emotional support, classroom organization, and instructional support. The framework has been rigorously studied in over 4,000 early childhood and elementary classrooms across the United States (Hamre et al., 2013; Bill and Melinda Gates Foundation [Gates Foundation], 2010b).

Results indicate that a supportive relationship in the classroom is crucial for students' academic motivation, positive behavioral outcomes, and high levels of academic performance (Hamre & Pianta, 2001; Rudasill, Gallagher, & White, 2010). Positive interactions between a teacher and students encourage engagement during classroom instruction. For example, having a teacher with a warm disposition and who fosters a positive classroom environment leads students to improved academic skill and better academic performance (Hamre & Pianta, 2005; Pianta, La Paro, & Hamre, 2008).

Testifying further to this importance, early interactions in the classroom appear to have lasting effects. Hamre and Pianta (2001) discovered relational negativity (i.e., conflict) in kindergarten to be related to impaired academic and behavioral outcomes through eighth grade. Similarly, those students who were exposed to interactions characterized by conflict were less engaged in school during future years. Examined in more detail later in this dissertation, oppositional, neglectful, and discouraging relationships with teachers seem to contribute to another effect—inequities in the promotion of core developmental skills. For those students in kindergarten, high levels of teacher-student conflict and low levels of emotional closeness were strongly associated with students being male, Black, and low achieving, and from low income homes.

Due to the lasting effects of early interactions in the classrom, it is crucial for researchers to recognize, identify, and measure the quality of teacher-student relationships. It is the thesis of this study that a primary influence on students' achievement is having a teacher who effectively supports students' social and academic development through sympathetic, organized, affirming, and academically effective interactions in the classroom. In order to improve the quality of the teacher-student relationship researchers must first document classroom interactions and their effects (Pianta, Hamre, & Allen, 2012).

Measures of Effective Teaching Project

Researchers have established the role of what ongoing interactions between a teacher and student have on students' engagement, learning, and development (Crosnoe & Benner, 2015). These interactions have been termed proximal because they represent face-to-face contact involving the student and have direct bearing on learning. From several scientific perspectives, including frameworks in child development, sociology, and ecological systems theories, proximal effects are seen to be profoundly influential to students, often more so than such distal factors as the district's policies and state's academic standards. Proximal interactions are especially important to students at the elementary school level because students of this age are receptive to forming relationships with affectionate adults. Moreover, elementary students spend one-quarter of their waking hours in the classroom, and generally this time is spent with a single teacher (Crosnoe & Benner, 2015).

The significance of teacher-student relationships must be verified with appropriate measures of proximal interactions in the classroom (Pianta et al., 2012). Unfortunately, the ability to understand the effects of these interactions has been restricted by methodological problems in measuring teacher quality (Hanushek et al., 1999). Investigators developing the MET wanted to move beyond correlational analyses and use random assignment of teachers to classrooms of students in order to make causal inferences about multiple indicators of teaching effectiveness on student outcomes (Gates Foundation, 2012b). Many studies have examined one indicator of teacher effectiveness in isolation rather than recognizing there are multiple indicators that make up the complexities of an effective teacher. In the studies with one indicator, such as recorded observations of a teacher performance, the design lacked random assignment and thus was correlational in nature. The MET was unique in that it provided data on multiple indicators along with random assignment. This study purposely selected one indicator of teacher quality (interactional quality) and random assignment, in order to best narrow in on a teacher's contribution to classroom achievement outcomes.

The data in the present investigation come~~s~~ from the MET project, the largest study of classroom teaching to date, supported by the Bill and Melinda Gates Foundation and compiled by the University of Michigan (Gates Foundation, 2012b). The MET researchers collected a variety of indicators of teacher effectiveness over a two-year period (academic year [AY] 2009-2010 and AY 2010-2011), including student and teacher self-perception data, student achievement outcomes, video-recorded lessons taught by teachers, and teachers' pedagogical and content knowledge related to the lessons (Gates Foundation, 2012b).

The MET project was unique in that researchers examined classrooms of participating teachers during the Year One design (AY 2009-2010) and then randomly assigned teachers to classrooms rosters of students within schools in the Year Two design (AY 2010-2011) (Gates Foundation, 2012b). The first year of the study assessed various measures of teaching effectiveness whereas the second year collected the same assessment data as Year One but used random assignment of teachers to classrooms to allow for causal inferences about teaching quality. Random assignment of teachers to classroom rosters minimized selection bias in the sorting of teachers to classrooms of students and allowed for the isolation of a teacher's unique contribution to students' academic achievement (Gates Foundation, 2010d). In this dissertation, sorting refers to the process of randomly assigning teachers in the sample to classrooms of students.

Year One

The Year One study design (AY 2009-2010), also known as the "business-as-usual year," included 2,741 fourth through ninth grade teachers working in 317 schools in six large school districts in the United States; these students were also known as the Year One full sample. The six participating districts were as follows: Charlotte-Mecklenburg (North Carolina) Schools, Dallas (Texas) Independent School District, Denver (Colorado) Public Schools, Hillsborough County (Florida) Public Schools, Memphis (Tennessee) City Schools, and the New York City (New York) Department of Education (Gates Foundation, 2012b). The same teachers from Year One were followed into Year Two, but in Year Two these same teachers were randomly assigned to a different classroom of students. Thus throughout this dissertation, business-as-usual refers to Year One when teachers went about their usual teaching practices in the classroom, and this year is compared to a condition in which teachers were randomly assigned to classroom rosters of students.

Year Two

A full sample of 2,086 teachers in 310 schools continued as the Year Two sample (AY 2010-2011) (i.e., Year Two full sample). Not all teachers could be randomized due to teachers leaving the study or the school deciding to no longer consent to randomization. Thus 1,159 teachers in 284 schools served as a sub-sample (i.e., Year Two randomization sample) of all the teachers present in Year Two (Gates Foundation, 2012b). The analytic sample included teachers who participated both

Year One and Year Two of the study (*N* = 592). There were no teachers in Year Two of the study who were not present in Year One.

In the MET project, in which Pianta and his colleagues served as research partners, investigators collected observational data on the quality of teacher-student interactions using the Classroom Assessment Scoring System (CLASS™) (La Paro, Pianta, & Stuhlman, 2004). The MET researchers were assigned global ratings for each video observation based on a 7-point scale, with low scores representing little evidence of the indicator (1,2); mid scores reflecting modest levels (3,4,5); and high scores reflecting substantial indicators of the dimension (6,7). The MET researchers gave global ratings of teachers based on these categories; however, the data included observational ratings for each of the seven indicators rather than a score for each category.

High-quality interactions in Pianta's research as well at the MET project were operationalized as teachers having a score of 6 or 7 (Gates Foundation, 2012a). However, as this dissertation will discuss in later chapters, very few teachers in the dissertation sub-sample received scores of 6 or 7. Therefore, this dissertation first explored the descriptive range of participating teachers' CLASS scores to identify whether a different cut-off score could be used or if the CLASS score should be treated as a continuous variable.

This dissertation contributes to the existing body of research on teacher quality by examining the associations between positive teacher-student interactions and academic achievement of students in upper elementary school classrooms. This focus adds to the literature in that previous research was limited to the early childhood years and lacked random assignment (Hamre & Pianta, 2005; Mashborn et al., 2008;

Rudasill et al., 2010). Random assignment in the current investigation generated the expectation that any differences in classroom achievement would be based on variations in the quality of interaction rather than being due to any pre-existing differences between classrooms or teachers.

A second contribution of this investigation was its analysis of differences in the distribution of teachers' interactional quality by student populations, for example, by level of socioeconomic backgrounds. In the MET project, socioeconomic status was addressed by comparing students who did and did not meet income eligibility for the National School Lunch Program, a federal assisted meal program (free or reduced lunch) (Gates Foundation, 2010c).

Students from low socioeconomic backgrounds are disproportionately taught by teachers who are less experienced, less frequently educated at selective institutions, and less successful at raising students' test scores (Lankford, Loeb, & Wyckoff, 2002; Peske & Haycock, 2006). The Education Trust fund published a report in 2006 discussing how students who identify as minority and/or from low socioeconomic backgrounds are more likely to be "short-changed" when it comes to teacher quality and experience (Clotfelter, Ladd, & Vigdor, 2007; Clotfelter, Ladd, Vigdor, & Wheeler, 2006; Kalogrides, Loeb, & Béteille, 2013; Peske & Haycock, 2006). Positive matching of favorable achievement outcomes with teachers who are skilled professional is consistent with previous research (Clotfelter et al., 2007; Hanushek & Rivkin, 2010b; Murnane, & Steele, 2007). Therefore, an interest of this dissertation was to consider the role of effective teachers being sorted to particular types of students and was considered in the framing of the results in Chapter IV.

Four research questions were analyzed to further examine the role of classroom teachers' interactional quality on classroom achievement outcomes in English/language arts (ELA) and mathematics. The first research question examined whether there was an association between the distribution of teacher interactional quality (CLASS score) and the classroom proportion of free or reduced lunch status. The second research question examined whether there was an association between teacher interactional quality and classroom proportion of free or reduced lunch receipt during Year One of the study when teachers went about their usual teaching practices in the classroom. The third research question differed from the second research question by asking whether there was an association between teacher interactional quality and classroom proportion of free or reduced lunch receipt when teachers were randomly assigned to classroom rosters of students. The fourth research question examined whether teacher interactional quality's impact on classroom achievement outcomes was different based on the year of the study.

Significance of the Study

Research examining indicators of teacher quality, particularly teachers' warm dispositions, responsiveness, and consistent interactions with students, concentrated on observational data. Measurements of observational data have the advantage of recording events as they happen, without bias by participants' memories or subjective filters. Observational data can be especially informative when teachers and students have habituated to the presence of the researcher and cameras or any other equipment they bring when the observations are corroborated over time with valid and reliable observational scales (Cash & Pianta, 2014; Gates Foundation, 2012b).

In this dissertation, observations played a crucial role in documenting teachers' interactions with students. The MET project used multiple measures of classroom, teacher, and student level characteristics and randomization of teachers to classrooms of students (Gates Foundation, 2010b). Given these attributes, the data afforded a desirable opportunity to examine the causal impact of teacher interactional quality on classroom academic achievement outcomes.

This dissertation was one of the first to use a research design that allowed for the examination of whether teachers higher in interactional quality caused higher classroom academic achievement. Causal inference is the main objective for the use of random assignment in the MET project. However, recognizing the inherent nature of the field of education it is difficult to say with certainty whether one variable caused another even with random assignment. Therefore, for the intention of this dissertation when the term cause or causality is used, an influential impact on the outcome is cautiously conceived.

In one study that examined the effect of random assignment with MET data, the investigators focused on observational data but rather on the classroom instructional environment using the Danielson framework (Danielson, 2013). These researchers found teachers with higher instructional quality scores to be predictive of student mathematics and language arts achievement scores for fourth through eighth grade (Garrett & Steinberg, 2014). Garrett and Steinberg's study still did not answer questions about the emotional support environment or the climate of interactions between teachers and students as determined by the CLASS™ domains, since the measure of interest known as the Danielson framework only measured the instructional environment.

In summary, this dissertation contributed to the empirical literature in two ways. In pursuit of the first goal, the investigation examined whether teachers higher in interactional quality caused or had an influential impact on classroom academic achievement for the under-studied developmental period of upper elementary school grades (4 and 5). As the second goal, this study examined the possible unequal distribution of teacher interactional quality to classrooms of students based on classroom-level characteristics such as proportion of high or low socioeconomic status.

Relevance of this Dissertation for Policy and Practice

Teacher quality involves a complex set of skills and should be conceptualized and measured by a constellation of practices. Integration of multiple measures including those from teachers, students, and district-level variables should advance knowledge of teacher effects on students' academic achievement and wellbeing. These results have relevance for teaching skills and understandings that can be cultivated in teacher preparation programs. The data from this study should also be applicable to current practice, district requirements, state regulations, and policy recommendations. Educational administrators are faced with having to make high-stake personnel decisions through hiring, retaining, or eliminating teachers, often using observational measures of effective teaching, such as the CLASS™ instrument (Gates Foundation, 2012b). In most cases, these decisions are made without considering the possible systematic sorting of teachers to students (Clotfelter et al., 2007). Therefore, findings should inform policy on the need to better understand the processes by which teachers are assigned to classrooms.

If preparation programs and school systems are able to better identify teacher qualities that have an impact on student learning, this information can be used to attract, prepare, support, and retain teachers who are skilled in their interactions and emotionally attuned to the needs of students. This information can be used as a foundation for states and districts as they develop mentoring, coaching, professional development, and teacher evaluation systems for strengthening the recruitment and retention of high quality teachers (Gates Foundation, 2010b).

Purpose

This dissertation used the largest educational dataset to date of students' learning and teachers' instructional practices, the MET project. The project allowed for the documentation of the influential impact of teacher-student interactions on classroom ELA and mathematics achievement outcomes as measured by the CLASS™ instrument. Breadth of student backgrounds in the dataset allowed for the analysis of teacher-student interactions on achievement outcomes for classrooms of students from different socioeconomic status backgrounds in the upper elementary school years. The following research questions were posed:

Q1 Is there a difference in the distribution of classroom teachers' interactional quality when classrooms have higher proportions of free or reduced price lunch status (i.e., low socioeconomic status) and when classrooms are assigned to teachers using business-as-usual practices?

Prior research demonstrates higher-quality teachers as defined by teacher experience are disproportionately assigned to more affluent and higher achieving students (Clotfelter et al., 2006). Therefore, an effort was made to extend the literature by examining the distribution of classroom teachers CLASS scores (i.e., interactional quality) during the business-as-usual Year One of the study. This analysis further examined whether there was a difference in classroom teachers CLASS scores when classrooms had higher proportions of free or reduced price lunch (i.e., low socioeconomic status).

> Q2 Is there a positive association between classroom teachers' interactional quality and classroom achievement outcomes under business-as-usual assignment practices? Is the association different for low socioeconomic students?

Research question Q2 examined whether the addition of classroom demographics was associated with teachers' interactional quality and whether teacher interactional quality was associated with classroom ELA and MATH achievement outcomes. This question hypothesizes that the impact of assignment to classrooms with a teacher higher in interactional quality would be positive. The second part of this research question asked whether the effect of classroom teachers' CLASS scores changed based on the proportion of classroom free or reduced price lunch status? In other words, the interaction effect would suggest whether a classroom teacher's CLASS score varied based on the proportion of students in the classroom with free or reduced price lunch status.

> Q3 Is there a causal impact of classroom teachers' interactional quality on classroom achievement outcomes under random assignment practices? Is the impact different for low socioeconomic students?

This question asked a similar question to Research Question Q2 but instead used Year Two when teachers were randomly assigned to classrooms. Random assignment was used to try to isolate the causal impact of teacher interactional quality on classroom achievement outcomes. This procedure removed the potential bias introduced by non-random sorting (i.e., assortative matching) that occurred when teachers were assigned to classrooms of students under business-as-usual practices. In other words, random assignment during Year Two of the study removed the possibility of teachers with higher interactional quality being matched with classrooms of students based on characteristics such as free or reduced price lunch status. Similar to Research Question Q2, it is hypothesized that the impact of assignment to classrooms with a teacher higher in interactional quality would be positive. An interaction effect would suggest whether a classroom teacher's CLASS score varied based on the proportion of students in the classroom with free or reduced price lunch status.

> Q4 How do the estimates of the association between classroom teachers higher in interactional quality on classroom achievement outcomes during random assignment compare with estimates of the association between classroom teachers' higher in interactional quality and classroom achievement outcomes under business-as-usual practices?

This question extends on Research Questions Q2 and Q3, which asked whether classroom achievement outcomes changed based on a classroom teacher's interactional quality. First looking at Year One of the Study and then Year Two of the study through separate regressions, Research Question Q4 extends on Research Questions Q2 and Q3 by specifically asking whether teacher interactional quality has an impact on classroom achievement outcomes differed based on the year of the study. And more specifically, the analysis pursues if the impact of teacher interactional quality on classroom achievement outcomes change based on the proportion of free or reduced lunch status and if the difference in impact was different based on the year of the study.

Limitations of the Study

The study was distinctive in the use of longitudinal data to examine the influential impact of teacher quality indicators on the achievement of students. The investigation examined the distribution of teacher interactional quality as measured by the CLASS™ when teachers were assigned to classrooms of students using business-as-usual practices in the first year of the study (AY 2009-2010). The distribution of teachers higher in interactional quality in Year One (business-as-usual) was then compared to the distribution when classrooms of students were randomly assigned to teachers in Year Two (AY 2010-2011). The goal of Year Two (AY 2010-2011) with random assignment was to account for possible sorting of teachers to classrooms of students based on student characteristics such as socioeconomic status. Random assignment further estimated the causal or influential impact of teacher interactional quality on classrooms of students' achievement outcomes by isolating the teacher effect. In other words, random assignment generated an opportunity to assess the impact of the independent variable (i.e., teacher interactional quality) on the dependent variable (i.e., classroom academic achievement), while averaging out any other variables that could account for the model. However, a restriction that always comes with any research study, even with the use of random assignment, is the limited generalizability of the results. Results were only generalizable to the specific sub-sample used in the dissertation.

A second limitation of this study was that the districts included in the sample were some of the largest school districts in the United States and not nationally representative of teachers. The MET researchers used opportunity sampling, a sampling tool utilizing the knowledge and attributes of the researcher to identify a sample. When convenience or opportunity sampling are used, there is a chance some other underlying participant characteristics created selection bias. With the MET study, for example, the districts that already had connections to the Gates Foundation were either receiving financial support to develop human resource systems or had previously worked with the foundation and were initially selected and schools and teachers were offered additional incentives to participate.

A third limitation of the study involved the teacher sample. The teacher sample differed from the national teacher population in regard to teaching experience, with the majority of the MET teachers having more years of teaching experience than the broader array of kindergarten-12 public school teachers. Furthermore, the student sample differed from the national population, with a smaller proportion of students identified as White (24%) compared to the national study body in kindergarten-12 public schools (54%) (Gates Foundation, 2012b). Thus, again, findings can only be generalized to samples with similar characteristics as the studied sample.

Lastly, a major limitation involved non-compliance with random assignment. With random assignment, it is assumed the two groups (e.g., business-as-usual year and randomization year) were equal in expectation on observed and unobserved characteristics unless there was unequal attrition between the two groups. When attrition is high, the direction of the bias in the estimates is difficult to detect. The MET sample for Year Two (random assignment) had a 24% attrition rate and was considered during analysis and interpretation of the findings for the present study. This non-compliance could reflect students requesting a transfer from the initially assigned teacher or teachers and/or principals purposely matching students to teachers (Garrett & Steinberg, 2014). Despite the observed noncompliance with randomization across school districts, the purposeful sorting of teachers to classrooms of students was likely more limited than if it had occurred under a natural context with no attempt at randomization (Garrett & Steinberg, 2014).

The outline of the dissertation is as follows. Chapter II summarizes relevant literature on teacher quality and a teacher's interactional quality impact on classroom academic outcomes, specifically for students with a low socioeconomic status. Chapter III develops a model for estimating the causal impact of teacher interactional quality on classroom ELA and mathematic achievement outcomes. In Chapter IV, analysis and results of the study will be discussed. In Chapter V, conclusions for the results are presented as are implications for future research and educational practice.

Definitions of Terms

Assortative matching: Also called sorting or the process of randomization. The sorting of individuals based on observable and unobservable characteristics (Clotfelter et al., 2007).

Balanced assessment in mathematics: This is a supplemental assessment measuring higher order reasoning skills (Gates Foundation, 2010c).

BLACK: A district administrative variable within the MET dataset, representing the proportion of Black students in the classroom.

Business-as-usual practices: During Year One of the MET study teachers and schools went about their everyday practices (Gates Foundation, 2010b).

Causal impact: The amount with which a treatment causes an effect on an outcome variable. The cause must precede the anticipated effect in time (Murnane & Willet, 2011). This dissertation will refer to causal impact as influential impact.

Classroom Assessment Scoring System™: An observational instrument developed at the Curry School of Education to assess and improve classroom quality in prekindergarten-12 classrooms (La Paro et al., 2004).

Classroom Assessment Scoring System score: A variable within the MET dataset, representing a teacher's observed score from the CLASS™.

Classroom organization: A CLASS™ domain measuring a teacher's demonstration of behavior management, productivity, and use of instructional learning formats (Gates Foundation, 2010a).

Emotional support: A CLASS™ domain measuring the overall classroom climate as well as a teacher's sensitivity and response to student perspectives in the classroom (Gates Foundation, 2010a).

English/language arts: A district administrative variable within the MET dataset, representing English/language art state assessment scores.

English language learners: A district administrative variable within the MET dataset, representing the proportion of English language learner students in the classroom.

Framework for teaching: An observational instrument encompasing research-based set of components of instruction (Danielson, 2013).

Interactional quality: The emotional climate, classroom organization, and instructional support in the classroom measured by the CLASS™ (Hamre et al., 2013; La Paro et al., 2004).

Instructional support: A CLASS™ domain measuring a teacher's use of concept development, language modeling, and the quality of their feedback to students (Gates Foundation, 2010a).

Low socioeconomic status: The condition in which students meet income eligibility for the National School Lunch Program, a federal assisted meal program (free or reduced lunch) (Gates Foundation, 2010c).

LUNCH: A district administrative variable within the MET dataset, representing the proportion of free or reduced lunch in the classroom.

MALE: A district administrative variable within the MET dataset, representing gender, with one indicating male and zero indicating otherwise.

MATH: A district administrative variable within the MET dataset, representing mathematic state assessment scores.

Measures for Effective Teaching Longitudinal Database: A project funded by the Gates Foundation, including multiple measures of teacher effectiveness.

Multiple measures: The use of a collection of assessments to measure a teacher's quality and/or effectiveness.

Opportunity sampling: A sampling tool utilizing the knowledge and attributes of the researcher to identify a sample.

Random assignment: Equal likelihood of being selected and assigned to a treatment and control condition; in this investigation, participating teachers were randomly assigned to a classroom roster of students at the grade level in which they taught.

Reliability: An evaluation of the consistency of a test or measure.

SPED: A district administrative variable within the MET dataset representing the proportion of special education students in the classroom.

Stanford 9 open-ended reading assessment: A supplemental assessment measuring higher order English-language skills (Gates Foundation, 2010c).

State standardized assessments: Existing state assessments designed to measure student progress on the state curriculum for federal accountability purposes (Gates Foundation, 2010c).

Student achievement: Student outcomes on low-stakes achievement tests.

Teacher-student interaction: The mutual and reciprocal actions between elementary school teachers and their students that promote the development of relationships, education practices, and other reciprocal engagements between teachers and students (Hamre et al., 2013).

Value-added measure: A statistical calculation of value-added estimates for state standardized assessments based on prior year achievement test score designed to be a stable predictor of student achievement in a particular teacher’s classroom (Gates Foundation, 2010c).

YEAR: A variable indicator for being observed during the business-as-usual year (as opposed to the random-assignment year).

CHAPTER II

REVIEW OF THE LITERATURE

This chapter examines the historical literature that serves as the foundation for the dissertation. The first section of the chapter focuses on teacher qualities and predictors for effective teaching. The second section provides an overview of what is known about the relationship between teacher quality and student achievement. The third section focuses on the theoretical framework for teacher-student interactions. The fourth section examines experiences and needs of students from low socioeconomic backgrounds at school. The last section provides a rationale for the study's methodology by discussing the evidence for random and non-random sorting of students into classrooms.

What Makes a High Quality Teacher?

Education researchers and policy makers agree that a teacher's quality is one of the most significant determinants of students' achievement (Darling-Hammond, 2000; Hanushek, 2011). Because of the presumed power of teachers' effectiveness with children, there has been interest in the association between teacher quality and students' academic achievement. However, researchers have varied in their definition of "quality" and more specifically what distinguishes a low-quality teacher from a high-quality teacher.

Administrative Records

Over the years, educational researchers have endeavored to define teacher quality with what little data were available. Information consisted mostly of administrative district records, including school demographics, teachers' credentials, and years of teaching in the district. Using these data, researchers have made recommendations regarding entry requirements into the teacher certification program (Goldhaber, 2011), the desirability of strengthening the credentials of teachers by requiring a master's degree (National Commission on Teaching and America, 1996), salary compensation and merit pay within the teacher labor market (Hanushek, Kain, & Rivkin, 1999; Murnane & Cohen, 1986), and recommendations for smaller classroom sizes (Jepsen & Rivkin, 2009). Findings produced from these studies have yielded weak predictive power in identifying the specific teacher characteristics related to students' academic achievement (Hanushek, 2011).

Teachers' knowledge, education, and training are among the most frequently studied aspects of teacher quality. Researchers have not consistently found teachers' education and training to be related to student achievement. In fact, little of the variation in students' performance has been explained by observable characteristics such as a teacher's education or experience (Rivkin, Hanushek, & Kain, 2005). There has also been a push for defining certification requirements in an effort to protect students from low-quality teachers. Kane et al. (2008) found teacher certification to have little impact on students' performance in the classroom. Consistent with these findings, Croninger et al. (2007) found no impact of teacher certification on elementary student reading achievement but did find modest effects for teacher degree type. Teachers who held an elementary education degree with two or more years of experience were associated with higher student achievement in reading but not mathematics. These same effects were not found for an early childhood degree. Even with modest effects for teacher degree type, there has been weak evidence for educational attainment such as a master's degree improving teachers' effectiveness (Croninger et al., 2007; Hanushek, Kain, & Rivkin, 2004; Hanushek & Rivkin, 2006).

Another aim of research has been to determine whether the supply of high-quality teachers can be increased with salary and merit pay (Hanushek et al., 1999; Murnane, & Cohen, 1986). Consistent with the research on educational attainment, the relationship between teacher salary and student outcomes has been fairly weak.

Student Achievement Outcomes

A long-term educational goal for all students is the successful completion of high school, an accomplishment that increases personal economic prospects, health, well-being, and the ability to contribute productively in society (Crosnoe & Benner, 2015). Factors that promote students' achievement are thus significant targets of analysis for educational researchers.

Accountability initiatives such as No Child Left Behind, Race to the Top, and MET share the premise that a teacher's evaluation should depend on his or her students' achievement gains (Gates Foundation, 2010c, 2012b). The Measure of Effective Teaching (MET) researchers collected existing student state assessments along with other indicators of teacher effectiveness to allow researchers and policy makers to answer questions on two schools of thought in education research. First, the MET data intended for standardized achievement scores to be used to examine classroom-to-classroom variation in student achievement and whether the variation in student achievement represents true teacher effects on achievement or whether there are other underlying student characteristics explaining the variation (Gates Foundation, 2012b; Rothstein, 2010). Second, standardized achievement scores were included in the dataset for researchers to study whether classroom variation in student achievement is due to specific teacher or teaching characteristics (Gates Foundation, 2012b).

The MET project along with other researchers opt for the use of state standardized tests because of the accessibility of the data for researchers and policy makers (National Board for Professional Teaching Standards, n.d.). Standardized achievement scores are publically available as part of district teacher evaluation systems. This was a benefit for researchers choosing to use the MET dataset because MET researchers were able to access these data for the six participating districts and over 93% of fourth through eighth grade students had state test scores reported from the year they were in the study (Gates Foundation, 2012b). Whereas, for supplemental reading and mathematics achievement measures administered by MET, there was only around a 75% to 79% completion rate (Gates Foundation, 2012b).

Another added benefit of using traditional state assessments is the breadth of reported data since these tests are administered state- or district-wide (National Board for Professional Teaching Standards, n.d.). The district administrative data reported to the MET project included data across districts, schools, classrooms, and students. These data in combination with other teacher effectiveness indicators such as teacher observation and student perception make for a rich dataset for researchers to answer questions on classroom-to-classroom variation in student achievement.

It should be noted that researchers have criticized the use of state standardized achievement for only measuring end-of-year achievement and not fully capturing the effect of a teacher on student learning (National Board for Professional Teaching Standards, n.d.). In response, investigators have shifted to specific teacher characteristics and designs that more definitively identify teachers' contributions to academic learning. For example, researchers have attempted to explain teacher quality through value-added scores by using statistical methods to identify the impact of teachers and schools after adjusting for students' prior achievement (McCaffrey, Lockwood, Koretz, Louis, & Hamilton, 2004; Murnane & Willet, 2011). There are various value-added models; however, one of the most common methods takes into account the student's prior year of achievement (Harris, 2011). For example, to estimate a teacher's added value, a researcher may obtain fourth and fifth grade test scores and student characteristic information (e.g., free or reduced lunch eligibility). The data may then be used to predict what the students' sixth grade test scores will look like. The teacher's value-added estimate is the average of the difference between the actual and predicted scores for a classroom of students.

Value-added measures have received much notoriety in recent years because of the presumption that the approach estimates a student's growth in learning attributable to the work of an individual teacher (Harris, 2011). Scholars disagree as to how the contributions of teachers should be calculated and how other factors in the students' lives should be identified. Despite reservations about value-added scores, many educators, investigators, and policy makers continue to attribute a significant portion of students' academic progress to instructional experiences arranged by teachers.

The MET dataset not only included traditional standardized test scores but also specially constructed value-added statistics calculated for each teacher within the school (Gates Foundation, 2012b; Raudenbush, 2015). These value-added measure scores were calculated from the six districts' report of prior year achievement scores. The districts only had 78% of students with reported state test scores for the year before they were in the MET study as opposed to 93% of students with reported scores for Year One of the study (Gates Foundation, 2012b). The MET researchers intended to eliminate school differences by using a regression model with school fixed effects (Raudenbush, 2015). Both Blazar (2015) and Garrett and Steinberg (2014) used MET value-added measure scores to reflect a teacher's effect on student learning and in both cases used hierarchical-linear models to account for student characteristics. Raudenbush (2015) makes the recommendation that the value-added measure should only be used with student fixed effects when student characteristics are being accounted for. The purpose of this dissertation was to examine classroom-level effects, thus would not account for student-level characteristics recommended for the value-added measure. This dissertation made the methodological decision to conduct classroom-level analysis since the variable of interest's observational Classroom Assessment Scoring System (CLASS) scores were collected at the classroom level and was appropriate for the research questions.

Random assignment and the use of multiple measures in the dissertation attempt to help isolate a teacher's unique contribution to classroom achievement and is a starting point before extending out to measure school, teacher, and student effects (Gates Foundation, 2010b). Teacher effectiveness is more reliably assessed when multiple measures such as classroom-based observations, achievement scores, and student learning objectives are considered together (Gates Foundation, 2010b; Kane & Staiger, 2012).

**Measures of Effective
Teaching Project**

The ability of scholars to discern the impact of teacher quality is limited by methodological problems measuring teacher quality (Hanushek, Kain, & Rivkin, 1999). Research has not only produced inconsistent findings but has been largely correlational in its design. The MET researchers wanted to move beyond correlational analyses and make causal inferences about teaching effectiveness (Gates Foundation, 2012b). The MET dataset is the largest study of teaching in United States elementary and secondary schools to date (Kane & Staiger, 2012). The MET also was the first dataset that enabled educational researches to use such a comprehensive array of records, including administrative data, classroom observations, students' perceptions, and students' achievement scores. The MET dataset is also noteworthy in that it incorporated random assignment of teachers to classrooms of students during one of the years of data collection. Random assignment of teachers to classrooms enabled an unbiased estimate of the average causal effect of teachers on students' achievement outcomes.

Why Do Teachers Matter?

There has been a need for a comprehensive dataset, such as the MET project, to inform teachers about skills that make them effective and targets of professional development by school districts. Even as far back as three decades ago, a group of researchers highlighted the extraordinary power schools have on child development (Rutter, Maughan, Mortimore, Ouston, & Smith, 1979). Students spend over one-fourth of their waking hours in school, and in elementary school the majority of these hours are spent in a single classroom with one teacher. Schools thus serve as a dominant setting for development, and what goes on in a teacher's classroom influences students' learning, engagement, and academic achievement outcomes (Crosnoe & Benner, 2015).

In recognition of powerful effects of teachers on children, United States federal initiatives such as No Child Left Behind and Race to the Top have mandated the appointment of highly qualified teachers in every classroom. As part of these efforts there has been an increased demand for teacher performance evaluations of instructional strategies and curricular alignment. With a teacher's performance being dependent on these evaluations, it is crucial for researchers to better understand and identify the elements of high quality teaching.

Policy makers and researchers have used a variety of definitions of teaching quality. Legislation in No Child Left Behind deems a highly qualified teacher as an individual with a bachelor's degree, state certification or licensure, and knowledge of each subject that he or she teaches (U.S. Department of Education, 2004). In comparison, Race to the Top defines a high quality teacher as an individual whose students achieve acceptable rates of academic growth (e.g., at least one grade level in an academic year) (U.S. Department of Education, 2009).

Educational researchers have been more interested in teachers' instructional practice. In one relevant study, Garrett and Steinberg (2014) used the MET data to measure teachers' instructional quality as measured by the framework for teaching (Danielson, 2013) causal impact on student achievement. The framework for teaching is a research-based set of components including planning and preparation, classroom environment, instruction, and professional responsibilities. Garrett and Steinberg (2014) defined teacher quality as observed instructional practice on the framework for teaching and found this measure to be highly correlated with students' English language arts and mathematics achievement. Students' achievement was more advanced when taught by educators with relatively high framework for teaching ratings.

Clouding the causal inferences in Garrett and Steinberg's (2014) research, consistent patterns of non-random sorting of students to teachers were detected, such that higher performing students were moved to teachers with higher framework for teaching scores. In the MET project's full randomization sample, only 30% of students complied with their initial teacher random assignment in one of the school districts, Memphis, and occurred at different levels in the other districts (Gates Foundation, 2012b). This non-compliance could reflect students requesting a transfer from the initially assigned teacher, or teachers or principals might have intervened in certain cases (Garrett & Steinberg, 2014). Despite the observed noncompliance with randomization across school districts, this positive matching of higher quality teachers to higher performing students was likely more limited than under a natural context and may yield an underestimate of the influence of teacher quality on students' achievement (Garrett & Steinberg, 2014).

As a supplement to observations of teacher quality, students have an important and unique perspective on the effectiveness of teaching. The MET researchers have demonstrated the validity of feedback students provide on the quality of instruction and learning environment, especially when students are asked to give feedback on specific aspects of teachers' practice (Gates Foundation, 2010b). For example, classrooms of students completed the Tripod Survey and were able to differentiate among effective and non-effective teachers. Ratings of individual teachers' strengths and weaknesses were relatively consistent across different groups of students (Gates Foundation, 2010b, 2012a). Furthermore, teachers with more favorable student perception feedback (as measured by the Tripod Survey) had better value-added scores in mathematics (Gates Foundation, 2012a). Although students' perceptions are not examined in this dissertation, it is worthwhile in the context of teacher quality effects to consider that the impact of these important factors extend beyond achievement scores.

The MET researchers have provided compelling evidence that teacher quality can be reliably measured through observations, student perceptions, and/or student achievement measures, and that these data are associated with positive gains in academic achievement. Results on teacher quality are compelling and indicate the need for more clarity around its components effects (Gates Foundation, 2010b).

Theoretical Grounding for Interactional Quality

The powerful role of teachers in students' academic learning has begun to be established in the literature. However, researchers have not been successful in explaining what exactly it is about a teacher that determines whether students will be successful. A teacher's experience, educational attainment, and salary are not consistently predictive of students' academic outcomes, and when there have been significant results the effects have been small in magnitude (Croninger et al., 2007; Hanushek et al., 1999; Hanushek & Rivkin, 2006; Jepsen & Rivkin, 2009; Kane et al., 2008; Murnane & Steele, 2007). It is the thesis of this study that a primary influence on students' achievement is having a teacher who effectively supports students' social and academic development through sympathetic, organized, affirming, and academically effective interactions in the classroom. In order to improve the quality of the teacher-student relationship, researchers must first document classroom interactions and their effects (Pianta et al., 2012).

A range of theoretical models converge on the expectation that ongoing sensitive and affectionate interactions with caregivers are essential to children's well-being. In the field of child development, for example, a child's security and willingness to explore the environment is seen to emerge out of first close relationships with one or more familiar caregivers. Adults who are sensitive and create an emotionally supportive, predictable, consistent, and safe environment encourage children to be self-reliant explorers of their environment (Ainsworth, 1979; Bowlby, 1969), and these same concepts have been transferred to and validated in the school environment (Birch & Ladd, 1998; Hafen et al., 2014; Hamre & Pianta, 2001).

Of course, there are differences in the roles and effects that adults play at home and at school. At home, a parent takes on numerous functions, for example, tending to the child's physical needs and socializing him or her to take on responsibilities. Teachers play many roles as well and take on the unique duty of imparting academic knowledge and skills. A student's ability to learn is influenced by who is teaching, what is being taught, and the cultural and physical context where the learning is occurring. How teachers implement instruction and build connections with their students are especially influential factors in learning. The importance of a positive relationship between an adult and a child is undisputed, yet the effects of supportive interactions extend beyond social-emotional development (Crosnoe & Benner, 2015).

Hamre and Pianta and colleagues introduced the teaching through interactions (TTI) framework of effective teaching as a lens through which to study classroom structures (e.g., how the school day is organized) and processes within the classroom (e.g., teacher-student interactions). These authors and their colleagues have rigorously tested and elaborated the framework in over 4,000 early childhood and elementary classrooms across the United States (Hamre et al., 2013) and more recently in secondary settings (Allen, Pianta, Gregory, Mikami, & Lun, 2011; Malmberg & Hagger, 2009). The conceptual framework is unique in that it includes three distinct domains (i.e., emotional support, classroom organization, and instructional support), and recognizes the behavioral, cognitive, emotional, and motivational components of teacher-student interactions (Pianta et al., 2012).

Over the past two decades, Hamre and Pianta have dedicated their efforts to identify and understand the complex social systems of the classroom, along with the added complexity of teacher-student interactions. The framework has identified three broad domains in an attempt to capture the dynamic of interactions, which includes everything from a teacher's warmth and sensitivity in the classroom to the regular use of scaffolding for increasingly deep academic understandings.

Emotional Support

Pianta's early work revolved around the influences of teacher-child relationships and the emotional support given by early childhood teachers in children's later success in school (Hamre & Pianta, 2001; Pianta, 1994, 1999; Pianta & Nimetz, 1991). Thus the first domain included in the Hamre et al. (2013) TTI framework emphasizes the emotional climate of the classroom and the teacher's emotional expressions, positive affect, sensitivity, and regard for student perspectives. The importance of an adult's expression of emotional support for children has long been recognized and is rooted in early attachment theory (Ainsworth, 1979; Bowlby, 1969). Teachers who are warm and sensitive tend to be more attuned and responsive to students’ social, emotional, and academic needs (Hamre & Pianta, 2005; Pianta et al., 2008).

Consistent with Pianta’s research, when teachers are more attuned and responsive, students are likely to report a greater enjoyment of school and learning and a positive sense of peer community (Gest, Madill, Zadzora, Miller, & Rodkin, 2014). If students feel emotionally connected and supported, then it should come as no surprise that these students on average have more positive academic attitudes, are more engaged, and have higher achievement scores (Crosnoe et al., 2004; Deci & Ryan, 2000).

Not only do students thrive in classrooms when teachers are sensitive to their feelings, they also flourish in classrooms where students are encouraged to speak their minds and converse with one another. Regard for student perspectives is included in the TTI framework and has been well documented in educational and motivational research. Students are most motivated to learn when adults support their need to feel competent and autonomous at school (Deci & Ryan, 2000). Students benefit most when teachers actively scaffold the learning experience with a balance of control, autonomy, and mastery in the classroom. For example, student learning is inhibited when there is a mismatch between a student’s need for autonomy and the teacher’s need to exercise control (Cornelius & Herrenkohl, 2004; Eccles, Wigfield, & Schiefele, 1998). Along with the need for meaningful choices, students are motivated to learn when they feel valued as an individual.

Classroom Organization

The second domain of the Hamre et al. (2013) TTI framework includes the way in which a teacher organizes behavior, time, and attention in the classroom. This domain includes effective behavior management as occurs with the promotion of positive behavior and the prevention of misbehavior, productivity in maximizing learning time, and the effective facilitation and use of learning formats (Pianta et al., 2008). For example, Pianta et al. (2005) discovered students' engagement, compliance, and cooperation with peers vary as a function of classroom activity settings (e.g., free choice/centers, whole-group teacher-led activities, or routines). Ideally, the classroom can be organized in ways that allow the maximization of instruction, student focus, and promotion of engagement, which all ultimately lead to greater student success.

Educational research has emphasized the role of organization and management in creating a well-functioning classroom. For example, most of the behavioral management research done in the 1970s has consistently shown classrooms with positive behavior management tend to have students making greater than average academic progress (Good & Grouws, 1977; Soar & Soar, 1979). Through their interactions with students, teachers can model and encourage students to develop skills to regulate their own behavior through clear expectations and routines. Consistent with attachment research, when classroom expectations are consistent and predictably enforced, students are more likely to feel safe and secure in that environment and aware of what is expected of them. Feeling secure in the classroom allows students to take emotional and academic risks and to be open and receptive to new information and feedback.

Instructional Support

The final domain of the Hamre et al. (2013) TTI framework encompasses the ways in which teachers facilitate concept development through induction of analysis and reasoning, integration with previous knowledge, and connections to the real world. A teacher's response to students can be evaluated in terms of quality of feedback, for example, with effective prompts and exchanges that encourage a deep level of understanding.

Constructivist theories and information-processing views of learning support Pianta's framework in that they each recognize the value of active participation in learning (Bruner, 1996; Vgygotsky, 1978). Students learn best when they are engaged in meaningful conversations about content and see connections with what they have already learned about the world (Brophy, 1986, 2010). In addition, a teacher who provides clear learning targets and specific feedback is likely to increase students' academic achievement (Brophy, 1986, 2010). Specific feedback that is immediate may enhance interest and effort and ultimately promote higher-order thinking.

The Impact of Teacher Interactional Quality

Research has established the role that direct and close interactions between a teacher and student, also known as proximal interactions, foster students' engagement, learning, and development. Proximal interactions in the classroom are not only important to recognize and measure because of the potential impact on learning but also because elementary students spend one-quarter of their waking hours in a classroom (Crosnoe & Benner, 2015). In most cases this time is spent with a single teacher especially in the elementary school setting.

In an investigation of kindergarten classrooms, the tendency for teachers to view their interactions with children negatively was associated with weak academic and behavioral outcomes in students through eighth grade (Hamre & Pianta, 2001). Other studies have linked teachers' observed instructional practices and interactions with students to achievement gains in pre-school through sixth grade (Cameron et al., 2005; Hamre & Pianta, 2005; Kane & Staiger, 2012; National Institute on Child Health and Development, 2005; Pianta et al., 2008; Reyes et al., 2012). Students exposed to more positive teacher-student interactions, as measured by the CLASS™, have greater feelings of well-being, more productive social skills (Mashburn et al., 2008), and less conflict with teachers (Hamre & Pianta, 2005).

Through a motivational lens, when students' have greater feelings of well-being and security in the classroom, beneficial academic outcomes are likely to follow. Positive interactions between a teacher and a student may allow a student to be more openly engaged and motivated during classroom instruction, in turn generating better academic performance. Therefore, having an affectionate teacher who fosters a positive classroom environment motivates students to achieve at high levels (Hamre, Hatfield, Pianta, & Jamil, 2014; Hamre & Pianta, 2001, 2005; La Paro et al., 2004; Mashburn et al., 2008; Pianta et al., 2008).

Factors that Moderate Teacher-Student Interactions

Attracting and retaining high-quality teachers in districts that serve students from low socioeconomic status, has been of keen interest for education researchers and policymakers. The districts serving students from low socioeconomic backgrounds tend to be urban, and these students tend to be particularly vulnerable to low quality teaching. Students who identify as minority and/or from low-income backgrounds face higher teacher turnover and tend to be taught more frequently by beginning teachers (Hanushek et al., 2004). Economically poor cities have a high turnover of teachers, with departing teachers tending not to leave the profession but rather to move from urban to suburban schools (Rivkin et al., 2005).

Economic disadvantage is an important phenomenon to study because of the pervasive effects it has on children. Poverty affects 45.3 million people in the United States and 14.7 million children every year (U.S. Census Bureau, 2014). In 2012, 11 million school-age children (5 to 17 years old) lived in economic poverty (National Center for Education Statistics, 2014). This means there are 11 million students in the schools who have the potential to experience such long-term negative effects as health problems and excessive levels of stress (Reiss, 2013; Shonkoff et al., 2012). The Shonkoff et al. (2012) research on the effects of adversity suggests students exposed to high levels of stress can be delayed in the development of linguistic, cognitive, and social-emotional skills. Similarly, Roy and Raver (2014) examined the longitudinal effects of exposure to poverty from preschool to third grade and found early exposure to poverty was related to delays in academic skills, low self-regulatory skills, and more behavior problems in third grade.

The risk of excessive activation of negative stress responses that lead to physiologic harm and long-term consequences for health are greatly reduced when children receive support from emotionally supportive adults (Shonkoff et al., 2012). Shonkoff et al. (2012) recommended an essential characteristic that makes high levels of stress responses tolerable, namely, an adult's relationship facilitating the child's adaptive coping skills and sense of control.

As previously summarized, the teacher-student relationship has the potential to have a positive impact on student outcomes. Because the tone of these relationships varies tremendously, such favorable effects are not always achieved. In fact, students from low socioeconomic backgrounds are at an increased relational risk for negative interactions with their teachers (La Paro et al., 2004). Schools with a high concentration of families that are economically distressed and mothers with little formal education are likely to provide teacher-directed instruction and unsupportive peer relationships (Pianta, La Paro, Payne, Cox, & Bradley, 2002). Similarly, Pianta et al. (2005) examined program, classroom, teacher attributes, and quality of teacher-child interactions in 238 prekindergarten classrooms across six states. The quality of these interactions was lower in classrooms with more than 60% of children from homes below the poverty line.

In addition to finding socioeconomic correlates of strained relationships at school, scholars have found gender and race to be associated with lower quality teacher-student interactions in kindergarten through sixth grade (Hamre & Pianta, 2001; Jerome, Hamre, & Pianta, 2009; McCormick & Connor, 2014). The general trend throughout elementary school suggests that boys experience greater levels of conflict and lower levels of closeness in the classroom, a result that has been especially strong for African American boys. Jerome et al. (2009) discovered that higher levels of teacher-student conflict in kindergarten were more strongly associated with students who were male, Black, low achieving, and disruptive. These students were at greater risk for increased conflict with teachers throughout elementary school. In addition, closeness between teacher and students decreases for both boys and girls throughout the middle elementary school years (Jerome et al., 2009), which puts this age group at heightened risk for teacher-student interactions.

On the positive side, teacher's interactional qualities such as emotional support and instructional guidance can moderate the manner in which students of color and students from economically disadvantaged backgrounds respond to risks in their lives (Hamre & Pianta, 2005; Jerome et al., 2009; Lee & Bierman, 2015). Hamre and

Pianta (2005) studied students five to six years of age identified as at-risk for school failure due to behavioral, attention, academic, and social problems. Students identified as at-risk who were placed in first grade classrooms with strong emotional and instructional support from teachers had higher achievement gains compared to at-risk peers placed in less supportive classrooms.

Biased Placement of Students According to Teacher Quality

Policy makers have recognized there is not only a need to increase the supply of high quality teachers but there is also the need to distribute teachers more equitably across schools, particularly to schools with high concentrations of students from low socioeconomic backgrounds. The Education Trust fund published a report in 2006 discussing how students who identify as minority and/or from low socioeconomic backgrounds are more likely to be "short-changed" when it comes to teacher quality and to be taught by less experienced teachers (Clotfelter et al., 2007; Clotfelter et al., 2006; Kalogrides et al., 2013; Peske & Haycock, 2006).

Students with more favorable outcomes are more likely to be matched with higher quality teachers, also known as positive-matching (Clotfelter et al., 2007; Hanushek & Rivkin, 2010b; Murnane & Steele, 2007). As discussed earlier, teacher mobility in districts is strongly related to student characteristics such as level of achievement (Hanushek et al. 2004). Teacher preference for working with populations similar to their own may also influence which schools they opt to teach at. For example, Hanushek et al. (2004) found non-Black and non-Hispanic teachers systematically prefer to teach non-Black and non-Hispanic students. In addition, higher-poverty communities have a higher rate of teacher turnover with teachers moving from urban to suburban schools (Rivkin et al., 2004). Teacher choice of schools thus complicates the estimation of teacher effects.

Of particular concern is the fact that more often than not, under-prepared teachers are disproportionately matched to high poverty schools. The Education Trust collaborated with three major school districts (Chicago, Cleveland, and Milwaukee) to examine the distribution of qualified teachers across schools in the district. In all three major urban districts, schools with high concentrations of students of color and from low-income backgrounds were disproportionately assigned to teachers who were new to the profession (Peske & Haycock, 2006). For instance, in Milwaukee, one in four teachers had fewer than three years teaching experience. Cleveland's highly qualified teachers were more likely to teach in schools with less poverty, fewer students of color, and a greater proportion of high achieving students.

In another analysis by Peske and Haycock (2006), multiple indicators of teacher quality, including academic knowledge, master of content, experience, and pedagogical skill, were combined to form a Teacher Quality Index and examine the distributional patterns of 140,000 teachers in Chicago. Of the schools serving the greatest proportion of students from low socioeconomic backgrounds, "84% were in the bottom quarter in teacher quality, and more than half (56%) of those fell in the very bottom 10% of teacher quality" (p. 7). Similarly, Steinberg and Sartain's (2015) examination of 44 elementary schools in Chicago Public Schools in 2008 to 2010 further supports the observation that higher quality principals and teachers are being systematically sorted into higher-achieving and lower-poverty schools.

Although students with favorable outcomes are more likely to be matched with higher quality teachers, it is also plausible whereby a high-quality teacher is matched with students with less favorable outcomes (e.g., low socioeconomic backgrounds). For example, principals may place a teacher with a natural disposition for working with students who achieve at low levels, exhibit behavior problems, and face financial hardships with these youngsters in hopes of boosting their accomplishments. Principals' expectation that well qualified teachers can make a difference for struggling students turns out to be well- founded. A teacher high in interactional quality can moderate the effects of poverty and foster positive attributes such as empathy, self-control, and academic learning.

Summary

In the research and policy literature on teachers, quality has taken on a range of meanings. This dissertation introduced a more circumscribed definition of quality, that of teacher interactional quality. I specifically argue for the importance of recognizing, understanding, and measuring teachers' interactions with students in the classroom. I contribute to the existing body of research on teacher quality by using a comprehensive educational dataset, the MET, analyzing the impact of randomized assignments of teacher to classrooms, and by examining students from the upper elementary school years (Hamre & Pianta, 2005; Mashborn et al., 2008; Rudasill et al., 2010).

Another distinct contribution of this investigation was to examine differences in the distribution of teacher interactional quality across classrooms serving different student populations, particularly students from low socioeconomic backgrounds. Students from low socioeconomic backgrounds are disproportionately taught by teachers who are less experienced, trained at less selective institutions, and less successful at raising student test scores (Lankford et al., 2002; Peske & Haycock, 2006).

These contributions are important to the field because positive teacher-student interactions have been shown to be predictive of such positive developmental outcomes as motivation, behavioral self-control, and academic advancement (Rimm-Kaufman, La Paro, Downer, & Pianta, 2005; Rudasill et al., 2010). These interactions also moderate the manner in which students of color and students from economically disadvantaged backgrounds respond to risks in their lives (Hamre & Pianta, 2005; Jerome et al., 2009; Lee & Bierman, 2015). Supportive gestures, organized classroom management, and effective instruction facilitate the child's adaptive coping skills, sense of control, overall adjustment, and academic achievement (Shonkoff et al., 2012).

CHAPTER III

METHODOLOGY

Data to be examined in this dissertation come from the Measures of Effective Teaching (MET) project, a large-scale dataset supported by the Gates Foundation and compiled by the University of Michigan. The project includes the "largest study of classroom teaching ever conducted in the United States" (Gates Foundation, 2010b, p. 4). The MET researchers collected a variety of indicators of teacher quality over a two-year period (academic year [AY] 2009-2010 and AY 2010-2011), including student and teacher self-perception data, student achievement outcomes, video-recorded lessons taught by teachers, and teachers' pedagogical and content knowledge for teaching (Gates Foundation, 2012b).

The MET project was unique in that researchers examined classrooms of participating teachers during the AY 2009-2010 school year and then randomly assigned teachers to classrooms of students in the AY 2010-2011 school year (Gates Foundation, 2012b). Year One of the study (business-as-usual) assessed various measures of teaching effectiveness, whereas the Year Two (randomization) collected the same assessment data as Year One but was specifically designed to make causal inferences about various indicators of teaching quality. The same teachers from Year One were followed into Year Two, but in Year Two these same teachers were randomly assigned to a different classroom of students. The randomization process will be discussed further under the discussion of Year Two.

The MET project's data have been collected and were available through a restrictive data use agreement with the University of Michigan. Reports, study user guides, and code books are available on the MET and the Inter-University Consortium for Political and Social Research (ICPSR), and information from these guides is synthesized below.

Access to the Measures of Effective Teaching Dataset

The dissertation research was approved by the Institutional Review Board of the University of Northern Colorado (see Appendices A and B). Data use agreements for both the University of Northern Colorado and the University of Michigan were reviewed by attorneys at both institutions and were endorsed by designated officials at each institution. The Institutional Review Board approval along with the signed Data use agreements were submitted as part of the application to ICPSR. The ICPSR approved the investigation and granted access to the MET data via a remote desktop in a data secure room at the University of Northern Colorado.

Data collection was supported by the Bill Gates Foundation and compiled by the University of Michigan. Data were accessed through the ICPSR MET Virtual Data Enclave (VDE) through the University of Michigan. To log into the VDE each time, a randomly generated secure identification (ID) passcode was generated on an external device (e.g., iPhone Duo SecurID application). After the recognition of the assigned username and password, the secure network prompted the user to enter the iPhone Duo passcode. All MET data and statistical program software were only accessible within the VDE with no Internet connection. All requested log files, syntax, and output had to be saved in the disclosure review folder in order for ICPSR to locate the documents when data requests were submitted. Each time these documents were to be accessed, an e-mail ticket had to be submitted to ICPSR from a personal computer with the location and name of the requested files in the disclosure review folder. The ICPSR then would remove all identifiable information before sending the requested files and documents back to the requester with an average seven- to ten-day turn-around period.

Recruitment and Sample

Year One Design: Business-As-Usual

The Year One study design (AY 2009-2010), also known as Year One full sample, included 2,741 fourth through ninth grade teachers working in 317 schools in six large school districts in the United States. The six participating districts were as follows: Charlotte-Mecklenburg (North Carolina) Schools, Dallas (Texas) Independent School District, Denver (Colorado) Public Schools, Hillsborough County (Florida) Public Schools, Memphis (Tennessee) City Schools, and the New York City (New York) Department of Education (Gates Foundation, 2012b). Specific information for the full sample for Year One and Year Two and the randomization analytic sample are displayed in Table 1. In addition, Table 1 highlights the sampling plan for each level of participants.

Table 1

Samples of the Measures of Effective Teaching Project for Year One and Year Two

Sampling plan	Year One Full teacher sample (AY 2009-2010)	Year Two Full teacher sample (AY 2010-2011)	Year Two Teacher randomization sample (AY 2010-2011)*
Districts	6 districts	6 districts	6 districts
Schools	Opportunity sampling (grade by subject exchange groups required). 317 schools.	310 schools continue	284 schools, teachers randomly assigned to classes.
Teachers	Opportunity sampling (teachers must be in exchange group at school). 2,741 teachers.	2,086 teachers continue	1,159 teachers randomly assigned to classes during summer.
Class sections	Opportunity sampling (specialist teachers nominate class sections for study). 4,497 class sections.	1,909 class sections present in second year of the study.	1,379 sections (one per teacher) randomly assigned by MET researchers.

Note. Randomization sample is a sub-group within the full-sample of teachers. The subset of teachers at grades fourth and fifth were the actual sample examined in this dissertation and are described Table 2 of this investigation. From *Measures of Effective Teaching (MET) Longitudinal Database (LDB): A User Guide to the "Core Study" Data Files Available to MET Early Career Grantees* (No. ICPSR34414) (p. 7), by Bill and Melinda Gates Foundation, 2012b, Ann Arbor, MI: Inter-University Consortium for Political and Social Research.

Districts. Districts were selected as a matter of convenience by the MET staff, and personnel within districts were recruited through the process of "opportunity" sampling over the period of July to November 2009 (Gates Foundation, 2012a, p. 8).

Large urban districts either receiving support from the Gates Foundation to develop human resource systems or having previously worked with the foundation were recruited to participate. “The final six districts were selected based on interest, a sufficient staff size, central office support for the MET program, a willingness and capacity to participate in all parts of the data collection process, and local political and union support for the project” (Gates Foundation, 2012b, p. 16). Each participating district received a grant from the Gates Foundation to assist in the hiring of at least one full-time district-level project coordinator to oversee the project.

Schools. Schools within participating districts had principals who likewise expressed willingness to take part in the investigation. Schools with tentatively interested principals were screened, and those with certain characteristics were excluded: schools serving only special education students, alternative schools, community schools, autonomous dropout and pregnancy programs, returning education schools, vocational schools, and schools with team teaching whereby it would be difficult to identify the effects of a specific teacher (Gates Foundation, 2012b).

Schools serving target grades 4 through 9 and those with a principal who agreed to participate and create equivalent groups of students that could be randomly assigned to a teacher during Year Two of the study were included. For the random assignment to be feasible, it was required for the school to have at least three teachers who were assigned to one of the MET project’s focal subject/grade combinations. That is, teachers with the following combinations were included: grades 4 to 8 English/language arts (ELA), grades 4 to 8 mathematics, grade 9 English, grade 9 algebra 1, and grade 9 biology (Gates Foundation, 2012b). “Schools that could not form at least two exchange groups with at least three participating teachers were eliminated from the study" (Gates Foundation, 2012b, p. 17).

A grant-funded district coordinator led the school recruitment efforts in each district (Gates Foundation, 2012b). Schools identified as eligible were invited to participate in the study via a standard letter describing the MET project, along with further encouragement and information provided by the district coordinators during informational meetings. The 317 participating schools were offered $1,500 in addition to $500 a year to pay for a school project coordinator and minor incentives such as school supplies. In addition, the video recording equipment required for the classroom observations was donated to the school at the end of the study.

Teachers. Teachers being recruited for participation within the schools were mailed an invitation to participate in the MET project and encouraged to participate from school principals, school-level coordinators, and the grand-funded district coordinator (Gates Foundation, 2012b). "Incentives of $1,000 at the beginning and $500 at the end of the study were offered to teachers in participating schools along with small budgets awarded to districts to provide thank-you gifts to participating teachers" (Gates Foundation, 2012b, p. 17). Once the principal from the recruited school agreed to participate, all teachers who met the study's target grade/subject combinations and agreed to participate, were assigned to an exchange group (Gates Foundation, 2012b). To ensure exchange groups would be possible for random assignment of classrooms of students in Year Two of the study, teachers were excluded if (a) they were team teaching (working with a second teacher in the classroom) or looping (staying with children at the end of one year, and taking on the next higher grade assignment), (b) the teacher was not planning to stay in the same school and teach the same subject the following year, and (c) there were less than two other teachers with the same grade/subject teaching assignment. This selection process resulted in 2,741volunteer teachers from 317 schools in six districts (Gates Foundation, 2012b).

Students. The students in the MET sample were included as a result of all these aforementioned processes. In other words, the “selection of teachers and their observed class sections determined the student sample for the study, and once students were identified, efforts were made to include all students from the classrooms selected for the study” (Gates Foundation, 2012b p. 19). Informational fliers and consent forms were provided to families, including a description of the process of passive consent, in which parents had the opportunity to remove their child from the study. One district, Hillsborough County Public Schools, was an exception in that it required active consent; students had to bring in signed permission slips to be included as part of the study. If students opted out of participating they did not take the student survey or supplemental assessments, and during video recording they were instructed to sit in a specific section of the room in order to not be video recorded. Regardless whether parents agreed to allow their children to participate in the study, administrative data and state assessment aggregated scores were obtained and used for the study.

Year Two Design: Randomization

For the Year Two study design (AY 2010-2011), the same teachers from Year One also known as the Year Two full sample continued in the study, which included 2,086 teachers in 310 schools and in six large school districts.

Randomization process. Year Two included a randomization component in which teachers were randomly assigned to classrooms. The randomization process began in Year One of the study and included schools that had at least three teachers in a grade teaching the same subject, also known as an exchange group (Gates Foundation, 2012b). At least two of the teachers had to be teaching in the same school at the time of randomization in order to be included in the study.

School principals completed spreadsheets for course schedules and a roster for all classrooms on the schedule in the spring and summer of 2010. The schools then sent the classroom schedules and classroom rosters to the MET project team. The MET project team, in turn, returned the district's teacher assignments for each district. In the MET project, a classroom of students was randomly assigned to one of the teachers within the exchange group, known as "randomization blocks" in a given school (Gates Foundation, 2012b, p. 11). The purpose of the random assignment of classrooms of students to teachers was to prevent selection bias in the sorting of teachers and classrooms of students. Furthermore, the design allowed researchers to examine relationships among measures across Year One and Year Two.

Randomization sample. A full sample of 2,086 teachers in 310 schools continued into the Year Two sample, but not all teachers could be randomized due to the exchange group leaving the study or the school withdrawing consent to randomization. During the summer of 2010, 1,159 teachers in 284 schools served as the randomization sample. More specifically, from Year One to Year Two, 11 schools including 60 teachers dropped from the MET study and were not included in Year Two data collection (Gates Foundation, 2012b). As Table 2 shows, "24% of the year one teacher sample was not included in the year two sample," with particular attrition rates between Years One and Two varying by districts, ranging from about "21% of teachers in Denver to about 27% in Dallas" (Gates Foundation, 2012b, p. 19).

Table 2

Focal Grade Sample for Year One and Year Two

Grade/subject	Full Year One Teacher sample (AY 2009-2010)	Full Year Two Teacher sample (AY 2010-2011)	Analytic sample
4th and 5th grade ELA	138	Randomized: 98 Non-randomized: 29	98
4th and 5th grade mathematics	102	Randomized: 67 Non-randomized: 31	67
4th and 5th grade ELA and mathematics	634	Randomized: 305 Non-randomized: 52	305

Note. Table modified to display only the focal grades/subjects used in the present study. From *Measures of Effective Teaching (MET) Longitudinal Database (LDB): A User Guide to the "Core Study" Data Files Available to MET Early Career Grantees* (No. ICPSR34414) (p. 20), by Bill and Melinda Gates Foundation, 2012b, Ann Arbor, MI: Inter-University Consortium for Political and Social Research.

Anticipated reasons for attrition included three possible scenarios. First, students left the school or district. Random assignment occurred in summer 2010 before schools were certain students would return to the same school or district in the fall. Second, teachers left the school or district. This may have included teaching a different subject or grade, a loss of interest, or illness during the study (Gates Foundation, 2012b). The final reason was because schools chose not to implement the randomization process in their schools.

Analytic Sample

Teachers who participated in Year One and also participated in Year Two were referred to as the analytic sample. Therefore, there were no teachers in Year Two who did not participate in Year One.

Present Study Sub-Sample of Interest

The MET project staff collected data for grades 4 through 9; however, the present study specifically examined elementary grades 4 and 5. For these two grades, MET focused on ELA and mathematics. The majority of participating grade 4 and 5 teachers were subject-matter generalists who taught multiple subjects to a single class of students as opposed to subject-matter specialists who taught the same subject to more than one class section of students per day (Gates Foundation, 2012b). Table 2 includes the sample of interest for the present study.

Data Collection

The MET project included multiple measures on indicators of teacher effectiveness: (a) teachers' pedagogical content knowledge, (b) students' perceptions of the classroom instructional environment, (c) teachers' perceptions of working conditions and support at their schools, (d) students' achievement gains on state standardized tests and supplemental tests, and (e) classroom observations and teachers' reflections. The dataset included a district ID, school ID, teacher ID, subject ID (e.g., ELA, mathematics, or both), and student ID, a coding scheme that allowed for the linkages between multiple data files.

For the present study, classroom observations of teacher-student interactions, classroom-level achievement data, and classroom-level demographic information were combined to create the database used for the analyses of the impact of teacher interactional quality on classroom achievement outcomes.

Conceptual Model

The theory of change driving this research, represented in the logic model in Figure 1, demonstrated classroom of students' assignment to high quality teacher-child interactions impact on achievement outcomes, particularly in the case of students eligible for free or reduced price lunch.

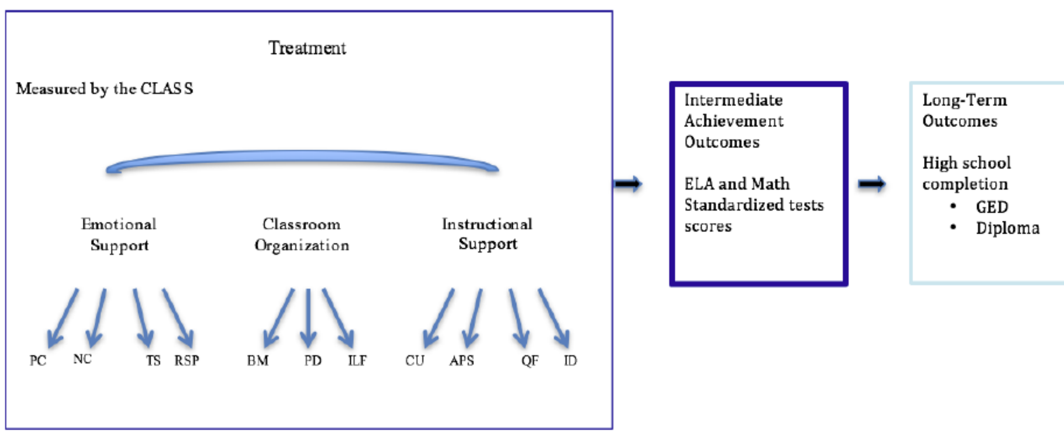


Figure 1. Conceptual model for this dissertation. Note: Tables 3, 4, and 5 provides a description of the three domains and dimensions.

Treatment: Observational Ratings of Interactions Between Teachers and Students

A primary component of the MET project is a tripartite observational scheme on the quality of teacher-student interactions in the classroom. The Classroom Assessment Scoring System (CLASS™) (La Paro et al., 2004) served as the common metric for measuring interactions between students and teachers and the treatment of primary interest in the investigation. The CLASS™ is an observational protocol based on the teaching through interactions framework (TTI) (Hamre et al., 2013), which organized teacher-child interactions into three domains: emotional support, classroom organization, and instructional support.

The three broad domains were measured using eleven dimensions of teacher-child interactions (see Tables 3, 4, and 5). The dimensions were based on several observable and measurable indicators. For example, the domain of emotional support referred to the emotional tone in a classroom, which can be measured along four dimensions: positive climate, negative climate (reverse coded), teacher sensitivity, and regard for student perspectives, which consists of multiple indicators such as respect, negative affect, responsiveness, and support for autonomy (Gates Foundation, 2012b; La Paro et al., 2004; Pianta et al., 2008).

The second domain, classroom organization, refers to the ways a classroom is structured to manage students' behavior, time, and attention, which can be measured along three dimensions: behavior management, productivity, and instructional learning formats. Last, the third domain, instructional supports, refers to the ways a teacher provides supports to encourage student conceptual understanding and student problem solving and can be measured along four dimensions: content understanding, analysis and problem solving, instructional dialogue, and quality of feedback (Pianta et al., 2008).

Table 3

Emotional Support Domains and Dimensions

Domain	Dimension	Indicator	Description
Emotional support	Positive climate	Relationships Positive affect Positive communication Respect	Reflects the overall emotional tone of the classroom and the connection between teachers and students
	Negative climate	Negative affect Punitive control Sarcasm/disrespect	Reflects overall level of expressed negativity in the classroom between teachers and students (e.g., anger, aggression, irritability)
	Teacher sensitivity	Awareness Responsiveness Addresses problems Student comfort	Encompasses teachers' responsivity to students' needs and awareness of students' level of academic and emotional functioning
	Regard for student perspectives	Flexibility and student focus Support for leadership and Autonomy Student expression Meaningful peer interactions	The degree to which the teacher's interactions with students and classroom activities place an emphasis on students' interests, motivations, and points of view, rather than being entirely teacher-driven

Note. Indicators were rated on a 7-value scale. From *Learning About Teaching Research Report*, by Bill and Melinda Gates Foundation, 2010b, Seattle, WA: Author.

Table 4

Classroom Organization Domains and Dimensions

Domain	Dimension	Indicator	Description
Classroom organization	Behavior management	Clear behavior Expectations Proactive Redirection of misbehavior Classroom order	Encompasses teachers' ability to use effective methods to prevent and redirect misbehavior by presenting clear behavioral expectations and minimizing time spent on behavioral issues
	Productivity	Maximization of learning Time Organization Transitions Preparation	Considers how well teachers manage instructional time and routines so that students have the maximum number of opportunities to learn
	Instructional learning formats	Active facilitation Multiple modalities Active engagement Clear learning targets	The degree to which teachers maximize students' engagement and ability to learn by providing interesting activities, instruction, centers, and materials

Note. Indicators were rated on a 7-value scale. From *Learning About Teaching Research Report*, by Bill and Melinda Gates Foundation, 2010b, Seattle, WA: Author.

Table 5

Instructional Support Domains and Dimensions

Domain	Dimension	Indicator	Description
Instructional support	Content understanding	Understanding Communication of concepts Focus on background Knowledge Content/procedural Knowledge Practice	Refers to both depth of the lesson content and the approaches used to help students comprehend the framework, key ideas, and procedures in an academic discipline. At a high level this refers to interactions among the teacher and students that lead to an integrated understanding of facts, skills, concepts, and principles
	Analysis and problem solving	Inquiry and analysis Novel application Metacognition	Assess the degree to which the teacher facilitates students' use of higher-level thinking skills, such as analysis, problem solving, reasoning, and creation through the application of knowledge and skills. Opportunities for demonstrating meta-cognition (i.e., thinking about thinking)
	Quality of feedback	Scaffolding Feedback loops Prompting thought Processes Providing information Encouragement and affirmation	Considers teachers' provision of feedback focused on expanding learning and understanding (formative evaluation), not correctness or the end product (summative evaluation)
	Instructional dialogue	Content driven exchanges Active role Facilitation/extended dialogue	Captures the purposeful use of dialogue-structured, cumulative questioning and discussion that guide and prompt students' understanding of content and language development

Note. Indicators were rated on a 7-value scale. From *Learning About Teaching Research Report*, by Bill and Melinda Gates Foundation, 2010b, Seattle, WA: Author.

Classroom Assessment Scoring System™ reliability. The CLASS™ has been validated in more than 4,000 classrooms across the United States and numerous international locations (Gates Foundation, 2010b). The CLASS™ was initially standardized on early-childhood classroom and most recently elementary and secondary classrooms (preschool through 12th grade). Recent validation studies have tested the three-domain conceptual framework against other models and found the three-factor model fit observational data collected from a range of studies, across a broad range of settings (e.g., rural vs. urban), and across preschool to fifth grade classrooms. Data from over 4,000 preschool to fifth grade classrooms suggest the proposed three-domain model fit better $\chi^2(728) = 62$ $p < .001$, CFI = 0.844, RMSEA = 0.47) than alternative one- or two-factor solutions (Hamre et al., 2013). However, this structure was not always found; Kane and Staiger's (2012) results from the MET project suggested a single overall factor for the secondary version of the CLASS™, with a significant element of effective teaching emerging from the separate domains. This may be because the indicators and descriptions varied slightly among the different versions of the CLASS™ instrument (e.g., infant/toddler, prekindergarten, lower elementary, upper elementary, secondary). Furthermore, the secondary CLASS™ instrument is relatively new.

To further validate the conceptual framework and address the concern of each domain of teacher-student interactions being distinct yet correlated with the other domains, Hamre et al. (2014), using a sample of 325 preschool classrooms, proposed a bi-factor model forcing all CLASS™ dimensions into two factors, responsive teaching and proactive management and routines (CFI = 0.96, RMSEA = 0.11) compared to the original three-factor model (CFI = 0.93, RMSEA = 0.13). These results suggested the bi-factor model including responsive teaching consisting of mostly the emotional support domains and proactive management and routines may be a better fitting model and suggested the dimension of instructional support played a small role for promoting close relationships with teachers.

These findings highlight discrepancies between predictive models using the bi-factor versus the three-factor approaches and require further exploration (Hamre et al., 2014). Many studies have further reported very high correlations among the three domains, limiting the ability to clearly examine the extent to which individual domains of interactions are associated with specific domains of a student's development (Kane & Staiger, 2012; Mashburn et al., 2008; Rudasill et al., 2010). This dissertation used the three-factor model that serves as the foundation for the Hamre et al. (2013) TTI framework and was found to be consistent across Hamre and Pianta's decade long research agenda. The three-factor solution has been the best fitting model in numerous studies and preferable to one- or two-domain solutions (Hamre et al., 2013; Pakarienen et al., 2010). Hamre et al. (2013) recommends using the three-factor solution over the two-factor solution until further research can be replicated and a better scoring system can be further validated.

Measures of Effective Teaching training and reliability. In order to better understand the domains and indicators as well as the reliability process for CLASS™ observational raters, I participated in a two-day prekindergarten CLASS™ training through Teachstone offered in Denver, Colorado, summer of 2015. To learn more about how the CLASS™ was specifically used in the MET Project, I attended a professional development course on observational measures and video analysis at the

American Educational Research Association, spring 2015. The training and process used by MET was very similar to the CLASS™ reliability workshops offered through Teachstone.

The MET researchers met with the CLASS™ developers and discussed the psychometric properties and the feasibility of implementation based on the cost in time and money to train observational raters and district coordinators to oversee the fidelity of implementation. Prior to the MET project, the CLASS™ had never been used on such a large scale, and the complexity and feasibility of the study needed to be considered. For the CLASS™, a large number of raters (N = 500) needed to be trained quickly within 30 to 50 hours in order to observe more than 20,000 lessons at a reasonable cost. Raters also needed to be trained to adequately capture the complexity of interactions in the classroom using the complex 48-matrix scale. Ultimately, the developer's philosophy and viewpoint influenced the final version of the instruments used in the MET project (American Educational Research Association, 2015).

With this being noted, MET researchers do not own rights to the CLASS™ instrument. The current published CLASS™ instrument is only available for purchase through Teachstone, and the variable labels provided in the MET data were indicative of the CLASS™ instrument (American Educational Research Association, 2015). Reliability estimates were not only low for the CLASS™ but also for other very well-known and respected observational protocols such as the Danielson framework (created by Charlotte Danielson) (American Educational Research Association, 2015). Due to negotiations between MET researchers and the instrument developers, reliability estimates were not published in the final MET reports and was recognized as a limitation of the MET project (American Educational Research Association, 2015). However, information on the estimates and reasons for low reliability were shared at the American Educational Research Association/MET training professional development meeting. Low reliability may have been influenced by the massive amount of raters being trained in a short period of time on very complex observational frameworks.

The MET researchers trained raters to observe teacher-student interactions and classroom effects using the observable indicators of the CLASS™. First, observers attended a workshop led by a CLASS™ certified trainer to attain initial reliability on the CLASS™. Training workshops consisted of guided practice with coding videotaped classroom footage. After the training workshops, a reliability test involving five or six cycles of 20 to 40 minute videos required coders to score at least 80% match (within one scale point) with the master codes on the global rating scales (American Educational Research Association, 2015). The CLASS™ raters were required to do a reliability re-certification test every 12 months.

Process. In this dissertation, data were obtained from observers who used the upper elementary version of the CLASS™ in grades 4 and 5. The majority of teachers were observed and video recorded four times throughout one academic year during. Observers watched a video of classroom interactions for a prescribed segment of time (e.g., 20 minutes) while they coded and took detailed field notes about specific teacher and student behaviors and interaction patterns (Gates Foundation, 2012b). Observers had 10 minutes to compare their field notes with the CLASS™ manual and record a final code for each dimension of the three domains. For example, the broad domain of emotional support included four dimension codes for (relationships, positive affect, positive communication, and respect) based on the multiple indicators defining each dimension (see Table 3).

Global ratings for each video observation were made on a 7-point scale assigned based on alignment with anchor descriptions at high (6,7), mid (3,4,5), and low (1,2). The MET researchers gave global ratings of teachers based on these categories; however, the data included observational ratings for each of the seven indicators rather than a score for each category. In the MET project when teachers were using the CLASS™, high-quality interactions were indicated with teachers being assigned a score of 6 or 7 (Gates Foundation, 2012a).

This dissertation hypothesized that high quality teacher-student interactions, as defined by the domains and dimensions of the CLASS™, facilitated classroom academic achievement. Treatment was defined as the classroom assignment to a teacher judged to be somewhere on a continuum of interactional quality. The MET data recorded the CLASS score on a scale from 1 to 7. Operationally, an average score was calculated for each domain, and then the three scores were averaged for one overall composite CLASS score. A high CLASS score represented a score between 6 and 7, the same level used by Pianta, Hamre, and their colleagues (Hamre et al., 2013). However, early MET grantee researchers' preliminary report findings from Year One suggest a small proportion of participating teachers received exemplar scores on the indicators of the CLASS™ with the exception of behavior management and productivity (Kane & Staiger, 2012). Therefore, this study first explored descriptives of participating teachers CLASS scores to investigate the range of teacher interactional quality.

Student Achievement Data:
Intermediate Outcomes

The MET project shares the premise that a teacher's evaluation should depend on his or her students' achievement gains (Gates Foundation, 2010c). In addition to observational data of teachers, MET researchers used existing student state assessments to examine teacher effects on student learning based on state curriculum for federal accountability purposes (Gates Foundation, 2010c). For grades 4 through 8, student achievement was measured using state assessments administered by each district in reading (ELA) and mathematics (Gates Foundation, 2012b). Each state's ELA test and mathematics test were administered according to state-specific timelines and procedures and were administered to all eligible students. Specific state standardized assessment names were not included in the published MET project's user guides. In general, these state assessments were multiple-choice tests and targeted the same academic areas but there was slight variation across tests and districts in testing dates (Gates Foundation, 2012b) (see Table 6). Therefore, in the reporting of the data in MET data files, MET researchers first standardized the student achievement scores to have a mean of zero and a standard deviation of one (for each district, subject, year, and grade level), also known as rank-based *z*-scores.

District Data: Classroom
Demographics

The MET researchers used data from the district-wide files to generate aggregated information at the classroom-level to include in the base analytic files. These generated aggregate variables used in this analysis included proportion of students of different race, participation in the federal free or reduced lunch subsidy program, and standardized state assessment scores (Gates Foundation, 2012b). The study more specifically assessed the impact of achievement gains for classrooms of students from low socioeconomic backgrounds by accessing the reported proportions of students receiving free or reduced lunch.

Table 6

State Standardized Assessment Schedule by District

District	State assessment administration
Charlotte	March 9-20; April 22-May 14; May 3-7; May 25- June 10
Dallas	March 22-April 2; April 26-30; May 10-14; May 19-26
Denver	March 1-19; April 26-May 6
Hillsborough	March 9-19; March 29-April 29; April 19-May 19
Memphis	April 12-16; April 29; May 11-12; May 19-21
New York City	April 26-28; May 5-7; June 14-24

Note. From *State Assessment and the MET Project*, by Bill and Melinda Gates Foundation, 2010c, Seattle, WA: Author.

Data Analysis

All analyses were completed using R, version 3.2.3 (R Core Team, 2015), and STATA, version 12 (StataCorp, 2011), statistical software programs. The specification is defined in equations (1) through (6) under Research Questions Q2, Q3, and Q4. Each equation assessed the importance of a teacher interactional quality on classroom achievement state standardized test scores in ELA and mathematics.

Exploratory analysis was done to examine the distributions of participating teachers during Year One of the study to determine how fourth and fifth grade teachers varied by interactional quality as measured by the CLASS™ instrument. Frequency plots were examined to see the overall distribution of classroom teachers and the range of CLASS scores.

Research Question Q1: Distribution of Classroom Teachers' Interactional Quality

Q1 Is there a difference in the distribution of classroom teacher's interactional quality when classrooms have higher proportions of free or reduced price lunch status (i.e., low socioeconomic status), and when classrooms are assigned to teachers using business-as-usual practices?

Based on findings by Clotfelter et al. (2006) indicating an unequal distribution of students' socioeconomic status to highly experienced teachers, the likelihood exists for teachers higher in interactional quality to be disproportionately assigned to more affluent students. This dissertation extends on previous research by specifically examining the relationship between teacher interactional quality and classroom proportion of free or reduced price lunch when classrooms of students were assigned to teachers going about usual practice in the school. Therefore, the business-as-usual year served as a baseline measurement of the distribution of the classroom when no random assignment had taken place.

A descriptive approach was used to examine this research question by examining scatterplots of classroom teacher CLASS scores in conjunction with classroom proportion of free or reduced price lunch. This line of analysis further investigated whether a relationship exists between classroom teacher interactional quality and classroom proportion of free or reduced price lunch. In other words, it examined whether teachers higher in interactional quality were more likely to be distributed among classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic status) or among classrooms with lower proportions of free or reduced price lunch (i.e., high socioeconomic status).

The hypotheses stated below predicted a difference in the distribution of classroom teacher CLASS scores based on the proportion of classroom free or reduced price lunch. Specifically, it is anticipated that classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic status) will be more likely to be assigned to classroom teachers with lower CLASS scores. Under the null hypothesis, classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic status) would be no more likely to be assigned to classroom teachers with a lower CLASS score than would classrooms with a lower proportion of free or reduced price lunch (i.e., high socioeconomic status).

H01 Classrooms with higher proportions of free reduced lunch status (i.e., low socioeconomic status students) will not suggest preferential assignment of classroom teachers to classrooms of students.

HA1 Classrooms with higher proportions of free reduced lunch status (i.e., low socioeconomic status students) will suggest preferential assignment of classroom teachers to classrooms of students.

Research Question Q2:
Business-as-Usual
Practices

Q2 Is there a positive association between classroom teachers' interactional quality and classroom achievement outcomes under business-as-usual assignment practices? Is the association different for low socioeconomic status students?

Two regressions were used to determine if the addition of information regarding classroom demographics was associated with the teacher's overall CLASS score, and whether the CLASS scores were associated with ELA and math achievement outcomes. The subscript *c* denotes the use of classroom-level variables. Year One, business-as-usual-sample was used for the model.

$$(1)\ ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$$(2)\ MATH_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of proportion of English Language Learners (ELL)
β_2 = The effect of proportion of Special Education (SPED) status
β_3 = The effect of proportion of Black students
β_4 = The effect of proportion of male students
β_5 = The effect of proportion of free-and-reduced price lunch
β_6 = The effect of teacher interactional quality score as measured by the CLASS™
β_7 = The effect of the interaction between teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

The dependent variable ELA_c and $MATH_c$ were the classroom ELA or MATH standardized test score, also known as the classroom achievement outcome. The parameters of interest, β_1 through β_5, in parentheses represent the effect of classroom demographics, including the classroom proportions for ELL status, SPED status, Black students, male and free or reduced price lunch status on classroom achievement outcomes. The β_6, represents the impact of exposure to a classroom teacher's interactional quality (CLASS score 1 to 7) on classroom achievement outcomes. In addition, the parameter β_7 measured the effect of the interaction between a classroom teachers' interactional quality and the classroom proportion of free or reduced price lunch status on classroom achievement outcomes. In other words, the interaction effect suggests a change in the effect of a classroom teacher's CLASS score on ELA or MATH for different values of the proportion of students in the classroom with free or reduced price lunch status.

As discussed in Chapter II, teacher quality defined by teacher experience had a modest positive impact on elementary school reading and mathematics achievement. However, there is a much larger teacher effect in schools with a large proportion of low socioeconomic status students, suggesting a greater impact of teacher quality for this subgroup (Nye, Konstantopoulos, & Hedges, 2004). Therefore, a goal of this dissertation was to estimate the effect of teacher interactional quality across a relatively heterogeneous subgroup to see whether classroom achievement outcomes benefited more than classrooms with a lower proportion of free or reduced price lunch students.

It was anticipated the parameter of interest β_6 using Year One data—when classrooms were assigned to a teacher higher interactional quality to be positive for both ELA and MATH classroom achievement outcomes and that the magnitude of the impact would be greater for classrooms with high proportions of free or reduced price lunch (i.e., low socioeconomic status). Under the null hypothesis, a change in classroom achievement scores will be a purely random effect and not due to teacher interactional quality.

H01 Assignment to a classroom teacher higher in interactional quality will suggest no impact on classroom achievement scores.

HA1 Assignment to a classroom teacher higher in interactional quality will suggest an impact on classroom achievement scores.

Research Question Q3:
Randomization

Q3 Is there an impact of classroom teachers' interactional quality on classroom achievement outcomes under random assignment practices? Is the impact different for low socioeconomic students?

To answer this research question, a re-estimate of equations (1) and (2) was done, using the same classroom achievement ELA and MATH outcomes, but this time using Year Two data when teachers were randomly assigned to classrooms of students. Equation (3) and (4) represented the estimated model (*c* indexes classroom-level variables).

$$(3)\ ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$$(4)\ MATH_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of the proportion of English Language Learners (ELL)
β_2 = The effect of the proportion of Special Education (SPED) status
β_3 = The effect of the proportion of Black students
β_4 = The effect of the proportion of male students
β_5 = The effect of the proportion of free-and-reduced price lunch
β_6 = The effect of teacher interactional quality score as measured by the CLASS™
β_7 = The effect of the interaction between teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

Random assignment allowed for isolation of the impact of teacher interactional quality on classroom achievement outcomes by removing the potential bias introduced by non-random sorting that occurs when teachers are assigned to classrooms of students under business-as-usual practices. In other words, random assignment removed the possibility of assortative matching of teachers higher in interactional quality with classrooms based on student characteristics such proportion of free or reduced price lunch status. Under random assignment, estimates of β_6 reflected the impact of being assigned to classroom teachers with higher CLASS scores on classroom ELA and MATH achievement outcomes.

As previously discussed in Research Question Q2, it was hypothesized that the impact of assignment to classrooms with a teacher higher in interactional quality would be positive and that the magnitude of the impact would be greater for classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic). Again, under the null hypothesis, a change in classroom achievement scores will be a purely random effect and not due to teacher interactional quality.

H01 Assignment to a classroom teacher higher in interactional quality will suggest no impact on classroom achievement scores.

HA1 Assignment to a classroom teacher higher in interactional quality will suggest an impact on classroom achievement scores.

Research Question Q4: Difference Between Business-As-Usual and Randomized Estimates for Year One and Year Two

Q4 How does the magnitude of the impact of classroom teachers higher in interactional quality on classroom achievement outcomes during random assignment compare with estimates of the association between teachers higher in interactional quality and student outcomes under business-as-usual practices?

This question extends Research Questions Q2 and Q3 by specifically asking whether teacher interactional quality impact on classroom achievement outcomes differed based on the year of the study. And more specifically, if the impact of teacher interactional quality on classroom achievement outcomes change based on the proportion of free or reduced lunch status, and if the difference in impact was different based on the year of the study.

To answer this question, a single model was created using all of the same data from Year One and Year Two, with an indicator for being observed during the business-as-usual year (as opposed to the random-assignment year). Where Year One = 0 and Year Two = 1.

$$(5)\ ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 YEAR_c + \beta_7 CLASS_c + \beta_8 LUNCH_c * YEAR_c + \beta_9 LUNCH_c * CLASS_c + \beta_{10} YEAR_c * CLASS_c + \beta_{11} LUNCH_c * YEAR_c * CLASS_c + \mathcal{E}_c$$

$$(6)\ MATH_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 YEAR_c + \beta_7 CLASS_c + \beta_8 LUNCH_c * YEAR_c + \beta_9 LUNCH_c * CLASS_c + \beta_{10} YEAR_c * CLASS_c + \beta_{11} LUNCH_c * YEAR_c * CLASS_c + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of proportion of English Language Learners (ELL)
β_2 = The effect of proportion of Special Education (SPED) status
β_3 = The effect of proportion of Black students
β_4 = The effect of proportion of male students
β_5 = The effect of proportion of free-or-reduced price lunch
β_6 = The effect of Year (0= year one; 1= year two)
β_7 = The effect of teacher interactional quality score as measured by the CLASS™
β_8 = The effect of the interaction between proportion of free-or-reduced price lunch status and year
β_9 = The effect of the interaction between proportion of free-or-reduced price lunch status and teacher interactional quality
β_{10}= The effect of the interaction between teacher interactional quality and year
β_{11} = The effect of the interaction between year, teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

The parameter for being assigned to a classroom teacher with a higher CLASS score indicated whether teacher interactional quality had an impact on classroom ELA or MATH achievement outcomes. The YEAR indicator examined whether there was a difference in classroom achievement outcomes between Year One and Year Two, for the average value of teacher interactional quality. In other words, the research question examined which year showed greater achievement on average.

The interaction term for CLASS and YEAR examined how much the relationship between teacher interactional quality and classroom achievement changed between Year One and Year Two. The interaction term for CLASS and LUNCH examined whether the effect of the classroom proportion of free or reduced price lunch on classroom achievement outcomes changed depending on the values of classroom teachers' interactional quality (i.e., CLASS scores). The third interaction, LUNCH and YEAR, examined whether the effect of classroom proportion of free or reduced price lunch changed from Year One to Year Two. Lastly, the three-way interaction between YEAR, CLASS, LUNCH examined whether the effect of classroom proportion of free or reduced price lunch on classroom achievement outcomes changed depending on classroom teachers CLASS scores and whether the effect changed from Year One to Year Two.

The coefficient for YEAR represented the average expected difference in classroom achievement outcomes between Year One and Year Two, for the average value of teacher interactional quality. Under the null hypothesis, if the estimated coefficient for YEAR is not significantly different from zero then there is no evidence for teachers' interactional quality impact on achievement outcomes to be different in the business-as-usual year in comparison to the random assignment year.

The interaction term for CLASS and YEAR, indicate whether the treatment effect differed between the two years of the study. If the estimated coefficient on the three-way interaction term of a classroom teachers' CLASS score, proportion of classroom free or reduced price lunch status, and year of the study design was statistically significant and positive, then there is evidence that the impact of teacher interactional quality on classroom achievement outcomes changed based on the proportion of free or reduced lunch status and that the difference in the impact was different based on the year of the study. A positive coefficient will provide evidence that the association between teacher interactional quality and achievement outcomes is greater than it was for the year of the study.

H01 If the estimated coefficient for YEAR is not significantly different from zero, there is no evidence the association between interactional quality and achievement outcomes are different in the business-as-usual year in comparison to the random assignment year.

HA1 If the estimated coefficient for YEAR is significantly different from zero, there is evidence the association between interactional quality and achievement outcomes are different in the business-as-usual year in comparison to the random assignment year.

Summary

Four research questions were analyzed to further examine the role of a classroom teachers' interactional quality on classroom achievement outcomes in ELA and mathematics. The first research question used descriptive statistics to examine whether there was a difference in the distribution of teacher interactional quality (CLASS score) based on the classroom proportion of free or reduced lunch status. For the second research question, a multiple regression model was used to examine whether there was a stronger association between teacher interactional quality and classroom proportion of free or reduced lunch receipt during Year One of the study when teachers went about their usual teaching practices in the classroom. The same regression model was used to answer the third research question, but differed by asking whether the association was stronger during Year Two of the study when teachers were randomly assigned to classroom rosters of students. The last research question added an indicator for year to the regression model to examine whether teacher interactional quality impact on classroom achievement outcomes was different based on the year of the study. Chapter IV of this dissertation discusses the results from Research Questions Q1, Q2, Q3, and Q4 and examines these results further in the context of the descriptive findings.

CHAPTER IV

ANALYSIS

The purpose of the present study was to examine the impact of teacher-student interactions on classroom English/language arts (ELA) and MATH achievement outcomes, as measured by the Classroom Assessment Scoring System (CLASS™) instrument. This chapter includes a description of the procedure for access to the Measures of Effective Teaching (MET) data, organization of data files, a descriptive review of the study's sample, and finally, the results of the statistical analyses developed to test the study's hypotheses.

Procedures

As outlined in Chapter III, data in this investigation came from the MET project, the largest study of United States classroom teaching to date. The MET researchers examined classrooms of participating teachers during the Year One design (academic year [AY] 2009-2010) and then randomly assigned teachers to classrooms rosters of students within schools in the Year Two design (AY 2010-2011) (Gates Foundation, 2012b). The first year of the study assessed various measures of teaching effectiveness, whereas the second year collected the same data and was specifically designed to make causal inferences about the effects of teaching quality.

Accessing the Data

Data collection was supported by the Bill Gates Foundation and compiled by the University of Michigan. Data were accessed through the Inter-University Consortium for Political and Social Research (ICPSR). The ICPSR makes the MET Virtual Data Enclave (VDE) available to approved users and is managed at the University of Michigan. The data log in process is detailed under data access in Chapter III.

In terms of data analysis, all requested log files, syntax, and output had to be saved in the disclosure review folder within the VDE. Anytime data wanted to be accessed outside of the VDE, an e-mail ticket request was submitted to ICPSR. The ICPSR typically took seven to ten days to remove the identifiable information and send the requested files back to the requester. Specific identifiable information could not be released to the requester from ICPSR, such as district identification (ID), school ID, teacher ID, or section ID information and districts or classrooms that had less than five in the sample. This sensitive information could be viewed within the VDE but could not be accessed outside of the VDE or reported in research findings.

Management of the Data

In order to combine multiple sources of data on teachers and their observed interactional quality on student outcomes, important variables such as district ID, school ID, teacher ID, and section ID were identified in all the data files of interest. The data files were then organized into a uniform format so that all files were either in long or wide format. Lastly, variables that were not of interest, such as variables related to sixth through eighth grade and students' perceptions were removed from the dataset. Thus only CLASS scores and relevant demographic variables were retained for analysis (see Appendices C and D).

Characteristics of the Data

Organization of the Data

The first step in the data analysis process was familiarizing with the multiple MET user guides and code books available on the ICPSR website and within the VDE. As a researcher I gained comfort with the coding conventions and data labels assigned by the MET researchers and the uniformity across the multiple data files and variables used in MET through a lengthy period of review and preliminary analysis. For this dissertation, classroom-level observation data were located in the Base Analytic: Section Files (#34309). The Base Analytic: Section Files included a data file for Year One and a separate data file for Year Two.

Missing Data

Missing data were analyzed using the merged dataset file, which included the full sample for Year One and the full sample for Year Two. Missingness patterns were examined using the Mice and VIM package in R. There were no missing values for any of the demographics except for the variable of interest LUNCH (i.e., free or reduced lunch). Figure 2, data matrix plot, visualized all cells of the data matrix by horizontal lines. Red lines indicated missing values and the grey scale was used for observed data. Small values were assigned a light grey, high values were assigned a dark grey, with values of zero displayed in white (Templ & Filzmoser, 2008). Figure 3, shows the missingness between DISTRICT, LUNCH (i.e., free or reduced lunch), overall CLASS score averages, and YEAR have a relationship. The solid blocks of red for LUNCH (i.e., free or reduced lunch) correspond to missingness in the district.

For example, District 56 did not report free or reduced price lunch status data, and thus the red represents the missingness for this district. And for YEAR, much less data for the CLASS score was missing for Year Two depicted at the bottom of the plot than Year One depicted at the top of the plot.

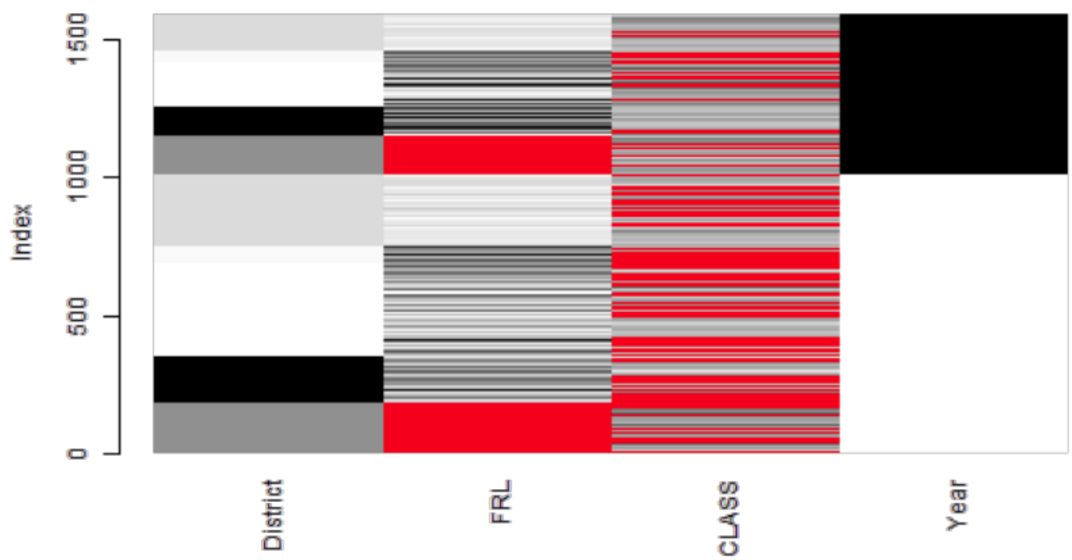


Figure 2. Data matrix plot of missingness. Red indicates missingness, and shading from white to black indicate relative size of entry values (white is the lowest observed value and black is the largest observed value).

The left-hand side of the barplot in Figure 3 shows a bar for each variable of interest and the bar height corresponds to the number of missing values in the variable. The right-hand side shows the variable combinations that were observed (i.e., horizontal axis) and the missing and non-missing values (i.e., vertical axis). The color red indicates missingness and the color blue represents observed data with corresponding frequencies on the right (Templ & Filzmoser, 2008).

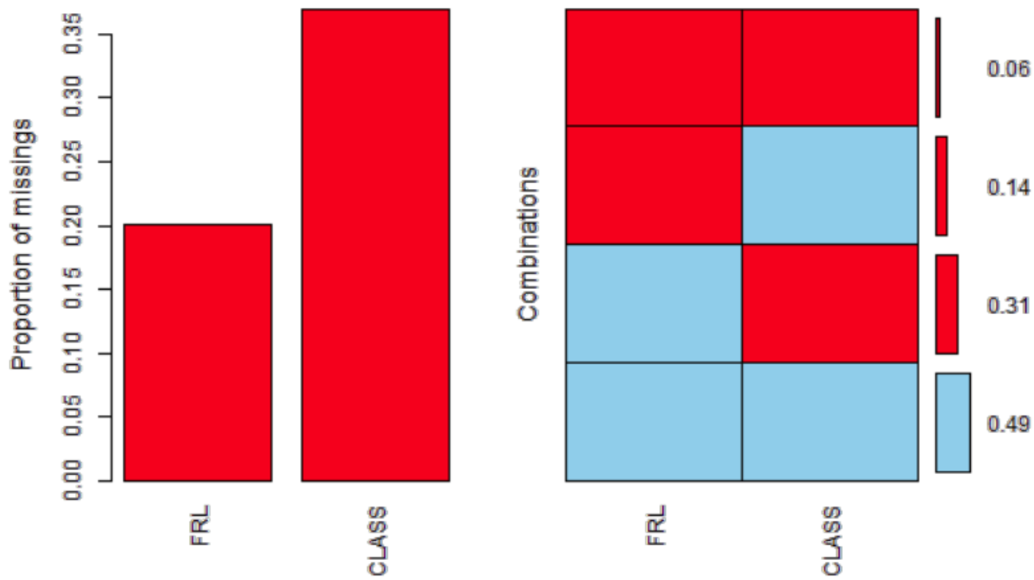


Figure 3. Aggregate plot analysis of missing data patterns. Red indicates missingness, blue indicates observed data. Proportion of missingness is represented on the left and patterns of missingness "co-missingness" on the right. The proportion of time the missingnes pattern was observed (adds to 100%).

There were four variables that had any sign of missingness (MATH, SPED, LUNCH, and CLASS score). However, MATH and SPED each had only one missing observation, and the missingness co-occurred with missingness in the CLASS scores. Therefore, only LUNCH and CLASS are displayed in Figure 2 since they were variables of interest and the only two variables with any amount of missingness. The barplot on the left shows the variable LUNCH (i.e., free or reduced lunch) had 20% of missingness whereas CLASS had more than 35% missingness. The plot on the right shows 49% of the data had no missing values and 6% missingness values when both LUNCH (i.e., free or reduced lunch) and CLASS variables were in the dataset. Also, the study was limited in the fact that the data were not missing completely at random, evidenced by Little's test ($p < .001$). This implies that there was a pattern in the missingness. Furthermore, the plots suggest different patterns for specific variables (e.g., LUNCH and CLASS) and that the data were missing not at random.

Imputation as a missingness technique was not used in this study because the CLASS variable of interest had a lot of missingness and there was no partial completion. In other words, it was not the case that there were two CLASS domains scores reported and only a score missing for the third domain. Instead, the dataset was missing all three CLASS domain scores. Furthermore, roughly 37% of the CLASS scores were missing in the dataset (see Figure 3). Therefore, CLASS scores were not missing completely at random which further complicates the analysis.

Similar problems existed with the LUNCH variable. For missinginess with the LUNCH variable, imputation also would not be ideal. The data were missing systematically for LUNCH. Every observation for LUNCH was missing for District 56, and this missingness did not occur for any other districts. Therefore, there is a pattern of missingness (i.e., an observed pattern) in the dataset, also known as missing at random. Furthermore, District 75 was eliminated from the sample since the district only reported observations for sixth, seventh, and eighth grade classrooms, and no observations were reported for fourth and fifth grade classrooms. The missingness patterns in the data represent a biased sample that reduces the generalizability of the sample.

Exclusionary Criteria

In organizing the data, observations that did not report data for the study's variables of interest were excluded. In the process, an analytic sample was first created and then any observation that had no missing values for the variables of interests were excluded. The first step in creating the analytic sample involved excluding teachers who did not participate in both Year One and Year Two of the study. Second, if a teacher participated in both years of the study, but the LUNCH value was not reported for the teacher/classroom, then the data were excluded. Third, if the teacher was not rated on any of the CLASS score domains, then the observation was excluded taking care of the concerns for missingness in the data. Teachers were then re-matched in order to ensure the teacher observations left in the sample were from Year One and Year Two and that data were recorded for LUNCH and CLASS scores. Lastly, one observation in the final dataset was removed because MET researchers coded the variable incorrectly as MALE rather than as a proportion.

Creation of the Analytic Sample

After the exclusion criteria were applied, there remained more missingness in the data. Teachers who participated in Year One who also were present in Year Two were identified as the analytic sample. Variables of interest were re-named for consistency across Year One and Year Two data files. An indicator variable was created for year with Year One = 0 and Year Two = 1. The created data files for Year One and Year Two were then merged into one data file, with the year indicator sorting variables by year of the study. For the analytic sample, the 303 fourth and fifth grade teachers who participated in Year One were the same teachers who participated in Year Two of the MET project.

Multiple Teacher Observations

In many cases in the base analytic section level files (i.e., classroom/teacher-level observation files), a teacher had two recorded CLASS scores. These two records were recorded for the same teacher, identifying two separates sections. In other words, there is one CLASS score observation for each observed classroom section taught by the teacher. For example, a teacher may have received one score for an ELA section and one score for a mathematics section. In some cases, a teacher taught two ELA sections or two mathematics sections and a score was recorded for each classroom section. Thus as the ratings of each section (i.e., ELA and mathematics) were independent of one another, the observations of the same instructor were kept in the dataset and treated as independent of one another.

Multiple Regression Assumptions

The first step in the analysis was to test the assumptions for each multiple regression model used to answer Research Questions Q2, Q3, and Q4. Multiple regression is a statistical analysis that examines the relationship between a number of predictor variables and one dependent variable (Tabachnick & Fidell, 2013). Multiple regression operates under a set of assumptions: linear relationship, outliers/ homoscedacity, normal distribution, no or little multicollinearity, and independence.

Assumptions were tested for each multiple regression model used, which included Research Question Q2 full sample for Year One, Research Question Q2 Year Two, as well as Research Question Q3 using the analytic sample as denoted in Figures 4, 5, and 6 by one, two, or three, respectively.

Linear Relationship

The first assumption required a linear relationship between the dependent variable and each predictor variable. Scatterplots were examined for an observed linear pattern evidenced by a linear rectangle shape rather than a curved shape for each of the three multiple regression models. The results from evaluation of visual plots showed no sign of a non-linear relationship between the outcome variable (ELA or MATH) and the independent variables in the three models (see Figures 4 and 5).

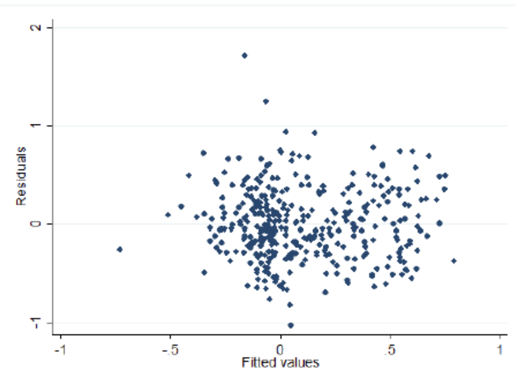


Figure 4.1. Year One ELA Achievement

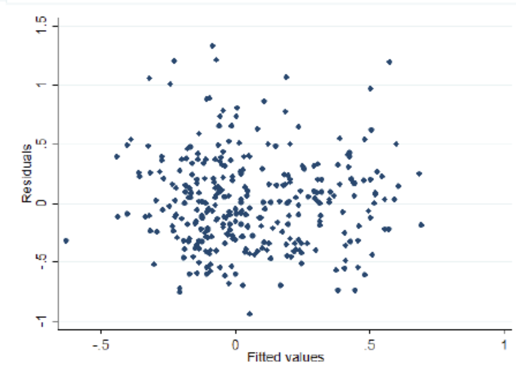


Figure 4.1. Year One MATH Achievement

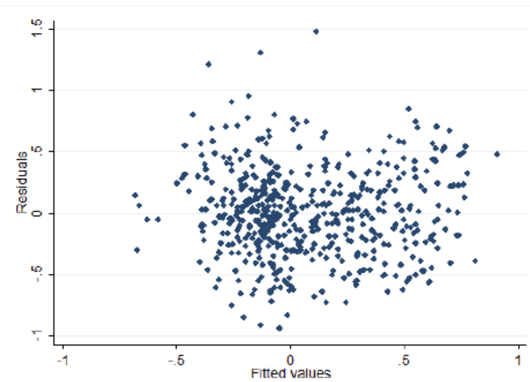


Figure 4.2. Year Two ELA Achievement

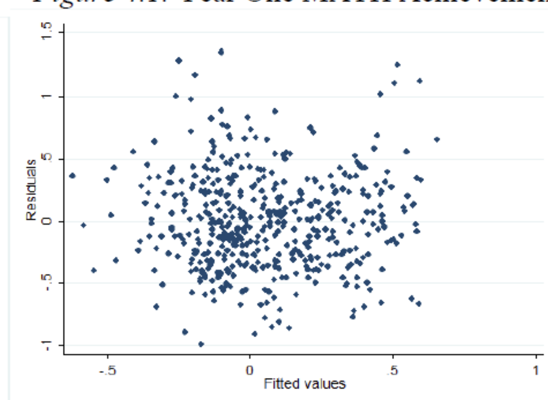


Figure 4.2. Year Two MATH Achievement

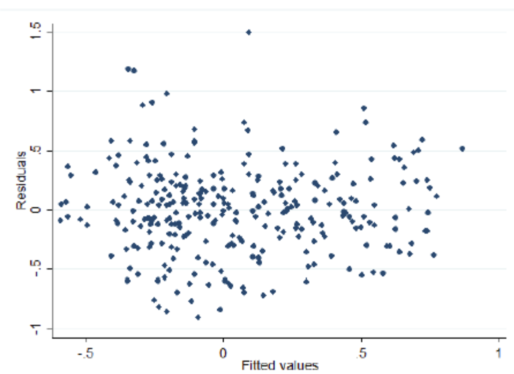


Figure 4.3. Analytic MATH Achievement

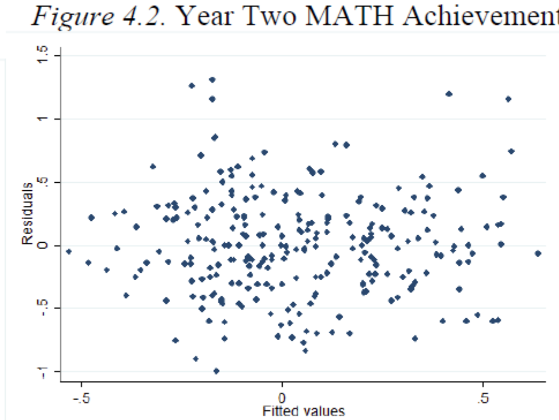


Figure 4.3. Analytic MATH Achievement

Figure 4. Residual plots test *for ELA and MATH achievement scores for* homoscedasticity assumption. Model for Year One full sample denoted by 1; model for Year Two full sample denoted by 2; model for analytic sample denoted by 3.

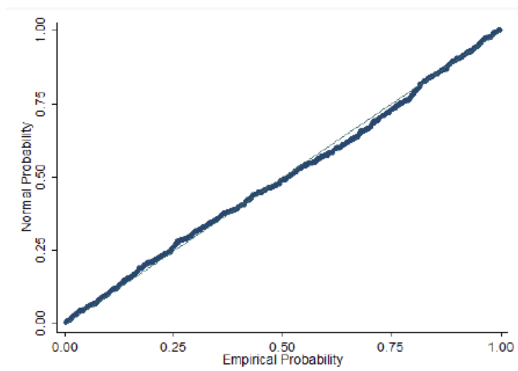


Figure 5.1. Year One ELA Achievement

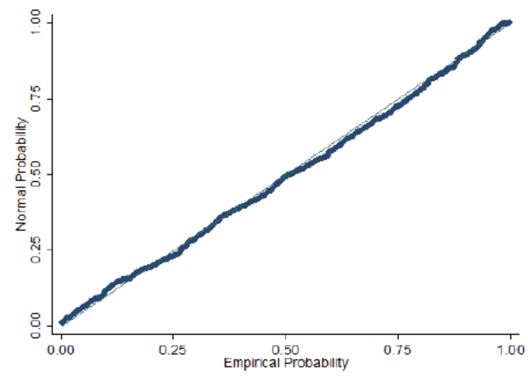


Figure 5.1. Year One MATH Achievement

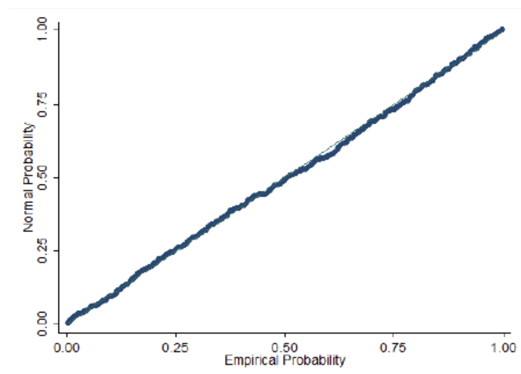


Figure 5.2. Year Two ELA Achievement

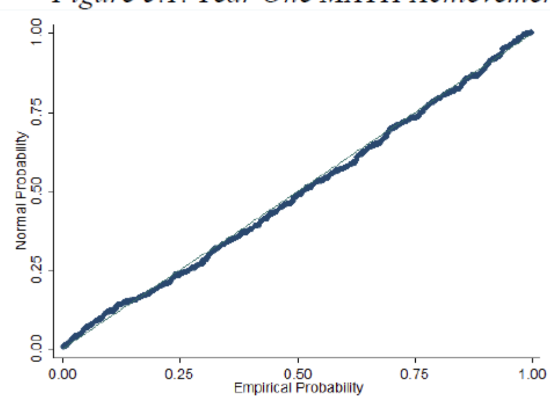


Figure 5.2. Year Two MATH Achievement

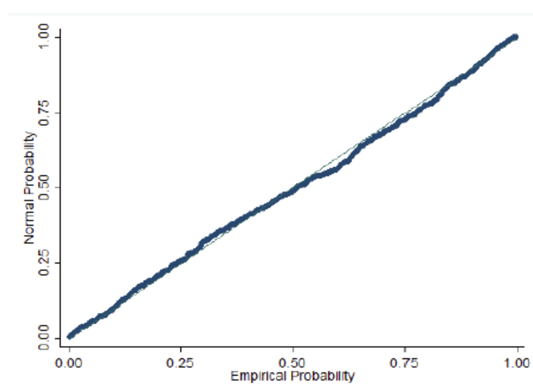


Figure 5.3. Analytic ELA Achievement

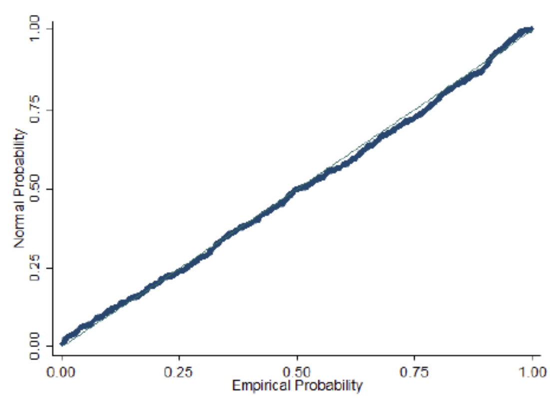


Figure 5.3. Analytic MATH Achievement

Figure 5. P-*plot normal distribution for ELA and MATH achievement* scores for normal distribution assumption. Model for Year One full sample is denoted by 1; model for Year Two full sample as denoted by 2; model for analytic sample is denoted by 3. Y-axis represents the expected values; x-axis represents the observed values.

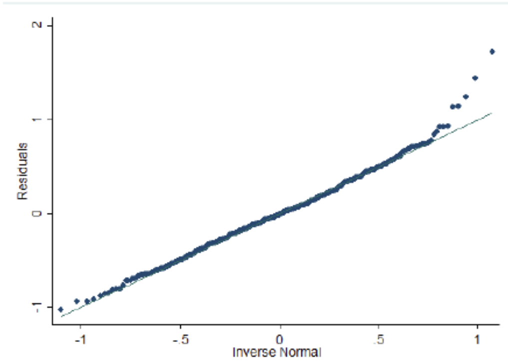


Figure 6.1. Year One ELA Achievement

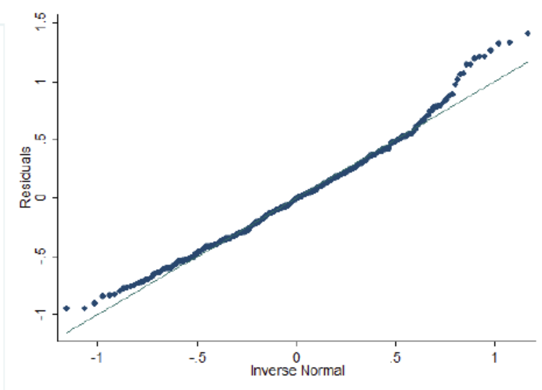


Figure 6.1. Year One MATH Achievement

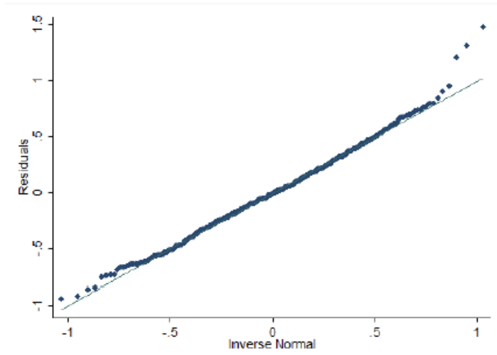


Figure 6.2. Year Two ELA Achievement

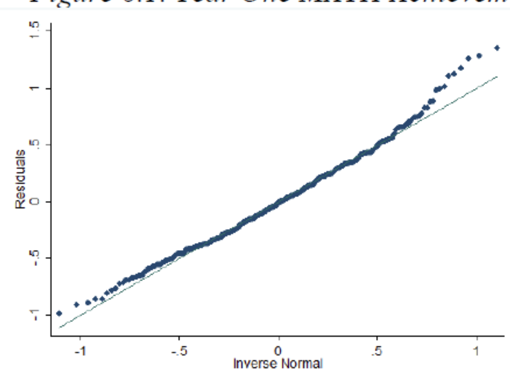


Figure 6.2. Year Two MATH Achievement

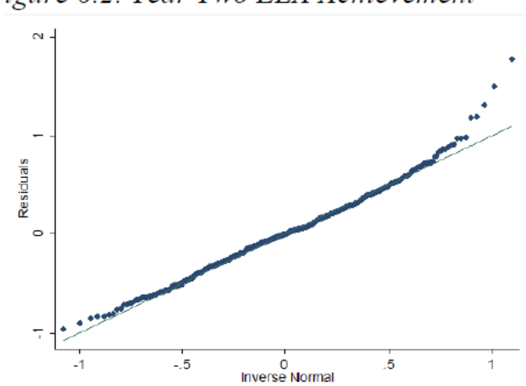


Figure 6.3. Analytic ELA Achievement

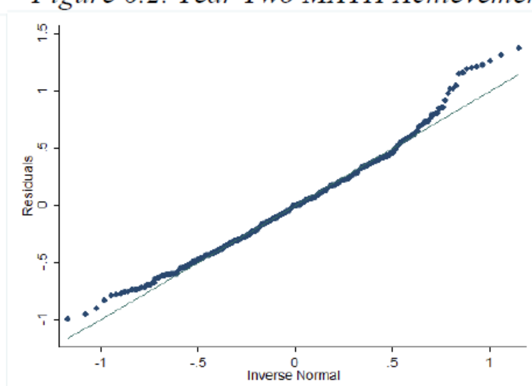


Figure 6.3. Analytic MATH Achievement

Figure 6. Q-*plot normal distribution for ELA and MATH achievement scores for normal* distribution assumption. Model Year One full sample denoted by 1; Model Year Two full sample denoted by 2; Model analytic sample denoted by 3. Y-axis represents expected values; x-axis represents the observed values.

No Significant Outliers and Homoscedasticity

The second step in evaluating the assumptions was to check residual plots versus predicted values to test for significant outliers and any signs of homoscedasticity between the predicted dependent variable scores and errors of prediction (Tabachnick & Fidell, 2013). Residual plots were generated for each of the three regression models used to answer Research Questions Q2, Q3, and Q4.

The assumption of homoscedasticity is that the standard deviations of errors of prediction are approximately equal for all predicted dependent variables scores. The plots were examined for any change in variance, patterns in the residuals, or obvious outliers in the data. The residuals appear to be distributed around the predicted dependent variable score and have a horizontal-line relationship with the predicted dependent variable scores. Therefore, there was no clear pattern of heteroscedasticity or no clear violation to homogeneity of variance for any of the three regression models (see Figure 4).

Normal Distribution

Regression analysis also requires all variables in the model to be normally distributed (Tabachnick & Fidell, 2013). Residual plots were generated for each regression model used to answer Research Questions Q2, Q3, and Q4. According to probability plots (*p*-plots) there was no evidence of a violation for normality for any of the models since the scatter points aligned closely to the reference line and showed a linear pattern (see Figure 5).

Multicollinearity

Thirdly, regression analysis assumes that the independent variables are independent of each other. A second independence assumption is that the standard mean error of the dependent variable is independent from the independent variables. Collinearity diagnostics were assessed, and there were no significant collinearity concerns for any of the predictor variables based on variance inflation factor which ranged from 1.05 to 3.40.

Correlations provided evidence for a significant relationship between the three CLASS domains regardless if a teacher taught ELA or mathematics. More specifically, there were strong positive correlations between emotional support and classroom organization as well as with instructional support (see Tables 7 and 8). In addition, there was evidence for a strong positive relationship between classroom organization and instructional support. These strong relationships are further evidence for multi-collinearity among the CLASS domains and should be taken into account when interpreting the data.

Descriptive Statistics

Descriptive statistics were examined for Year One's full sample, Year Two's full sample, and the analytic sample (see Tables 9, 10, 11, 12, 13, and 14).

Participants

Six districts were included in the original MET sample including all grade levels. Four districts were included in the present study's sample due to missingness and exclusionary criteria discussed previously in the above section. District-specific information was not reported in this dissertation due to ICPSR requirements and protection of identifiable information.

The present study included the focal grades of fourth and fifth grade. Year One's full sample included a total or 1,017 classrooms, *N* = 588 classrooms for Year Two's full sample, and *N* = 303 fourth and fifth grade classrooms had teachers that participated in both Year One and Year Two of the study (see Table 9).

Of those fourth and fifth grade classrooms, some teachers in the study were known as generalist teachers in that they taught both ELA and mathematics. Other teachers were known as specialist teachers and taught one subject, either ELA or mathematics. As mentioned earlier, if a teacher taught both ELA and mathematics, the observed score for ELA and the observed score for MATH were treated as two independent scores.

Table 7

Pearson Correlations Between Average English/Language Arts Specialist Teacher Classroom Assessment Scoring System Score Domains

Variable	Emotional support	Classroom organization	Instructional support
Year One:			
Emotional support	____		
Classroom organization	0.6346***	____	
Instructional support	0.7937***	0.5584***	____
Analytic sample:			
Emotional support	____		
Classroom organization	0.6113*	____	
Instructional support	0.7820*	0.5193*	____

*p < .05, **p < .01, ***p < .001

Table 8

Pearson Correlations Between Average Mathematics Specialist Teacher Classroom Assessment Scoring System Score Domains

Variable	Emotional support	Classroom organization	Instructional support
Year One:			
Emotional support	____		
Classroom organization	0.6255***	____	
Instructional support	0.8015***	0.6134***	____
Analytic sample:			
Emotional support	____		
Classroom organization	0.5851*	____	
Instructional support	0.7938*	0.6230*	____

*$p < .05$, **$p < .01$, ***$p < .001$.

Table 9

Grade Level by Year

Grade level	Year One full sample	Year Two full sample	Analytic sample
4th grade	502	276	139
5th grade	515	312	164
Total	1,017	588	303

Note. Total column includes middle school ELA and middle school mathematics classrooms.

Table 10

Teacher-Subject Area by Year

Teacher's subject taught	Year One full-sample	Year Two full sample	Analytic sample
Elementary ELA + MATH	215	132	82
Elementary ELA	636	353	166
Elementary MATH	166	103	55
Total	1,017	588	303

Note. Total column includes middle school ELA and middle school mathematics classrooms.

Table 11

Number of Classroom Sections Taught by Classroom Teachers

Number of sections taught	Year One full sample	Year Two full sample	Analytic sample
One section	731	576	297
Two sections	286	12	6
Total	1,017	588	303

Note. Total column includes middle school ELA and middle school mathematics classrooms.

Table 12

Classroom Demographic Variables by Year

Classroom demographics	Year One full sample	Year Two full sample	Analytic sample
Male %	.498	.498	.504
SPED %	.095	.110	.119
ELL %	.139	.145	.118
LUNCH %	.443	.473	.447
BLACK %	.406	.414	.423

Note. Special education (SPED) represents proportion of special education. English language learner (ELL) represents proportion of English language learners. LUNCH represents the proportion of students with free or reduced price lunch. BLACK represents proportion of Black students.

Of the students in the classrooms, 50% identified as male and 40% to 42% identified as BLACK. A smaller proportion of students were identified as receiving services such as special education (10%) or English language learner support (11% to 15%). Classrooms had an average proportion of 44% to 48% of students who were identified as receiving free or reduced price lunch services. For the breakdown of characteristics of students by year, please see Table 12 and for the break own of proportion of student demographics by the actual number of classrooms please refer to Appendix C.

Table 13

Pearson Correlations of Demographic Variables by Year

Variable	LUNCH	MALE	SPED	ELL	BLACK
Year One:					
LUNCH	____				
MALE	0.0186	____			
SPED	0.2464*	0.1848*	____		
ELL	0.3809***	0.5094	0.0566	____	
BLACK	-0.3123***	0.0055	-0.24461***	-0.2718***	____
Year Two:					
LUNCH	____				
MALE	0.0572	____			
SPED	0.0379	0.0997	____		
ELL	0.5362***	0.0990***	0.0382*	____	
BLACK	-0.3789***	-0.0065	0.0855*	-0.3299*	____
Analytic:					
LUNCH	____				
MALE	0.0099	____			
SPED	-0.0245	0.0716	____		
ELL	0.4823***	0.5584***	0.1233*	____	
BLACK	-0.3619***	0.0091	0.0447	-0.3743*	____

*$p < .05$, **$p < .01$, ***$p < .001$

Table 14

Classroom Assessment Scoring System Domains Average Score by Subject and by Year

CLASS domains by subject taught	Year One full sample		Year Two full sample		Analytic sample	
ELA:	*M*	*SD*	*M*	*SD*	*M*	*SD*
Emotional support	4.571	.436	4.602	.399	4.582	.397
Classroom organization	4.429	.4077	5.434	.357	5.439	.356
Instructional support	3.639	.522	3.683	.446	3.674	.431
Domain average	4.547	.402	4.573	.353	4.553	.348
MATH:						
Emotional support	4.440	.459	4.483	.394	4.431	.400
Classroom organization	5.397	.424	5.373	.386	4.534	.395
Instructional support	3.533	.505	3.629	.448	3.551	.445
Domain average	4.457	.412	4.495	.366	4.446	.367

Note. Domain average score represents the overall average mean of the three domains.

Results

The purpose of the current study was to examine the impact of teachers' interactional quality (CLASS score) on classroom achievement outcomes. This section of the dissertation discusses the analyses and results for four research questions. Research Question Q1 asked whether there was a difference in the distribution of teacher interactional quality (CLASS score) based on the classroom proportion of free or reduced lunch status. Research Question Q2 then asked whether there was a stronger association between teacher interactional quality and classroom proportion of free or reduced lunch receipt during Year One of the study when teachers went about their usual teaching practices in the classroom. Research Question Q3 re-examines Research Question Q2 but differs by asking whether the association was stronger during Year Two of the study when teachers were randomly assigned to classroom rosters of students. Research Question Q4 was interested in whether teacher interactional quality impact on classroom achievement outcomes was different based on the year of the study. The findings from the analyses are presented and elaborated throughout the chapter.

Observational Ratings of Interactions Between Teachers and Students

The present study's preliminary examination of the distribution of the number of classrooms that had a classroom teacher with a CLASS score from the 1 to 7 range revealed the majority of classrooms did not have a teacher with a score of 6 or 7 (high CLASS score) (see Table 14 and Appendix D). This is consistent with recent work done by the early MET grantees. They found a similar ceiling effect with fourth- through eighth grade classroom teachers receiving a score of 6 for dimensions representing the classroom organization domain and in very few cases in emotional support or instructional support (AERA, 2015; Gates Foundation, 2012b). Preliminary research also found classroom teachers were more likely to receive lower scores on the dimensions of instructional support (AERA, 2015; Gates Foundation, 2012b). For the dissertations sample, highlighted in Table 14, the overall average CLASS domain scores clustered around 3 to 5, considered the mid-range by CLASS™ and MET researchers (Gates Foundation, 20112b; La Paro et al., 2004).

When initially designing the investigation, the treatment of a classroom of students to a classroom teacher with a high CLASS score was intended to be a dichotomous variable of whether you had a teacher with a high CLASS score or did not have a teacher with a high CLASS score. However, due to the pattern in this dissertation that most CLASS scores fell within the 3 to 5 range, it was no longer appropriate to have the variable treated as a dichotomous variable. The composite average of all three domains was used as one CLASS Average score in the model for descriptive analysis and each research question's statistical model. This decision was made due to the precedence in other research on the CLASS™ and due to the patterns of high correlations among the separate CLASS scores (Hamre et al., 2014; Hamre et al., 2013; Kane & Staiger, 2012; Mashburn et al., 2008; Rudasill et al., 2010).

Distribution of Classroom Teachers' Classroom Assessment Scoring System Scores

As a first step in the analysis, distributions of fourth and fifth grade teachers' interactional quality, as measured by the CLASS™ instrument, were examined. Year One full sample from the base analytic: Section files (#34309) were used for the analysis since the focus of each research question asked about the classroom-level teaching practices and classroom-level achievement outcomes. For distributions of classroom teacher CLASS scores for the full sample of Year One and Year Two, as well as the analytic sample, refer to Appendix D.

For Year One, the business-as-usual year, summary statistics revealed fourth and fifth grade teachers' CLASS score ranged from 3 to 5 on the emotional support (domain 1) with the average cluster around 4 and 5 (see Appendix D). In very few cases a classroom teacher received a score of 6 or 7 as can be seen in Figures 7 and 8.

And in these isolated cases when a teacher received a high rating as defined by MET researchers (Gates Foundation, 2010c) it was in classroom organization (domain 2).

Research Questions Q2, Q3, and Q4 pertained to the CLASS domain average score, thus the CLASS average score was used in each model. Descriptive analyses highlighted in Figures 7 and 8 include the plotted frequency distribution of the CLASS Domain average score as well as additional information on each CLASS domain distribution. The CLASS domain average is centered around a CLASS score of 3 to 5 (see Appendix D).

For the additional frequency distributions broken down by domain, there was a slight left skewed pattern (i.e., negatively skewed) for both ELA and mathematics classroom teacher observation scores. The CLASS scores tended to be higher for mathematics classroom teachers compared to ELA classroom teachers. Another interesting pattern was that ELA and mathematic classrooms teachers received lower CLASS scores for the instructional support (domain 3) than the other two domains. The slight left-hand skew on all these domains may represent the ceiling effect as well as more variation in classroom teachers' observed CLASS scores for the three domains on the low-to-mid scores than the mid-to-high scores.

These patterns were similar not only for ELA and mathematics classrooms but were also reflected in Year One, Year Two, and the analytic sample plots. The focus of this research question was to examine Year One business-as-usual year when teachers went about their usual teaching practices in the classroom. For plots comparing the full sample for Year One and Year Two, and the analytic sample, refer to Appendix D.

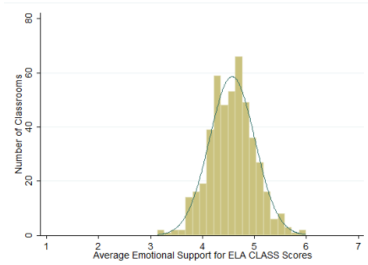


Figure 7.a. Emotional Support

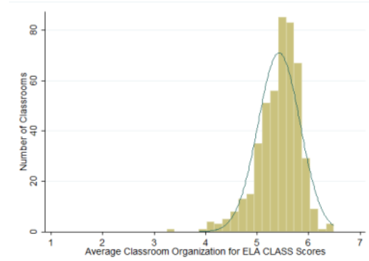


Figure 7.b. Classroom Organization

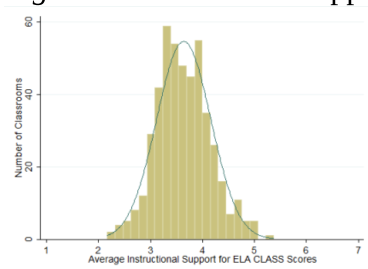


Figure 7.c. Instructional Support

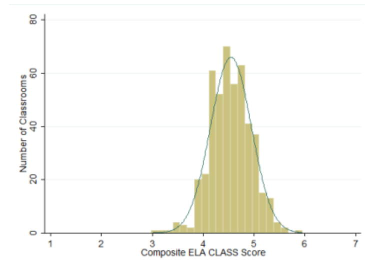


Figure7.d. Domain Average

Figure 7. Plotted frequencies for ELA classroom teachers Classroom Assessment Scoring System scores.

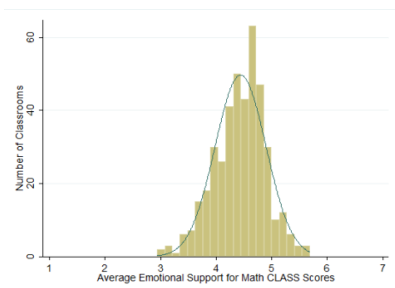


Figure 8.a. Emotional Support

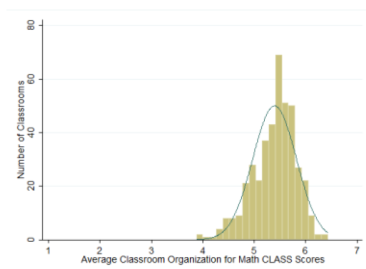


Figure 8.b. Classroom Organization

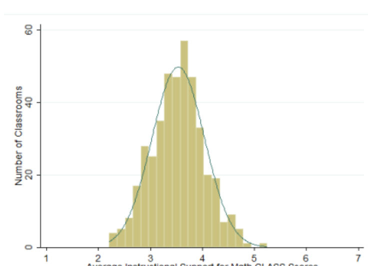


Figure 8.c. Instructional Support

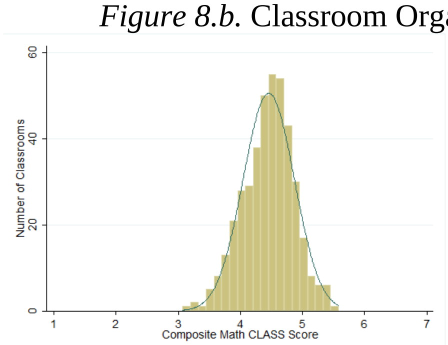


Figure 8.d. Domain Average

Figure 8. Plotted frequencies for MATH classroom teachers Classroom Assessment Scoring System scores.

Research Question Q1: Distribution of Classroom Teachers' Interactional Quality Results

Q1 Is there a difference in the distribution of teacher's interactional quality by classroom proportion of free or reduced price lunch status, when classrooms have higher proportions of free or reduced price lunch status (i.e., low socioeconomic status), and when classrooms are assigned to teachers using business-as-usual practices?

This first research question used Year One (business-as-usual) data for the analysis in order to examine the distribution of classroom teachers' CLASS scores when teachers would go about their classroom practices doing what they normally would do. The business-as-usual year served as a baseline measurement of the distribution of the classroom when no random assignment had taken place. The analysis also allowed for an examination of the distribution of classrooms teachers CLASS scores on classroom student ELA and MATH outcomes when there was a higher classroom proportion of free or reduced lunch status.

It was anticipated that classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic status) would be more likely to be assigned to classroom teachers with lower CLASS scores. Under the null hypothesis, classrooms with higher proportions of free or reduced price lunch (i.e., low socioeconomic status) would be no more likely to be assigned to classroom teachers with a lower CLASS score than would classrooms with a lower proportion of free or reduced price lunch (i.e., high socioeconomic status).

Visual plots suggest no relationship is present (see Figures 9 and 10). Statistics further suggest the cause of the relationship is unclear and that there is no presence of any other non-linear pattern. The focus of this research question was to examine Year One (the business-as-usual). For plots comparing Year One and Year Two, and the Analytic Sample, refer to Appendix E.

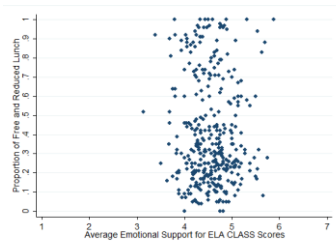


Figure 9.a. Emotional Support

Figure 9.b. Classroom Organization

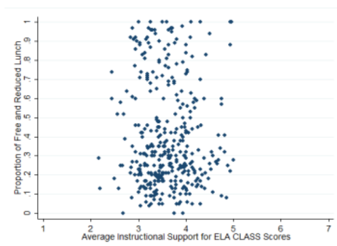


Figure 9.c. Instructional Support

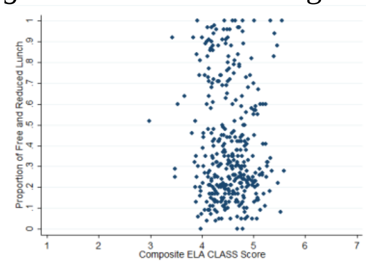


Figure 9.d. Domain Average

Figure 9. Scatterplot of ELA classroom teacher Classroom Assessment Scoring System scores by proportion of students with free or reduced price lunch.

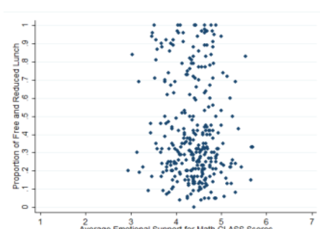


Figure 10.a. Emotional Support

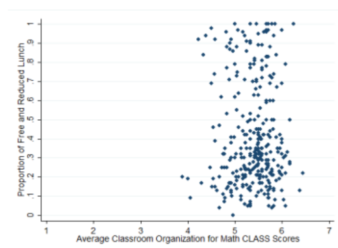
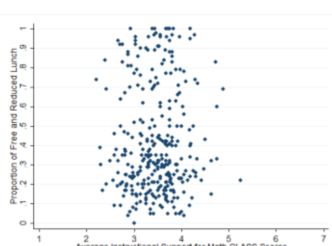
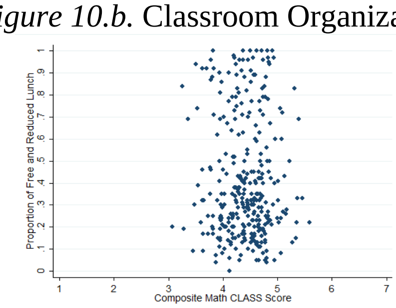


Figure 10.b. Classroom Organization



10.c. Instructional Support



10.d. Domain Average

Figure 10. Scatterplot of MATH classroom teacher Classroom Assessment Scoring System scores by proportion of students with free or reduced price lunch.

Since both the predictor (CLASS) and outcome variable (LUNCH) were continuous, correlations examined whether there was a difference in the distribution of classroom teachers' interactional quality by classroom proportion of free or reduced price lunch status, when teachers went about their usual teaching practices in the classroom during Year One (business-as-usual).

As discussed above, visual plots suggested no relationship which is further supported by correlational analysis (see Figures 9 and 10). There appears to be no relationship between teacher interactional quality and classroom proportion of free or reduced price lunch. However, there was a weak positive relationship for classroom ELA teachers' classroom organization and free or reduced price lunch status $r($1,010 = 0.0463, $p < .05$) (see Table 15). Upon further examination of the plot (see Figures 9 and 10), no positive linear relationship was visible. Thus from visual inspection of the plot, an influential outlier may have inflated the correlation estimate. Given the modest indication of an association that could have been the result of an outlier or the sample size. Therefore, the significance-level may not be convincing even with a larger sample size. For plots subdivided by class domain, subject, and year see Appendix E.

Table 15

Pearson Correlation Between ELA Achievement, Classroom Assessment Scoring System Score, and LUNCH Status

Variable	Emotional support	Classroom organization	Instructional support	CLASS average
LUNCH	0.3571	0.0463*	0.4779	0.1854

*$p < .05$, **$p < .01$, ***$p < .001$

Research Question Q2: Business-As-Usual Practices Results

Q2 Is there a positive association between classroom teachers' interactional quality and classroom achievement outcomes under business-as-usual assignment practices? Is the association different for low socioeconomic status students?

A multiple regression was employed to determine if the addition of information regarding classroom demographics and classroom teacher's overall CLASS score had an impact on classroom ELA and MATH achievement. A model was first run for ELA classroom teacher's overall CLASS score and ELA classroom achievement and then again for mathematics classroom teachers' overall CLASS score and mathematics classroom achievement. The composite average of all three domains was used as one CLASS score in the model, instead of using three separate models for each domain. This decision was based on the concerns for multicollinearity between the three domains. All those included in parentheses are demographic variables and all others outside of the parenthesis include variables of interest and the interaction effect. The subscript *c* denotes the use of classroom level variables. Year One, business-as-usual-sample was used for the model.

$$(7)\ ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$$(8)\ MATH_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of the proportion of English Language Learners (ELL)
β_2 = The effect of the proportion of Special Education (SPED) status
β_3 = The effect of the proportion of Black students
β_4 = The effect of the proportion of male students
β_5 = The effect of the proportion of free-and-reduced price lunch
β_6 = The effect of teacher interactional quality score as measured by the CLASS™
β_7 = The effect of the interaction between teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

Teachers' interactional quality and classroom achievement outcomes. Within the context of education, the model summary and residual plots (see Figure 4.1) for ELA classroom achievement offered evidence that the model had reasonable if not good variation explained for classroom ELA achievement (R^2 = 0.375, R^2adjusted = 0.3622), and MATH classroom achievement R^2= 0.2856, R^2adjusted = 0.2694. The six predictors together explained 38% (36% adjusted) of the variability in ELA classroom achievement and 29% (27% adjusted) of MATH classroom achievement (see Tables 16 and 17). R-squared and adjusted R-squared should be considered together when interpreting the model-fit. Adjusted R-squared is a modified version of R-squared and is adjusted for the number of predictors in the model. The two statistics should have relatively similar values.

Table 16 shows that the six independent variables statistically significantly explained ELA classroom achievement, $F(7, 354) = 37.45$, $p < .001$. For mathematics classroom achievement, classroom lunch status was not a significant predictor in the model.

Table 16

Pearson Correlation Between MATH Achievement, Classroom Assessment Scoring System Score, and LUNCH Status

Variable	Emotional support	Classroom organization	Instructional support	CLASS average
LUNCH	0.1191	0.7663	0.4779	0.6159

*$p < .05$, **$p < .01$, ***$p < .001$

Table 17

Multiple Regression Analysis for Teachers' Interactional Quality on ELA Achievement for Year One

ELA Achievement	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	-.3767	.4238	---	0.375	0.375
MALE	-.007	.2019	-.0428	-0.99	0.321
SPED	-.7474	.2205	-.7473	-0.99	0.321
ELL	-1.194	.1470	-.3998	-3.39	<.001
BLACK	-.6892	.0570	-.6044	-12.09	<.001
LUNCH	2.058	.7891	1.234	2.61	0.010
ELA CLASS Average	.2659	.0895	.2301	2.97	0.003
Interaction ELA CLASS and LUNCH	-.5103	.1734	-1.385	-2.94	0.003
				R^2=	0.3745
				Adjusted R^2=	.3622

Note. Dependent variable: ELA achievement' predictors: MALE, SPED, ELL, BLACK, LUNCH, ELA CLASS average; significance determined at the *p < .05 **p < .01 level (N = 362).

In Year One when teachers go about their usual business in the classroom, teachers' interactional quality appears to significantly predict both ELA and mathematics classroom achievement. As can be seen in Table 16, there was evidence of a significant effect from an ELA classroom teachers' CLASS average, meaning an increase in ELA CLASS average was associated with an expected increase in the mean ELA classroom achievement when accounting for all the other predictor variables. For a one-unit increase in classroom teachers' CLASS score, the classroom average ELA scores expected to increase by .27, accounting for all other variables in the model. More specifically, when ELA classroom teacher CLASS scores increased by one standard deviation unit, the ELA classroom achievement scores were expected to increase by .27 standard deviations when accounting for all other variables in the model. For MATH, when classroom teacher CLASS scores increased by one standard deviation, the MATH classroom achievement scores were expected to increase by .26 standard deviations when accounting for all other variables in the model. Because of the magnitude of the association and level of significance, this pattern is likely to be seen again in another population if replicated.

Is the association different for low socioeconomic status students? The second part of Research Question Q2 asked whether the effect of classroom teachers' CLASS scores change based on the proportion of classroom free or reduced price lunch status. Because the dissertation suspects teacher interactional quality to have a different effect on classroom achievement depending on the proportion of free or reduced lunch, an interaction effect was added to the model. Furthermore, an interaction plot for ELA and MATH classroom achievement was created to better understand the relationship between CLASS and LUNCH (see Figures 11 and 12). Standard deviation of one was used for the visual interaction plot, with the range from 4 to 5 to be consistent with the data's actual range of classroom teachers' CLASS scores.

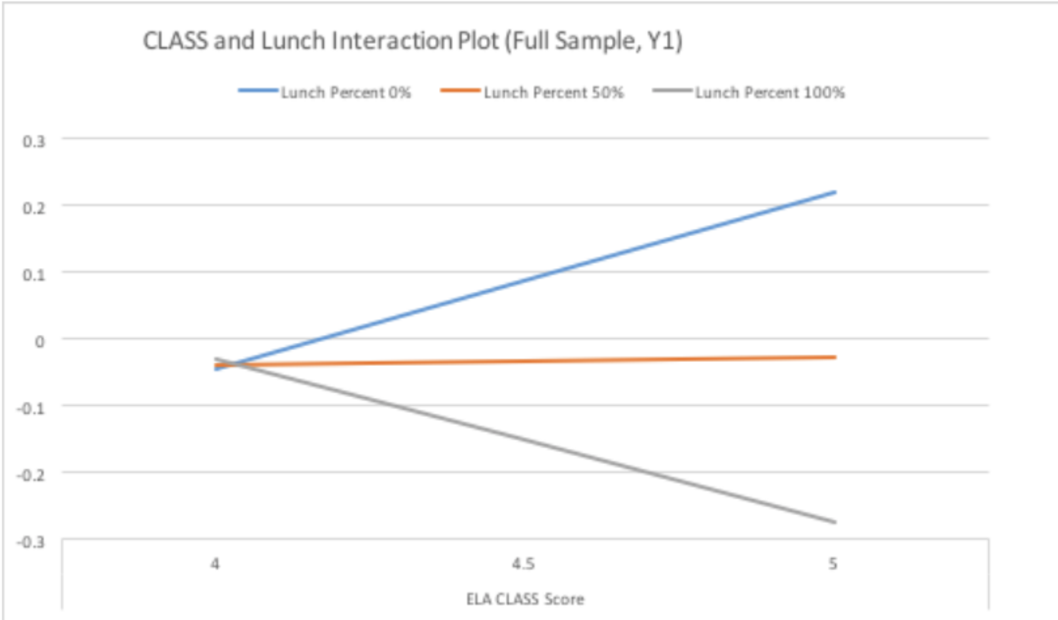


Figure 11. English/language arts Classroom Assessment Scoring System score and LUNCH interaction plot for year one business-as-usual.

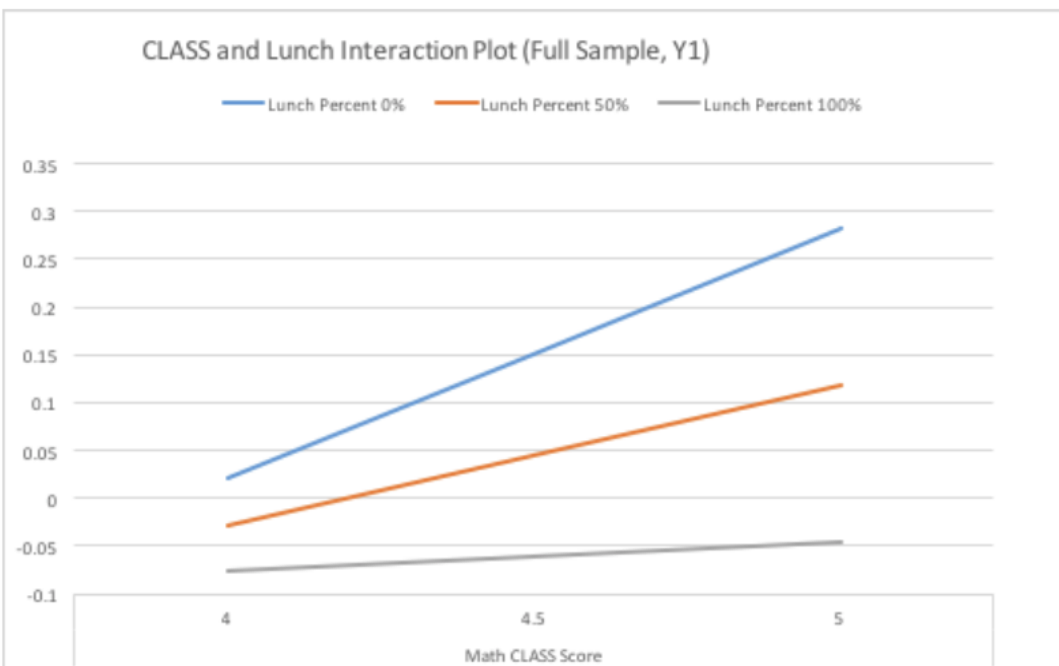


Figure 12. MATH Classroom Assessment Scoring System score and LUNCH interaction plot for year one.

Interaction plots. Classroom proportion of free or reduced price lunch also appears to be a significant predictor for ELA classroom achievement but not for MATH classroom achievement. When the model allowed classroom teachers' interactional quality to interact with free or reduced price lunch, the interaction was only significant for ELA and not for MATH outcomes. Therefore, the impact of a classroom teacher's CLASS score on ELA classroom achievement is dependent on the proportion of free or reduced price lunch students in the classroom.

Another pattern evidenced in Figure 11, ELA classrooms that had teachers with higher CLASS scores had higher ELA classroom achievement outcomes. However, for classrooms in the 50% range of free or reduced price lunch status, there does not appear to be an effect on ELA achievement. And for classrooms with 100% free or reduced price lunch status and higher CLASS scores, there was a decrease in ELA classroom achievement. In other words, classrooms with a lower proportion of free or reduced lunch (higher socioeconomic status) fared better in classrooms with teachers higher in interactional quality.

Teacher interactional quality (i.e., CLASS score) was a statistically significant predictor for ELA classroom achievement outcomes. Even though the interaction for MATH classroom achievement was not significant, the interaction plot displays a similar pattern to ELA (see Figure 11). Therefore, there was evidence to reject the null hypothesis, for the ELA model because the association was different for classrooms of students based on free or reduced price lunch status, and there was evidence that teacher interactional quality did matter and was not just due to random fluctuation. However, the effect was in the opposite direction than hypothesized.

Figures 11 and 12 were created to help visualize and better explain the relationship between CLASS score and LUNCH status and Tables 16 and 17.

Table 18

Multiple Regression Analysis for Teachers' Interactional Quality on MATH Achievement for Year One

MATH achievement	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	-.5265	.4557	---	-1.16	.249
MALE	-.0868	.2352	-.0181	-.037	.712
SPED	-.8073	.2622	-.1646	.308	.002
ELL	-.9895	.1659	-.3278	-5.96	<.001
BLACK	-.5825	.0669	-.5007	-8.70	<.001
LUNCH	.8305	.8474	.4940	.98	.328
MATH CLASS Mean	.2624	.0967	.2375	2.71	.007
Interaction MATH CLASS and LUNCH	-.2315	.1918	-.6108	-1.21	0.249
				R^2=	.2856
				Adjusted R^2=	.2694

Note. Dependent variable: Math achievement; Predictors: MALE, SPED, ELL, BLACK, LUNCH, MATH CLASS Average; Significance determined at the *p < .05 **p < .01 level. (N = 312)

Research Question Q3:
Randomization Results

Q3 Is there an impact of classroom teachers' interactional quality on classroom achievement outcomes under random assignment practices? Is the impact different for low socioeconomic status students?

This research question asked a similar question to Research Question Q2, but used the Year Two random assignment full-sample. To answer this research question, a re-estimate of equation one and two was performed, using the same classroom achievement ELA and math outcomes, but this time using Year Two's full sample when teachers were randomly assigned to classrooms of students. As previously, the model was first computed for ELA classroom teachers' overall CLASS score and ELA classroom achievement and then again for mathematics classroom teachers' overall CLASS score and MATH classroom achievement. The composite average of all three domains was used as one CLASS score in the model, instead of using three separate models for each domain. All those included in parentheses are demographic variables and all others outside of the parenthesis include variables of interest and the interaction effect. The subscript *c* denotes the use of classroom level variables. Year Two full sample, random assignment year was used for the model.

$$(9)\ ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5 LUNCH_c) + \beta_6 CLASS_c + \beta_7 CLASS_c * LUNCH_c + \mathcal{E}_c$$

$$(10)\ MATH_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_c + \beta_3 BLACK_c + \beta_4 MALE_c + \beta_5\ LUNCH_c) + \beta_6 CLASS\_c + \beta_7 CLASS\_c * LUNCH\_c + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of the proportion of English Language Learners (ELL)
β_2 = The effect of the proportion of Special Education (SPED) status
β_3 = The effect of the proportion of Black students
β_4 = The effect of the proportion of male students
β_5 = The effect of the proportion of free-and-reduced price lunch
β_6 = The effect of teacher interactional quality score as measured by the CLASS™
β_7 = The effect of the interaction between teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

Teacher's interactional quality and classroom achievement outcomes. The model summary and residual plots (see Figure 4.2) for ELA and MATH classroom achievement offered evidence that the model reasonably fit and explained the outcome variables well (R^2= .4495, R^2adjusted = .4355) (R^2= 0.2679, R^2adjusted = 0.2476), respectively (see Tables 19 and 20). Together the six predictors explained 45% (44% adjusted) of the variability in ELA classroom achievement and 27% (25% adjusted) variance in math classroom achievement. Again, for the complexity of the education context, explaining 27% to 44% of the variance in classroom ELA and math achievement with only six predictors is representative of typical teacher effects in the classroom (Jackson et al., 2014). The two variables of interest, CLASS score and LUNCH status, were not significant predictors of ELA or MATH classroom achievement. The results from the model highlighted in Tables 19 and show that the results failed to reject the null. In other words, when teachers were randomly assigned to classrooms of students, their CLASS score did not significantly explain the variation in classroom ELA or MATH achievement outcomes. Thus there was evidence of non-random fluctuation and there would be the same achievement scores regardless of classroom teachers' CLASS scores.

Table 19

Multiple Regression Analysis for Teachers' Interactional Quality on ELA Achievement for Year Two

ELA achievement	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	.0542	.5768	---	0.09	0.928
MALE	-.5956	.2741	-.0992	-2.17	0.031
SPED	-.8287	.2453	-.1566	-3.38	<0.001
ELL	-.9309	.1542	-.3184	-6.04	<0.001
BLACK	-.7768	.0678	-.6239	-11.46	<0.001
LUNCH	.9732	.9598	.6049	1.01	0.311
ELA CLASS Average	.2253	.1183	.1606	1.91	0.058
Interaction ELA CLASS and LUNCH	-.2966	.5768	-.8262	-1.41	0.160
				R^2=	0.4495
				Adjusted R^2=	.4355

Note. Dependent variable: ELA achievement; Predictors: MALE, SPED, ELL, BLACK, LUNCH, ELA CLASS average; significance determined at the $*p < .05$ $**p < .01$ level ($N = 285$).

Table 20

Multiple Regression Analysis for Teachers' Interactional Quality on MATH Achievement for Year Two.

MATH achievement	Unstandardized coefficients		Standardized coefficients	*t*	Sig.
	B	Std. error	Beta		
(Constant)	-.3308	.6928	---	-0.48	0.631
MALE	-.1778	.3159	-0.316	-0.56	0.574
SPED	-.5829	.2648	-.1239	-2.20	0.029
ELL	-.6806	.1770	-.2454	-3.85	<0.001
BLACK	-.5345	.0803	-.4545	-6.66	<0.001
LUNCH	-.0617	1.034	-.0391	-0.06	0.952
MATH CLASS Average	.2277	.1430	.1815	1.59	0.113
Interaction MATH CLASS and LUNCH	-.0614	.2277	-.1770	-0.27	0.788
				R^2=	0.2679
				Adjusted R^2=	0.2476

Note. Dependent variable: MATH achievement; Predictors: MALE, SPED, ELL, BLACK, LUNCH, MATH CLASS average; significance determined at the *p < .05 **p < .01 level (N = 260).

Is the association different for low socioeconomic students? In addition to CLASS and LUNCH not significantly adding more information to the model, the interaction effect between CLASS score and LUNCH status were not significant for either the ELA or MATH model. Therefore, evidence suggests classroom teachers' interactional quality did not change based on the proportion of free or reduced price lunch status in ELA or mathematics classrooms.

Research Question Q4: Difference Between Business-As-Usual and Randomized Estimates for Year One and Year Two Results

Q4 How does the magnitude of the impact of classroom teachers higher in interactional quality on classroom achievement outcomes during random assignment compare with estimates of the association between teachers higher in interactional quality and classroom achievement outcomes under business-as-usual practices?

As discussed above in results for Research Question Q2, for the business-as-usual year, teacher interactional quality and free or reduced price lunch proportion was associated with classroom achievement outcomes. Whereas, for Research Question Q3 using the random assignment year, these variables of interest were not significant predictors of classroom achievement outcomes. This research question extends on Research Questions Q2 and Q3 by specifically asking whether the effect of teacher interactional quality, classroom free or reduced price lunch status, and classroom achievement outcomes depend on the year of the study.

To answer this research question, a regression was employed to determine if the addition of information regarding year of the study and classroom teachers' overall CLASS scores had an impact on classroom ELA and MATH academic achievement. To further understand the relationship among the variables in the model, a second interaction effect was added to examine whether classroom LUNCH status changed by year. And a third interaction effect examined whether CLASS scores changed by LUNCH status. A three-way interaction further investigated the interaction between CLASS and LUNCH effect on classroom achievement outcomes based on the year of the study. A YEAR predictor (dummy coded for year 1 = 0 and year 2 = 1) was added to the model as well as three two-way interactions and a single three-way interaction.

$$(11)\quad ELA_c = \beta_o + (\beta_1 ELL_c + \beta_2 SPED_C + \beta_3 BLACK_C + \beta_4 MALE_c + \beta_5 LUNCH_C) + \beta_6 YEAR_C + \beta_7 CLASS_c + \beta_8 LUNCH_c * YEAR_c + \beta_9 LUNCH_c * CLASS_c + \beta_{10} YEAR_c * CLASS_C + \beta_{11} LUNCH_c * YEAR_c * CLASS_c + \mathcal{E}_c$$

$$(12)\quad MATH_c = \beta_o + (\beta_1 ELL + \beta_2 SPED + \beta_3 BLACK + \beta_4 MALE + \beta_5 LUNCH) + \beta_6 YEAR + \beta_7 CLASS + \beta_8 LUNCH * YEAR + \beta_9 LUNCH * CLASS + \beta_{10} YEAR * CLASS + \beta_{11} LUNCH * YEAR * CLASS + \mathcal{E}_c$$

$ELA_c MATH_c$= Classroom ELA or MATH standardized test score
β_1 = The effect of proportion of English Language Learners (ELL)
β_2 = The effect of proportion of Special Education (SPED) status
β_3 = The effect of proportion of Black students
β_4 = The effect of proportion of male students
β_5 = The effect of proportion of free-or-reduced price lunch
β_6 = The effect of year (0= year one; 1= year two)
β_7 = The effect of teacher interactional quality score as measured by the CLASS™
β_8 = The effect of the interaction between proportion of free-or-reduced price lunch status and year
β_9 = The effect of the interaction between proportion of free-or-reduced price lunch status and teacher interactional quality
β_{10}= The effect of the interaction between teacher interactional quality and year
β_{11} = The effect of the interaction between year, teacher interactional quality and proportion of free-or-reduced price lunch status
$\mathcal{E}_c$= Classical error

As the same procedure for Research Question Q2 and Q3, the model was first run for ELA classroom teacher's overall CLASS score and ELA classroom achievement and then again for mathematics classroom teachers' overall CLASS score and mathematics classroom achievement. The composite average of all three domains was used as one CLASS score in the model, instead of using three separate models for each domain. All those included in parentheses are demographic variables and all others outside of the parenthesis include the variables of interest and interaction effects. The subscript *c* denotes the use of classroom level variables.

The model summary and residual plots (see Figure 4.3) for ELA and MATH classroom achievement offered evidence that the model reasonably fit and explained the outcome variables well (R^2=.4374, R^2adjusted = .4254) (R^2 = 0.2833, R^2adjusted = 0.2660), respectively (see Tables 21 and 22). Together the seven predictors explained 44% (43% adjusted) of the variability in ELA classroom achievement and 28% (26% adjusted) variance in MATH classroom achievement.

The effect of teacher interactional quality on ELA classroom achievement existed for both the business-as-usual year as well as the year when teachers were randomly assigned to classrooms of students (see Tables 17, 21, and 22). Looking more closely at the interaction results for ELA, the interaction between CLASS score and LUNCH status was significant at the .05 level. This same pattern was observed in research question two, business-as-usual-year with significance (see Table 17). Therefore, the effect of the classroom proportion of free or reduced price lunch on classroom achievement outcomes did depend on a classroom teachers' interactional quality (i.e., CLASS scores) and these effects existed for both years of the study (see Tables 21 and 22).

Table 21

Multiple Regression Analysis for Teachers' Interactional Quality and Year of the Study on ELA Achievement

ELA achievement	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	-.1782	.4660	---	0.38	0.702
MALE	-.2364	.1828	-.0439	-1.29	0.196
SPED	-.8294	.1689	-.1729	-4.91	<0.001
ELL	-1.100	.1100	-.3894	10.01	<0.001
BLACK	-.7499	.0465	-.6295	-16.13	<0.001
LUNCH	1.5021	.8480	.9383	1.77	0.077
YEAR	-.2386	.7115	-.2511	-0.34	0.738
ELA CLASS average	.2340	.0997	.1850	2.35	0.019
Interaction YEAR and LUNCH	-.3074	1.2909	-.2026	-0.24	0.812
Interaction CLASS and LUNCH	-.4039	.1866	-1.135	-2.16	0.031
Interaction YEAR and CLASS	.0499	.1547	.2409	0.32	0.747
Interaction YEAR, LUNCH, CLASS	0.745	.2843	.2208	0.26	0.793
				R^2=	0.4374
				Adjusted R^2=	.4254

Note. Dependent variable: ELA achievement; predictors: MALE, SPED, ELL, BLACK, LUNCH, ELA CLASS average; significance determined at the $*p < .05**p < .01$ level (N = 526); sample included analytic sample.

Table 22

Multiple Regression Analysis for Teachers' Interactional Quality and Year of the Study on MATH Achievement

MATH achievement	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	-.0621	.5371	---	-0.12	0.980
MALE	-.1150	.2149	-.2176	-0.54	0.593
SPED	-.7071	.1923	-.1556	-3.68	<0.001
ELL	-.8722	.1258	-3196	-6.93	<0.001
BLACK	-.5423	.0550	-.4682	-9.87	<0.001
LUNCH	-.1249	.9435	-.0795	-0.13	0.895
YEAR	-.5761	.8092	-.6297	-0.71	0.477
Math CLASS average	.1518	.1165	.1299	1.30	0.193
Interaction YEAR and LUNCH	.3321	1.399	.2289	0.24	0.812
Interaction CLASS and LUNCH	-.02167	.2136	-.0622	-0.10	0.919
Interaction YEAR and CLASS	.1431	.1823	.6999	0.79	0.433
Interaction YEAR, LUNCH, CLASS	-.0846	.3146	-.2633	-0.27	0.788
				R^2=	0.2833
				Adjusted R^2=	0.2660

Note. Dependent variable: Mathematics achievement; predictors: MALE, SPED, ELL, BLACK, LUNCH, Math CLASS average; significance determined at the $*p < .05$ $**p < .01$ level ($N = 467$); sample included analytic sample.

In terms of MATH achievement, teacher interactional quality significantly explained mathematic achievement during the business-as-usual year in research question two (see Table 18). But after accounting for YEAR of the study in research question four, these variables of interest no longer explained a significant amount of variation in mathematic classroom achievement.

For the LUNCH and YEAR interaction, the effect of classroom proportion of free or reduced price lunch did not change over Year One or Year Two of the study. For the third two-way interaction, YEAR and CLASS, a non-significant interaction clearly showed classroom teachers' interactional quality was not dynamic and thus did not change over Year One or Year Two of the study.

The single three-way interaction between YEAR, LUNCH, CLASS examined whether the effect of free-reduced lunch status on achievement outcomes was dependent on teacher interactional quality and whether the interaction between LUNCH and CLASS changed across years. The lack of a significant relationship of CLASS score and LUNCH status on classroom achievement outcomes suggest achievement scores did not change based on the year or explain any additional variation in classroom achievement. The pattern shown in research question two showed that teacher CLASS scores positively affected classrooms with low proportions of free or reduced price lunch status (high socioeconomic status) and negatively impacted the classrooms with high proportions of free or reduced price lunch status (low socioeconomic status). The three-way interaction in this research question suggests a pattern is present but does not specify where the pattern is present in the different years.

Thus the results from the model highlighted in Tables 21 and 22 failed to reject the null. These results clearly show that the interactions with the year indicator were not significant (i.e., different than zero), lending no evidence of different effects of the business-as-usual year in comparison to the random assignment year. In other words, these results failed to reject the null and there appears to be no significant difference between non-random sorting (business-as-usual) and random sorting (random assignment) of teachers to classrooms of students.

Summary

The current study provided the opportunity to examine the effect of teacher interactional quality on classroom ELA and math achievement outcomes. Descriptive findings suggested no evidence for a relationship between teacher interactional quality and the classroom proportion of free or reduced price lunch during Year One business-as-usual year of the study.

Findings from the multiple regression model provided evidence that both teacher interactional quality and classroom proportion of free or reduced lunch were statistically significant predictors for classroom achievement outcomes during Year One. In other words, in Year One when teachers go about their usual business in the classroom, teachers' interactional quality appears to significantly explain the variation in both ELA and math classroom achievement. Also, as a classroom teacher's CLASS score increased, the effect on ELA and mathematics classroom achievement scores changed based on the classroom proportion of free or reduced price lunch. Interaction plots patterns suggest if the classroom had a lower proportion of free or reduced price lunch (i.e., high socioeconomic status) and a teacher with a higher CLASS score, there was a positive increase in classroom achievement scores. However, when the classrooms had a higher proportion of free or reduced price lunch (e.g., low socioeconomic status) and a teacher with a higher CLASS score, there was a decrease in classroom achievement scores. Therefore, classroom achievement outcomes may increase or decrease based on the proportion of free or reduced price lunch status in the classroom. However, these same patterns were not found for Year Two when teachers were randomly assigned to classrooms of students. During Year Two, Teacher interactional quality and the proportion of free or reduced lunch are no longer statistically significant in the multiple regression model.

After looking at Year One and Year Two separately, the last research question asked how much more effective was teacher interactional quality on classroom achievement outcomes in Year One compared to Year Two of the study. In other words, during which year of the study did teacher interactional quality have a greater impact on classroom achievement scores, on average. Based on the results from the model, there was a difference in the coefficients from Year One and Year Two suggesting teacher interactional quality was more effective in Year Two (random-assignment) than in Year One (business-as-usual). Because this coefficient was positive, there was a positive change in the classroom achievement outcomes. However, teacher interactional quality and free or reduced lunch were not statistically significant predictors for classroom achievement outcomes nor did the magnitude of the effects change. Discussion of these findings will be elaborated on in Chapter V.

CHAPTER V

DISCUSSION

This dissertation contributes to the existing body of research on teacher quality by examining the impact of positive teacher-student interactions on academic achievement of students in upper elementary school classrooms. This focus adds to the literature in that previous research was limited to the early childhood years and lacked random assignment of teachers to classrooms (Hamre & Pianta, 2005; Mashburn et al., 2008; Rudasill et al., 2010). A second contribution of this investigation was its analysis of differences in the distribution of teachers' interactional quality by student populations, for example, by level of socioeconomic backgrounds. This chapter focuses on the interpretation of major findings from Chapter IV, as well as discussion on the implications and limitations to the study. Future directions for research and educational applications are also proposed.

Introduction

Teacher quality in the classroom has been measured primarily with students' academic performance and perceptions of teachers' performance. These data have certain advantages, for example, in being fairly straightforward and economical to collect, but they also have serious disadvantages. A goal of research in this area should be to select a strong predictor of classroom achievement in order to better tease out the sources of error in measuring teacher quality. To achieve this goal, three types of classroom-level data were examined: Classroom Assessment Scoring System (CLASS™) teacher observation scores, student standardized achievement test scores, and classroom proportion of free or reduced lunch status.

Teacher quality was presumed to be a teacher's interactional effectiveness with students based on an observational score (i.e., the CLASS score) they received while being observed interacting with students in the classroom. Using the teaching through interactions (TTI) theoretical framework of Bridget Hamre, Robert Pianta, and colleagues, this dissertation examined the extent to which a tripartite composite of interactional quality was associated with classroom English/language arts (ELA) and mathematics achievement outcomes. The framework contained three broad domains in an attempt to capture the comprehensive dynamics of teacher-student interactions in the classroom, those related to emotional support, classroom organization, and instructional support.

The purpose of the dissertation was to examine the impact of teacher interactional quality on classroom ELA and MATH achievement outcomes. Fourth and fifth grade classrooms were examined, as past research on teacher interactional quality has heavily focused on early childhood classrooms and neglected the important upper elementary grades, a transitional time for students, one in which academic challenges are intensified, the changes of puberty begin or are anticipated, and inter-personal relationships remain important. This dissertation also examined the distribution of classroom teachers' interactional quality based on classroom proportion of free or reduced price lunch status.

The data in this investigation come from the Measures of Effective Teaching (MET) project, the largest study of classroom teaching to date, supported by the Bill and Melinda Gates Foundation and compiled by the University of Michigan. The MET researchers collected a variety of indicators of teacher effectiveness over a two-year period (academic year [AY] 2009-2010 and AY 2010-2011), including student and teacher self-perception data, student achievement outcomes, video-recorded lessons taught by teachers, and teachers' pedagogical and content knowledge for teaching (Gates Foundation, 2012b).

Summary of the Findings

Four research questions were analyzed to examine the role of classroom teachers' interactional quality on classroom achievement outcomes in ELA and mathematics. The first research question used descriptive statistics to identify whether there was a difference in the distribution of teacher interactional quality (CLASS score) based on the classroom proportion of free or reduced lunch status. For the second research question, a multiple regression model was used to examine whether there was an association between teacher interactional quality and classroom proportion of free or reduced lunch receipt during Year One of the study when teachers went about their usual teaching practices in the classroom. The similar regression model was used to answer the third research question, but differed by asking whether there was an association during Year Two of the study when teachers were randomly assigned to classroom rosters of students. The last research question added an indicator for year to the regression model to examine whether teacher interactional quality impact on classroom achievement outcomes was different based on the year of the study.

Overall, fourth and fifth grade classroom teachers' interactional quality (i.e., CLASS scores) fell in the mid-range on all three domains, with the exception of a few cases of teachers receiving a score of 6 on classroom organization domain only. The pattern displayed teachers receiving the highest CLASS scores on the classroom organization domain and the lowest CLASS scores on instructional support. This pattern was observed through descriptive statistics for the Year One's full sample as well as with the Year Two's full sample and the analytic sample. Scores were similar across ELA and mathematics classroom teachers.

These results could be explained by a possible ceiling effect, which has also been found in early MET grantee research (AERA, 2015; Gates Foundation, 2012b). The CLASS™ observational raters may have been hesitant to rate "too" high because of the belief that there are few cases of exemplary teaching, and thus a teacher had to be exceptional to receive the highest rating. Another possible explanation for these patterns could be overlap between the classroom organization, emotional support, and instructional support domains. As discussed in Chapter II literature and as supported in Chapter IV results, many studies have reported high correlations (i.e., multicollinearity) among the three domains, limiting the ability to clearly examine the extent to which individual domains of interactions are associated with specific domains of a student's development (Kane & Staiger, 2012; Mashburn et al., 2008; Rudasill et al., 2010).

These strong associations may suggest the domains are measuring something similar, perhaps a style of interacting with students that spans across distinct types of communication. Hamre et al. (2014) have also suggested that the dimension of instructional support plays a small role in promoting close relationships between students and teachers. Through continued validation efforts, they have proposed a bi-factor structure as a better fitting model (Hamre et al., 2014). The bi-factor model includes a new responsive teaching domain consisting of emotional support dimensions and proactive management and routines from the classroom organizatio*n* domain, a framework that may be more sensitive to distinguishing distinct types of teacher-student communication in the classroom.

Research Question Q1: Distribution of Classroom Teachers' Interactional Quality Summary

Scatterplots were used to answer the first research question, whether there was a difference in the distribution of teacher interactional quality based on proportions of free or reduced price lunch status. In addition to descriptive visual plots, correlations between CLASS score and LUNCH were examined. The analysis provided evidence that there was no relationship between teacher interactional quality and classroom proportion of free or reduced price lunch, except for a weak positive relationship in the classroom ELA teachers' classroom organization score and free or reduced price lunch. This result in the descriptive statistics provides some evidence that participating teachers were able to carry out reasonably high-quality interactions with students across the spectrum of income levels in the families they serve. With or without an outlier, the significance level may or may not be convincing even with a larger sample size. Or it is possible the relationship depends on another variable not included in the model or even within the MET dataset.

Research Question Q2: Business-As-Usual Practices Summary

A regression was employed to answer the second research question, whether classroom teachers' interactional quality and classroom demographics were associated with ELA and MATH classroom achievement outcomes when teachers were not randomly assigned to their classrooms during Year One of the study and specifically whether this association was different for classrooms with high and low proportions of free or reduced price lunch.

In general, classroom teachers' interactional quality seemed to matter for classroom achievement. Results showed classroom teachers' CLASS scores significantly predicted both ELA and mathematics classroom achievement and that the strength of the associations was about the same for ELA as for MATH. However, when the model allowed teachers' interactional quality to interact with free or reduced lunch, the interaction was only statistically significant for ELA and not for MATH classroom achievement. This finding is not consistent with early grantee MET researchers' research. Their preliminary findings from Year One indicated that teachers had stronger effects on mathematics achievement than on reading or ELA, as measured on the state assessments (Gates Foundation, 2010c; Hanushek & Rivkin, 2010a). These same researchers also found the variance in teacher effects to be much larger for mathematics than for reading. This pattern could be a result of current limitations of state ELA tests that use multiple-choice questions to measure reading comprehension (Gates Foundation, 2012a).

Another interpretation offered by researchers is that families have more profound effects on children's reading and verbal performance. This interpretation may help explain the direction of teacher effects on achievement outcomes in this dissertation. Early literacy environments and chronic stress can negatively impact students' initial academic skills in low socioeconomic households and communities (Aikens & Barbarin, 2008). An effective teacher may have a positive impact on students' reading skills and achievement but because the student already was slightly behind, their rate of growth between the later elementary years may be slower than students not from higher income backgrounds (Kieffer, 2012).

Research Q3: Randomization
Summary

The third research question asked a similar question as the second research question but used the random assignment year when teachers were assigned to classrooms of students. This question asked whether classroom teachers' interactional quality and additional information regarding classroom demographics were associated with ELA and MATH classroom achievement and additionally whether this association was different for classrooms with higher proportions of free or reduced price lunch.

For Year Two when teachers were randomly assigned to classrooms of students, neither teacher interactional quality nor classroom proportion of free or reduced price lunch significantly explained the variation in ELA or MATH classroom achievement outcomes. Regardless, the overall model explained 45% of the variability in ELA classroom achievement, further indicating that the model included strong predictors for ELA classroom achievement. Although teacher interactional quality was not a statistically significant predictor of ELA classroom achievement at the $p < .05$ level, it was emerging significance. Furthermore, for the year when teachers were randomly assigned to classrooms of students, classroom achievement outcomes did not significantly change based on proportion of free or reduced price lunch in the classroom (interaction effect).

Research Question Q4: Difference Between Business-As-Usual and Randomized Estimates for Year One and Year Two Summary

The fourth research question extended the second and third research questions by asking whether the effect of teacher interactional quality, classroom free or reduced price lunch status, and classroom achievement outcomes depend on the year of the study. The overall model explained 44% of the variability in ELA classroom achievement, again indicating that the model included strong predictors for ELA classroom achievement for both years of the study. The effect of teacher interactional quality on ELA classroom achievement existed for both the business-as-usual year as well as the year when teachers were randomly assigned to classrooms of students. Moreover, the effect of the classroom proportion of free or reduced price lunch on classroom achievement outcomes did depend on a classroom teachers' interactional quality (i.e., CLASS scores), and these effects existed for both years of the study.

In terms of MATH achievement, teacher interactional quality significantly explained mathematic achievement during the business-as-usual year in Research Question Q2. But after accounting for YEAR of the study in Research Question Q4, these variables of interest no longer explained a significant amount of variation in mathematic classroom achievement. Reasons for why findings may have differed by year are elaborated on below.

Overall Summary

Overall, the effects of teacher interactional quality on ELA classroom achievement were statistically significant for both years of the study, when teachers went about their usual classroom practices and when teachers were randomized to classrooms of students. In comparison, teacher interactional quality significantly explained variation in MATH classroom achievement outcomes only during the business-as-usual year when teachers went about their usual teaching practices in the classroom. For this same year, teacher interactional quality and classroom proportion of free or reduced price lunch were associated with classroom ELA achievement outcomes and not MATH achievement outcomes. Teacher interactional quality impact on ELA classroom achievement outcomes changed based on the proportion of free or reduced lunch in the classroom during the business-as-usual year but not during the year when teachers were randomly assigned to classrooms of students.

These different findings across years suggest the associations between teacher interactional quality, free or reduced lunch, and achievement outcomes changed between Year One and Year Two. However, when the model accounted for the year of the study, the results suggest the differences between the two years were not statistically significant, and nothing additional in classroom achievement outcomes was explained.

Why were there no differences between the years in the final model after the first two models suggested a possible relationship? One possible explanation is that the significance in the model when YEAR was added may have been affected by the number of predictor variables, including the additional predictors and four interaction terms. Anytime more parameters are estimated from a dataset, there is a cost of precision and an inflation of Type 2 errors. As a result of the loss of degrees of freedom, detecting significance may have become more difficult. Therefore, it is possible the loss of significance shows the appropriate conclusion that YEAR did not explain more variance in classroom achievement outcomes. With a lack of significance, this study cannot say whether these results could be replicated in another study.

A second possible explanation has to do with the successive nature of the research questions. Research Question Q4 may have used a more appropriate regression model than the earlier more simplistic models. Therefore, the loss of significance in the randomization year may have been due to associations during the business-as-usual year that would not be there if teachers were properly randomized, which is considered further in the limitations of the study below.

The sample used for Research Question Q4, when teachers were randomly assigned to classrooms of students, may somehow have been inherently different than the sample of teachers used for Research Question Q2 (business-as-usual). First of all, the MET researchers purposely selected urban districts because schools within these districts traditionally have higher percentages of poverty, higher percentages of minority students, and are often considered lower performing schools.

In other large districts outside of the MET study, highly qualified teachers in Cleveland were more likely to teach in schools with less poverty, fewer students of color, and a greater proportion of high achieving students (Peske & Haycock, 2006). In Chicago schools serving the greatest proportion of students from low socioeconomic backgrounds, “84% were in the bottom quarter in teacher quality, and more than half (56%) of those fell in the very bottom 10% of teacher quality” (Peske & Haycock, 2006, p. 7). Therefore, teachers considered high in teacher interactional quality may have opted to leave the MET study after the first year of the study for what they perceived to be a more favorable school or district. Or it is possible that these mediocre teachers were in the MET district sample because they did not have the option for mobility within the district to move to more desirable schools (e.g., lower poverty, higher performing schools). This pattern could be another possible explanation for why the dissertation's sample included a large distribution of mid-range quality teachers, as operationalized by the CLASS™ instrument.

Another possible explanation for unobserved characteristics of the teacher sample was the circumstances in which the observational data were collected. During Year Two of the study, when teachers were randomly assigned to classrooms of students, the teachers may have consciously or subconsciously adjusted their behavior on the days their lessons were recorded. Teachers were responsible for scheduling their days of video recording. Furthermore, teachers were trained and were responsible for all video recording as well as for uploading video to a secure website. A large camera rig and two microphones to capture the teacher and student voices were present in the classroom. All of these factors may have influenced a teacher's teaching behavior during both years of the study. During the second year of the study, it is possible that the dynamics of random assignment to classes affected the relevance and impact of teachers' interactional quality on student performance. It appears that random assignment may have been confounded with attrition, raising questions about the actual meaning of the intervention.

All of these differences may have influenced the findings by creating associations for Research Question Q2 that were not really there or by masking associations for Research Question Q3. As with any experiment, causal conclusions should be made with great caution whenever there is any issue with randomization or the experimental process.

Limitations of the Study

As with any research there are always limitations and recommendations for follow-up research. One of the major limitations of this dissertation was the sole focus on classroom-level variables. One area for investigation would be to use a mixed model with a "random teacher effect" or a hierarchical-linear model to account for the multiple levels and complexity of the data. Value-added measure scores may be more appropriate to use with a hierarchical-linear model since value-added measure accounts for student achievement at the student level. However, investigating classroom-level variables was a good place to start to explore and generate follow-up questions for future research. In addition, classroom-level analysis was appropriate for the research questions since the variables of interest, observational CLASS scores, were collected at the classroom level. A longitudinal model may be a more appropriate model to use than the regression model for Research Question Q4 since the effect of year was the focus of the research question.

A second limitation was how the CLASS scores were used in the models for the dissertation. The original CLASS™ instrument, developed by La Paro et al. (2004), includes a 7-point scale, with low scores representing little evidence of the indicator (1,2); mid scores reflecting modest levels (3,4,5); and high scores reflecting substantial indicators of the dimension (6,7). The scores are intended to be used as categories or ranks of low, mid, or high. The MET dataset used in this dissertation included observational ratings for each of the seven indicators rather than a score for each category. Rather than treating the variables as continuous, a non-categorical model may be a better fit for the data due to the true framework of the CLASS™.

A third limitation was that the highly complex structure of the MET dataset had some disadvantages. Classroom teachers taught multiple sections of classes. Some teachers taught only ELA, some taught only mathematics, and a smaller proportion taught both ELA and mathematics. It was also possible for a teacher to have one score in Year One and two scores in Year Two. Relationships between the observations were most likely correlated. Regardless, researchers and the structure of the data treated each observation as an independent observation score. A mixed model random teacher effect would further account for individual teacher characteristics. An equivalent concern was the structure of the data outcome variables (ELA and MATH) as being independent of one another. There very well could have been a relationship between the two sets of scores that was not being accounted for.

The amount of missingness in the MET data was also of concern. Roughly 37% of the focal-subject dataset were missing observed CLASS scores and were removed from the dataset. One district systematically did not report data for free or reduced lunch status. A second district did not report data for fourth or fifth grade classrooms. There may have been something unique about each of these districts as to reasons why specific data were systematically not reported. As a result of exclusion criteria, large amounts of data were eliminated from the sub-sample for this study. Furthermore, a decision had to be made on whether to include the full sample for Year One and Year Two or to conduct the analysis using the analytic sample of the teachers who participated in both Year One and Year Two. The decision to use the analytic sample further reduced the sample size. Therefore, the generalizability of the results applies to fourth and fifth grade classroom teachers with observed and recorded

CLASS score observations as well as free or reduced price lunch scores reported by each district.

A final major limitation of the dissertation and the MET project was due to the difficulties in randomly assigning teachers to rosters of students. The MET researchers ideally had wanted the assigned students to have been taught by the actual teacher in which the roster was assigned (Gates Foundation, 2013). However, MET researchers could not force students, teachers, or principals to comply, and because assignments were made the summer before school began it was unknown which students or teachers would actually be in the assigned school when the school year began. Some students transferred to other schools and some teachers transferred to other classrooms in the same school, while other teachers taught different course sections or grades than originally planned (Gates Foundation, 2013). And in some cases, schools did not implement the randomization. Therefore, many students' actual teacher was different from their assigned teacher. One method MET researchers suggest using in order to get the most out of random assignment is by generating instrumental variable estimates of the difference between students' assigned teacher and actual teacher (Garrett & Steinberg, 2014; Gates Foundation, 2013). This approach is most appropriate for models accounting for school, teacher, and student level differences.

Recommendations for Future Research

Results from the dissertation showed the effects of teacher interactional quality on ELA classroom achievement were statistically significant for both years of the study, when teachers went about their usual classroom practices and when teachers were randomized to classrooms of students. Whereas, teacher interactional quality statistically significantly explained variation in MATH classroom achievement outcomes only during the business-as-usual year when teachers went about their usual teaching practices in the classroom.

Other MET researchers have found the opposite pattern for other teacher quality indicators, including the instructional effectiveness using the Danielson framework, wherein teachers had the most impact on mathematics achievement (Gates Foundation, 2012a). Follow-up research should see if classroom teacher effects in ELA are comparable to those found in mathematics when using the MET project's supplemental standardized tests that measures higher-order thinking in addition to basic skills. Each district reported data on the mandated district standardized assessments. In addition, MET researchers collected two supplemental assessments, the Stanford 9 Open-Ended assessment as well as the Balanced Assessment in Mathematics. The Stanford 9 tests higher-order ELA skills by asking students to explain the thinking behind each reading passage, whereas the Balanced Assessment in Mathematics measures higher-order mathematical reasoning skills (Gates Foundation, 2010c).

Some researchers (Gates Foundation, 2012a) have questioned whether these standardized achievement measures reflect the true effectiveness or classroom teachers or just random variation in student performance. They have further criticized the limited measurement of these basic-skill assessments with the use of multiple-choice items. Thus researchers have looked toward value-added measures to examine a group of teachers and the teacher's value-added with different groups of students (Gates Foundation, 2010b; Rivkin et al., 2005). Value-added measures have shown the powerful effects a teacher has on students' mathematics and reading achievement

(Rivkin et al., 2005). More recently, MET researchers (Gates Foundation, 2010b) found a teacher's record of value-added scores to be the strongest predictor of their students' achievement gains in every grade and subject. Mihaly, McCaffrey, Staiger, and Lockwood (2013) used the MET data and found that one year of data from value-added for state tests was highly correlated with a teacher's stable impact on student achievement gains. Teachers with high value-added scores on state standardized tests also appear to promote deeper conceptual understanding among their students.

On the flip side, other researchers have urged the need for caution when using value-added measures (Raudenbush, 2015; Rothstein, 2010). The perspective questions sampling variation of value-added measures and the possible fluctuation from year to year. There could be very talented and attentive students in one year that result in gains in the classroom that would be difficult to replicate in another group. There could also be a few students who disrupt learning for the classroom or contextual factors such as distractions during test taking. The statistical models used in computing value-added measure scores are also quite complex and not without limitations. Even with the use of value-added measures, these standardized achievement assessments still only cover a sample of all the knowledge taught in a given year, and often times the measurement depends on the inclusion or exclusion of certain lessons by the teacher in that given year (Gates Foundation, 2012a).

Researchers should always be cautious in the interpretation of findings from standardized assessments as well as value-added measures when making systematic decisions on the hiring or firing of teachers. Furthermore, the implications from examining ELA higher-order writing, reading skills, and mathematical skills should provide a greater understanding. This analysis, in turn, may help in the design of new literacy and mathematics assessments to measure common core standards in ways that are more sensitive to instructional effects than the current district standardized assessments (Gates Foundation, 2012a).

Contributions to the Literature and to Educational Practice

Although the MET project was the first of its kind and made great progress toward finding an effective, holistic method of evaluating teachers, there were also some disadvantages (Gates Foundation, 2012a). It was the first educational research study to attempt such a large scale of randomization in the schools, which proved to be a challenge. This project and data have been a spring board for deeper conversations in educational research on the possibility of combining measures of classroom observation, student perception surveys, and student achievement gains.

This dissertation tapped into the complexity of data available using classroom-level data. Its focus was to examine one level that allowed for an intentional design and selection of predictor variables. As discussed in Chapter II, research on teacher quality has found inconsistent findings for the effectiveness of teacher quality indicators such as teacher education, experience, certification, and salary in explaining student achievement outcomes in the classroom (Hanushek et al., 1999; Kane et al., 2008; Murnane & Cohen, 1986; Rivkin et al., 2005). As Pianta et al. (2012) have argued, to leverage our knowledge about teacher quality, we need to spend less attention on curriculum design, classroom size, and teacher experience and more on how teachers are supported to interact and build relationships with their students, such that students become engaged and have ample opportunities for learning.

One of the goals for this dissertations was to focus on observational measures in order to better recognize teacher-student interactions that make a difference in student learning outcomes. Further examination of observational measures such as the CLASS™ should help provide teachers with feedback and support on teaching practices. This is important feedback to provide to our teachers, since federal and state legislation are holding teachers accountable to demonstrate an impact on student learning. It has been well established in previous research before MET and confirmed by MET researchers that teacher interactional quality can have a positive influence on achievement outcomes (Blazar, 2015; Garrett & Steinberg, 2014; Gates Foundation, 2012a).

The findings from this dissertation suggest teacher interactional quality based on the CLASS™ had a greater impact on ELA achievement outcomes than MATH achievement outcomes in fourth and fifth grade classrooms. The CLASS™ is a general content observational rubric. However, certain dimensions of teacher-student interactions may be more likely to be encouraged depending on the content area. For example, ELA classrooms may encourage student expression (i.e., emotional support) by being responsive to student perspectives in generating ideas for thesis topics. In contrast, a mathematics classroom may promote certain dimensions of classroom organization by actively engaging students in the use of interesting activities and instructional centers for problem solving.

It is also worth noting that emotional support, classroom organization, and instructional support look different for fourth graders than they do for ninth graders. Developmentally appropriate practice and how teachers can express positive interactions across grade levels is an important area for future research. Thus further exploration of teachers' interactions with students as well as modeling of what positive interactions look like within each CLASS domain, content area, and grade level are necessary for fostering the continued professional growth of teachers (Peske, & Haycock, 2006)). Pianta et al. (2012), have found that when additional supports are provided to teachers with regard to teacher-student interactions, there is an increase in student engagement.

One student population of concern in terms of student engagement is those students from low socioeconomic backgrounds. As discussed in Chapter II, students from low socioeconomic backgrounds are more likely to be taught by teachers who are less experienced, trained at less selective institutions, and less successful at raising student test scores (Lankford et al., 2002; Peske & Haycock, 2006). Moreover, these students in preschool are at an increased likelihood to have higher levels of conflict and lower levels of emotional closeness in the classroom (Hamre & Pianta, 2001; Jerome et al., 2009).

This dissertation's focus on the free or reduced price lunch population makes important contributions to the field because positive teacher-student interactions with students from low income backgrounds have been shown to be predictive of positive developmental outcomes such as motivation, positive behavioral outcomes, and positive academic performance (Rimm-Kaufman, La Paro, & Downer, & Pianta, 2005; Rudasill et al., 2010). Furthermore, these positive teacher-student interactions moderate how students respond to risks in their life by facilitating adaptive coping skills and a sense of control through stable and responsive relationships in the classroom (Hamre & Pianta, 2005; Jerome et al., 2009; Lee & Bierman, 2015; Shonkoff et al., 2012). Thus research needs to further examine the role of teacher-student interactions in classroom achievement for students from varied socioeconomic backgrounds in order to identify positive teacher qualities that enhance student engagement.

Another contribution of this dissertation was the identification of strong associations for teacher interactional quality and ELA classroom achievement outcomes in both years of the study. This pattern of results warrants a further investment in studying early literacy environments in the school and the types of positive teacher-student interactions and teacher dispositions that enhance learning in these classrooms.

In addition, the results raise the question of whether standardized achievement and value-added measures are the most informative outcome for students from low socioeconomic backgrounds. It is possible that a teacher high in interactional quality can moderate the effects of poverty by fostering multiple aspects of social-emotional development. Future research should see if teachers with higher CLASS scores have an impact on social-emotional facets of a child’s life in addition to on academic outcomes.

Lastly, this dissertation focused on fourth and fifth grade classroom indicators and outcomes because interactions are important in engagement during the elementary school years (Crosnoe & Benner, 2015). Engagement has been shown to decline throughout schooling with the greatest decline during secondary years (Crosnoe & Benner, 2015). Low engagement during these later years in schooling may deter students from successful high school graduation. Especially for students identified as financially at-risk, early interventions for positive teacher interactions and engagement are especially important (Lee & Bierman, 2015). These students on average are more likely to have lower standardized assessment scores and lower school activity engagement and are more likely to drop out of school before high school graduation (Caro, McDonald, & Willms, 2009; Lazar, 1982; Quinn, 2015).

If preparation programs and school systems are able to better identify teacher qualities that have an impact on student learning, this information can be used to attract, prepare, support, and retain teachers who are skilled in their interactions and emotionally attuned to the needs of students. This information can be used as a foundation for states and districts as they develop mentoring, coaching, professional development, and teacher evaluation systems for strengthening the recruitment and retention of high quality teachers (Gates Foundation, 2010b).

One of the major venues for developing effective teachers is through teacher preparation programs. These programs have the ability to identify desirable teacher dispositions and positive interactional styles early on in the program through multiple observations and reflective opportunities. Increased dialog may encourage reflective practices and provide specific feedback to prospective teachers. Information for specific characteristic of students within a school, such as ethnicity and economic status, should be incorporated into the teacher preparation program’s curriculum and field experience. Having multiple opportunities during field experiences with students from diverse backgrounds can give prospective teachers practice and enhance their awareness of students’ needs, in addition to the interactional styles that are most effective in encouraging student learning and engagement.

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APPENDIX A

UNIVERSITY OF NORTHERN COLORADO
INSTITUTIONAL REVIEW BOARD
APPROVAL

UNIVERSITY of NORTHERN COLORADO

Institutional Review Board

DATE:	September 3, 2014
TO:	Kristin Klopfenstein, PhD
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[651773-1] The Student Teacher Relationship as a Measure of Effective Teaching
SUBMISSION TYPE:	New Project
ACTION:	APPROVED
APPROVAL DATE:	September 3, 2014
EXPIRATION DATE:	September 3, 2015
REVIEW TYPE:	Expedited Review

Thank you for your submission of New Project materials for this project. The University of Northern Colorado (UNCO) IRB has APPROVED your submission. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on applicable federal regulations.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

Please note that any revision to previously approved materials must be approved by this committee prior to initiation. Please use the appropriate revision forms for this procedure.

All UNANTICIPATED PROBLEMS involving risks to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to this office.

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to this office.

Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the appropriate forms for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of September 3, 2015.

Please note that all research records must be retained for a minimum of three years after the completion of the project.

If you have any questions, please contact Sherry May at 970-351-1910 or Sherry.May@unco.edu. Please include your project title and reference number in all correspondence with this committee.

Hello Kristin,

UNIVERSITY OF
NORTHERN COLORADO

Institutional Review Board

DATE:	March 30, 2016
TO:	Kristin Klopfenstein, PhD
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[651773-3] The Student Teacher Relationship as a Measure of Effective Teaching
SUBMISSION TYPE:	Amendment/Modification
ACTION:	APPROVED
APPROVAL DATE:	March 26, 2016
EXPIRATION DATE:	August 5, 2016
REVIEW TYPE:	Expedited Review

Thank you for your submission of Amendment/Modification materials for this project. The University of Northern Colorado (UNCO) IRB has APPROVED your submission. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on applicable federal regulations.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

Please note that any revision to previously approved materials must be approved by this committee prior to initiation. Please use the appropriate revision forms for this procedure.

All UNANTICIPATED PROBLEMS involving risks to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to this office.

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to this office.

Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the appropriate forms for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of August 5, 2016.

Please note that all research records must be retained for a minimum of three years after the completion of the project.

If you have any questions, please contact Sherry May at 970-351-1910 or Sherry.May@unco.edu. Please include your project title and reference number in all correspondence with this committee.

APPENDIX B

UNIVERSITY OF NORTHERN COLORADO
INSTITUTIONAL REVIEW BOARD
CONTINUATION APPROVAL

UNIVERSITY OF
NORTHERN COLORADO

Institutional Review Board

DATE:	August 5, 2016
TO:	Kristin Klopfenstein, PhD
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[651773-4] The Student Teacher Relationship as a Measure of Effective Teaching
SUBMISSION TYPE:	Continuing Review/Progress Report
ACTION:	APPROVED
APPROVAL DATE:	August 5, 2016
EXPIRATION DATE:	August 5, 2017
REVIEW TYPE:	Expedited Review

Thank you for your submission of Continuing Review/Progress Report materials for this project. The University of Northern Colorado (UNCO) IRB has APPROVED your submission. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on applicable federal regulations.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

Please note that any revision to previously approved materials must be approved by this committee prior to initiation. Please use the appropriate revision forms for this procedure.

All UNANTICIPATED PROBLEMS involving risks to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to this office.

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to this office.

Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the appropriate forms for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of August 5, 2017.

Please note that all research records must be retained for a minimum of three years after the completion of the project.

If you have any questions, please contact Sherry May at 970-351-1910 or Sherry.May@unco.edu. Please include your project title and reference number in all correspondence with this committee.

UNIVERSITY of NORTHERN COLORADO

Institutional Review Board

DATE:	August 10, 2015
TO:	Kristin Klopfenstein, PhD
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[651773-2] The Student Teacher Relationship as a Measure of Effective Teaching
SUBMISSION TYPE:	Continuing Review/Progress Report
ACTION:	APPROVED
APPROVAL DATE:	August 5, 2015
EXPIRATION DATE:	August 5, 2016
REVIEW TYPE:	Expedited Review

Thank you for your submission of Continuing Review/Progress Report materials for this project. The University of Northern Colorado (UNCO) IRB has APPROVED your submission. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on applicable federal regulations.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

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All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to this office.

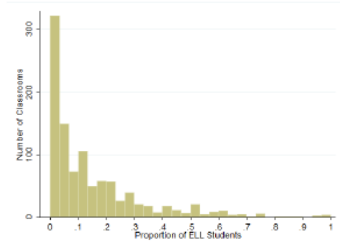
Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the appropriate forms for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of August 5, 2016.

Please note that all research records must be retained for a minimum of three years after the completion of the project.

If you have any questions, please contact Sherry May at 970-351-1910 or Sherry.May@unco.edu. Please include your project title and reference number in all correspondence with this committee.

APPENDIX C

DESCRIPTIVES



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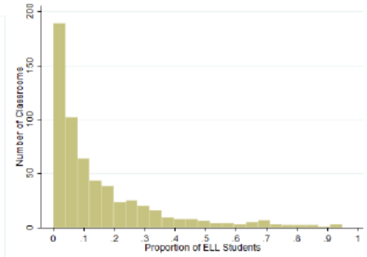

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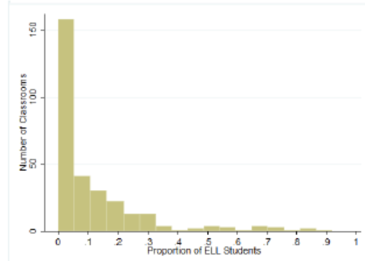

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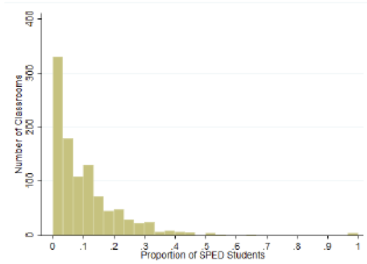

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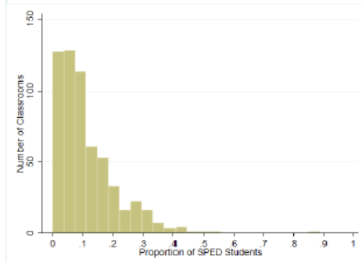

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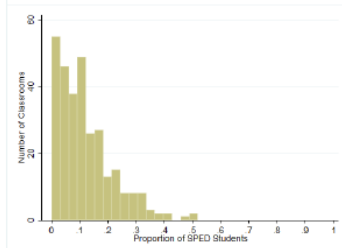

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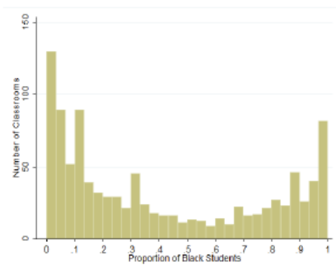

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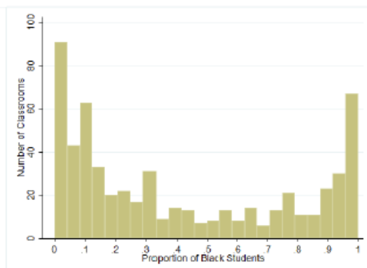

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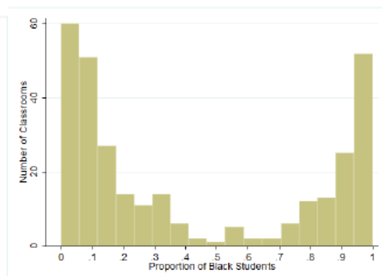

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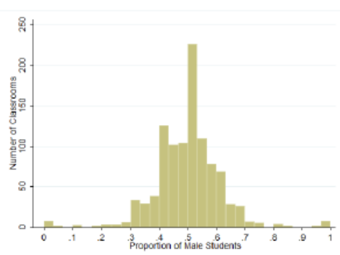

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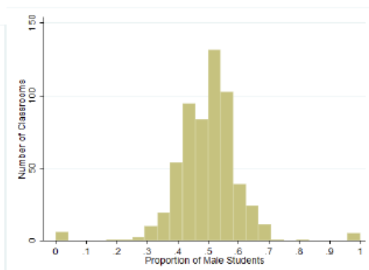

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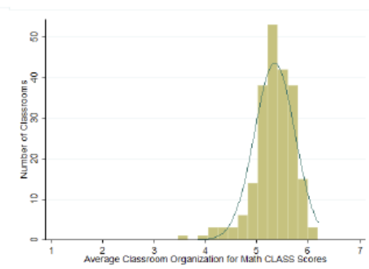

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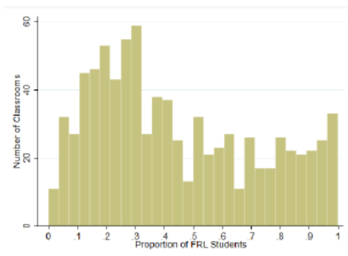

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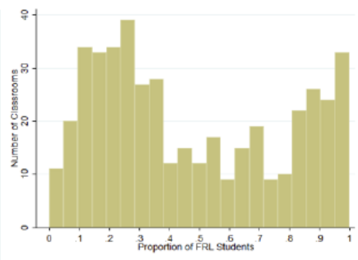

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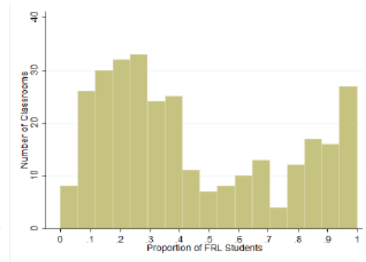
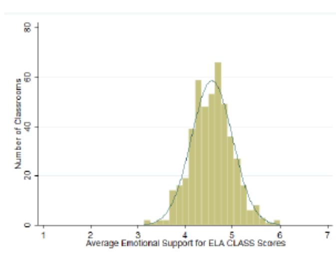


C.13.3. LUNCH

Figure 13. Plotted frequencies of the proportion of student demographics in the classrooms. C represents Appendix C. 13 represents the Figure number. Year One indicated by 1; Year Two indicated by 2; Analytic Sample indicated by 3.

APPENDIX D

CLASS SCORE BY YEAR



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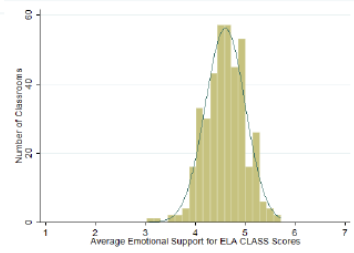

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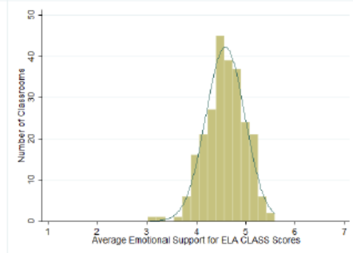

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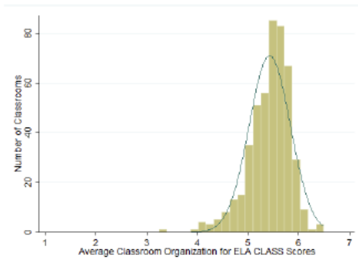

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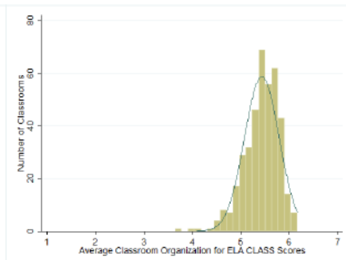

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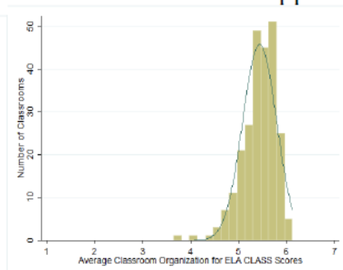

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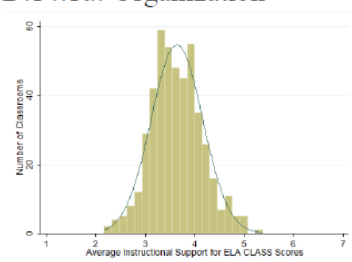

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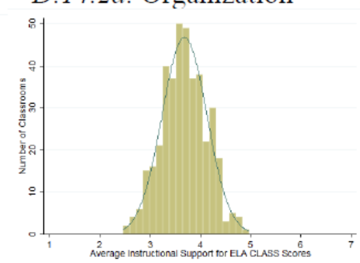

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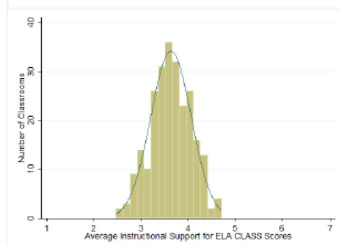

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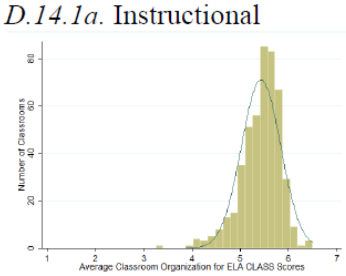
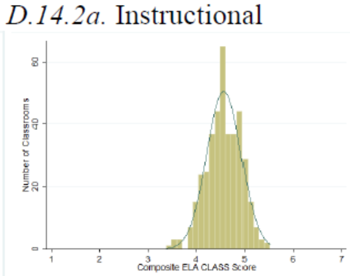


D.14.1a. Domain Average



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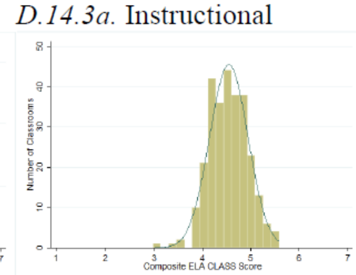

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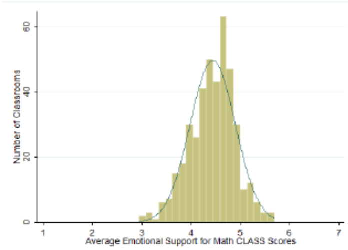
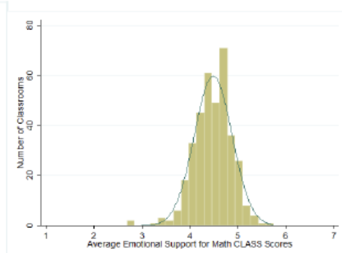


D.14.1b. Emotional Support



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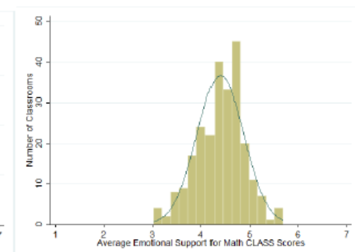

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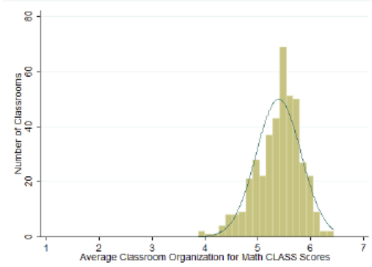

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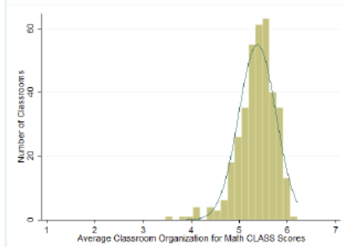

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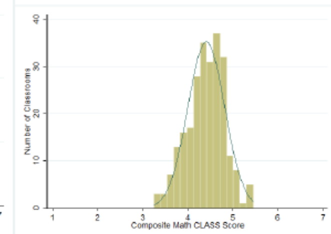

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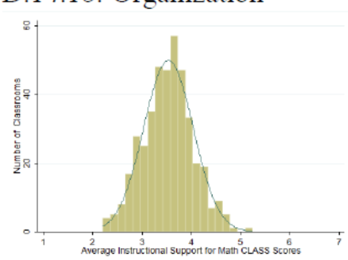

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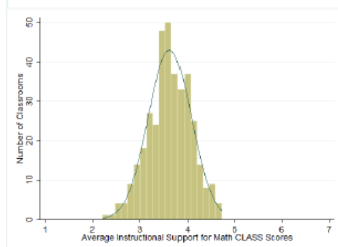

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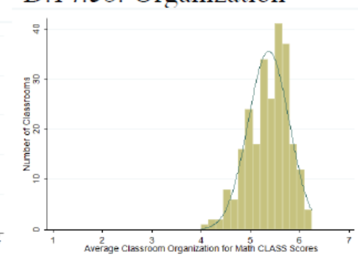

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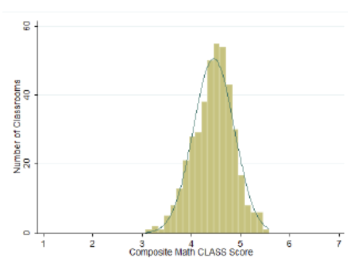
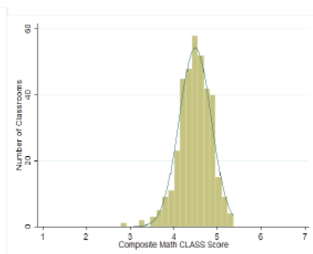
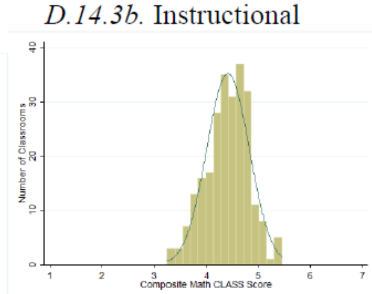


D.14.1b. Domain Average



D.14.2b. Domain Average



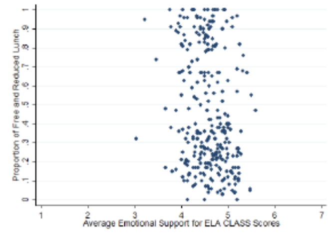
D.14.3b. Domain Average

Figure 14. Plotted frequencies ELA classroom teachers CLASS score by year. D represents Appendix D. 14 represents the Figure number. a represents ELA classrooms. Year One indicated by 1; Year Two indicated by 2; Analytic Sample indicated by 3.

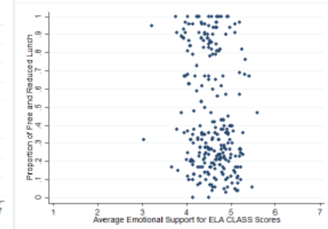
APPENDIX E

RESEARCH QUESTION Q1 SCATTERPLOTS

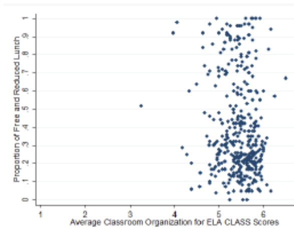
E.15.1a. Emotional Support



E.15.2a. Emotional Support

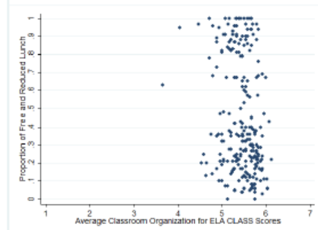


E.15.3a. Emotional Support

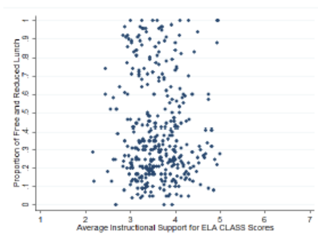


E.15.1a. Organization

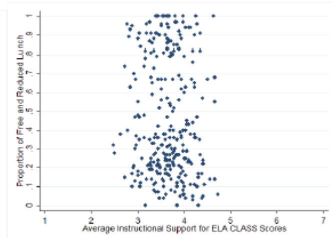
E.15.2a. Organization



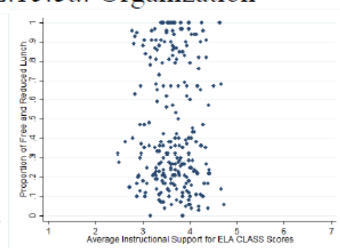
E.15.3a. Organization



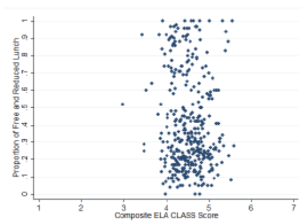
E.15.1a. Instructional



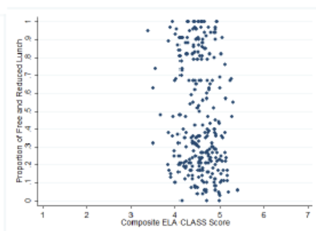
E.15.2a. Instructional



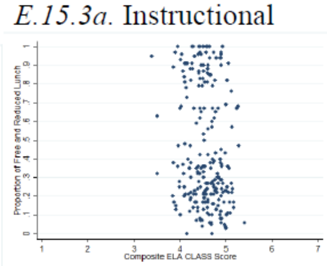
E.15.3a. Instructional



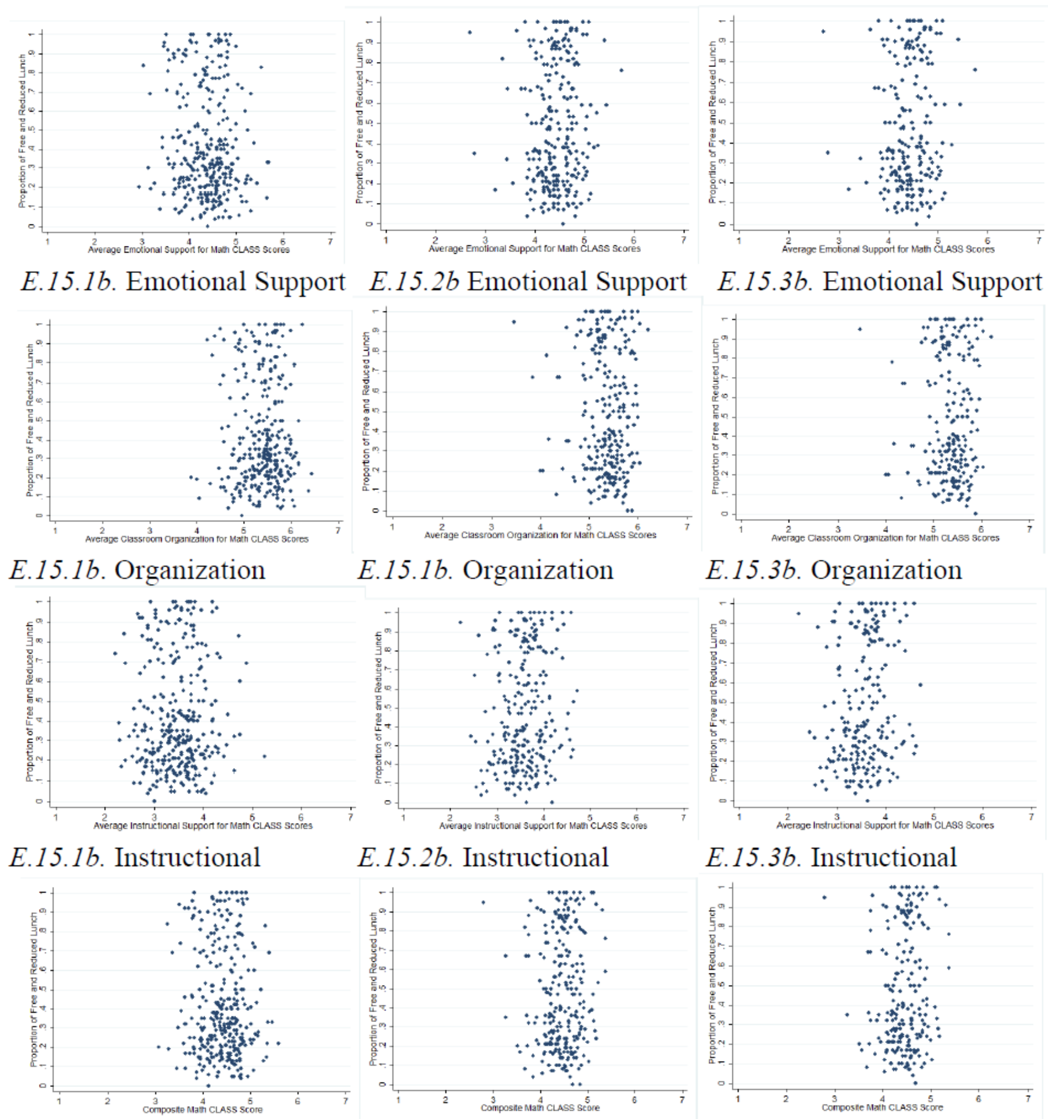
E.15.1a. Domain Average



E.15.2a. Domain Average



E.15.3a. Domain Average



E.15.1b. Emotional Support *E.15.2b* Emotional Support *E.15.3b.* Emotional Support

E.15.1b. Organization *E.15.1b.* Organization *E.15.3b.* Organization

E.15.1b. Instructional *E.15.2b.* Instructional *E.15.3b.* Instructional

E.15.1b. Domain Average *E.15.2b.* Domain Average *E.15.3b.* Domain Average

Figure 15. Scatterplot of MATH classroom teacher CLASS scores by proportion of students with free or reduced price lunch. E represents Appendix E. 15 represents the Figure number. b represents Math classrooms. Year One indicated by 1; Year Two indicated by 2; Analytic Sample indicated by 3

APPENDIX F

SYNTAX CODE

```
******Data Organization for Year One Full-
Sample************************************
**** Base-Analytic 4th-8th Grade Year One Files
**This is STATA code using the "da34309-0001_REST.dta"

*Read in data
use "H:\original data\da34309-0001_REST.dta", clear
log using "H:\logs\RQ1_RQ2_output_031416.log", replace

*Create dataset using just the ID variables for CLASS Year 1 Phase II (Math +ELA,
ELA, Math)
#delimit ;

keep DISTRICT_ICPSR_ID SCHOOL_ICPSR_ID SECTION_ICPSR_ID
TEACHER_ICPSR_ID GRADE_LEVEL SCF_SUBJ
N_VIDEO_PER_SECTION_CLASS SD_LUNCH C2_NVIDEO C2_NSEG
C2_NSCORES C2_SUBJ C2_AVG_POSITIVE_CLIMATE
C2_AVG_NEGATIVE_CLIMATE C2_AVG_TEACHER_SENSITIVITY
C2_AVG_REGARD_FOR_STUDENT_PERSP
C2_AVG_BEHAVIOR_MANAGEMENT C2_AVG_PRODUCTIVITY
C2_AVG_INSTRUCTIONAL_LEARNING_F
C2_AVG_CONTENT_UNDERSTANDING
C2_AVG_ANALYSIS_AND_PROBLEM_SOLV
C2_AVG_QUALITY_OF_FEEDBACK C2_AVG_INSTRUCTIONAL_DIALOGUE
C2_AVG_STUDENT_ENGAGEMENT C2_AVGEMOSUPPDOM
C2_AVGCLASSMANDOM C2_AVGINSTSUPPDOM C2_TOT_RATERS
C2_HMEAN_NSEG C2_HMEAN_NSEG_HMEAN_RATERS C2E_NVIDEO
C2E_NSEG C2E_TOT_RATERS C2E_NSCORES
C2EAVG_POSITIVE_CLIMATE C2EAVG_NEGATIVE_CLIMATE
C2EAVG_TEACHER_SENSITIVITY
C2EAVG_REGARD_FOR_STUDENT_PERSP
C2EAVG_BEHAVIOR_MANAGEMENT C2EAVG_PRODUCTIVITY
C2EAVG_INSTRUCTIONAL_LEARNING_F
C2EAVG_CONTENT_UNDERSTANDING
C2EAVG_ANALYSIS_AND_PROBLEM_SOLV
C2EAVG_QUALITY_OF_FEEDBACK
C2EAVG_INSTRUCTIONAL_DIALOGUE
C2EAVG_STUDENT_ENGAGEMENT C2EAVG_DOMAIN1
C2EAVG_DOMAIN2 C2EAVG_DOMAIN3 C2E_HMEAN_NSEG
C2E_HMEAN_NSEG_HMEAN_RATERS C2M_NVIDEO C2M_NSEG
C2M_TOT_RATERS C2M_NSCORES C2MAVG_POSITIVE_CLIMATE
C2MAVG_NEGATIVE_CLIMATE C2MAVG_TEACHER_SENSITIVITY
C2MAVG_REGARD_FOR_STUDENT_PERSP
C2MAVG_BEHAVIOR_MANAGEMENT C2MAVG_PRODUCTIVITY
C2MAVG_INSTRUCTIONAL_LEARNING_F
C2MAVG_CONTENT_UNDERSTANDING
C2MAVG_ANALYSIS_AND_PROBLEM_SOLV
```

```
C2MAVG_QUALITY_OF_FEEDBACK
C2MAVG_INSTRUCTIONAL_DIALOGUE
C2MAVG_STUDENT_ENGAGEMENT
C2MAVG_DOMAIN1 C2MAVG_DOMAIN2 C2MAVG_DOMAIN3
C2M_HMEAN_NSEG
C2M_HMEAN_NSEG_HMEAN_RATERS ;

#delimit cr

*Frequency table for grade level
tab GRADE_LEVEL
des GRADE_LEVEL

*Only look at grade 4 and 5
keep if GRADE_LEVEL==4 | GRADE_LEVEL==5
count

*Check for teacher duplicates
duplicates report TEACHER_ICPSR_ID

*List of duplicates in dataset
duplicates examples TEACHER_ICPSR_ID

*Create variable for 1=duplicates 0= not duplicates
duplicates tag TEACHER_ICPSR_ID, generate(duptag)

*Frequencies of duplicate identifier, double check worked correctly
tab duptag

*Table summary for teacher subject taught
by SCF_SUBJ, sort: gen


******Year 1 Created Datafile to
Merge*********************************************
**** Base-Analytic 4th-8th Grade Year One Files
**This is STATA code using the "da34309-0001_REST.dta"
*Making Year 1 data file

use "H:\original data\da34309-0001_REST.dta", clear
log using "H:\Analytic Sample\Correlation (RQ1)\Correlation (RQ1)_6.07.2016.log"

*Year 1 Variables for overall regression model combining RQ3 RQ4 RQ5
#delimit ;

 keep GRADE_LEVEL SCF_SUBJ SD_MALE SD_LUNCH SD_SPED SD_ELL
SD_RACE_BLK SD_RACE_WHT
```

```
 ELA_SCORE10 MATH_SCORE10 C2_AVGEMOSUPPDOM
C2_AVGCLASSMANDOM C2_AVGINSTSUPPDOM
 C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3
C2MAVG_DOMAIN1 C2MAVG_DOMAIN2 C2MAVG_DOMAIN3 ;

#delimit cr

*Only look at grade 4 and 5
keep if GRADE_LEVEL==4 | GRADE_LEVEL==5
count

*Generate an indicator for year in order to tell which row aligns with which year when
we merge year 1 and year 2
gen year=0

*Label the indicator for clarity
label variable year "generated year indicator"

*creating variable names to match year 2 (namely matching score variables)
clonevar ELA = ELA_SCORE10
clonevar MATH = MATH_SCORE10

*creating average variables (not in year 1s dataset)
gen C2_AVG_OVERALL_MEAN =
(C2_AVGEMOSUPPDOM+C2_AVGCLASSMANDOM+C2_AVGINSTSUPPDOM
)/3
gen C2EAVG_OVERALL_MEAN =
(C2EAVG_DOMAIN1+C2EAVG_DOMAIN2+C2EAVG_DOMAIN3)/3
gen C2MAVG_OVERALL_MEAN =
(C2MAVG_DOMAIN1+C2MAVG_DOMAIN2+C2MAVG_DOMAIN3)/3

*dropping the old variables in place of the new
drop ELA_SCORE10 MATH_SCORE10


****** Year 2 Created Datafile to Merge
********************************************
****Base-Analytic 4th-8th Grade Year Two  Files
**This is STATA code using the "da34309-0003_REST.dta"
*Making Year 2 Datafile

use "H:\original data\da34309-0003_REST.dta", clear
log using "H:\logs\RQ3toRQ5_Merge_Dataset_041916.log", replace

*Year 1 Variables for overall regression model combining RQ3 RQ4 RQ5
#delimit ;
```

```
 keep GRADE_LEVEL SCF_SUBJ SD_MALE SD_LUNCH SD_SPED SD_ELL
SD_RACE_BLK SD_RACE_WHT
 ELA_SCORE11 MATH_SCORE11 C2_AVGEMOSUPPDOM
C2_AVGCLASSMANDOM C2_AVGINSTSUPPDOM
 C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3
C2MAVG_DOMAIN1 C2MAVG_DOMAIN2
 C2MAVG_DOMAIN3 ;

#delimit cr

*Only look at grade 4 and 5
keep if GRADE_LEVEL==4 | GRADE_LEVEL==5
count

*Generate an indicator for year in order to tell which row aligns with which year when
we merge year 1 and year 2
gen year=1

*Label the indicator for clarity
label variable year "generated year indicator"

*matchin names with year 1 and year 2 dataset (create cloned variable of correct
name, delete variable of incorrect name)
clonevar ELA = ELA_SCORE11
clonevar MATH = MATH_SCORE11

*creating average variables (not in year 2s dataset)
gen C2_AVG_OVERALL_MEAN =
(C2_AVGEMOSUPPDOM+C2_AVGCLASSMANDOM+C2_AVGINSTSUPPDOM
)/3
gen C2EAVG_OVERALL_MEAN =
(C2EAVG_DOMAIN1+C2EAVG_DOMAIN2+C2EAVG_DOMAIN3)/3
gen C2MAVG_OVERALL_MEAN =
(C2MAVG_DOMAIN1+C2MAVG_DOMAIN2+C2MAVG_DOMAIN3)/3

*dropping the old variables in place of the new
drop ELA_SCORE11 MATH_SCORE11


******Merging of Year 1 and Year
2*********************************************
*Merging the datasets

use "C:\Users\hessc\Desktop\Year1_Analytic_Selected_Variables.dta"
log using "H:\logs\RQ3toRQ5_Merge_Dataset_041916.log", replace

append using "C:\Users\hessc\Desktop\Year2_Analytic_Selected_Variables.dta"
```

****** Missingness
****
*****Checking the missingness patterns in the merged data file
***Year One and Year Two
**This is R code using the "MergedYear1and2_Analytic_Selected_Variables.dta"

```
# the grab function ----
source("..//grab_Function.R")

#reading in the data from a created csv ---
dat <- read.csv("MergedDataToGoIntoR_5.19.2016.csv")

#several observations used "Male" instead of a proportion: removing those (marked
them as missing)
dat <- dat[!(dat$SD_MALE=="Male"),]
dat$SD_MALE <- as.numeric(as.character(dat$SD_MALE)) #changing SD_MALE
to be numeric

# Installing packages for missingness patterns:
options(repos = (ICPSRrepos ="file:Z:/R"),
      pkgType = "win.binary",
      install.packages.check.source = "no")

#install.packages("mice")

#library(foreign)

# Examining the missingness ---
#overall
apply(dat, 2, function(x) sum(is.na(x)))

#by year
year1misssum <- apply(dat[dat$year==0,], 2, function(x) sum(is.na(x)))
year2misssum <- apply(dat[dat$year==1,], 2, function(x) sum(is.na(x)))
misssum <- rbind(year1misssum, year2misssum)
rownames(misssum) <- c("Year 1", "Year 2")
misssum <- cbind(misssum, total=table(dat$year))
misssum
#edit(misssum)

#look at the 1 missing sped row
dat[is.na(dat$SD_SPED),]
t(dat[is.na(dat$SD_SPED),])

#looking at missing lunch values
```

```
dat[is.na(dat$SD_LUNCH),]
apply(dat[is.na(dat$SD_LUNCH),], 2, function(x) sum(is.na(x)))
# 5.23.2016 ----

#### loading packages
grab(mice, VIM, BaylorEdPsych, mvnmle)

#### Load the asam dataset (Analytic Sample)
asam <- read.csv(file = "..\\Merging Data\\Analytic
Sample\\5.20.2016MergedCleanAnalyticSample.csv")

####creating a missing data dataset
#pull out repetitive or misleading class scores
mdat <- dat[,c(1, 10, 25, 22)] #missing data (variables of interest): mdat
#names are unreadable for mdat, changed the names
names(mdat) <- c("District", "FRL", "CLASS", "Year")

#### matrixplots
matrixplot(mdat)
#matrixplot(asam) #remember that all of the missing data was removed for this, so no
missingness

#making a matrix plot file with code
png(file="missingDataMatrixPlot.png", bg="transparent", width=600, height=360)
  matrixplot(mdat)
dev.off()

#### flux
# making a flux dataset
fdat <- dat[, c(5, 7:12, 22:25)]#flux data: fdat
flux(fdat)
fluxplot(fdat)

#### little's test
LittleMCAR(dat[,-(1:7)])

#### aggregate plot
aggr(mdat[,2:3], numbers=TRUE)

#making a aggregate plot file with code
png(file="missingDataAggregatePlot.png", bg="transparent", width=600, height=360)
  aggr(mdat[,2:3], numbers=TRUE)
dev.off()

******RQ1*********************************************************
*********
```

```
***** CLASS score by LUNCH status by reported LUNCH percent in the teacher's
classroom
***Year One Full-Sample
**This is STATA code using the " H:\Full

******Descriptives Full-Sample Year 1 and
2****************************************
****Full-Sample
**This is STATA code using the  "H:\Full
Sample\MergedYear1and2_Analytic_Selected_Variables.dta"

*Note that all of these demographics will give the number of CLASSROOMS with the
given demographic information.

**********************************Tables********************************
********
***Tables for descriptives
*Make a table of number of classrooms in grade by year
tabulate GRADE_LEVEL year

*Teacher subjects by year
tabulate SCF_SUBJ year

*Average proportions by year (MALE, SPED, etc). Also includes overall mean
* (weighted, based on MET)
tabstat SD_MALE SD_SPED SD_ELL SD_LUNCH SD_RACE_BLK, statistics(
mean ) by(year)

*District by year (frequencies)
tabulate DISTRICT_ICPSR_ID year

*Missing data in class and LUNCH for year 1 and 2
misstable summarize C2_AVG_OVERALL_MEAN SD_LUNCH if year==0
misstable summarize C2_AVG_OVERALL_MEAN SD_LUNCH if year==1

*Class domains by subject by year
tabstat C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3
C2EAVG_OVERALL_MEAN C2MAVG_DOMAIN1 C2MAVG_DOMAIN2
C2MAVG_DOMAIN3 C2MAVG_OVERALL_MEAN , statistics( mean sd ) by(year)

*Finding how many teachers taught 1, 2, and 3 sections (stored in "c" variable)
*NOTE The count=2 are TWICE the number of teachers that taught 2 sections
* (because this is the number of sections with teachers that taught two sections)
* so, each teacher is given a 2 for each section they taught (and counted twice)
egen c=count(1), by( TEACHER_ICPSR_ID year)
tabulate c year
drop c
```

```
********************************Plots*******************************
********
****Histograms for CLASS
*Histograms for year 1 English Teacher Domain Scores
histogram C2EAVG_DOMAIN1 if year ==0, xtitle("Average Emotional Support for
ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_EMO.png", as(png) replace

histogram C2EAVG_DOMAIN2 if year ==0, xtitle("Average Classroom Organization
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_CO.png", as(png) replace

histogram C2EAVG_DOMAIN3 if year ==0, xtitle("Average Instructional Support
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_IS.png", as(png) replace

*Histograms for year 1 Math Teacher Domain Scores
histogram C2MAVG_DOMAIN1 if year ==0, xtitle("Average Emotional Support for
Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_EMO.png", as(png) replace

histogram C2MAVG_DOMAIN2 if year ==0, xtitle("Average Classroom
Organization for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7))
ytitle("Number of Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_CO.png", as(png) replace

histogram C2MAVG_DOMAIN3 if year ==0, xtitle("Average Instructional Support
for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_IS.png", as(png) replace

*Histograms for year 1 Composite ELA and Math Teacher Domain Scores
histogram C2EAVG_OVERALL_MEAN if year ==0, xtitle("Composite ELA CLASS
Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_Composite.png", as(png) replace

histogram C2MAVG_OVERALL_MEAN if year ==0, xtitle("Composite Math
CLASS Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_Composite.png", as(png) replace
```

```
*Histograms for year 2 English Teacher Domain Scores
histogram C2EAVG_DOMAIN1 if year ==1, xtitle("Average Emotional Support for
ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_EMO.png", as(png) replace

histogram C2EAVG_DOMAIN2 if year ==1, xtitle("Average Classroom Organization
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_CO.png", as(png) replace

histogram C2EAVG_DOMAIN3 if year ==1, xtitle("Average Instructional Support
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_IS.png", as(png) replace

*Histograms for year 2 Math Teacher Domain Scores
histogram C2MAVG_DOMAIN1 if year ==1, xtitle("Average Emotional Support for
Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_EMO.png", as(png) replace

histogram C2MAVG_DOMAIN2 if year ==1, xtitle("Average Classroom
Organization for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7))
ytitle("Number of Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_CO.png", as(png) replace

histogram C2MAVG_DOMAIN3 if year ==1, xtitle("Average Instructional Support
for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_IS.png", as(png) replace

*Histograms for year 2 Composite ELA and Math Teacher Domain Scores
histogram C2EAVG_OVERALL_MEAN if year ==1, xtitle("Composite ELA CLASS
Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_Composite.png", as(png) replace

histogram C2MAVG_OVERALL_MEAN if year ==1, xtitle("Composite Math
CLASS Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_Composite.png", as(png) replace

*********************************Plots*****************************
********
***Histograms for Demographics
```

```
*Histogram for year 1 Demographic Proportions
histogram SD_MALE if year ==0, xtitle("Proportion of Male Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_Male_Proportion.png", as(png) replace

histogram SD_SPED if year ==0, xtitle("Proportion of SPED Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_SPED_Proportion.png", as(png) replace

histogram SD_ELL if year ==0, xtitle("Proportion of ELL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_ELL_Proportion.png", as(png) replace

histogram SD_LUNCH if year ==0, xtitle("Proportion of FRL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_LUNCH_Proportion.png", as(png) replace

histogram SD_RACE_BLK if year ==0, xtitle("Proportion of Black Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y1_Black_Proportion.png", as(png) replace

histogram SD_RACE_WHT if year ==0, xtitle("Proportion of White Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y1_White_Proportion.png", as(png) replace

*Histogram for year 2 Demographic Proportions
histogram SD_MALE if year ==1, xtitle("Proportion of Male Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_Male_Proportion.png", as(png) replace

histogram SD_SPED if year ==1, xtitle("Proportion of SPED Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_SPED_Proportion.png", as(png) replace

histogram SD_ELL if year ==1, xtitle("Proportion of ELL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_ELL_Proportion.png", as(png) replace
```

```
histogram SD_LUNCH if year ==1, xtitle("Proportion of FRL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_LUNCH_Proportion.png", as(png) replace

histogram SD_RACE_BLK if year ==1, xtitle("Proportion of Black Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y2_Black_Proportion.png", as(png) replace

histogram SD_RACE_WHT if year ==1, xtitle("Proportion of White Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y2_White_Proportion.png", as(png) replace



**********************Scatter
Plots***************************************
***SES by CLASS
*Scatterplots for year 1 LUNCH by English CLASS score
twoway (scatter SD_LUNCH C2EAVG_DOMAIN1) if year ==0, xtitle("Average
Emotional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN2) if year ==0, xtitle("Average
Classroom Organization for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN3) if year ==0, xtitle("Average
Instructional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_IS.png", as(png) replace

*Scatterplots for year 1 LUNCH by Math CLASS score
twoway (scatter SD_LUNCH C2MAVG_DOMAIN1) if year ==0, xtitle("Average
Emotional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_EMO.png", as(png) replace
```

```
twoway (scatter SD_LUNCH C2MAVG_DOMAIN2) if year ==0, xtitle("Average
Classroom Organization for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN3) if year ==0, xtitle("Average
Instructional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_IS.png", as(png) replace

*Scatterplots for year 1 LUNCH by Composite CLASS scores (both ELA and Math)
twoway (scatter SD_LUNCH C2EAVG_OVERALL_MEAN) if year ==0,
xtitle("Composite ELA CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_Composite.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_OVERALL_MEAN) if year ==0,
xtitle("Composite Math CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_Composite.png", as(png) replace

*Scatterplots for year 2 LUNCH by English CLASS score
twoway (scatter SD_LUNCH C2EAVG_DOMAIN1) if year ==1, xtitle("Average
Emotional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN2) if year ==1, xtitle("Average
Classroom Organization for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN3) if year ==1, xtitle("Average
Instructional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_IS.png", as(png) replace

*Scatterplots for year 2 LUNCH by Math CLASS score
twoway (scatter SD_LUNCH C2MAVG_DOMAIN1) if year ==1, xtitle("Average
Emotional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
```

```
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN2) if year ==1, xtitle("Average
Classroom Organization for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN3) if year ==1, xtitle("Average
Instructional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_IS.png", as(png) replace

*Scatterplots for year 2 LUNCH by Composite CLASS scores (both ELA and Math)
twoway (scatter SD_LUNCH C2EAVG_OVERALL_MEAN) if year ==1,
xtitle("Composite ELA CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_Composite.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_OVERALL_MEAN) if year ==1,
xtitle("Composite Math CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_Composite.png", as(png) replace

*Histogram for year 1 outcomes (ELA and Math)
histogram ELA if year==0, xtitle("State Assessment (2010) ELA Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_LHV_ELA_Student_Outcome.png", as(png) replace

histogram MATH if year==0, xtitle("State Assessment (2010) Math Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_LHV_Math_Student_Outcome.png", as(png) replace

*Histogram for year 2 outcomes (ELA and Math)
histogram ELA if year==1, xtitle("State Assessment (2011) ELA Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_LHV_ELA_Student_Outcome.png", as(png) replace
```

```
histogram MATH if year==1, xtitle("State Assessment (2011) Math Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_LHV_Math_Student_Outcome.png", as(png) replace


******Descriptives Analytic Sample
**********************************************
****Analytic Sample
**This is STATA code using the  "H:\Analytic
Sample\5.20.2016AnalyticSample_FromCSV.dta"

*Note that all of these demographics will give the number of CLASSROOMS with
* the given demographic information.

**************************Tables*************************************
*Make a table of number of classrooms in grade by year
tabulate GRADE_LEVEL year

*Teacher subjects by year
tabulate SCF_SUBJ year

*Average proportions by year (MALE, SPED, etc). Also includes overall mean
* (weighted, apparently)
tabstat SD_MALE SD_SPED SD_ELL SD_LUNCH SD_RACE_BLK, statistics(
mean ) by(year)

*District by year (frequencies)
tabulate DISTRICT_ICPSR_ID year

*Missing data in class and LUNCH for year 1 and 2
misstable summarize C2_AVG_OVERALL_MEAN SD_LUNCH if year==0
misstable summarize C2_AVG_OVERALL_MEAN SD_LUNCH if year==1

*Class domains by subject by year
tabstat C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3
C2EAVG_OVERALL_MEAN C2MAVG_DOMAIN1 C2MAVG_DOMAIN2
C2MAVG_DOMAIN3 C2MAVG_OVERALL_MEAN , statistics( mean sd ) by(year)

*Finding how many teachers taught 1, 2, and 3 sections (stored in "c" variable)
*NOTE The count=2 are TWICE the number of teachers that taught 2 sections
* (because this is the number of sections with teachers that taught two sections)
* so, each teacher is given a 2 for each section they taught (and counted twice)
egen c=count(1), by( TEACHER_ICPSR_ID year)
tabulate c year
drop c
```

```
****************************Plots********************************
****Histograms for CLASS
*Histograms for year 1 English Teacher Domain Scores
histogram C2EAVG_DOMAIN1 if year ==0, xtitle("Average Emotional Support for
ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_EMO.png", as(png) replace

histogram C2EAVG_DOMAIN2 if year ==0, xtitle("Average Classroom Organization
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_CO.png", as(png) replace

histogram C2EAVG_DOMAIN3 if year ==0, xtitle("Average Instructional Support
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_IS.png", as(png) replace

*Histograms for year 1 Math Teacher Domain Scores
histogram C2MAVG_DOMAIN1 if year ==0, xtitle("Average Emotional Support for
Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_EMO.png", as(png) replace

histogram C2MAVG_DOMAIN2 if year ==0, xtitle("Average Classroom
Organization for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7))
ytitle("Number of Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_CO.png", as(png) replace
histogram C2MAVG_DOMAIN3 if year ==0, xtitle("Average Instructional Support
for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_IS.png", as(png) replace

*Histograms for year 1 Composite ELA and Math Teacher Domain Scores
histogram C2EAVG_OVERALL_MEAN if year ==0, xtitle("Composite ELA CLASS
Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_ELA_Composite.png", as(png) replace

histogram C2MAVG_OVERALL_MEAN if year ==0, xtitle("Composite Math
CLASS Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_Math_Composite.png", as(png) replace

*Histograms for year 2 English Teacher Domain Scores
```

```
histogram C2EAVG_DOMAIN1 if year ==1, xtitle("Average Emotional Support for
ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_EMO.png", as(png) replace

histogram C2EAVG_DOMAIN2 if year ==1, xtitle("Average Classroom Organization
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_CO.png", as(png) replace

histogram C2EAVG_DOMAIN3 if year ==1, xtitle("Average Instructional Support
for ELA CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_IS.png", as(png) replace

*Histograms for year 2 Math Teacher Domain Scores
histogram C2MAVG_DOMAIN1 if year ==1, xtitle("Average Emotional Support for
Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_EMO.png", as(png) replace

histogram C2MAVG_DOMAIN2 if year ==1, xtitle("Average Classroom
Organization for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7))
ytitle("Number of Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_CO.png", as(png) replace
histogram C2MAVG_DOMAIN3 if year ==1, xtitle("Average Instructional Support
for Math CLASS Scores") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of
Classrooms") graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_IS.png", as(png) replace

*Histograms for year 2 Composite ELA and Math Teacher Domain Scores
histogram C2EAVG_OVERALL_MEAN if year ==1, xtitle("Composite ELA CLASS
Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_ELA_Composite.png", as(png) replace

histogram C2MAVG_OVERALL_MEAN if year ==1, xtitle("Composite Math
CLASS Score") frequency xlabel(1[1]7) xsc(r(1 7)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_Math_Composite.png", as(png) replace


*****************************Plots*********************************
****Histograms for Demographics
*Histogram for year 1 Demographic Proportions
```

```
histogram SD_MALE if year ==0, xtitle("Proportion of Male Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_Male_Proportion.png", as(png) replace

histogram SD_SPED if year ==0, xtitle("Proportion of SPED Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_SPED_Proportion.png", as(png) replace

histogram SD_ELL if year ==0, xtitle("Proportion of ELL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_ELL_Proportion.png", as(png) replace

histogram SD_LUNCH if year ==0, xtitle("Proportion of FRL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y1_LUNCH_Proportion.png", as(png) replace

histogram SD_RACE_BLK if year ==0, xtitle("Proportion of Black Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y1_Black_Proportion.png", as(png) replace

histogram SD_RACE_WHT if year ==0, xtitle("Proportion of White Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y1_White_Proportion.png", as(png) replace

*Histogram for year 2 Demographic Proportions
histogram SD_MALE if year ==1, xtitle("Proportion of Male Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_Male_Proportion.png", as(png) replace

histogram SD_SPED if year ==1, xtitle("Proportion of SPED Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_SPED_Proportion.png", as(png) replace

histogram SD_ELL if year ==1, xtitle("Proportion of ELL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_ELL_Proportion.png", as(png) replace
```

```
histogram SD_LUNCH if year ==1, xtitle("Proportion of FRL Students") frequency
xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms") graphregion(color(white))
fcolor(khaki)
graph export "..\Plots\Y2_LUNCH_Proportion.png", as(png) replace

histogram SD_RACE_BLK if year ==1, xtitle("Proportion of Black Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y2_Black_Proportion.png", as(png) replace

histogram SD_RACE_WHT if year ==1, xtitle("Proportion of White Students")
frequency xlabel(0[.1]1) xsc(r(0 1)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki)
graph export "..\Plots\Y2_White_Proportion.png", as(png) replace

*Histogram for year 1 outcomes (ELA and Math)
histogram ELA if year==0, xtitle("State Assessment (2010) ELA Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_LHV_ELA_Student_Outcome.png", as(png) replace

histogram MATH if year==0, xtitle("State Assessment (2010) Math Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y1_LHV_Math_Student_Outcome.png", as(png) replace

*Histogram for year 2 outcomes (ELA and Math)
histogram ELA if year==1, xtitle("State Assessment (2011) ELA Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_LHV_ELA_Student_Outcome.png", as(png) replace
histogram MATH if year==1, xtitle("State Assessment (2011) Math Rank Based Z-
Score") frequency xlabel(-2[1]2) xsc(r(-2 2)) ytitle("Number of Classrooms")
graphregion(color(white)) fcolor(khaki) normal
graph export "..\Plots\Y2_LHV_Math_Student_Outcome.png", as(png) replace

*************Scatterplots*****************
******SES by CLASS
*Scatterplots for year 1 LUNCH by English CLASS score
twoway (scatter SD_LUNCH C2EAVG_DOMAIN1) if year ==0, xtitle("Average
Emotional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN2) if year ==0, xtitle("Average
Classroom Organization for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
```

```
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN3) if year ==0, xtitle("Average
Instructional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_IS.png", as(png) replace

*Scatterplots for year 1 LUNCH by Math CLASS score
twoway (scatter SD_LUNCH C2MAVG_DOMAIN1) if year ==0, xtitle("Average
Emotional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN2) if year ==0, xtitle("Average
Classroom Organization for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN3) if year ==0, xtitle("Average
Instructional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_IS.png", as(png) replace

*Scatterplots for year 1 LUNCH by Composite CLASS scores (both ELA and Math)
twoway (scatter SD_LUNCH C2EAVG_OVERALL_MEAN) if year ==0,
xtitle("Composite ELA CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_ELAbySES_Composite.png", as(png) replace
twoway (scatter SD_LUNCH C2MAVG_OVERALL_MEAN) if year ==0,
xtitle("Composite Math CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y1_MathbySES_Composite.png", as(png) replace

*Scatterplots for year 2 LUNCH by English CLASS score
twoway (scatter SD_LUNCH C2EAVG_DOMAIN1) if year ==1, xtitle("Average
Emotional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_EMO.png", as(png) replace
```

```
twoway (scatter SD_LUNCH C2EAVG_DOMAIN2) if year ==1, xtitle("Average
Classroom Organization for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2EAVG_DOMAIN3) if year ==1, xtitle("Average
Instructional Support for ELA CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_IS.png", as(png) replace

*Scatterplots for year 2 LUNCH by Math CLASS score
twoway (scatter SD_LUNCH C2MAVG_DOMAIN1) if year ==1, xtitle("Average
Emotional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_EMO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN2) if year ==1, xtitle("Average
Classroom Organization for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0
1)) ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_CO.png", as(png) replace

twoway (scatter SD_LUNCH C2MAVG_DOMAIN3) if year ==1, xtitle("Average
Instructional Support for Math CLASS Scores") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_IS.png", as(png) replace

*Scatterplots for year 2 LUNCH by Composite CLASS scores (both ELA and Math)
twoway (scatter SD_LUNCH C2EAVG_OVERALL_MEAN) if year ==1,
xtitle("Composite ELA CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_ELAbySES_Composite.png", as(png) replace
twoway (scatter SD_LUNCH C2MAVG_OVERALL_MEAN) if year ==1,
xtitle("Composite Math CLASS Score") xlabel(1[1]7) xsc(r(1 7)) ysc(r(0 1))
ylabel(0[.1]1) ytitle("Proportion of Free and Reduced Lunch")
graphregion(color(white))
graph export "..\Plots\Y2_MathbySES_Composite.png", as(png) replace
```

```
******RQ1*************************************************************
*********
***** CLASS score by LUNCH status by reported LUNCH percent in the teacher's
classroom
***Year One Full-Sample
**This is STATA code using the " H:\Full
Sample\MergedYear1and2_Analytic_Selected_Variables.dta

* finding correlations between LUNCH and CLASS composite score (for ELA and
Math)
*  to see if there is a significant linear relationship between them (For RQ1).
*  Will also use the plots (scatterplot comparing the two) to offer evidence that
*There isn't a non-linear relationship, either.

*Read in data
use ""H:\Full Sample\MergedYear1and2_Analytic_Selected_Variables.dta”
log using "H:\Full Sample\Correlation (RQ1)\Correlation (RQ1)_6.07.2016.log”

pwcorr C2EAVG_OVERALL_MEAN SD_LUNCH if year==0, star(.05) sig

*Finding the above correlations for the different domains within ELA and math (as
well).
*Bottom row of the table (top piece is correlation, bottom is p-value).

pwcorr C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3
SD_LUNCH if year==0, star(.05) sig

pwcorr C2MAVG_OVERALL_MEAN SD_LUNCH if year==0, star(.05) sig

pwcorr C2MAVG_DOMAIN1 C2MAVG_DOMAIN2 C2MAVG_DOMAIN3
SD_LUNCH if year==0, star(.05) sig

end do-file
exit, clear


******RQ1*************************************************************
*********
*****CLASS score by LUNCH status by reported LUNCH percent in the teacher's
classroom
***Year Two Analytic Sample
**This is STATA code using the " H:\Full
Sample\MergedYear1and2_Analytic_Selected_Variables.dta

* Finding correlations between LUNCH and CLASS composite score (for ELA and
Math)
*  To see if there is a significant linear relationship between them (For RQ1).
```

* Will also use the plots (scatterplot comparing the two) to offer evidence that
* there isn't a non-linear relationship, either.

*Table #
pwcorr C2EAVG_OVERALL_MEAN SD_LUNCH if year==0, star(.05) sig

*Table #
pwcorr C2MAVG_OVERALL_MEAN SD_LUNCH if year==0, star(.05) sig

*Finding the above correlations for the different domains within ELA and math (as well).
*Bottom row of the table (top piece is correlation; bottom is p-value).

*Table #
pwcorr C2EAVG_DOMAIN1 C2EAVG_DOMAIN2 C2EAVG_DOMAIN3 SD_LUNCH if year==0, star(.05) sig

*Table #
pwcorr C2MAVG_DOMAIN1 C2MAVG_DOMAIN2 C2MAVG_DOMAIN3 SD_LUNCH if year==0, star(.05) sig

end of do-file
exit, clear

******RQ2***
***** CLASS score association with classroom achievement outcomes
***Year One Full-Sample
**This is STATA code using the "

*Read in data
use "H:\Full Sample\MergedYear1and2_Analytic_Selected_Variables.dta"
log using "H:\Full Sample\Normal Multiple Regression (RQ2)\Normal Multiple Regression (RQ2)_6.07.2016.log", replace

*Note: average domain variables for CLASS were used (in place of using each domain separately)
* As there was a collinearity issue. Note that all domains were significant when analyzed
* independent of the other domains (without collinearity). With collinearity, only domain
* 2 was significant.

*Note: SD_WHITE is removed from the below analysis (though it was initially proposed)
* Due to collinearity with SD_BLACK. SD_BLACK was retained in place of SD_WHITE due to

```
* side interest of the present study (3 way interaction between male, black, and
CLASS,
* three way interaction wasn't significant for math or ela).
*showing all of the output at once (no "more" button)
set more off

*Running models with interactions (between CLASS and LUNCH)
*Table#
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0, beta
*Table #
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0, beta

* Outliers and homoscedasticity (for all possible models)

* Standardized residuals vs. Predicted values for ELA/MATH Scores
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0
rvfplot, graphregion(color(white))
graph export "RQ2_ELA_Residual_Plot_6.7.2016.png", as(png) replace

regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0
rvfplot, graphregion(color(white))
graph export "RQ2_Math_Residual_Plot_6.7.2016.png", as(png) replace

* Normality (qq and pp plots) for ELA and Math
*ELA (eint is english with interaction)
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0
predict eint, resid
pnorm eint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ2_ELA_PP_Plot_6.7.2016.png", as(png) replace
qnorm eint, graphregion(color(white))
graph export "RQ2_ELA_QQ_Plot_6.7.2016.png", as(png) replace

*Math (mint is math with interaction)
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==0
```

```
predict mint, resid
pnorm mint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ2_Math_PP_Plot_6.7.2016.png", as(png) replace
qnorm mint, graphregion(color(white))
graph export "RQ2_Math_QQ_Plot_6.7.2016.png", as(png) replace




******RQ3*********************************************************
*********
***** Casual impact of CLASS score on classroom achievement outcomes
***Year Two  Analytic Sample
**This is STATA code using the "H:\Full
Sample\MergedYear1and2_Analytic_Selected_Variables.dta"

use "H:\Full Sample\MergedYear1and2_Analytic_Selected_Variables.dta"
log using "H:\Full Sample\Normal Multiple Regression (RQ3)\Normal Multiple
Regression (RQ3)_6.07.2016.log", replace

*Analysis for RQ3
*Note: average variables for CLASS were used (in place of using each domain
separately)
* as there was a collinearity issue. Note that all domains were significant when
analyzed
* independent of the other domains (without collinearity). With collinearity, only
domain
* 2 was significant.

*Note: SD_WHITE is removed from the below analysis (though it was initially
proposed)
* due to collinearity with SD_BLACK. SD_BLACK was retained in place of
SD_WHITE due to
* side interests from the research team (3 way interaction between male, black, and
CLASS,
* which wasn't significant for math or ela).

*showing all of the output at once (no "more" button)
set more off

*Running models with interactions (between CLASS and SES)
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1, beta
```

```
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1, beta

* outliers and homoscedasticity (for all possible models, perhaps only report 1 set of
these)

* Standardized residuals vs. Predicted values for ELA/MATH Scores
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1
rvfplot, graphregion(color(white))
graph export "RQ3_ELA_Residual_Plot_6.7.2016.png", as(png) replace

regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1
rvfplot, graphregion(color(white))
graph export "RQ3_Math_Residual_Plot_6.7.2016.png", as(png) replace



* normality (qq and pp plots) for ELA and Math
*ELA (eint is english with interaction)
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2EAVG_OVERALL_MEAN c.C2EAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1
predict eint, resid
pnorm eint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ3_ELA_PP_Plot_6.7.2016.png", as(png) replace
qnorm eint, graphregion(color(white))
graph export "RQ3_ELA_QQ_Plot_6.7.2016.png", as(png) replace

*Math (mint is math with interaction)
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK SD_LUNCH
C2MAVG_OVERALL_MEAN c.C2MAVG_OVERALL_MEAN#c.SD_LUNCH if
year==1
predict mint, resid
pnorm mint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ3_Math_PP_Plot_6.7.2016.png", as(png) replace
qnorm mint, graphregion(color(white))
graph export "RQ3_Math_QQ_Plot_6.7.2016.png", as(png) replace
```

******RQ4***
****
***** Association of CLASS score on classroom achievement outcomes compare to Causal estimates of CLASS score on classroom achievement outcomes
***Year Two Analytic Sample
**This is STATA code using "H:\Analytic Sample\5.20.2016AnalyticSample_FromCSV.dta"

use "H:\Analytic Sample\5.20.2016AnalyticSample_FromCSV.dta"
log using "H:\Analytic Sample\Normal Multiple Regression (RQ4)\Normal Multiple Regression (RQ4)_6.07.2016.log", replace

*Analysis for RQ4
*Note: average variables for CLASS were used (in place of using each domain separately)
* as there was a collinearity issue. Note that all domains were significant when analyzed
* independent of the other domains (without collinearity). With collinearity, only domain
* 2 was significant.

*Note: SD_WHITE is removed from the below analysis (though it was initially proposed)
* due to collinearity with SD_BLACK. SD_BLACK was retained in place of SD_WHITE due to
* side interests from the research team (3 way interaction between male, black, and CLASS,
* which wasn't significant for math or ela).

*showing all of the output at once (no "more" button)
set more off

*Running models with interactions (between CLASS and SES). Note that, while math is insignificant below,
* removing year from the analysis (and the interactions with year) makes math significant again
* (so the lack of significance of math is due to the addition of year, NOT due to the switch to the analytic
* sample from the full sample)
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK c.SD_LUNCH##year##c.C2EAVG_OVERALL_MEAN, beta
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK c.SD_LUNCH##year##c.C2MAVG_OVERALL_MEAN, beta

* outliers and homoscedasticity (for all possible models, perhaps only report 1 set of these)

```
* Standardized residuals vs. Predicted values for ELA/MATH Scores
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK
c.SD_LUNCH##year##c.C2EAVG_OVERALL_MEAN
rvfplot, graphregion(color(white))
graph export "RQ4_ELA_Residual_Plot_6.7.2016.png", as(png) replace

regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK
c.SD_LUNCH##year##c.C2MAVG_OVERALL_MEAN
rvfplot, graphregion(color(white))
graph export "RQ4_Math_Residual_Plot_6.7.2016.png", as(png) replace

* normality (qq and pp plots) for ELA and Math
*ELA (eint is english with interaction)
regress ELA SD_MALE SD_SPED SD_ELL SD_RACE_BLK
c.SD_LUNCH##year##c.C2EAVG_OVERALL_MEAN
predict eint, resid
pnorm eint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ4_ELA_PP_Plot_6.7.2016.png", as(png) replace
qnorm eint, graphregion(color(white))
graph export "RQ4_ELA_QQ_Plot_6.7.2016.png", as(png) replace

*Math (mint is math with interaction)
regress MATH SD_MALE SD_SPED SD_ELL SD_RACE_BLK
c.SD_LUNCH##year##c.C2MAVG_OVERALL_MEAN
predict mint, resid
pnorm mint, graphregion(color(white)) xtitle("Empirical Probability") ytitle("Normal
Probability")
graph export "RQ4_Math_PP_Plot_6.7.2016.png", as(png) replace
qnorm mint, graphregion(color(white))
graph export "RQ4_Math_QQ_Plot_6.7.2016.png", as(png) replace
```