THE STABILITY OF TEACHER EFFECTS ON STUDENT MATH AND READING ACHIEVEMENT OVER TIME: A STUDY OF ONE MIDSIZE DISTRICT

BY

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ABSTRACT

Increased attention on teacher accountability via student achievement gains has brought proposed policy changes which recommend teachers receive performance pay as recognition for effective teaching. In response to the growing consensus that teachers' contributions to student learning should be a part of the teacher evaluation process, education reformers have begun implementing pay-for-performance models that reward teacher performance by the scores their students receive on high-stakes testing through the use of sophisticated value-added models. There is currently a broad scope of value-added models based on student academic achievement gains, and the majority of studies centering on these diverse models indicate little stability in teacher scores across time. This study takes into account the previous research on value-added growth models, and explores the uncharted territory of measuring teacher stability on state assessment scores in one midsize district over a longer period of time. Results from this study showed weak to moderate correlations from one year to the next in stability of teacher scores, with more stability evidenced in math than in reading. As a result of the instability of teacher scores over time, teacher characteristics attributed to stable and unstable teachers respectively could not be determined.

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Chapter One

The purpose of this study was to examine the stability of teacher effects on student math and reading assessment scores over time. This study also examined teacher characteristics of the same high-, low-, and average-ranked teachers to determine if a relationship exists between stable teacher scores and teacher characteristics that could later have implications for personnel selection or for policies to further define teacher effectiveness. Driving this study is the question, **is there stability of teacher test scores over time?**

Only a handful of studies have analyzed teacher performance stability using value-added models, with even fewer studies addressing stability of teacher test scores longitudinally. A few studies have focused on the stability of teacher effects over time in metropolitan school districts, such as San Diego, Chicago Public Schools, and several large school districts in Florida (Aaronson et al., 2007; Kane and Staiger, 2008; Sass, 2009). From these studies, results show at best a moderate-to-weak correlation in stability of teacher scores over time across the one to two years studied. The results published from these studies typically show instability in teacher test scores, but to varying degrees. Relevant to the important policy implications that could stem from these results, replication of similar studies is needed to make informed decisions regarding implementation on what some educational reformers are calling the fourth major change[1] in teacher compensation plans.

This study examines one typical midsize district. If teacher effectiveness is going to be measured in achievement gains or by student performance on standardized assessments, it is

[1] Three major phases in teacher compensation in the United States: 1) "The Boarding Round" where teachers taught in exchange for room and board in a community, reflective of the bartering mentality. 2) The "Position Based" salary system which required some pre-service training and reflected the societal systems in place with unequal salaries in regards to gender and race. 3) "Single Salary Schedule"-known today as the standardized system for teacher pay with factors such as experience and advanced degrees defined on salary schedules.

logical to examine long-term effects of teachers on student assessment performance. If teachers cannot consistently achieve high rankings on assessments over multiple years, then the means by which we evaluate teachers, in this case average scores of state assessments, is either 1) misinforming, or 2) provides evidence that teachers are not consistently effective. In these circumstances, the probability of their students passing the state assessment has more to do with varying cohorts and other factors than with consistently high performance on the part of teachers.

If this method of evaluation is not reliable, administrative personnel decisions could unwittingly be made in error, and educational reformers would likewise be implementing a new teacher evaluation system that is anything but effective, which could have detrimental impacts on the teaching profession. The stability of teacher performance on student state scores has been studied over shorter, one-to-two year time frames. As a result, ineffective or potentially ineffective teachers could be retained or financially rewarded for unstable performance over time if these results were used alone for teacher evaluation policy decisions. This study examined teacher performance on student test scores over a three to six year fixed period to assess if teacher performance could be predicted or, in other words, if the data showed that a portion of teachers could be consistently ranked as "stable" or "unstable." Those considered stable as high and low performers (also referred to as effective and non-effective based on value-added theory) were analyzed to examine if a relationship exists between teacher characteristics of those with stable scores and unstable scores, respectively.

Chapter Two

Review of Literature

The U.S. Department of Education's Race to the Top initiative has four key program policies; three of these policies directly or indirectly address management of teacher quality.[2] With a new emphasis on teacher accountability and measurement of teacher effectiveness growth models, educational reformers across the nation are approaching the issue of measuring teacher quality more precisely. From educational researchers and policymakers comes the consensus that current teaching evaluation systems lack the ability to adequately improve instruction or decision making regarding personnel (Darling-Hammond et al., 2011).

In response to a new policy of improving student achievement outcomes, educational leaders and state departments of education have shown increased interest in assessing teacher performance to account for teacher contribution to learning gains. This method of accountability, often referred to as value-added models or VAMs, evaluates individual teacher performance from year to year, taking into account student characteristics such as socioeconomic status, to statistically account for teacher outputs. Implementation of these growth models in school districts has resulted in several pay-for-performance compensation plans, where effective teachers are financially compensated for student achievement gains on high-stakes testing.

From consensus that teachers are the most crucial student-based resource in student achievement and an understanding that good teaching results in the greatest student gains, policy makers have turned their attention to value-added models of assessing individual teacher effectiveness, often a component of teacher evaluation, by using performance scores of students

[2] Race to the Top encourages policies designed to 1) recruit and retain effective teachers; 2) build longitudinal data systems that will provide feedback on teacher effectiveness; 3) assist in turning around the lowest performing schools.

to measure that effectiveness. These results are often used in evaluation systems to inform administrative decisions on teacher retention and compensation. With increased emphasis placed on measuring teacher effectiveness in the classroom, individual school districts have not only implemented varying pay-for-performance (also known as merit pay) programs, but also used teacher effectiveness scores to publicly rank teachers. Additionally discussed is the concept of making personnel decisions based on teachers' statistically calculated performance scores.

From adopting contracts for pay-for-performance teaching in Denver, Colorado to implementing value-added models to inform personnel decisions in Tennessee, the effort to measure teacher effectiveness and to make decisions based on these measurements all rest on the assumption that "teacher quality is a stable attribute in teachers" (Goldhaber and Hansen, 2010). In its simplest form this assumption implies that effective teachers in the present will continue to be effective teachers in the future, and that ineffective teachers will remain ineffective in the future.

Defining Teacher Effectiveness

Research shows that teachers are the most influential school-based resource in student learning and that good teaching does matter (Ferguson, 1991; Darling-Hammond, 2000; Wright, Horn, and Sanders, 2007). Additionally, William Sanders (2000) concludes that teacher effectiveness is the single largest factor contributing to the difference in academic growth of populations of students. While few argue over effective teaching as the most critical school-based factor in student learning, defining how teachers influence learning is a challenge.

Studies demonstrate that students who are consistently taught by effective teachers benefit much more so than students not consistently taught by effective teachers (Gordon et al.,

2006). Sanders and Horn's (1998) study showed that second grade students had comparable student achievement results, yet in the fifth grade had very different outcomes in performance. These results were not due to student socioeconomic status (SES), class sizes, or even attendance, but to the teachers the students had over the years (Sanders and Horn, 1998; Schacter, 2010). While few argue that teacher quality and teacher effects on student achievement are the most critical school-based attribute to student gains in the classroom, defining what teacher effectiveness actually is can be a complicated task. Lewis et al. (1999) states, "teacher quality is a complex phenomenon, and there is little consensus on what it is and how to measure it." The term teacher effectiveness itself remains a challenging concept when one considers the multiple contexts a teacher performs within in their line of work, as well as the variable components of those contexts. A review from the National Institute of Child Health and Human Development echoed this educational observation, "Rigorous experimental and qualitative research that defines and characterizes effective teaching methodologies that demonstrate improved student performance is limited."

Conversations continue over best ways to determine teacher effectiveness. Earlier definitions of teacher effectiveness have been described in various ways. For example, Clark's study in 1993 states, "the definition involves someone who can increase student knowledge, but it goes beyond this in defining an effective teacher." Million's (1987) definition of effective teaching relies more on the teacher's lesson design and delivery. Papanastasiou (1999) states that, "no single teacher attribute or characteristic is adequate to define an effective teacher". Vogt (1984) relates effective teaching to a teacher's skill in providing instruction to different students of varying abilities while assessing various learning styles and including appropriate instructional methods. Wenglinsky (2000) says that the learning that happens in the classroom is

what is most important and that teacher effectiveness ultimately comes down to classroom practices. Absent in these earlier studies of teacher effectiveness is the connection of student achievement data with teacher performance --- if this is a viable piece in determining effectiveness of teachers. Clark (1993) shared that the problem lies in determining how best to measure student achievement. Only recently has attention turned to measuring student achievement, and therefore, teacher effectiveness, using standardized scores, achievement data, and student gains (Markley, 2004). "One area that was avoided by most authors was the idea of using student achievement as a measure of effectiveness" (Clark, 1993). Currently, the definition of an effective teacher by the Department of Education's Race to the Top is "a teacher whose students achieve acceptable rates (e.g., at least one grade level in an academic year) of student growth." The question remains, however, from numerous researchers' reviews, "whether a teacher who is effective or ineffective once is equally effective or ineffective a second time" (p 7 Newton et al., 2010).

In the narrowest modern definition, teacher effectiveness can be defined merely by student gains a teacher achieves in his or her classroom, meaning a teacher can be ranked or perceived as more or less effective than their peers simply by the scores their students receive on the state assessment that year compared to other teachers (Goe et al., 2008). In this definition, it is difficult to determine if the achievement growth reflected in the test scores was achieved by a narrowing of curriculum or implementation of good instructional practices rich in student engagement, motivating activities, and a productive student environment. "The major research finding is that student achievement is related to teacher competence in teaching," (Kemp and Hall, 1992). While this statement is dated, the question that needs to be answered is how student achievement is accurately and fairly measured, through what means of measurement, and how

the measurement relates to teacher effectiveness. In this time of educational reform, legislators continue to look at defining teacher effectiveness through a measurement of standardized scores, a definitive change from researchers' definitions of teacher effectiveness 30 years ago in the 1980s.

The popular definition of teacher effectiveness in 2012 comes largely from policy makers in support of using value-added mathematical models to assess teacher performance based on their students' test scores. A standard definition of teacher effectiveness for recent educational reformers is a teacher's ability to produce "higher than average" student scores on standardized assessments (Goe et al., 2008). In a similar fashion, states are moving toward models of measuring teacher effectiveness through measurement of their students' performance on standardized tests (i.e., test scores). This study examines the pragmatism of this practice and the stability of teacher math and reading scores over time in identifying the effective teachers from the least effective teachers using a value-added model of measurement.

Evaluating and Measuring Teacher Effectiveness: An Analysis of Methods Used

The process of evaluating and measuring teacher effectiveness has changed over time due to increased attention from both state and federal policy makers. Largely as a result of No Child Left Behind (NCLB) and President Obama's Race to the Top, legislators across the country are hesitant to increase education funding without having an adequate tool for assessing teacher accountability (Markley, 2004). School reforms holding teachers accountable for student learning on high-stakes assessments have become increasingly popular. Yet, the focus on effective teaching started before NCLB legislation in 2001. When *A Nation At Risk Report* (National Commission on Excellence in Education 1983) was published, the nation was

informed that education was in trouble, and as a result, Clark's (1993) study later describes how education evolved into "… teacher-proof curriculums, test-based instructional management, and student competence testing. …" Spurred also by this national report were numerous studies about student achievement tied to teacher performance on entrance and exit exams, in attempts to identify effective teachers (Summers & Wolfe, 1977; Pugach & Raths, 1983; Lovelace, 1984; Evertson, Hawley, & Zlotnik, 1985). Later analysis in measuring effective teaching evolved to studying teacher experience compared to student achievement. From several studies came the findings that for teachers with master's degrees and five or more years of teaching experience, there was little to no evidence of *increased* student achievement over their less experienced counterparts (Darling-Hammond, 1995; Ferguson and Ladd, 1996). As the literature shows, past research on teacher quality lacks a specific method or even a specific form of measurement to accurately assess effective teaching. Teacher exams, higher degrees, and years of experience have all proved to be rather inconclusive in identifying characteristics of effective and ineffective teachers.

NCLB policy and Adequate Yearly Performance (AYP) performance measurements brought about several growth models to measure school performance: status, improvement, growth, and value-added are the four generic types of models used (Goldschmidt et al., 2005). By looking at the evolution of these models, observations can be made that educational reformers have developed methods measuring teacher accountability by examining student achievement. When defining the four accountability prototypes, a status model compares a snapshot of student performance against a target or national goal, such as AYP performance targets. An improvement model compares student performance from the current year to student performance in the same grade the previous year, assessing growth of two different cohorts of

students. For example, performance would be assessed based on growth of fourth grade scores this year compared with last year's fourth grade scores. The third type of performance measure is the growth model, which tracks individual student growth from one year to the next using preferably two points of baseline data each year. Growth models account for the relationship between the beginning academic status and growth of students, often measured by a target goal for all students. Lastly, value-added models are the most recent form of analyzing teacher effectiveness and are a type of growth model (Aaronson et al., 2007; Goldschmidt et al., 2005). Value-added models are a statistical calculation in which states or districts take into account student background specifics as mathematical controls, and, therefore, are meant to separate student performance from outside contributing factors when studying student performance gains (Kane and Staiger, 2008). Value-added assessment is used specifically to calculate and track individual student progress on state assessments each school year. The simplified idea in value-added models is to calculate the value the teacher adds for each student. This contribution can be measured in a model of statistical calculations developed by Dr. William Sanders who at the time was a researcher at the University of Tennessee (Weldon, 2011). The idea of using a value-added model, in contrast to comparing raw assessment data, is that teachers will be measured based on their impact or contribution to the students' learning, no matter if they are an advanced or remedial student in the content area (Walden, 2011). Factors such as SES, school quality, student ability, and family inputs are examples of some of the factors considered in the statistical analysis for measuring teacher effectiveness. The idea of using value-added models to measure teacher effectiveness is debated thoroughly in research, with seemingly more critics than supporters for this method of evaluation (Rothstein, 2009a; Kane and Staiger, 2002b; Sass, 2008; Aaronson, 2007). While most studies conducted of this nature have focused on one to two years

of teacher performance data, "… all the extant analyses suggest that value-added measures of teacher performance, are, at best, moderately stable over time" (Sass, 2008).

Value-Added Models as the Tool to Measure Teacher Effectiveness

Nearly all proposals to use value-added models seeking to hold teachers accountable for student performance gains have been met with mixed reactions from both teachers and administrators as practitioners in the field. Overall, the hesitancy is largely due to belief that test scores cannot reliably measure teacher effectiveness (Alliance for Excellent Education, 2008). Darling-Hammond (2007) suggests that effectiveness measures be used to inform improvement practices, for example, teacher training programs, reviewing value-added models, and in improving accountability models, but not as a way to rank teachers in terms of quality. Current research exists which both criticizes and supports value-added models as tools for measuring teacher effectiveness (Aaronson, 2007; Koedel and Betts, 2007; Rothstein, 2008; 2009a, 2009b; Kane and Staiger, 2002b; Sass, 2008; Harris and Sass, 2008; Jacob and Lefgren, 2008; McCaffrey et al., 2008).

Benefits of Using Value-Added Analysis The argument for value-added measurement states that by tracking a teacher's performance and the related value added to a student's learning from year to year, the teacher's effectiveness can be accurately measured. Researchers Aaronson and colleagues (2007) think that measuring teacher effectiveness through value-added models has some accuracy and value state, "when value-added is done carefully and supplemented with other measures of student learning, it can generate reliable data that can be used to help teachers improve."

The goals behind the use of value-added models also speak to how much impact individual teachers have on individual student achievement, as opposed to evaluating the entire school on general student performance. Supporters of value-added analysis used in conjunction with accountability systems think that it provides a more reasonable method of measuring teacher impact on student performance because of its measurement of student growth, rather than of student attainment levels, where students may enter a classroom at high levels of achievement but not excel specifically as a result of the teacher's instruction. Additionally, variable factors affecting student performance, such as socioeconomic status (SES) are removed from the statistical calculations in value-added models, in theory, providing teachers an equal playing field for performance comparisons.

Those in support of value-added measures also claim that retaining or selecting teachers based on value-added scores can lead to positive gains in student achievement. Value-added models are also said to more accurately measure student progress and can also track the same student over time much better than with systems such as AYP, which compares one cohort's scores against the grade levels' former cohort's scores (Braun, 2005).

In a significant study recently published by Harvard University, Chetty, Friedman, and Rockoff (2011) explored the debate over the effectiveness of using value-added models by examining two issues: 1) whether value-added measures provide unbiased accounts of teacher impact on student achievement, and 2) if value-added measures impact students in the long term. In this research, Chetty and colleagues studied school district data on 2.5 million students in grades 3-8, taking into account parent tax records and analyzing changes in teaching staff. Their results indicate that students assigned to higher-ranked, value-added teachers were indeed more likely to attend college, as well as select more prestigious colleges. These same results showed

the populations of students assigned to higher-ranked value-added teachers were also more likely to save for retirement, have a higher socioeconomic status, and overall earn higher salaries (Chetty et al., 2011). Their study concluded that replacing a teacher ranked in the bottom 5 percent of the value-added teaching pool would increase a student's lifetime income by more than $250,000 for the average classroom sample. The major conclusion from the study was that good teachers have long-term effects on student scores over time, and student value-added test score gains can indeed identify quality teachers (Chetty et al., 2011). The study also emphasizes that good teachers do have "added value," and that the implications for determining teacher effectiveness and teacher quality are worth exploring. Sanders and Horn's work (1995) is often brought into discussions of support for value-added model implementation. Their findings show that "assessment should be a tool for educational improvement, providing information that allows educators to determine which practices result in desired outcomes and which do not."

Despite concerns of value-added models measuring teacher performance by student test scores, a popular study from Sanders and River (1996) states, "... students benefiting from regular yearly assignment to more effective teachers (even if by chance) have an extreme advantage in terms of attaining higher levels of achievement." In this study, results of student performance as related to identified effective and less effective teachers over a three-year time span showed a value-added difference in student achievement between students assigned to identified effective teachers each year and students assigned to the less effective teachers each year (Sanders and River, 1996).

Weaknesses and Criticisms of Value-Added Analysis While Sanders and River's study shows that students clearly benefit from learning from more effective teachers as identified by value-

added models, other research heavily criticizes the effectiveness of using value-added models in accurately identifying effective teachers (Rothstein, 2009a, 2009b; Kane and Staiger, 2002b; Gordon, Kane, and Staiger, 2006; Baker et al., 2010; Goe et al., 2008; Alliance for Excellence in Education, 2008). Concerns when using value-added models to assess teacher performance include 1) the use of one-time, high-stakes testing for an important measurement such as teacher performance, 2) issues regarding the standardized testing instrument itself, and 3) instability of teacher data as research has demonstrated (McCaffrey, 2008; Koedel and Betts, 2008; Kane and Staiger, 2002b). As opposed to Aaronson and colleagues' (2007) suggestion that value-added analysis generates reliable data when supplemented with other student learning measures, value-added models are typically known for use as one high-stakes test for statistical measurement. The use of a high stakes assessment as an evaluation of teacher effectiveness is cause for concern to some. Used in isolation, as opposed to current practices of also using teacher qualifications and employing a variety of styles of evaluations to assess teacher effectiveness, these measures of student learning are said to focus solely on the end result of what effective teaching should accomplish (Alliance for Excellence in Education, 2008). Standardized tests in themselves are not perfect, and every assessment has limitations in measuring student learning. Research shows us that standardized assessments are not "explicitly designed to measure teacher quality; test scores have margins of error, and some tests do not align to curriculum standards (Braun, 2005; Gore, 2007; Elmore, 2002). Furthermore, judging teachers on a "single" assessment is said to not be an effective measurement of the students' learning (Alliance for Excellent Education, 2008).

While research shows that good teaching matters and that it could be the single most important value added for increasing student achievement, researchers also show that there are limitations and concerns to evaluating teacher performance through student test scores alone

(Darling-Hammond, 2000; Wright, Horn, and Sanders, 2007). The narrowed definition of teacher effectiveness as defined by value-added models alludes to a teacher's ability to produce higher than expected student gains on test scores. In Goe et al.'s (2008) synthesis of evaluating teacher effectiveness, there remains concern that rewarding teacher performance based on student high-stakes test scores will result in a narrowed curriculum focus, or that the practices of teaching to the test will become an even greater issue when teacher's jobs are on the line and they feel pressure to generate expected to above-expected student scores. Additionally, critics of high-stakes testing to measure teacher performance state that implementation of value-added models in their present form takes the assumption of teacher effectiveness too far. In this argument, value-added does not credit the student with enough responsibility for and ownership of active learning, but places the sole accountability for student learning on the teacher, with the premise that it is only through the teachers inputs that students learn (Kane and Staiger 2008).

Furthermore, those who oppose using value-added models to evaluate teacher effectiveness argue that they are a poor indicator of teacher quality (Gordon, Kane, and Staiger 2006; Baker et al., 2010). A recurring concern is that high performing students will continue to hit the target despite the teacher's performance, while low achieving students may continue to struggle to meet proficiency standards despite a teacher's best teaching. These same reformers argue that the best way to assess a teacher's effectiveness is to measure their performance over time on several assessments (Kane and Staiger, 2006). Critics of value-added analysis are also concerned that using one form of assessment to speak for a student's full range of learning can result in inaccurate data, reiterating that one of the most challenging aspects of any incentive program is the measurement of the outputs (Eberts, Hollenbeck, and Stone, 2002).

The current debate over measuring teacher effectiveness extends to whether we should evaluate effectiveness based on teacher "inputs," teacher "outputs," or a mix of both (Stronge et al., 2011). Teacher inputs can be defined more by what teachers do and how they well they do it, such as classroom instructional practices, for example; where teacher outputs reflect what teachers accomplish, or what students learn. The pay-for-performance model is a teacher output model based on student standardized assessment performances, but it assumes that student test score gains are a direct result of effective instruction. Although research examining the broad array of value-added models relies on "very strong and often untestable statistical assumptions about the roles of schools, multiple teachers, student aptitudes, efforts, and families in producing student learning gains," these same models continue to gain increasing attention from policy makers due to the "scientific appearance" of their method of calculation, as well as conceptual appeal (Newton et al., 2010). McCaffrey and colleagues (2003) point out the use of assessment data in value-added models is subject to error, as any tool has statistical limitations in measuring such a complex value-added subject as student learning.

In the study from Chetty et al. (2010), which supports the use of value-added models, Chetty and colleagues discovered that two important issues must be taken into consideration before acknowledging that existing value-added models positively impact student achievement long term. The first issue to consider is whether value-added measures will encourage a narrowing of the curriculum on high-stakes tests or incite cheating from teachers to achieve higher scores. The second issue is the potential personnel costs that implementation of value-added models can add to a school district through increased turnover rates for underperforming teachers (Chetty et al., 2011). From an economic standpoint, the study also demonstrates the worthwhile investment of parents paying an additional retention bonus to teachers performing at

one standard deviation above their colleagues as determined by their mean assessment scores (Chetty et al., 2011). In public education, however, this option is generally not applicable to school finance formulas, leaving the financial responsibility of increased teacher turnover costs and retention bonuses to the school districts to support and sustain.

While select education reformers and policy makers have moved forward with implementation of value-added models, some conclude that growth models, specifically the Tennessee Value-Added Assessment System (TVAAS)[3], may become "black box mechanisms" (Kupermintz et al., 2001). The concern lies in the value-added models sharing little insight as to what actually makes a teacher effective or ineffective in the classroom. Caution is needed when looking at implementing value-added models or using student test scores as the only way to measure teacher effectiveness (Newton et al., 2010).

Some critics of value-added models feel that too strong a connection, and emphasis on that connection, has been made between student success on state assessments and good teaching practices (i.e., effective teaching). The TVAAS assumes that effective teachers will naturally demonstrate student gains and success in the classroom (Sanders and Horn, 1998). There is concern that by linking teacher effectiveness with student performance gains, policymakers and educational reformers may misconstrue the definition of teacher effectiveness to one measured by student performance gains only, rather than a definition which also includes characteristics of teacher quality and the use of research-based practices for improving instruction (Kupermintz et al., 2001). Researchers show concern that value-added ratings cannot truly "disentangle" their results from contributed factors which impact their scores (Darling-Hammond, 2011). Students may receive additional tutoring or learn how to calculate physics problems using skills taught

[3] Based on pilot studies of William Sanders' 1980s value added model later supported by the Tennessee Educational Improvement Act of 1992.

from a math teacher, and these effects are difficult to measure from classroom instruction. Effects of reading instruction are equally difficult to determine in terms of accountability to one instructor, as parents may play a role in the support of their child's reading growth.

Among concerns regarding value-added models is the reliability of tracking methods so that teacher performance information is transferred when instructors move to new school districts or states. Statutes in 19 states currently link student promotion to teacher performance on a district or state assessment (ECS, 2000). Seven of these states, however, do not have unique state ID numbers assigned to teachers, so teacher movement from one district to another is not tracked on an individual basis. Critics share concern that implementation of these models without better tracking systems in place will lead to inaccurate information reported at the state level concerning district teacher performance over time. While the number of states that have teacher-assigned ID numbers is growing, the logistics and ability to track teacher performance continues to be a challenge to state departments of education.

The purpose of assigning ID numbers to teachers extends beyond analyzing teacher effectiveness longitudinally, according to the Data Quality Campaign. The purpose of tracking teacher performance among districts is to also provide states with information regarding most and least effective teacher preparation programs, school working condition effects on teachers, experience of teachers in schools of high and low SES in relation to academic growth, and teacher preparation in tested subject areas in relationship to low-income student performance on state assessments (Berry et al., 2007). California, Florida, Louisiana, New York, North Carolina, Tennessee, Texas, and Utah are already using various value-added models, also referred to as "data systems," to measure teacher effectiveness.

High schools especially have the most difficulty in accurately and statistically determining a teacher's "added value" to student performance gains because students see multiple teachers in any given day. Student achievement, for example, in the Humanities, is influenced by many teachers, with often more than one class with embedded reading skills in a student's schedule each semester. To more accurately employ the use of value-added models in high schools, it is suggested that secondary education systems look toward using an end-of-course exam to measure the impact a teacher makes on a student, instead of using standardized assessments given intermittently throughout their high school years in limited subject areas. Another criticism of value-added models is the complexity of how teacher performance is calculated. The statistical nature that value-added models require to provide accurate data necessitate the translation of the statistical information concerning value-added data into a user-friendly model that teachers can use to guide and inform their own instruction over the years.

An additional issue that arises when measuring teacher test score performance data in secondary levels of education is the practice of assigning higher achieving students to the more experienced teachers, therefore leaving the less experienced teachers to teach classes with higher English Language Learners (ELL) and special education student populations. This practice creates the potential for the more advanced students to be assigned to the more experienced teachers. These students would then naturally outperform the students of the less experienced teachers newer to the teaching field (Weldon, 2011). The reason for skepticism in using value-added models to some researchers and even policy makers is due to the fluctuation of teacher performances in their students' assessment scores when analyzed over time, in some cases with uneven distribution within the same school district (Viadero, 2008a). This is partially due to

potential for bias because of nonrandom assignment of students to teachers, as well as concern that student performance data is missing (Viadero, 2008a).

Another concern regarding the broad array of teacher effectiveness models based on student test scores is the idea of evaluating teachers through a statistical tool which is essentially driving the definition of teacher effectiveness, rather than having researchers accurately define teacher effectiveness first, and then measuring it (Campbell et al., 2003). Campbell and colleagues further explain that just because society has the capability to match teachers to their student scores and use this measurement to assess teacher effectiveness, does not mean it is the only way to measure teacher effectiveness with their students. Value-added models are said to be such an extreme example of a data-driven evaluation tool that defines teacher effectiveness to the extent that in some states it affects teachers' employment status and has been used to publicly rank teachers.

Adequate research can be found both supporting and criticizing value-added models as a means to evaluate teacher effectiveness. No matter what model is used for this method of teacher evaluation, from Denver's recently adopted pay-for-performance contract, to teacher tenure retention programs based on student outcomes in Tennessee, there are attempts to manage teacher performance based on the assumption that teacher quality is a "stable attribute," meaning there are simply good teachers who teach well, and poor teachers who teach poorly (Goldhaber et al., 2010).

Overall, the use of assessment scores to measure student effectiveness, even in the most carefully designed statistical ways, can only tell us that a student and, therefore, his or her teacher, did or did not meet the academic expectations set. It does not inform administrators or policymakers as to which instructional practices were or were not used effectively, or which

practices need to be changed by that instructor. Braun (2005) asks policymakers to consider that evaluating teachers by performance on student state or standardized assessment scores may leave out a great deal of teacher impact and other contributable factors. Also to be considered is that teachers are not randomly assigned classes (e.g., advanced versus remedial), and the lack of yearly assessments in multiple high school subjects add to additional inconsistencies in teacher effectiveness data.

Kupermintz et al. (2001) call for "more systematic studies" of models that use standardized assessments to measure teacher effectiveness. Specifically, more attention to studying "the potential confounding of teacher effects and other independent factors contributing to student academic progress, the dependency estimates of teacher effects on model assumptions … and the explicit links between student score gains and instructional practices" (Kupermintz et al., 2001).

Teacher Performance Stability Data

Prior research studies on value-added models of teacher effectiveness have found teacher effectiveness rankings and ratings vary greatly from class to class as well as from year to year (Newton et al., 2010; Koedel and Betts, 2007, McCaffrey et al., 2008). For example, Newton and colleagues (2010) found that teacher rankings of performance and, therefore, stability, varied "substantially" from one year to the next. Their study ranked teacher performance using multiple models to evaluate stability and still found that teacher stability varied greatly over types of courses and types of students, as well as when using the statistical model that made different assumptions concerning the external influences that should be controlled.

The handful of studies measuring the performance stability of teachers over time show mixed results and have typically studied teacher performance over a two-year period, with a few studies measuring performance up to five years (Newton et al., 2010; Rothstein, 2010; Kane and Staiger, 2008; McCaffrey, 2003; Aaronson et al., 2007; Koedel and Betts, 2009; Harris and Sass, 2007; Kane and Staiger, 2002b). Some of these studies have found some consistency in teacher performance scores from year to year, but none overwhelming so. What is not known is the degree of measurement error from the actual teacher effectiveness occurring in the classroom. This is due to the shorter time frame of the two-year studies.

Researchers are starting to explore the impact that a larger time span of study has on the effects of value-added results regarding teacher performance. The primary reason for including multiple years of teacher data (rather than a single year) is "to improve the statistical power in estimating teacher effectiveness ----a natural consequence of spanning multiple years of teacher observations is the increased number of student observations used to estimate a teacher's value-added effect" (p 5 Goldhaber and Hansen, 2010). Ballou (2005) was one of the first to acknowledge this finding. Based on one year of teacher performance, his findings showed less than a third of teachers had significantly differing effects from the average as shown in math scores. Using a three-year estimate, more than half the math scores showed statistically different effects from the average, which demonstrates the increased variance that can be observed over a longer period of observation.

Koedel and Betts' (2009) study also acknowledges variations in using value-added models as ways to measure teacher effectiveness, with cautionary suggestions regarding measurement practices. The study shows that even detailed value-added models estimating teacher effects across cohorts can produce biased teacher estimates, but not as large a bias as

Rothstein's (2009a, 2009b) studies found in contrast and critique to Ronald Ferguson's research (2010) funded by the Bill Gates Foundation, which supported the stability of value-added models. While biased teacher estimates are largely due to non-random student assignment to teachers, suggested practice for those using value-added models is to attempt to randomize student assignment to teachers and utilize multiple years of cohort studies in statistical calculations (Koedel and Betts, 2009).

Rothstein's two studies on variations of teacher effectiveness (2009a, 2009b) are the most popular critical studies addressing the bias of value-added models primarily due to nonrandom assignment of students to teachers and instability of teacher results. Results of his studies measuring teacher effectiveness using several different value-added models conclude that even the best value-added models may be biased, with bias stemming from the nonrandom assignment of students to teachers (Rothstein, 2009b). Rothstein's initial study showed little replication of teacher effectiveness over time, and stated that the effects of stable teachers "wear off" or are inconsistent when analyzed over a longer period of time (2009a). Rothstein's research was a direct analysis of Ronald Ferguson's (2010) research, critiquing Ferguson for interpreting his initial findings incorrectly, as viewed by Rothstein.

In the small handful of studies concerning stability of teacher performance on test scores, the majority of the research describes irregularities and inconsistencies in measurement studies. McCaffrey and colleagues (2008) found instability in value-added rankings of teachers when studying five urban school districts. From this study's rankings of top teachers, 20-30 percent fell in the same quintile a year later, with a similar proportion of teachers once in the top quintile falling to the bottom two quintiles a year later. Additionally, Kane and Staiger's (2002a, 2002b) multiple studies confirmed that there is high variability of student scores within several years'

time between cohorts in small schools. It was shown in Kane and Staiger's (2002b) study that when smaller schools' test score levels and gains were graphed, nearly all the smaller schools were represented in either the highest or lowest ranked categories of performance. This could be attributed to the variance in sampling in less populated districts, where several excelling students can greatly impact achievement levels for the cohort. When the scores from 1998-1999 were studied, researchers also found that small schools were most likely to show the biggest changes in mean scores and gains from one year to the next (Kane and Staiger, 2008). In conclusion, empirical studies addressing stability of teacher effectiveness rankings over time have been inconclusive and the issue needs further investigation (Newton et al., 2010).

Other studies conducted have measured teacher effectiveness by one assessment score, such as the state math assessment. Value-added models have shown that some teachers have higher value-added scores in some subjects than others. Without measuring teaching effectiveness in at least math and reading subjects, it becomes difficult to identify the effective teachers from non-effective teachers using just one score (Berry et al., 2007). From Kane and Staiger's study (2002b) of teacher stability of test scores, two causes of variation over time could be identified: sampling error and what was termed "non-persistent changes" in performance. Sampling errors referred to contributors in individual student scores after variables had been controlled for, and non-persistent changes refer to all other factors that contribute to teacher changes of performance measurements other than sampling errors, which, for example, could include disruptions during the test day or the parallels of test items to specific concepts taught. Researchers caution that school performance data is very difficult to accurately measure when looking at one year's worth of data or when results are compared from different tests (Lockwood et al., 2007; Gates Foundation, 2010).

When examining the stability of teacher impact on student test scores, trend data should be considered in a longitudinal fashion rather than assessing teacher performance on a yearly basis. "The best way to reduce sampling error is to include information from more students … this can be accomplished by pooling estimates across years, for example, using a three-year average of performance measures rather than a measure from a single year" (Buddin et al., 2007). Only a few studies have measured the variability of teacher effects on test scores. What has been discovered is that assessing performance over multiple years results in different data than assessing teacher data for one year. A study performed by Aaronson, Barrow, and Sanders (2007) compared teacher rankings in the Chicago Public Schools over a two-year time span. They discovered that 36 percent of teachers ranked in the lowest quartile in performance two years in a row. Twenty-nine percent moved into the next quartile the second year, with 35 percent moving up into the top half of the quartile distribution. Among the higher ranking teachers, Aaronson et al. (2007) found that 57 percent of teachers remained in the top half of the quartile distribution for both years, 23 percent moved down to the third lowest quartile, and 20 percent fell down into the lowest two quartiles of performance. While some studies support the statistical findings of value-added models, research has shown that variances exist in the stability of results found, depending on models, sampling variation, or other factors to be determined.

Teacher Performance Stability Using Alternative Instruments to State Assessments. Further examination of teacher effects can be done by looking at stability of student results using a different test instrument than state assessment scores. The state of Florida gives a norm referenced test called the Stanford Achievement Test (NRT) and a high-stakes "criterion-referenced" exam called the "Sunshine State Standards" (SSS) to students in third through tenth

grades. In ranking elementary teachers in a two-year period based on the stability of their scores on both tests, it was discovered that there is less variability in scores on different tests given at the same time than with the same test over time, meaning year to year testing provides the least consistent performance and stability of scores. This was represented with 42 percent of teachers ranking in the top quintile when administering the NRT assessment and also ranking in the top quintile in student scores on the SSS. The correlation in teacher effects on both assessments given the same year was .48, much higher than the correlation of .27 on the NRT student scores given from one year to the next (Sass, 2008). While variability of the correlations could be attributed to different responses to accountability pressures, different content being tested, or different proficiencies scores in maximum achievement, one observation from looking at multiple studies is that teacher stability on student scores has some value-added, but to what extent is an area that needs further research.

Considerations in Regard to Teacher Stability Performance Data. Measuring teacher effectiveness on one particular test administered once a year is disconcerting to researchers in the field. Particularly disruptive students or inclement weather on test days are examples of factors that could throw off consistency of testing on a one year basis. However, if a teacher's stability of test scores in a five-year span, for example, has one "off" year, perhaps other factors should be considered. In these cases, the teacher's scores should then return to the high performance ranking they had been in the past. The concern with this approach from Kane and Staiger's study (2008) is that states will focus on the outlier schools, the highest and lowest performing, therefore targeting the smaller schools that statistically fall most into these two categories due to their sampling size and variability in test scores. Kane and Staiger (2008) point out that a

student's baseline data and trajectory of scores is not equal to all students. In their analysis of North Carolina student performance on assessments, they found that students with higher educated parents have higher baseline scores, but also gained more from year to year.

While many research studies have established, at minimum, that a certain degree of value-added is seen when measuring teacher effectiveness through student performance gains in test scores, Goe and colleagues (2008) found that value-added cannot be determined based on the relationship between teacher scores and student gains alone. Rather, the researchers explain, a teacher's effectiveness should be determined by the relationship between that teacher's performance*s* and the intended value-added, whether that value-added is student participation rates or value-added scores. Their argument yields the suggestion that perhaps teacher effectiveness could be better defined in a broader scope, as one single measurement of a teacher's performance in one year does not often provide an accurate picture of a teacher's true performance.

Teacher Characteristics as Contributable Factors to Student Achievement

There is a general consensus that teacher quality is essential to academic performance, but little agreement as to which specific teacher characteristics factor into the definition of what makes a good teacher (Hanushek and Rivkin, 2006). Specific teacher characteristics relating to student achievement remains a debatable topic to many due to the difficult nature in measuring teacher quality. Faced with these challenges in assessing teacher quality, researchers defer to utilizing measurable proxies such as certification, experience, salary, and advanced degrees, among other teacher characteristics, to discover patterns of teacher qualities in effective teachers. Research can only account for teacher attributes as 3 percent of overall value-added in student

test scores (Rivkin et al., 2005; Goldhaber et al., 1999). One study in 1998 showed a slightly higher percentage of 7.5 percent in the overall value-added of student achievement resulting directly from teacher quality, with estimates that the percentage could actually be as high as 20 percent (Hanushek et al., 1998). The following research on teacher characteristics is by no means an exhaustive account of all literature on teacher quality effects, but provides popular descriptors used as teacher characteristics for this study.

Experience. Assessing multiple studies on teacher quality, teaching experience has been linked to student score achievement. Research has demonstrated that novice teachers on average produce smaller learning gains than more experienced teachers, and that teacher effectiveness tends to increase over the first five years in a position, although effects of experience are not conclusive after that five-year mark (Harris and Sass, 2007; Nye et al., 2004; Clotfelter et al., 2007). Hanushek, Kain, O'Brien, & Rivkin (2005), would disagree; however, with research that shows very little increase in student performance gains after the first year of teaching. Teacher experience as a reliable characteristic to determine teacher effectiveness remains debatable.

Certification. In a quantitative analysis study by Darling-Hammond (2000), teacher qualities affecting student achievement were measured controlling for student language and socioeconomic status. Teacher preparation programs and teacher certification were by far the strongest predictors correlating with student achievement in reading and math. Studies found in math content areas especially, that deep knowledge of content is a teacher attribute that correlates with positive student achievement. Math licensure test scores, certification, math degrees, and math professional development all correlate to student achievement scores (Harris and Sass, 2007; Goldhaber and Brewer, 1999; Clotfelter et al., 2007). Studies such as these, which demonstrate the positive effects of teacher quality in areas such as teacher preparation,

certification, and years of experience, provided key findings that impacted teacher-quality standards and resulted in the federal No Child Left Behind Act of 2001, which specifically states that core teachers must be "highly qualified."

An additional study by Wilson and Young (2005) substantiates the positive impact teacher certification has on student achievement. After conducting eight large-scale studies comparing certified math teachers' to uncertified math teachers' impact on student achievement between 1985 and 2002, seven of the eight studies found positive correlations between teacher certification and student achievement.

Undergraduate College Selection. A teacher's selection of undergraduate college has been considered to affect teacher quality. Studies dating back to the 1970s show teachers who were more selective in choosing an undergraduate college later showed higher student achievement (Ehrenberg & Brewer, 1994; Summers & Wolf, 1977). Clofter and colleagues (2004) pulled a data set from administrators across North Carolina and discovered as part of their study that teachers who attended more competitive colleges (as ranked in *Barron's Guide to Undergraduate Colleges*) went on to produce higher student achievement (Clofter et al., 2004). Kennedy and colleagues (2008) offers the "bright, well-educated hypothesis"---that wealthier, and, therefore, potentially more educated students often attend the most competitive universities as the reason behind the data showing higher achievement from students attending more competitive universities. Findings in the study suggest that "bright, well-educated people add 3-4 percent in student achievement gains" (Kennedy et al., 2008).

Advanced Degrees. Studies have found that teachers with graduate degrees are generally not more effective in increasing student achievement than their colleagues who possess a bachelor's degree (Darling-Hammond 1995; Ferguson and Ladd, 1996). In a review of five different studies

performed by Rice (2003) it was determined that advanced degrees for teachers have no significant impact on their students' performance. Clofter et al., (2007) found similar findings in that elementary teachers who possessed a master's degree were actually *less* effective, on average, than their colleagues without graduate degrees if advanced degrees were earned more than five years after they began teaching. The one study Rice (2003) found that did show achievement gains related to teachers with advanced degrees was for black students assigned to such a teacher in an urban school setting.

While there is little to no effect of teachers with advanced degrees to student achievement in elementary students, this is not the case in secondary schools, according to three studies with similar findings. Both Goldhaber and Brewer's (1997; 1998) and Clotfelter et al.'s, (2007) studies showed that high school students assigned to teachers with graduate degrees in math and science did show increased achievement compared to students assigned to teachers with bachelor's degrees.

Salary. Research shows that teacher salary is a weak predictor of teacher performance (Koedel and Betts, 2007; Darling-Hammonds, 1995; Ferguson and Ladd, 1996). The newer policy conversation regarding teacher compensation ties teacher salary to student achievement (most often referred to as pay-for-performance) as the prior literature review describes. There are a vast number of studies examining pay-for-performance through a variety of lenses, and scholars continue to state that it is difficult for researchers to attempt to answer all the questions in just one study.

Other Characteristics: Race as a factor of increased student achievement has been studied, but comes with its own set of cautions, and the research has produced mixed results (Ferguson, 1998). Findings of these studies require careful analysis, and they often show a stronger relation

to urban settings than in less racially diverse environments. Higher teacher scores in entrance and exit exams also show very low correlations to student achievement in the classroom.

Research shows inconsistent and, at times, inconclusive answers in regards to identifying the teacher characteristics that can be used to define a good teacher. Overall findings show there is little empirical evidence to create informed, reliable systems to reward or compensate teachers based on qualifications or characteristics.

As the literature shows, the definition of teacher effectiveness changes dramatically when adopting and implementing value-added models as the primary instrument to evaluate teachers. Measuring and evaluating teachers with value-added models would be the fourth major change to teacher evaluation and compensation in the United States if pay-for-performance plans persist. The research shows multiple studies in support and in criticism of the stability of value-added models as the sole measurement of teacher effectiveness, most analyzing teacher score performance over one to two years. Before implementing reforms concerning teacher compensation, evaluation, or reward systems, policymakers are encouraged to examine the stability of teacher performance on student test scores **over multiple years in various-sized school districts** to examine the stability and validity of value-added measurement for school districts and teachers across the nation.

Chapter 3

Methods

Research Design. The purpose of the study is to analyze the stability of teacher test scores over a three-to-six-year period. The study was purposefully conducted in a fairly large school district for the state, size 5A[4] (the second largest sized school district in Kansas), although much smaller than metropolitan studies conducted. The rationale for this sample size was that if a larger school district in the state struggles to show stability of teacher performance as measured by student test scores, then smaller districts may struggle even more to show stability due to variation of sampling size. This study evaluated the consistencies of teacher mean test scores from year to year and looked for consistency in high and low teacher rankings year to year in math and reading state assessment scores of students assigned to teachers. From teachers considered to have stable results from year to year, demographic characteristics were analyzed in attempts to derive any patterns to what might distinguish a high performing teacher from a low performing teacher.

Participants and Sampling. In this study, the participants were elementary and middle school teachers in a midsize school district of nearly 3,600 students in the state of Kansas. There are approximately 12 elementary classes at each grade level in the district from four different elementary schools, averaging three classes at every grade level in each school. The middle school serves 7th and 8th graders only and administers the state assessment in reading and math to students in both grades. The sampling size consisted of 48 teachers: 36 elementary teachers who

[4] Kansas divides school districts into leagues based on enrollment for athletic competitions and championships. This district studies is classified as 5A, with 6A schools as the largest 32 districts in the state of Kansas, followed by the next largest 32 districts classified as 5A, and the next 32 classified as 4A until the remaining districts are classified as 1A. All districts are re-evaluated each year according to changes in enrollment. Average daily attendance is 3480 students a day.

had both math and reading state assessment data available (one 6th grade teacher had math alone), and 12 teachers from the middle school (6 math teachers and 6 English teachers who, because of their teaching assignments, had much larger data sets to study as they taught multiple sections of math and English courses). Overall, there were 42 sets of math scores and 41 sets of reading scores in the years between fall 2006 and spring 2012. This comprised 83 different data points of math and reading student scores tracked over time for this study.

Teachers in the study had three to six years of state assessment score data and remained at the same school at the same grade level for the designated years. Two elementary school teachers were the exception, as they had only two years of student assessment data, but in both math and reading. Teacher test scores utilized for this study required a teacher to be responsible as the primary instructor for 3rd, 4th, 5th, 6th, 7th, or 8th grades. The test scores collected were both math and reading state standardized assessment scores. Kindergarten, 1st, and 2nd grade teachers were excluded because they do not administer state assessments. High school teachers were excluded because of a model in which students could retake the assessment one time in the following school year under a different teacher. Descriptive characteristics, such as teacher graduate degrees, teaching experience, and salary, as a few examples, were collected for the random sample of teachers studied was varied. This information was used as a second component of the study to identify if patterns could be identified among teachers with stable high or low performance rankings. Table 1 shows a breakdown of teacher data in consecutive years.

Teacher Years Taught in Same Subject, Grade, and School Table 1

6 Yrs Math Scores	**5 Yrs Math Scores**	**4 Yrs Math Scores**	**3 Yrs Math Scores**	**2 Yrs Math Scores**	**Teacher Totals**
13 teachers	8 teachers	14 teachers	5 teachers	2 teachers	42 teachers
6 Yrs Reading Scores	**5 Yrs Reading Scores**	**4 Yrs Reading Scores**	**3 Yrs Reading Scores**	**2 Yrs Reading Scores**	**Teacher Totals**
11 teachers	11 teachers	10 teachers	7 teachers	2 teachers	41 teachers

Of the 3,600 students in attendance in this public school district, 49.92 percent are female and 50.08 percent are male. 33.35 percent of these students receive free or reduced lunches. Student ethnicities among the district are 5.89 percent African American, 13.19 percent Hispanic, 73.28 percent White, and 7.64 percent Other. This district currently does not have merit pay or pay-for-performance programs in place, although discussions are in place to adopt a new teacher evaluation tool for the following year which will include student achievement as a component to teacher evaluation.

Data Collection. Collecting student performance data on math and reading state assessments was a two-part process. The public school state assessment database used by all Kansas school districts, The Center of Kansas Educational Testing and Evaluation (CETE), can only provide teacher-student matched state assessment scores for the 2010-2011 and 2011-2012 school years due to their data collection process, with complete records for the 2011-2012 year. To match teacher-to-student performance data on state assessment scores, it was necessary to first pull student state assessment scores from the CETE website by year; and then cross-list each student by student ID; and in some cases class, content area, and year, with class rosters obtained from the school district's archived student database records. An unexpected challenge in the data collection process was a two-year period in two elementary schools during which 6th grade students were assigned to a homeroom teacher for most classes, yet traveled to another teacher for math or reading instruction. The archived student records allowed for each of the students' actual math and reading teachers to be identified with the correct student score, rather than relying on homeroom assignments. The impact of this arrangement, especially for reading, is discussed more in the discussion of findings.

Also collected were the following teacher characteristics to serve as proxies for teacher descriptors in the study. This information was collected from the school district's personnel database to later be used in attempts to establish characteristics of consistently high and low ranking teachers.

Teacher Characteristic Descriptors Table 2

Teacher Characteristics
Total years of teaching experience
Years of teaching experience in the school district
Years of teaching experience at the specified grade level
Other Grade Levels Taught
Age
Undergraduate College
Advanced Degrees (Content Related/Not Content Related)
Areas of Certification
Traditional vs. Alternative Certification
Teacher Salary
ELL Certification

To maintain teacher confidentiality, each teacher whose scores were collected for this research study was assigned an identification number for the remainder of the study. Also, the at-risk student population was accounted for through percentages of students receiving free and reduced lunches. Percentage numbers of free and reduced lunches for each class for every school year identified in the study was collected. This information was accessed and provided by the Food Service Director of the school district.

Data Analysis. First, reading and math state assessment scores were pulled from the state database housing site, CETE, for the 48 elementary and middle school staff included in this

study for the last six years of testing data. The state tests in both math and in reading were redesigned in 2004-2005 and piloted in 2005-2006. According to the state testing department, state assessments have not incurred significant changes with regard to grade level tests since the 2006-2007 data, the start of the data procured for this study.

For data compilation, each teacher was assigned their own Excel workbook with a file each for math and reading, within each file were tabs for each year of assessments. Those tabs contained the names of students individually assigned to them with state assessment score performance for each individual for every year of available data.

Once student scores were matched with the corresponding math and reading teachers responsible for direct instruction in the content area, another spreadsheet was created, identifying which teachers had test scores in math, in reading, or in both, for each of the six years researched. Teacher characteristics such as years of teaching, advanced degrees, salary, and additional certifications, for example, were pulled and organized by teacher in a separate worksheet.

The next step was to determine the SES associated with each class for each year in the study. Free and reduced lunch data was used to account for the effects of student SES (specifically identifying at-risk populations). Using a formula in Excel, percentages of students receiving free and reduced lunches was calculated for each class in each year of the study. That percentage was assigned to each teacher as his or her percentage of at-risk students. An additional Free/Reduced column was added to include these percentages in the Excel worksheets for math and reading scores for every teacher for each year.

State assessment averages for every subject, at every grade level, and for each teacher for each class were calculated for each year using Excel. Then, a new list was made using only the

math and reading averages, also shown for each grade level and teacher for each year. District averages for each grade, subject, and teacher were then calculated and added to the table. Lastly, the district standard deviation was calculated to assess how each of the average scores varied from the average of the subject, grade, and year. The district standard deviation was also added to the table (see Appendix Table 1A). The purpose of this information was to calculate the Z Scores by class to normalize the data.

Once Z Scores were established, two separate files were created, one for reading and one for math, in which teacher residuals, Z Scores for each class, and the free and reduced percentage for each class were listed for all years. Teachers without scores for the year were taken out of that year's list. A regression was then used to compute how far above and below the actual score the teacher was from the predicted score based on the effects of the free and reduced percentages. This showed the adjusted test scores of teachers taking out the effects of student socioeconomic status. The residuals were graphed on a scatter plot in Excel with a line of best fit established to provide a visual.

To determine correlations from one year to the next, a new spreadsheet was created in which teacher residual data was displayed in rows, using the three to six years of data. Correlations were calculated between year 1 and year 2, between year 2 and year 3, and so on throughout the three to six years for each individual teacher.

To analyze stability or non-stability in teacher scores over time, teachers were ranked by adjusted Z Scores (residuals) across the years, accounting for SES as part of the statistical model. Grade levels were still associated with these teachers, as movement of one teacher could be compared only with that of other teachers in their grade level to account for concerns of assessments differing from one grade level to the next. Teachers were also ranked in both math

and reading adjusted scores and their movement tracked by placing them in quartiles of performance, Quartile 1 for top performers and Quartile 4 for bottom performers, so that movement between quartiles could be noted by percentages of teachers staying in the same quartile from year to year, and of those in moving from one quartile to another. Data was tracked and analyzed in several ways: by percentage of movement per grade level from one year to the next in both math and reading, through non-consecutive year placement consistencies in quartiles over time in both subjects, and by comparing quartile rankings of the top and bottom performers in each grade level with prior years of quartile rankings in both math and reading. This data compared both teacher performance and movement against other years to establish stability. Lastly, teachers who showed relative stability, as either top or bottom performers, were analyzed for similarities in characteristics and qualifications that might be useful in future personnel policies and desired teaching qualifications.

Chapter 4

Findings

The initial purpose of this study was to examine the research question, **is there stability in teacher test scores over time?** The plot graphs of Teacher Z Scores versus Free and Reduced Lunch Percentage Scores (in Figures 1 and 2 below) for reading and math depict teachers who scored above or below the projected scores with a line of best fit, essentially enabling comparison between them, and the ranking of teachers in terms of yearly performance. Tables A3 and A4 found in the Appendix show the statistical regressions calculated for both math and reading. Findings from the residuals graphed conclude that more variability is shown in reading residuals from line of best fit than in math. Both regression calculations showed a large and significant relationship between free and reduced lunch and achievement scores, as could be expected based on studies of at-risk students and achievement gains (Lampley and Johnson, 2010; Johnson, 2006).

Figure 1

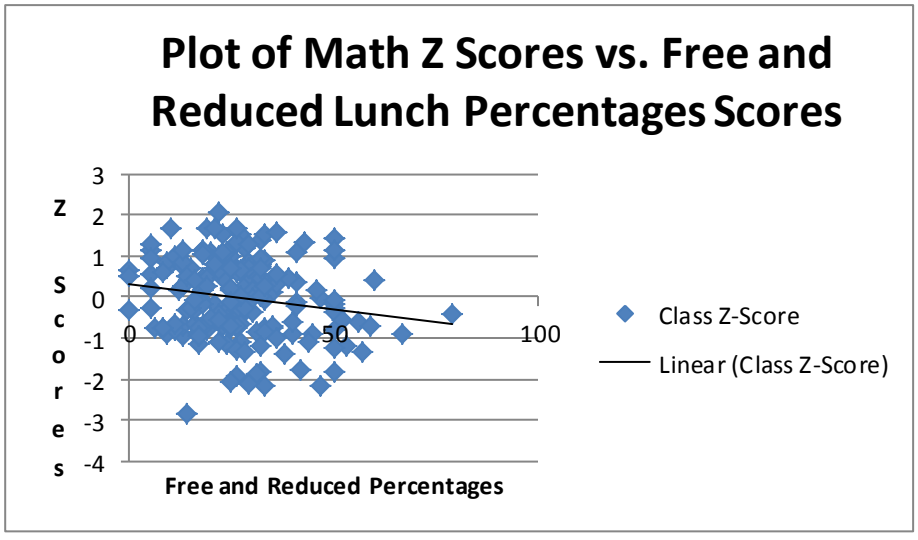
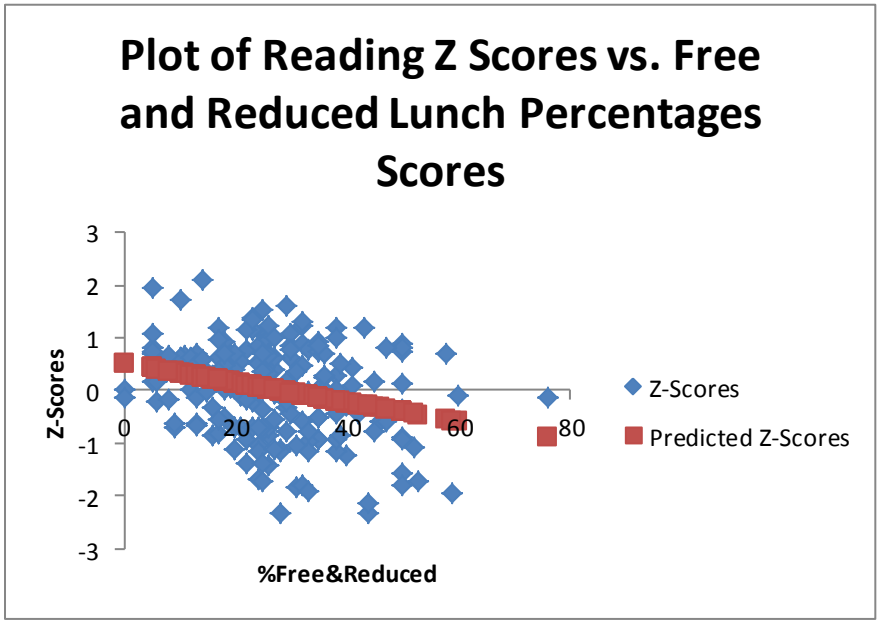


Figure 2



Correlations of Data from Year to Year. Correlations of year to year teacher performance were calculated for math and reading separately based on the residual data from one year to another. Examinations of the patterns of correlation coefficients in math scores show there are positive correlations between year to year residual scores. These correlations were moderate at best, ranging from 0.4 to 0.7, with higher correlations in the more recent years of adjusted scores district wide (see Table 3). The average correlation across all years was 0.48, which makes 23 percent of the variance, leaving more than three fourths of the teacher performance attributable to something other than teacher effects.

Math Year to Year Correlations Table 3

	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
2006-2007					
2007-2008	**0.441591**				
2008-2009	0.355849	**0.546657**			
2009-2010	0.331904	0.302457	**0.539203**		
2010-2011	0.251733	0.316154	0.488774	**0.72359**	
2011-2012	0.379666	0.362823	0.419883	0.607361	**0.631889**

Correlations between year to year teacher performance in reading across grade levels were also positive, but show very weak correlation coefficients of 0.18 and 0.2 for the first three years of the study (from 2006-2007 through 2008-2009). In the latter two years of the study, the correlations were moderate at 0.5 and 0.6, but still not strong. Table 4 shows year to year comparisons of correlation coefficients for reading. The average correlation across all six years was 0.3, showing a variance of 9 percent, leaving ninety-one percent of the variance not accounted for by teacher effects.

Reading Year to Year Correlations Table 4

	2006-2007	*2007-2008*	*2008-2009*	*2009-2010*	*2010-2011*
2006-2007					
2007-2008	**0.181927**				
2008-2009	-0.10924	**0.210295**			
2009-2010	0.503478	0.273599	**0.201883**		
2010-2011	0.172313	0.221492	0.217091	**0.547867**	
2011-2012	0.157634	-0.0988	0.36133	0.358376	**0.61526**

From the correlation findings in both math and reading scores, correlations for teacher math scores shows moderate stability, at best, from one year to another, meaning teachers' scores from one year had weak to moderate relationships with the next year of scores. Reading scores

were more volatile than math scores, with extremely low correlations in comparing the years 2006-2007, 2007-2008, and 2008-2009 with the following years. In years 2009-2010 and 2010-2011, a more moderate relationship was found with the consecutive year of reading scores.

Teacher Performance Movement over Time. After teachers' scores were normed and adjusted to remove the effects of socioeconomic status, teachers were ranked by quartile for each subject and year. (Tables A5 and A6 in the Appendix show teacher quartile rankings for math and reading across all years of data). Stability of scores was first tracked by analyzing the adjusted teacher scores from year to year, showing the percentage of teachers with stable scores from year to year and those who moved quartiles from one year to the next. Table 5 below shows the breakdown of tracked teacher math movement by grade level and the variability of teacher stability from one year to the next. The findings show in math that with the exception of Year 3 to 4 and Year 4 to 5 data, teacher movement in this district varies from one quartile to another, with percentages of overall movement from year to year being 83, 68, 45, 43, and 59 percent. Teachers who stayed in the same quartile from one year to the next showed anywhere from 16 to 54 percent stability, with an average of 32 percent over the six years of data. The overall mean of the six years of percentile movement tracked shows that 39 percent of all teachers will move either up or down one quartile from year to year (shown at the bottom of Table 5). Also found was that 20 percent (or fewer) of math teachers jumped two quartile rankings or more (either up or down) from year to year, with a mean average of 11 percent over six years of data. At the bottom of Table 5 below are the mean percentages of 32, 39, and 11 percent of all math teachers who, respectively, stayed within their ranked quartile from one year to the next, moved to a

quartile above or below, or moved either up or down two quartiles away from their previous ranking.

The findings for math at all grade levels show a bell curve of stability, with teachers moving up or down one quartile from one year to the next as the majority of movement in percentages, averaging 40-50 percent from year to year. Approximately 30 percent of the time teachers stayed in the same quartile from one year to the next when looking at years overall (with the exception of 4th grade). The least often occurring teacher score movement was movement two or more quartiles away, for example, from the top quartile to the bottom, which showed the most variability of teacher stability. This frequency of movement to two or more quartiles away ranged from 0-33 percent from year to year and on average accounted for less than 20 percent of movement.

Math Teacher Movement in Percentage from Year to Year — Table 5

3rd Grd Math Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	17%	43%	38%	22%	20%
Movement to Quartile Above/Below	60%	83%	43%	50%	78%	52%
Movement Two Quartiles Away	33%	0%	14%	0%	0%	16%
4th Grade Math Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	50%	57%	50%	60%	44%	43%
Movement to Quartile Above/Below	50%	29%	30%	20%	44%	28%
Movement Two Quartiles Away	0%	14%	14%	10%	11%	8%
5th Grade Math Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	25%	50%	43%	43%	27%
Movement to Quartile Above/Below	50%	50%	17%	29%	57%	14%
Movement Two Quartiles Away	50%	25%	33%	29%	0%	23%
6th Grade Math Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	0%	75%	50%	38%	27%
Movement to Quartile Above/Below	100%	0%	25%	33%	50%	35%
Movement Two Quartiles Away	0%	100%	0%	17%	12%	22%
7th Grade Math Teacher Movement (only 3 teachers tracked)	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	0%	67%	67%	100%	39%
Movement to Quartile Above/Below	100%	100%	33%	33%	0%	44%
Movement Two Quartiles Away	0%	0%	0%	0%	0%	0%
8th Grade Math Teacher Movement (only 3 teachers tracked)	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	0%	33%	100%	50%	31%
Movement to Quartile Above/Below	100%	100%	0%	0%	50%	42%

Movement Two Quartiles Away	0%	0%	66%	0%	0%	11%
Overall Math Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	**16%**	**27%**	**54%**	**54%**	**41%**	**32%**
Movement to Quartile Above/Below	**67%**	**54%**	**27%**	**32%**	**54%**	**39%**
Movement Two Quartiles Away	**16%**	**14%**	**18%**	**11%**	**5%**	**11%**

The results of reading teacher movement from one year to the next provide similar results, although reading percentages of movement overall were slightly more variable than results of math movement alone. Similar to what is found in math percentages, there is an increase of teacher stability percentages in reading in both Year 3 to Year 4 and again in Year 4 to Year 5. On average, the majority of teacher movement is in movement one quartile up or down in ranking from year to year. Despite this, the percentage of reading teachers whose scores stayed in the same quartile from one year to the next, those who moved up or down one quartile to the next, and teachers jumping two quartiles up or down (essentially moving to the bottom or to the top) all varied from 0-100 percent for each category and specific grade level, showing the significant variance of teacher performance from year to year.

Overall means of reading movement varied less from one year to the next, while individual teacher movement between quartiles was more volatile. The mean average of reading scores for those maintaining the same quartile from one year to the next was 29 percent. The mean of reading teachers moving up or down one quartile included the largest number of teachers at 40 percent. Reading teachers who moved two quartiles away (top to bottom or bottom to top) had a mean of 11 percent. Table 6 below shows both grade level stability as well as overall stability across years.

Grade level reading teacher movement between quartiles shows more variability from year to year, although averages of movement were similar to math's average percentages of movement across the six years of data. Because only three middle school teachers were tracked

in math and reading, the volatility in stability in scores is noticeable and may have had an additional impact on the results of this study due to limited sampling size.

Tracking quartile rankings of teacher movement over time by percentages provided numbers that could be compared to one another. It also revealed patterns established in the overall consistency of teachers to either stay in the same quartile from one year to the next or move from one quartile to another, in which case these numbers illustrated the degree of movement. The findings show that teacher performance does change over time and, in fact, is more variable year to year, even when the effects of student SES is taken out, allowing teacher performance figures to be compared to one another. Teacher performance rankings are more stable when evaluating overall stability in quartiles across the years than it appears when tracking performance stability from one year to the next.

Reading Teacher Movement in Percentage from Year to Year — Table 6

3rd Grade Reading Teacher Quartile Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	50%	17%	38%	30%	23%
Movement to Quartile Above/Below	100%	20%	67%	25%	33%	41%
Movement Two Quartiles Away	0%	25%	17%	38%	33%	19%
4th Grade Reading Teacher Quartile Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	0%	27%	25%	20%	12%
Movement to Quartile Above/Below	100%	56%	36%	50%	40%	47%
Movement Two Quartiles Away	0%	30%	27%	10%	20%	15%
5th Grade Reading Teacher Quartile Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	50%	16%	33%	14%	19%
Movement to Quartile Above/Below	0%	50%	50%	33%	71%	34%
Movement Two Quartiles Away	100%	0%	33%	17%	14%	27%
6th Grade Reading Teacher Quartile Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%		50%	17%	43%	18%
Movement to Quartile Above/Below	0%		50%	67%	43%	27%
Movement Two Quartiles Away	100%	100%	0%	17%	14%	39%
7th Grade Reading Teacher Quartile Movement (only 3 teachers tracked)	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	100%	0%	0%	50%	50%	33%
Movement to Quartile Above/Below	0%	50%	0%	0%	50%	17%
Movement Two Quartiles Away	0%	50%	100%	50%	0%	25%

8th Grade Reading Teacher Quartile Movement (only 3 teachers tracked)	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	0%	33%	33%	33%	100%	33%
Movement to Quartile Above/Below	0%	33%	33%	0%	0%	11%
Movement Two Quartiles Away	100%	33%	33%	66%	0%	39%
Overall Reading Teacher Movement	**Yr 1 to Yr 2**	**Yr 2 to Yr 3**	**Yr 3 to Yr 4**	**Yr 4 to Yr 5**	**Yr 5 to Yr 6**	**Mean**
Same Quartile	**17%**	**27%**	**52%**	**48%**	**30%**	**29%**
Movement to Quartile Above/Below	**67%**	**59%**	**27%**	**32%**	**54%**	**40%**
Movement Two Quartiles Away	**11%**	**14%**	**18%**	**14%**	**5%**	**11%**

Tracking Highest and Lowest Teacher Performers over Time

The second way teacher stability of scores was analyzed was by taking the top and bottom performing teachers in both reading and in math (symbolizing the top and bottom 10 percent) starting with the 2011-2012 quartile rankings, as it had more participating teachers than the 2006-2007 school year. The top and bottom teacher quartile rankings were tracked over the years of data available to evaluate stability of teacher scores. Quartile rankings of the top and bottom teachers in 2011-2012 were compared with the same teacher quartile rankings across the years to determine stability of teacher rankings.

Teacher Movement in Math Quartiles The findings shows there was more consistency in math teachers' quartile rankings from year to year than consistency in those of reading teachers' from year to year. The results for math also show there is more stability within the top and bottom scorers over time when a time *span* is analyzed, rather than year to year analysis. In other words, a teacher is more likely to fall in the top quartile for three *of* six years (over the span of six years) than she or he is to maintain three years in a row at the top quartile.

Through the comparison of top math teacher performers with up to five other years of rankings, *on average*, throughout grade levels in the 2011-2012 year of data, there was 68 percent consistency of the top teachers tracked staying in the same quartile for the years of their

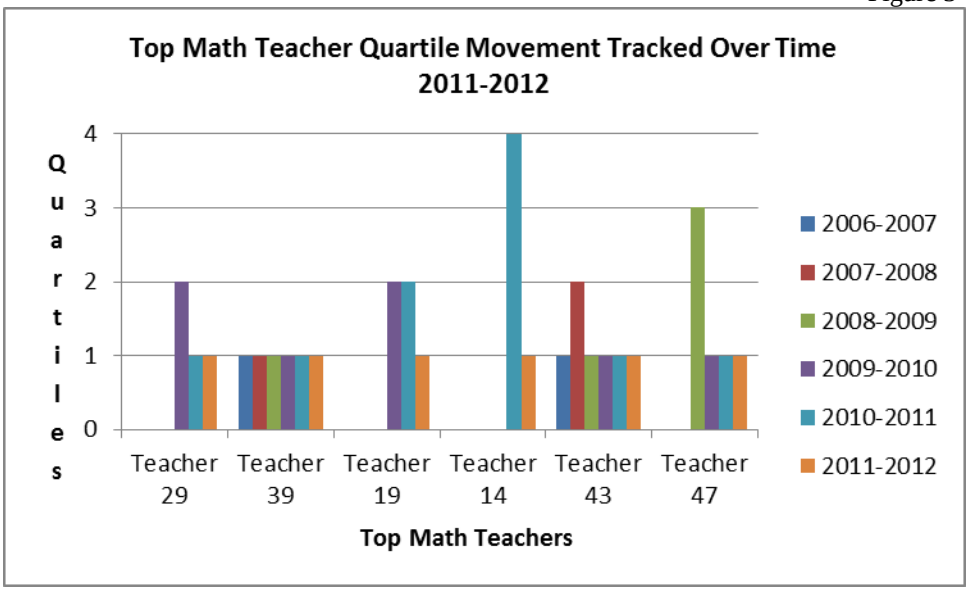
analyzed data, although this was not the overall stability from year to year. When tracking movement of math teachers who either stayed in the same quartile or moved one quartile down, there was an average of 88 percent consistency within the grade levels over time.

The bottom performers showed only moderate stability over time (again, not consecutively year to year). Fifty-four percent of top teachers in 2011-2012 state math scores maintained the same quartile ranking for all years of data over time, and 77 percent of teachers stayed either in the first quartile or moved to the second quartile. When top and bottom scorers were tracked in movement from year to year, the averages were much lower. Movement measured from 2011-2012 data was closer to overall teacher percentages, with an average of 37 percent of teachers maintaining the same quartile from one year to the next, 28 percent average of top performers moving up or down one quartile, and 3 percent average of teachers moving from the bottom to top quartiles. Bottom performers showed very similar results: 38 percent of 2011-2012 top and bottom teachers maintained the same quartile, 32 percent moved from one quartile to the next, and an increased average of 21 percent movement was found in teacher adjusted scores of those jumping two quartiles to the top. These percentages were found by averaging the means of each the three categories of movement: stable, moving one quartile up or down, and moving more than two quartiles away, across the years.

When tracking the highest and lowest performing math teachers over the available years of test data and tracking the consistency of their scores in the same quartile over time, the results showed a similar pattern of instability, shown in Figure 3. Only one of the top teachers from each grade level was able to maintain the top quartile ranking every year for all six years. A clear disadvantage in attempting to accurately track teacher movement in performance rankings is the lack of the full six years of data for all teachers. Figure 3 shows that the top performing teacher

in the 2011-2012 year for her grade fell to the fourth quartile the following year and has an absence of data for previous years. (Note: the 4th quartile is the bottom quartile of rankings.)

Figure 3



The graphed results in Figure 3 show a higher average of stability in math scores than in the reading scores calculated, yet movement for each teacher between quartiles each year can be visibly seen. Of the top math teachers, one from each grade; these top ranking teachers typically stayed in the first (top) quartile from one year to the next. A summary of teacher movement in quartiles from one year to the next for only the top math teachers is shown in Table 7 below. Average means of math quartile movement relatively matched the overall mean movements from Table 5, which shows means of all math teacher movement, with respective averages of 32 percent in the same quartile, 39 percent moving up or down one quartile, and 11 percent moving two quartiles to the top or bottom for all math teachers. Averages of top math teacher movement across the years was 38 percent in the same quartile, 28 percent moving up or down one quartile, and 3 percent moving two quartiles to the top or bottom for all math teachers. Math findings

showed slightly more stability in top performing teachers as a group than when looking at all math teachers. (Note: Table 7 means do not add up to 100 percent due to not all teachers having six years of data to use in year to year comparisons. Respectively, yearly comparisons of quartile rankings were only used for teachers who had scores for both years compared, which were then compared to one another).

Summary of Top Math Teacher Movement Percentages Year to Year 2011-2012 Table 7

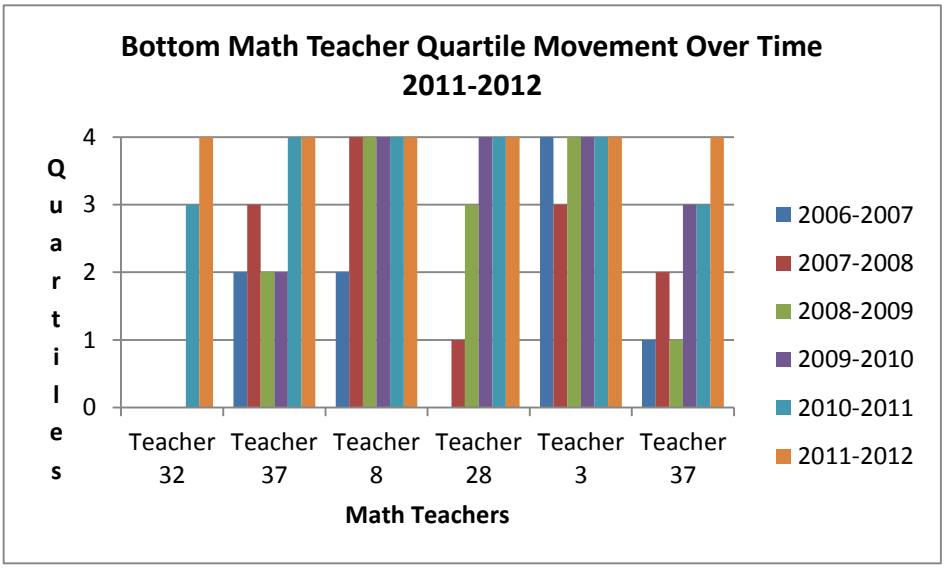
Top Math Teachers All Grades Tracked 2011-2012 Year	Year 1 to Year 2	Year 2 to Year 3	Year 3 to Year 4	Year 4 to Year 5	Year 5 to Year 6	Mean
Same Quartile	50%	50%	66%	80%	66%	37%
Movement to Quartile Above/Below	50%	50%	33%	20%	17%	28%
Movement Two Quartiles Away	0%	0%	0%	0%	17%	3%

This pattern of instability, with the exception of about one third of top performing teachers, shows that while some top ranking teachers can be recognized as top performers and even rewarded as such, the other two thirds of top performers are moving out of the top quartile the very next year.

Similar findings can be seen in the 2011-2012 bottom performers for each grade level when tracked across the years to determine stability of bottom performance. Slightly more stability was found in the bottom teachers compared to the averages of all teachers. For lowest scoring teachers in 2011-2012 who maintained the same quartile from one year to the next there was a mean average of 38 percent of bottom teachers who stayed in the same quartile. Thirty-two percent of teachers showed movement up or down of one quartile from one year to the next, and 21 percent of teachers moved up at least two quartiles to the top quartile. Again, these averages closely mirrored the overall average of movement between quartiles for all math teachers of 32 percent same quartile, 39 percent up or down a quartile, and 11 percent moving from top to bottom or from bottom to top. Figure 4 depicts bottom math teacher quartile movement, which

was the lowest performing teacher quartile in each grade level for the 2011-2012 year, and tracked their performance across the span of data available.

Figure 4



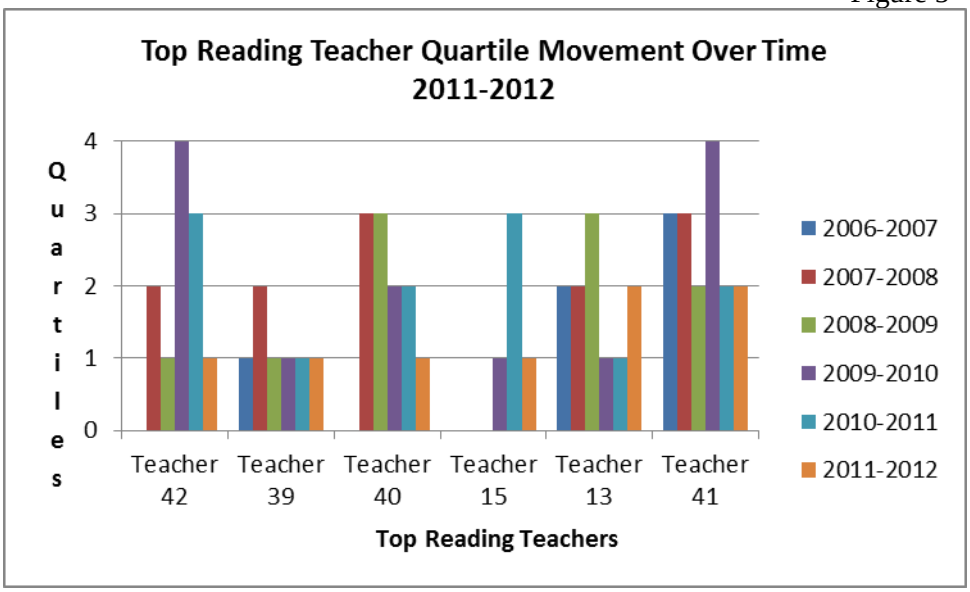
Findings of math teacher movement in quartiles from year to year and on average showed more stability than reading teacher movement, with reading scores proving to be stable both over time and from year to year. Overall, the top performers in math would float between the top two quartiles, sometimes drifting down to the third and in one case the forth quartile, but otherwise it is a fairly accurate statement that the top performing teachers typically ranged in the top 50 percent of scores over time. Bottom performers were slightly more variable, with movement spanning all four quartiles, although typically ranging in the bottom 50 percent. Table 8 depicts percentages of teacher movement from one year to the next for the very bottom teachers graphed in Figure 4, as a mean percentage in each of the three categories.

Summary of Bottom Math Teacher Movement Percentages Year to Year 2011-2012 Table 8

Bottom Math Teachers All Grades Tracked 2011-2012 Year	Year 1 to Year 2	Year 2 to Year 3	Year 3 to Year 4	Year 4 to Year 5	Year 5 to Year 6	Mean
Same Quartile	0%	20%	60%	80%	66%	38%
Movement to Quartile Above/Below	75%	60%	20%	0%	34%	32%
Movement Two Quartiles Away	25%	60%	20%	20%	0%	21%

Teacher Movement in Reading Quartiles. Movement of reading teachers proved to be more volatile, with year to year percentages in reading movement varying more widely than math. When top and bottom reading teachers were tracked in quartile movement from year to year, the overall consistency of reading teachers maintaining a quartile over the years of data available was lower than math. For example, in 2011-2012 top scoring reading teachers could only maintain a 49 percent average for staying within that quartile (compared to math with a 68 percent average). Only 66.5 percent of reading teachers on average were able to stay in the same quartile or within one quartile of movement. Figure 5 and Table 9 show two different illustrations of top reading teacher quartile movement from one year to the next, providing a visual that shows the variability from year to year with each top teacher tracked. (Note: 1st quartile represents the top, "most effective," teachers and the 4th quartile the bottom, "least effective," teachers.)

Figure 5

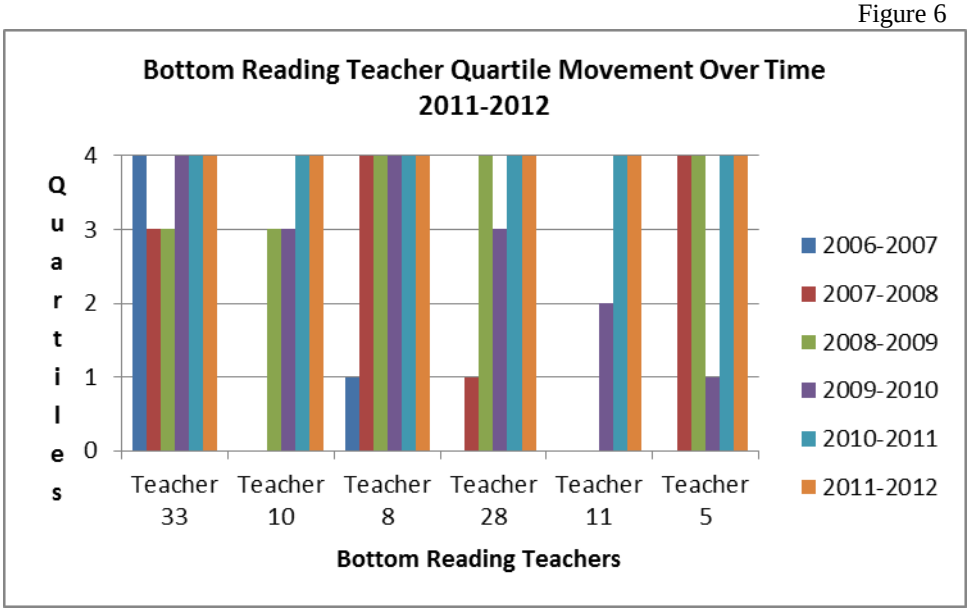


Summary of Top Reading Teacher Movement Percentages Year to Year 2011-2012 Table 9

Top Reading Teachers All Grades Tracked 2011-2012	Year 1 to Year 2	Year 2 to Year 3	Year 3 to Year 4	Year 4 to Year 5	Year 5 to Year 6	Mean
Same Quartile	66%	20%	40%	50%	33%	35%
Movement to Quartile Above/Below	33%	80%	20%	17%	33%	31%
Movement Two Quartiles Away	0%	0%	40%	33%	33%	18%

The reading teachers ranked in the bottom quartile in 2011-2012 showed slightly higher percentages of stability in this lowest performance category, and averaged 67 percent consistency within the same quartile from year to year and 85 percent consistency in maintaining either the same quartile or moving only one quartile above or below. Again, this overall consistency was not year to year, but number of times the teacher fell within the same category over the years of available data. Figure 6 tracks the very bottom ranked teacher in each grade level across all years of accessible data and depicts the movement of teacher rankings in quartiles from one year to the next, again with the 4th quartile as the lowest performing teachers.

Figure 6



Overall, the year to year percent of stability for bottom reading teachers in the same quartile from one year to the next was extremely unstable. Teachers varied in stability from 0-100 percent in staying within the same quartile from one year to the next. Across the six years of

comparisons, mean averages of teachers staying in the same quartile was 38 percent, the largest group. Table 10 below shows the percentages of stability for the bottom teachers tracked over time, one for each grade level. Similar to math, the means of top and bottom reading teachers does not add up to 100 percent due to the fact that not all teachers had data to compare from one year to the next.

Summary of Bottom Reading Teacher Movement Percentages Year to Year 2011-2012 Table 10

Bottom Reading Teachers All Grades Tracked 2011-2012	Year 1 to Year 2	Year 2 to Year 3	Year 3 to Year 4	Year 4 to Year 5	Year 5 to Year 6	Mean
Same Quartile	0%	75%	20%	33%	100%	38%
Movement to Quartile Above/Below	50%	0%	40%	33%	0%	21%
Movement Two Quartiles Away	50%	25%	17%	33%	0%	21%

A last look at instability of teacher scores can be seen in overall movement of bottom reading teachers from one year to the next. When tracking bottom ranked reading teachers only from year to year for stability, 66 percent of teachers maintained the bottom quartile from Year 5 to Year 6. Only 55 percent of those same teachers maintained the same quartile from Year 4 to Year 5 to Year 6. When tracking these quartile rankings to examine the relationship between Year 3 to Year 4, only 33 percent of those same teachers maintained the bottom quartile, showing, in this case, that instability increases the broader the span of years that are studied.

Top performers in reading were slightly more variable than top performers in math. The top performing reading teachers in 2011-2012 typically maintained 1st and 2nd quartile rankings, but on occasion dipped into third and fourth quartiles more so than did those in math. Bottom performing reading teachers tended to stay in the bottom 50 percent (3rd and 4th quartiles).

Stability of Value-Added Teacher Rankings in Dual Subject Teachers

Of the top and bottom performing teachers who taught both math and reading in 2011-2012, elementary teacher rankings were studied for commonalities in teachers' rankings between

math and reading subjects. Findings showed only one elementary teacher ranked as a top performer in both math and reading, and two of the very bottom-ranked elementary teachers were consistently the worst performing teacher for their grade in both math and in reading for the 2011-2012 school year. Of the 36 elementary teachers who had student scores in both math and reading, 11 (31 percent) of these teachers remained in the same value-added category in math and in reading in the 2011-2012 school year. An additional 16 (44 percent) of elementary teachers with both math and reading scores were ranked within one quartile of their math or reading score.

Characteristics of Top and Bottom Performing Teachers

Goldhaber (2002) proposed a question that directly relates to the latter part of this study, "What does the empirical evidence have to say about the specific characteristics of teachers and their relationship to student achievement?" (p 50). The purpose in assessing this relationship is to evaluate the connection between effective and non-effective teachers and their respective, specific characteristics, which could then lead to better identification of good teachers. The results of this study showed that of the top and bottom teachers analyzed for stability of math scores over time, there were two math teachers who maintained top quartile performance in either five or six years out of the six years of data available. Similarity in characteristics between these two consistently top performers included their both having taught 30 years or more, being of similar age, and both teachers possessing a master's degree. Differences in characteristics included gender; certification (one taught middle school math and the other fourth grade); and their colleges, as one attended a Division II university and the other a Division I. The bottom math scorers who had four to five consistent years of bottom scores were equally inconclusive in identifying similar characteristics. Differences included age, building level certification, grade

taught, and colleges attended. Two of the teachers had master's degrees in their fields. The only similarity these teachers had in common was their gender, years of experience (13-15), and age, as both teachers were in their 30s.

Of the top and bottom teachers analyzed for stability of both math and reading scores over time, there was only one teacher who maintained the top reading quartile at over 50 percent consistency and was one of the top performers in math over time as well. There were three teachers identified as consistently in the bottom reading quartile with 66 percent consistency or more. These teachers had little in common but approximate age (30-40 years) and that their gender was female. These teachers graduated from different universities, one maintained an additional ELL certification, two were elementary and one middle school certified, and their years in the teaching profession ranged from 15-20. One of these teachers additionally had an additional endorsement in math certification and a behavioral license to work with emotionally disturbed students. In this case, two of the three bottom performing teachers had master's degrees in their fields. The small sampling size directly contributed to the instability of teacher scores over time, making results in identifying characteristics of stable teachers, effective or non-effective, inconclusive.

The findings presented in Chapter 4 address the research question, **is there stability of teacher test scores over time?** Overall, results show there were weak to moderate correlations in year to year analysis of teacher effects on student test scores over time, with weaker correlations in reading than in math. While there is approximately an average of 30 percent stability of teacher scores from one year to the next, the majority of teacher movement in consecutive years accounts for 50 percent of all quartiles, which demonstrates quite variable movement and instability of teacher scores when examined over time.

Chapter 5

Discussion of Findings

Few would argue that the teacher is the common denominator in student achievement (Stronge et al., 2011; Palardy and Rumberger, 2008). Student achievement is just one measure of teacher performance, however, with value-added models as one specific tool that could be used to determine teacher effectiveness. In an era of educational reform and increased accountability pressures nationwide, policy makers continue to look for better ways to measure, identify, and assess effective teachers. This endeavor, however, must first look at teacher performance over time, not only in two or three year data snapshots, in which this data can appear more stable in shorter time spans than it does when examined over a longer period. Additionally, caution should be exercised in using value-added models alone for major evaluation purposes, as results tend towards moderate to low stability over time.

Teacher Movement over Time as Compared to Other Findings

Results from this study aligned very closely to results found in both Koedel and Betts (2007) and McCaffrey et al., (2008) with the caution that they split the teacher rankings in quintiles rather than quartiles. Where this study found top and bottom rankings teachers to stay in the same top and bottom quartiles from year to year 37 percent of the time, the Koedel and Betts and McCaffrey studies found that 25-33 percent of their teachers tracked in the top and bottom quintiles stayed in the same quintiles from year to year, and roughly 10-15 percent of teachers moved up from the bottom quintile or down from the top quintile. In total, their results showed an average of 12 percent of the lowest and highest performing teachers moving up from bottom quintiles or down from top quintiles. McCaffrey and colleagues (2008) found instability in value-added rankings in an analysis of five urban school districts in various parts of the country, results

that are also comparable to this study's findings. Yet, their results show more instability due to the use of quintiles instead of quartiles. These research findings showed that of the teachers ranked in the bottom quintile of teacher effectiveness in one year, only 25-35 percent were ranked in the same quintile the following year. Of teachers in the top quintile one year, only 20-30 percent were ranked in the same quintile a year later, while about the same percentage of teachers fell to the bottom quintile of performance.

McCaffrey and colleagues (2008) discovered a moderate correlation at best of 0.2 to 0.3 between value-added rankings of math teachers in various elementary and middle school years in Florida schools when studying the stability of teacher effectiveness on student achievement gains. This study found slightly more moderate correlations of 0.48 on average in math. Ranking teachers in quintiles, McCaffrey and colleagues' results showed that consistent to this study, 25-30 percent of teachers were stable in their quintile ranking from one year to the next, while 10-15 percent of teachers moved from the bottom quintile to the top, with an equal number falling from the top quintile to the bottom the following year. Put into a context in which teachers would receive bonuses for scoring in the top 20 percent using value-added measurements, about one third of the teachers would receive a bonus two years in a row, and one in 10 teachers who receive a bonus one year would be ranked in the bottom quintile of teachers the next year (Sass, 2008). In this same study by McCaffrey et al. (2008), they found many of the inconsistencies discovered could be attributed to "student-level variation in test performance over time" and not to true teacher changes in their teaching productivity (Sass, 2008). Explained differently, student learning gains from year to year alter without concrete explanation. Changes in family dynamics, peer-related issues, and motivation all contribute to the variability found in studies using teacher value-added models in their student scores from year to year. "Financial awards [given] to

teachers based on these models would likely result in substantial differences in the so-called "best" teachers from year-to-year" (Buddin et al., 2007). McCaffrey and colleagues' 2008 study was the only study (other than this) that tracked teacher stability over five years of teacher scores based on these models. While the study had a much larger sample size of five major metropolitan areas, the results from their study were very similar to the results of this research, perhaps because of the similarities in studying longer time spans.

Newton et al. (2010) ran a similar study across five different school districts using several different models and ranked teachers by movement across deciles. Their results were also similar, with variances accounted for between the models used. Comparing their data over years to the data from this study, the numbers were similar to those found in this midsized district. Newton and colleagues (2010) found that only 20-30 percent of teachers in the bottom 20 percent of scores had the same rankings the following year. The same results were found for teachers scoring in the top of the distribution from one year to the next. This study's results actually showed more stability in teachers remaining in one quartile from one year to the next than Newton and his colleagues found. Overall, Newton and his colleagues found that most teacher scores moved to other parts of the decile distribution from one year to the next. Similar to the findings from McCaffrey et al. (2008), Newton and colleagues, supported by Briggs and Dominique (2011), found that observations of teacher effectiveness changes "significantly" depending on the statistical methods used.

Williams and Sanders (1995) found different results, however. Their study shows the correlation of predicted scores to actual scores was 0.8, where the correlations found in math and reading in our study averaged 0.48. In Williams' study, the variance accounted for was about two- thirds, or 64 percent, showing that 33 percent of the variance in the actual scores was not

accounted for in the model constructed (Sanders, 2009). Newton et al., (2010) found similar results as well. While they compared teacher rankings over years based on five different models for two years of data, (2005-2006 and 2006-2007), they found a modest correlation of 0.4 for reading teachers and a more moderate correlation of 0.6 for math, although the correlation was lower without the inclusion of fixed school effects. Newton et al.'s English teacher data correlation of 0.4 was nearly identical to the average of 0.48 found in this study for reading teachers. Their correlation of 0.6 for math was slightly higher than the 0.5 correlation found in this study. Newton and colleagues' study also found that while correlations were much higher in year-to-year performance, teacher rankings were also found to be unstable in the two-year period they studied. Fluctuation of teacher rankings varied the greatest across courses and years, rather than from year to year time frames, in some cases moving eight deciles over time (Newton et al., 2010). As a result of more student variables accounted for in this value-added model, Newton and colleagues were able to clearly find that student characteristics do affect teacher performance and should be accounted for in use of value-added models. This study closely resembled work from McCaffrey et al. (2008), and Koedel and Betts (2007), but over a longer duration of time and in a mid-sized district.

Rationale for Volatility in Teacher Test Scores

Before assessing policy implications for the use of value-added models in teacher pay-for-performance plans, considerations must be given first to understanding why teacher performance appears unstable over time. "It should be noted that even value-added measures have a certain degree of "noise"— measurement error that reduces the validity of performance distinctions between teachers and schools—that needs to be considered" (Center for Educators

Compensation Reform, 2012). If instability of teacher performance is tied to testing "noise," then legitimate concerns about tying financial incentives or rewards to measures that include elements beyond a teacher's control must be given consideration. The work of McCaffrey and colleagues suggests that additional statistical layers be put into place to account for such factors to make results more accurate. Yet as Sass (2008) discusses, "such procedures come at a cost of reducing the transparency of teacher quality measures," or in other words, further complicate an already complex evaluation system for teachers. Policymakers should consider the negative impact that a difficult to understand statistical model could have on prospective teachers heading into the field.

McCaffrey et al. (2008) also found unexplainable student learning gain variations from one year to the next. He found that the causes of unstable teacher results have more to do with student variation in test performance over the years due to factors not necessarily tied to teacher performance. Sass (2008) supports the notion that, unlike student variation of scores from year to year with relatively unknown causes, variation of teacher performance from one year to the next may be attributed to additional factors, stating "….the observed variation in measured teacher performance over time is not necessarily a bad thing". Teacher movement in rankings over time may be attributed to teacher quality variance from one year to another, alluding to changes in teacher productivity, or increased teaching competency due to additional training. Instability of teacher scores over time appearing as a much smaller percentage could potentially identify weak instructors or show a declining pattern of effectiveness. However, compared to studies with a majority of consistently unstable scores, which this study also discusses, it leaves room for doubt in counting on value-added models as the sole evaluation tool of teacher performance.

Another consideration that affects teacher movement over time is the type of instrument used to test students and evaluate teachers. States such as California and Texas have changed

their statewide testing instrument over the past several years, which inspired a comparison study from Harris and Sass (2010) in the state of Florida in which stability of student scores were compared with those of the Sunshine State Standards test (SSS) and the Stanford Achievement Test (NRT), a norm-referenced assessment. Results from this study showed that 70 percent of teachers ranking in the top quartile on the SSS ranked in the top two quartiles of the NRT. However, cross-exam correlations measuring teacher effects is .48, much higher than the year to year correlation of NRT teacher scores of 0.27. This shows that different high stakes assessments could result in different teacher rankings and must be considered, especially when assessments change or if teachers are rewarded based on student performance over time.

Kane and Staiger (2008) found that volatility of test scores comes from two major sources. The first is sampling variation, or lack thereof, especially found in elementary classrooms where numbers of students testing per grade level is often fewer than 65. While averaging test scores often reduces fluctuation, the smallest variances demonstrate an impact in these averages. In the case of this school district, there was little diversity among students, and the number of special education students placed in individual classrooms was not accounted for in the study. Some public education classes are designed to support special education students with a paraprofessional or co-teaching support staff. While this was not part of the study, it could have affected teacher scores if students were not truly assigned at random to teachers over the course of the six years studied or had unaccounted for assistance. While socioeconomic status was controlled for and is a large predictor of at-risk students (Placier, 1993), a measurement of poverty through SES is often not entirely accurate, as some parents do not apply for these programs. Controlling for these factors in addition to SES may show different results. The second source of volatility in teacher test scores could be attributed to one-time factors such as

disruptions in the test environment, student illness, or even "favorable chemistry" between certain students and their teacher. This volatility could change from year to year, affecting student performance, and may explain the oddities found in student variance in performance from year to year, therefore also impacting teacher performance and their rankings of effectiveness.

Few studies have examined the relationship of teacher effects on the stability of student test scores for more than one to three years at a time. Examining this relationship over a longer period of time in a midsize school district provides a different lens through which assessing teacher performance as part of an evaluation or personnel tool should be viewed in before statewide implementation begins. A midsize district, such as the one used in this study, would have a difficult time establishing consistency of stable scores over time, and therefore would struggle to make accurate evaluative personnel decisions due to the instability of teacher scores.

Policy Implications

The importance of these findings is applicable to policy discussions regarding how teachers may be evaluated based on student performance. The results of this study show that because teacher performance can vary significantly from year to year, one-or two-year snapshots of standardized student test score data cannot accurately assess a teacher's effectiveness or ranking, nor is this ranking stable over time. These findings should be considered in regard to teacher pay-for-performance plans, by which teachers are financially rewarded for higher student performance. For example, based on these findings, if teachers were rewarded bonuses for their performance based on value-added scores from one year to the next, about 30 percent of teachers would be rewarded for two years of consistent data, and one in 12 teachers who received the

bonus for their initial performance would fall into the bottom ranked teachers for the next year. Policy makers must consider the implications of rewarding teachers for high student achievement if teachers cannot consistently produce quality results from one year to the next, especially when teacher quality measurements remain uncertain. The same scenario applies for teachers ranked in the bottom quartiles of this study. As more consistency was found in teacher scores over a time span rather than from year to year (especially in reading), policy makers must take into consideration that using value-added data for personnel reasons, such as teacher dismissal, based on student testing data performance for one or two years at a time may not be a responsible decision. Even when assessing stability of teacher scores over the years versus from one year to the next, the highest percentage of consistency on average in non-consistent performance of teachers staying in the same quartile across the years was 67 percent, showing that major policy changes still cannot be made based on semi-stable results over time.

It was more difficult to establish stability of reading teachers than it was math teachers, perhaps due to outside contributable factors such as parent or other teacher and course support in reading instruction. Math results may have been more stable because the majority of math instruction occurs in the math classroom, while more parents and outside sources, including other teachers, play a role in reading development. Comparative studies typically did not separate reading and math scores, so additional study in this area would be needed to assess if math teachers actually have more stable scores than reading teachers over time.

Using Value-Added Models for Teacher Evaluation Purposes

With Obama's Race to the Top Initiative, policy makers are looking for a more quantifiable, objective method for measuring teacher performance than the established measures.

Implementation of value-added models has resulted in pay-for-performance programs, monitoring of school and teacher performance according to VAM standards, and public ranking of teaching personnel. In some districts value-added models have become embedded in teacher evaluation programs, in some cases affecting tenure status. This study was designed to observe the stability of teacher scores on standardized assessments over time, not for use in pay-for-performance or teacher evaluation programs. However, because value-added models such as the one used in this study are currently being considered for use in teacher evaluation systems statewide, caution must be exercised in how this data is used. While the observation-only style of evaluations is said to be flawed (Peterson, 2000; Stronge & Tucker, 2003), relying solely on another single system of measurements, such as value-added models, as the sole method of observation is equally flawed (Peterson, 2006). Based on a review of the results of this study, it is not recommended to make high-stakes decisions based on one to two years of teaching data, especially in smaller school districts where volatility of data may be increased due to sample size. Secondly, since stability of teacher test scores was not established, it is suggested that valued-added models should be utilized as only one part of a teacher evaluation program, and not as the sole basis for high-stakes decisions regarding teacher personnel issues.

Debate continues whether value-added models can identify teacher effectiveness with sufficient accuracy to be used for evaluation purposes, and yet the question remains: *How should we use the results of value-added models?* The findings here show there is enough evidence of instability in the scores for policymakers to question the stability of teacher scores over time when measuring effectiveness through value-added statistical models. "The research base is currently insufficient to support the use of VAMs for high-stakes decisions about individual teachers or schools" (McCaffrey et al., 2005). A further complication to be considered is the

appropriate use of value-added scores of elementary teachers who are responsible for both math and reading instruction and who would be evaluated for performance in both areas.

Also to be considered is if the amount of data available for each teacher is sufficient for objective personnel decisions to be made. The accuracy of the measurement of a teacher's performance using value-added models varies depending on the amount of data available for calculation. "Teachers with less data are evaluated with less precision" (Kupermintz et al., 2001). This study showed that evaluating a teacher based on a two-year performance of test scores might lead to a different personnel or evaluative decision than would looking at a teacher's performance over the course of multiple years. Consecutive year-to-year data is much less stable than the overall consistency of rankings across a given time span.

High school teacher performance numbers were specifically omitted from this study, as the state's current testing procedures allows for a student to retest the following year under a different teacher, which would skew the data. Yet another point of concern in using value-added models with secondary schools is the course assignment and impossible-to-track impact that other teachers may directly have on one subject area's test scores, such as reading. For example, a high school social studies teacher may be effective at teaching students how to read complex texts and answer questions by use of specific, research-based strategies. The same student may employ these reading techniques on their reading assessment, yet it would be their English teacher that would benefit from the student's knowledge and ability used on the reading state assessment. The situation of the social studies teacher may also apply to a particularly effective former teacher whose teaching directly impacts the student's performance the following year in the same subject. Policy makers must also consider how they would evaluate teachers who have high value-added scores in math but not in reading or vice versa, as is sometimes the case in this

study for elementary teachers. Findings from this research showed that only 16 percent of the elementary teachers studied had the same value-added rankings for both reading and math, with another 44 percent of teachers ranked in a quartile above or below their reading quartile rankings compared to their math quartile rankings. If teachers are evaluated on value-added performance scores, variable performances between math and reading performance should be taken into consideration. Assessing how to most fairly hold all teachers accountable for standardized assessment performance continues to be a challenge across most states, especially in secondary schools, where elective teachers may be evaluated differently.

While discourse continues over the use of value-added models for teacher evaluation and personnel decisions, considerations should be given to using student achievement data, (i.e., teacher performance data), as one of the pieces for evaluating teachers. Harris and Sass (2007) along with Jacob and Lefgren (2008) both found that principals can effectively identify which teachers will have the most impact on student achievement, and that principals are better predictors of teacher " value-added inputs" than are characteristics such as experience or education. Value-added performance measures could be utilized in tandem with performance measures and additional evaluation criteria such as student and parent surveys, portfolios which demonstrate evidence of student learning, other pre- and post-assessments, classroom walkthroughs, and other evidence of student learning as specific accomplishments tied to the curriculum.

Study Limitations and Further Considerations

This study was purposefully designed to assess teacher effects on student scores over time in a midsize district. Sampling size could be considered an issue, as only approximately 10

different sets of teacher test scores were tracked in each grade level, with even fewer (an average of three) for middle school grades. This most likely increased the variability of movement in the results from one year to the next. However, this was partly the purpose of the study in assessing how a midsize district might fare under a policy which evaluates teachers based on test scores over time. Because of the smaller sample size of teachers, relative to those of the national studies conducted, quartiles, rather than quintiles, were used to rank teachers. This may have inadvertently accounted for the similarity of teacher movement between present and outside studies. However, if quintiles had been used in this study, due to the smaller sample size much larger variance and teacher movement between quintiles would have been seen.

While the district size was unique to this study, there were also several limitations to and challenges in the study that must be considered. First, there was the absence of a collection tool that could provide teacher performance on test scores or even tie student performance to a specific teacher. This required student names to be matched to their teachers using data from two different data systems. An unexpected challenge with collecting data for the study was found in the 6^{th} grade of one elementary school, where students traveled to another 6^{th} grade teacher in their building for all math instruction for two consecutive years, and for one year, traveled to another teacher for reading instruction. This posed an additional difficulty as there was missing data for those years of instruction for the other 6^{th} grade teachers, and a much larger data set for the teachers who taught these multiple sections of math and reading to the students who traveled to them. A known challenge going into this study was the range of data to be assessed and the fact that not all math and reading teachers had six years of consecutive data in in the same building and grade level. Teachers had three to six years of test scores for this study. Assessing percentages of movement from one year to the next was challenging when teachers had data sets

missing within this time span of data pulled. In those cases, missing data sets and teachers were disregarded as if the teacher was not there, which reduced the teacher sample size for those years and accounted for increased variability in some cases where data was slimmer in some years than in others. This reveals an issue that states would realistically face in tracking teachers over time. When teachers switch grade levels or even buildings, additional factors such as student characteristics and different assessments given should be considered before comparing data over the years. Notwithstanding these challenges, researchers have found that, despite various gaps in data, estimates of school and teacher effects tend to be consistent from year to year (Grant, Stronge, and Ward, 2011).

Scheerens and Bosker studied a similar concept in the late 1990s, but without accounting for SES and prior achievement. They found that "when student achievement was measured at a single point in time, about 15-20 percent of the variance in student achievement lies among schools, another 15-20 percent lies among classrooms within schools, and the remaining 60-70 percent of variance lies among students."

Since then, studies of a similar nature to this one conducted over shorter time spans have produced mixed results, with some showing statistical support for the concept of value-added models and others showing instability in the results found (Goldhaber & Hansen, 2008, 2010; Sanders & Horn, 1994; Sass, 2008). Viadero (2008a) found that teacher performance does fluctuate over time and is not distributed evenly through different school districts. One criticism applicable to the district studied here is the question of whether students are truly assigned at random to teachers. Students are sometimes purposefully assigned to teachers for various special education supports, and due to limited resources such as assistive personnel for these students,

there may not be an equal distribution of students with disabilities across all grade levels. In theory, results can be biased if students are not randomly assigned to teachers (Viadero, 2008b).

Teacher Characteristics Findings for Top and Bottom Performing Teachers

The results examined when attempting to find consistencies in teacher characteristics among top and among bottom performers in math and in reading turned out to be inconclusive for two reasons. First, there was too much movement between quartiles to accurately track student scores as related to teacher effectiveness and to identify as effective enough teachers to find patterns of characteristics and form accurate conclusions. Second, the few teachers whose scores showed enough stability to analyze their qualifications did not have enough characteristics in common to form conclusions for future personnel decisions. Teachers with master's degrees and 10+ years of experience were identified both as top and bottom performers. Additional certifications, such as ELL, made no notable differences in performance, as measured by the VAM, nor did alumni colleges, or age or salaries paid, as no patterns could be established. While initially this could have been partly due to the small sampling size, research has shown it difficult to determine what characteristics make teachers more effective than others (Strong, John Gargani, and Özge Hacifazlioglu, 2011). More so "teacher aptitude", as scholar Gregory Gilpin references in his study, has a positive correlation of 0.132 to teacher salaries, showing a rather weak correlation, and thus, a rather weak rationale for higher paid teachers with higher test scores than lower paid teachers (Gilpin, 2012). In a study of similar of a similar nature by Grant, Stronge, and Ward (2011), the researchers were not able to find any relationship between teacher experience and effectiveness, either, even when comparing achievement results of teachers with less than five years, five to 10 years, and more than 10 years of experience. Overall, these researchers found no significant differences in achievement between these groups, nor were any

findings substantial enough to formulate a conclusion in this study, other than that due to the unstable results, patterns of high and low performing teacher characteristics could not be established.

Lastly, the stability of teacher scores over time does not imply that top performing teachers are the best teachers or demonstrate best practices. Student achievement on standardized test scores was the variable measured to determine teacher effectiveness. The fact that states and school districts are looking at using this as a tool for evaluation, personnel decisions, and even as a reward system often gives it more credence than suggested as warranted by the results of this study.

Conclusion and Future Studies

It would be beneficial to run consecutive studies of a similar nature in a different school district of the same size to assess if the results can be replicated. Additional areas of interest suggested by this study are to find out to what degree that students are actually randomly assigned to teachers and to include special education student percentages, percentages of assistant teachers present to help, and additional instruction provided such as literacy tutors for reading or "wheel classes" for math that are currently offered in this district as well as in other, similar districts in the area. Additionally, reading instruction varies widely. It is important to mitigate the effects of prior reading instruction from another teacher on the teacher effectiveness score for the reading teacher evaluated. Lastly, it may be advisable to run this study again in both a larger and a smaller district to see if volatility of the sample size increases or decreases with school size, or if similar results are found. Replication of this study's results by ranking teachers

by quintiles as larger studies have (rather than the quartiles used in this study due to limited sample size) would show even more variability in the stability of teacher scores over time.

Research suggests that effectiveness of teachers cannot clearly be determined by characteristics such as salary, advanced degrees, or even years of experience (Hanushek et al., 2005; Ballou and Podgursky, 2000; Murnane, 1975; and Ehrenberg and Brewer, 1994). For future efforts to improve the quality found in the teaching profession, research also demonstrates that linking teacher evaluation systems to student performance may in fact discern effective teachers from non-effective teachers, as measured by student performance scores (Mohrman, Mohrman, & Odden, 1996; Odden, 2000; Odden & Kelley, 2002). Yet any tool utilized for high-stakes decision making such as teacher evaluation and teacher retention must be an instrument which accurately and fairly measures teacher performance. In the case of using value-added methods of calculating teacher effectiveness, researchers have found that teacher valued-added levels vary from year to year (Goldhaber & Hansen, 2008; Koedel & Betts, 2009; McCaffrey, Sass, & Lockwood, 2008; Sass, 2008).

> "There is a growing consensus that one year of value-added data may not be sufficiently reliable for making high-stakes decisions about individual teacher effectiveness—particularly when determining teacher tenure or hiring/firing decisions." (Schochet & Chiang, 2010).

There are a variety of value-added models that use statistical calculations to assess teacher performance. Policy makers must carefully evaluate the effectiveness of these models on all sizes of districts and consider creating evaluation systems that use multiple points of data collection to accurately evaluate teacher effectiveness. There is clearly a call for more data in this area, and the results of this study show three findings. First, teachers should not be evaluated

based on year to year performance. Second, financial incentives or rewards should not be granted based on one source of data. Third, teacher characteristics of effective teachers or non-effective teachers have yet to be determined using value-added models such as these. Problems with "omitted variable bias," sampling variation, reverse causation, and measurement error are all concerns of studies in the past several years (Ferguson and Brown, 2000). Caution is advised before applying a "one size fits all" approach to state level teacher evaluation systems, as smaller school districts may not be able to sustain the results desired per value-added models due to sampling variation and non-random student assignment. While there are positives to the progressive nature of value-added models in determining teacher effectiveness, further studies should be conducted until a specific tool, model, or statistical formula can show stable results over time to determine teacher effectiveness, despite district size. With the correct tool or evaluation system in place, new data can be discovered which may impact the education system as we know it today, and inform the decisions made in shaping the education system of the future.

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Appendix

Data Table for Math (2011-2012 as one example of data collected for each year) Table A1

Teacher	Grade	Year	Class Avg Math	District Average	District SD	Class Z-Score	% FandR
Teacher 1	3rd	2011-2012	74.57894737	83.93386495	4.844084	-1.931204677	26
Teacher 29	3rd	2011-2012	90.16666667	83.93386495	4.844084	1.286683257	29
Teacher 31	3rd	2011-2012	X	83.93386495	4.844084		
Teacher 32	3rd	2011-2012	81.13043478	83.93386495	4.844084	-0.578732779	22
Teacher 33	3rd	2011-2012	79.52936815	83.93386495	4.844084	-0.90925278	67
Teacher 7	3rd	2011-2012	86.28	83.93386495	4.844084	0.484329973	32
Teacher 42	3rd	2011-2012	87	83.93386495	4.844084	0.632964887	27
Teacher 44	3rd	2011-2012	87.17391304	83.93386495	4.844084	0.66886704	22
Teacher 45	3rd	2011-2012	86.68181818	83.93386495	4.844084	0.567280266	36
Teacher 46	3rd	2011-2012	82.86363636	83.93386495	4.844084	-0.220935186	41
Teacher 4	4th	2011-2012	78.13043478	78.25856436	5.1418683	-0.024918876	30
Teacher 10	4th	2011-2012	76.35714286	78.25856436	5.1418683	-0.369791953	50
Teacher 10	4th	2011-2012	71.81428571	78.25856436	5.1418683	-1.25329517	50
Teacher 16	4th	2011-2012	84.07142857	78.25856436	5.1418683	1.130496529	50
Teacher 20	4th	2011-2012	81	78.25856436	5.1418683	0.533159449	0
Teacher 21	4th	2011-2012	X	78.25856436	5.1418683		
Teacher 23	4th	2011-2012	77.94444444	78.25856436	5.1418683	-0.061090619	50
Teacher 25	4th	2011-2012	X	78.25856436	5.1418683		
Teacher 35	4th	2011-2012	76.85714286	78.25856436	5.1418683	-0.272551033	28
Teacher 38	4th	2011-2012	71.2772	78.25856436	5.1418683	-1.357748588	28
Teacher 39	4th	2011-2012	86.875	78.25856436	5.1418683	1.67574026	21
Teacher 8	5th	2011-2012	64.045625	77.66271364	7.4234619	-1.834331305	50
Teacher 19	5th	2011-2012	85.68181818	77.66271364	7.4234619	1.080237846	23
Teacher 22	5th	2011-2012	77.98730769	77.66271364	7.4234619	0.043725429	27
Teacher 26	5th	2011-2012	72.1355	77.66271364	7.4234619	-0.744560109	25
Teacher 27	5th	2011-2012	83.63636364	77.66271364	7.4234619	0.804698676	21
Teacher 30	5th	2011-2012	81.28571429	77.66271364	7.4234619	0.488047312	14
Teacher 40	5th	2011-2012	78.86666667	77.66271364	7.4234619	0.162182151	46
Teacher 6	6th	2011-2012	79.04166667	79.6831947	5.8550769	-0.109567823	25
Teacher 2	6th	2011-2012	79.77272727	79.6831947	5.8550769	0.015291443	32
Teacher 9	6th	2011-2012	82.16	79.6831947	5.8550769	0.423018408	16
Teacher 14	6th	2011-2012	85.13636364	79.6831947	5.8550769	0.931357358	32
Teacher 15	6th	2011-2012	81.25	79.6831947	5.8550769	0.267597733	33
Teacher 18	6th	2011-2012	76.2748	79.6831947	5.8550769	-0.582126377	52
Teacher 28	6th	2011-2012	67.58	79.6831947	5.8550769	-2.067128226	25
Teacher 36	6th	2011-2012	86.25	79.6831947	5.8550769	1.121557485	13
Teacher 3	7th	2011-2012	68.81521739	70.06278111	1.7643215	-0.707106781	26
Teacher 34	7th	2011-2012	X	70.06278111	1.7643215		
Teacher 43	7th	2011-2012	71.31034483	70.06278111	1.7643215	0.707106781	32
Teacher 47	8th	2011-2012	78	77.62365591	0.5322309	0.707106781	25
Teacher 24	8th	2011-2012	X	77.62365591	0.5322309		
Teacher 37	8th	2011-2012	77.24731183	77.62365591	0.5322309	-0.707106781	25

Data Table for Reading (2011-2012 as one example of data collected for each year) Table A2

Teacher	Grade	Year	Class Avg Reading	District Average	District SD	Class Z-Score	%FandR
Teacher 1	3rd	2011-2012	82.68421053	79.18929157	2.852554	1.225189243	26
Teacher 29	3rd	2011-2012	78.54166667	79.18929157	2.852554	-0.227033322	29
Teacher 32	3rd	2011-2012	77.22727273	79.18929157	2.852554	-0.687811193	23
Teacher 33	3rd	2011-2012	75.179375	79.18929157	2.852554	-1.405728345	25
Teacher 7	3rd	2011-2012	79.08333333	79.18929157	2.852554	-0.037145036	33
Teacher 42	3rd	2011-2012	82.90909091	79.18929157	2.852554	1.304023982	32
Teacher 44	3rd	2011-2012	82.47826087	79.18929157	2.852554	1.152990915	22
Teacher 45	3rd	2011-2012	77.9047619	79.18929157	2.852554	-0.45030856	38
Teacher 46	3rd	2011-2012	76.69565217	79.18929157	2.852554	-0.874177684	39
Teacher 4	4th	2011-2012	79.13043478	79.03216768	4.615056	0.021292721	30
Teacher 10	4th	2011-2012	70.96866667	79.03216768	4.615056	-1.747216168	53
Teacher 12	4th	2011-2012	74.68285714	79.03216768	4.615056	-0.942417651	50
Teacher 16	4th	2011-2012	79.57142857	79.03216768	4.615056	0.116848172	50
Teacher 20	4th	2011-2012	83.57142857	79.03216768	4.615056	0.98357649	38
Teacher 21	4th	2011-2012	X	79.03216768	4.615056		
Teacher 23	4th	2011-2012	82.77777778	79.03216768	4.615056	0.811606586	50
Teacher 25	4th	2011-2012	X	79.03216768	4.615056		
Teacher 31	4th	2011-2012	X	79.03216768	4.615056		
Teacher 35	4th	2011-2012	79.85714286	79.03216768	4.615056	0.178757338	29
Teacher 38	4th	2011-2012	75.5025	79.03216768	4.615056	-0.764815733	29
Teacher 39	4th	2011-2012	85.22727273	79.03216768	4.615056	1.342368245	23
Teacher 8	5th	2011-2012	66.166875	78.34626556	6.681598	-1.822825999	50
Teacher 19	5th	2011-2012	85.04545455	78.34626556	6.681598	1.002632749	27
Teacher 22	5th	2011-2012	78.41038462	78.34626556	6.681598	0.009596365	27
Teacher 26	5th	2011-2012	73.62	78.34626556	6.681598	-0.707355569	25
Teacher 27	5th	2011-2012	83.01818182	78.34626556	6.681598	0.699221391	18
Teacher 30	5th	2011-2012	78.2962963	78.34626556	6.681598	-0.00747864	15
Teacher 40	5th	2011-2012	83.86666667	78.34626556	6.681598	0.826209703	47
Teacher 6	6th	2011-2012	83.08333333	81.34138603	4.981914	0.349654207	25
Teacher 9	6th	2011-2012	83.16666667	81.34138603	4.981914	0.366381378	17
Teacher 14	6th	2011-2012	82.68181818	81.34138603	4.981914	0.269059655	36
Teacher 15	6th	2011-2012	85.56521739	81.34138603	4.981914	0.847833	35
Teacher 18	6th	2011-2012	76.032	81.34138603	4.981914	-1.065732107	52
Teacher 28	6th	2011-2012	72.819	81.34138603	4.981914	-1.710664917	25
Teacher 36	6th	2011-2012	86.04166667	81.34138603	4.981914	0.943468783	17
Teacher 11	7th	2011-2012	79.28089888	80.03175379	1.061869	-0.707106781	24
Teacher 13	7th	2011-2012	80.7826087	80.03175379	1.061869	0.707106781	25
Teacher 17	7th	2011-2012	X	80.03175379	1.061869		
Teacher 5	8th	2011-2012	79.45918367	80.96954063	1.334392	-1.131868592	27
Teacher 48	8th	2011-2012	81.46067416	80.96954063	1.334392	0.368057775	31
Teacher 41	8th	2011-2012	81.98876404	80.96954063	1.334392	0.763810817	30

Summary Output of Math Regressions (Plotted in Table 3) Table A3

SUMMARY OUTPUT-MATH REGRESSIONS

Regression Statistics	
Multiple R	0.17248248
R Square	0.0297502
Adjusted R Square	0.02467036
Standard Error	0.91293041
Observations	193

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4.8810708	4.8810708	5.8565218	0.01645598
Residual	191	159.187408	0.83344192		
Total	192	164.068478			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.30758444	0.1485255	2.07092012	0.03971071	0.01462354	0.60054533	0.01462354	0.60054533
%FandR	-0.01200998	0.00496275	-2.42002517	0.01645598	-0.02179881	-0.00222114	-0.02179881	-0.00222114

RESIDUAL OUTPUT-MATH

Observation	*Predicted Class Z-Score*	*Residuals*
1	0.091404817	0.322619
2	-0.172814718	-0.71535
3	-0.208844655	1.550214
4	-0.052714929	0.276532
5	-0.016684993	-1.07436
6	-0.088744866	-0.66356
7	0.247534542	0.322797
8	0.151454711	-1.10686
9	-0.36497438	-0.26361
10	-0.028694972	0.123797
11	0.187484648	1.48338
12	-0.641203894	0.244249
13	0.247534542	0.889996
14	-0.112764824	-0.62781
15	-0.088744866	0.088745
16	0.031354923	-0.73846
17	0.019344944	0.687762
18	0.151454711	-0.85856
19	0.199494627	0.507612
20	0.235524564	-0.96968
21	-0.328944444	-0.84675
22	-0.076734887	0.98864
23	-0.040704951	0.094997
24	-0.292914507	1.713162
25	-0.016684993	-0.45991
26	-0.196834676	-1.57102
27	0.307584437	0.336499
28	-0.292914507	1.218391
29	0.091404817	-0.78394
30	0.019344944	-0.29747
31	0.007334965	0.151012
32	0.16346469	0.847139
33	-0.14879476	-1.24808
34	0.043364902	0.931307
35	-0.112764824	0.393214
36	-0.064724908	0.206481
37	0.091404817	0.363135
38	-0.028694972	0.720689
39	0.019344944	-1.16588
40	-0.112764824	-0.59434
41	-0.004675014	0.711782

Observation	*Predicted Class Z-Score*	*Residuals*
100	0.103415	-0.158881
101	0.055375	0.7296424
102	0.175475	0.8094107
103	0.211505	-0.955143
104	-0.41301	0.8197218
105	-0.23286	-0.690687
106	-0.05271	0.4966323
107	-0.07673	0.8664753
108	-0.12477	-0.883037
109	0.175475	-0.843289
110	-0.07673	1.4422536
111	0.079395	-0.866973
112	-0.01668	-0.320819
113	0.091405	1.0336778
114	0.091405	1.0611246
115	0.079395	-0.716954
116	0.067385	-0.582355
117	-0.07673	-1.11407
118	-0.01668	1.5690764
119	-0.18482	0.0580996
120	-0.29291	-0.507814
121	-0.00468	1.327815
122	0.151455	0.6935893
123	-0.00468	-0.752141
124	-0.01668	-0.650845
125	-0.29291	0.1149437
126	-0.0407	0.7402452
127	-0.401	-0.328368
128	-0.0407	-2.065003
129	-0.25688	0.2206996
130	0.211505	0.4170194
131	-0.12477	0.4436991
132	0.163465	0.0185739
133	0.079395	0.1836425
134	0.103415	-0.862876
135	-0.08874	1.6274067
136	-0.37698	-0.959939
137	0.151455	0.1332944
138	0.103415	-1.268891
139	0.031355	0.4429033
140	-0.12477	1.7033829

42	0.031354923	-0.73846
43	0.05537488	0.651732
44	0.007334965	-0.64193
45	-0.064724908	-0.80196
46	0.043364902	2.002321
47	-0.040704951	0.438481
48	0.091404817	-0.18543
49	0.05537488	-0.22006
50	0.115424775	-0.79888
51	0.007334965	0.997852
52	-0.112764824	0.250322
53	-0.076734887	-1.74073
54	0.247534542	-0.01672
55	0.199494627	-1.09486
56	-0.028694972	0.282655
57	0.115424775	-0.45165
58	-0.088744866	-0.77131
59	0.151454711	0.606916
60	0.031354923	1.491862
61	0.019344944	-1.16896
62	0.307584437	-0.62588
63	0.043364902	-0.44932
64	-0.028694972	1.224143
65	0.247534542	1.027904
66	-0.172814718	-0.42419
67	0.139444733	-2.98734
68	0.127434754	0.59924
69	-0.040704951	0.90039
70	-0.004675014	-1.27565
71	0.139444733	-0.44548
72	0.103414796	-0.97714
73	-0.028694972	-0.18825
74	0.019344944	1.071318
75	-0.004675014	-0.29243
76	0.175474669	-0.99325
77	0.067384859	1.047499
78	0.139444733	-0.46784
79	-0.004675014	0.600427
80	0.247534542	0.678516
81	-0.088744866	-2.06003
82	-0.076734887	0.88738
83	0.091404817	0.363798
84	-0.016684993	-0.38708
85	0.007334965	-0.67856
86	-0.076734887	0.841254
87	-0.028694972	0.739132
88	-0.292914507	0.018994
89	-0.25688457	-1.907
90	-0.088744866	0.331612
91	0.247534542	-0.53311
92	0.199494627	0.665627
93	0.091404817	0.067568
94	-0.052714929	-0.29872
95	0.103414796	-1.01572
96	-0.184824697	0.538432
97	0.079394838	1.576728
98	-0.064724908	-1.79525
99	0.079394838	0.40307

141	0.007335	0.2212039
142	-0.08874	0.0249901
143	-0.1608	0.6166472
144	0.091405	-0.247203
145	-0.00468	1.666943
146	0.211505	-0.955732
147	0.127435	-0.380584
148	-0.22085	-0.892203
149	0.103415	-1.063029
150	-0.18482	1.2925622
151	0.043365	-1.123822
152	-0.05271	0.2401565
153	-0.08874	0.9817607
154	0.091405	0.9533779
155	0.103415	-1.051625
156	0.115425	-0.211997
157	-0.00468	-1.92653
158	-0.0407	1.3273882
159	0.043365	-0.622098
160	-0.49708	-0.412169
161	-0.07673	0.5610649
162	-0.01668	0.6496499
163	0.043365	0.6255021
164	-0.12477	0.6920551
165	-0.18482	-0.03611
166	-0.05271	0.0277961
167	-0.29291	-0.076877
168	-0.29291	-0.960381
169	-0.29291	1.423411
170	0.307584	0.225575
171	-0.29291	0.2318239
172	-0.02869	-0.243856
173	-0.02869	-1.329054
174	0.055375	1.6203654
175	-0.29291	-1.541417
176	0.031355	1.0488829
177	-0.01668	0.0604104
178	0.007335	-0.751895
179	0.055375	0.7493238
180	0.139445	0.3486026
181	-0.24487	0.4070567
182	0.007335	-0.116903
183	-0.07673	0.0920263
184	0.115425	0.3075936
185	-0.07673	1.0080922
186	-0.08874	0.3563426
187	-0.31693	-0.265192
188	0.007335	-2.074463
189	0.151455	0.9701028
190	-0.00468	-0.702432
191	-0.07673	0.7838417
192	0.007335	0.6997718
193	0.007335	-0.714442

Summary Output of Reading Regressions (Plotted in Table 4) Table A4

SUMMARY OUTPUT-READING	
Regression Statistics	
Multiple R	0.2612257
R Square	0.0682389
Adjusted R Square	0.0632023
Standard Error	0.8720771
Observations	187

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	10.30407	10.304068	13.54874	0.0003048
Residual	185	140.6959	0.7605186		
Total	186	151			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.5079713	0.152026	3.3413475	0.0010087	0.208044	0.8078986	0.208044	0.8078986
%Free&Reduced	-0.018528	0.005033	-3.680861	0.0003048	-0.0284579	-0.0085971	-0.0284579	-0.008597

RESIDUAL OUTPUT-READING

Observation	*Predicted Z-Scores*	*Residuals*
1	-0.23313	-1.00262
2	-0.28871	1.494832
3	-0.04785	0.15693
4	0.007728	-0.08718
5	-0.14049	-0.80692
6	0.415334	0.396645
7	0.267113	-0.89186
8	0.044783	-0.41707
9	-0.4184	-0.48175
10	-0.19607	0.491914
11	0.322696	1.414083
12	-0.90012	0.767719
13	0.415334	0.644271
14	-0.14049	-0.78671
15	-0.14049	0.140492
16	0.155948	0.551158
17	0.341224	-1.04833
18	0.285641	-0.28564
19	-0.34429	-0.25267
20	-0.15902	0.408322
21	-0.0108	-1.12396
22	0.044783	1.469418
23	0.007728	-0.03951
24	-0.27018	-0.16076
25	0.507971	-0.49234
26	-0.4184	1.139791
27	0.396806	-0.5979
28	0.267113	-0.94474
29	0.063311	-1.74393
30	-0.02933	1.620138
31	0.304169	0.358294
32	-0.19607	-0.96952
33	0.100366	0.653106
34	-0.14049	1.049672
35	-0.14049	-0.35657
36	0.118893	-0.23558
37	0.026256	1.026969
38	0.100366	-1.0369
39	0.155948	0.551158

Observation	*Predicted Z-Scores*	*Residuals*
94	0.081838	1.296607
95	-0.06638	-1.77802
96	0.063311	0.48203
97	0.193003	0.434784
98	0.174476	0.757931
99	0.359751	-0.53027
100	-0.60368	0.513068
101	-0.32577	0.505468
102	-0.02933	-0.27902
103	-0.04785	0.913528
104	-0.08491	-1.72776
105	0.396806	-0.21884
106	-0.08491	0.98258
107	0.174476	0.194407
108	-0.10344	0.866595
109	0.137421	-1.26946
110	0.137421	0.545321
111	0.174476	0.290625
112	-0.10344	-1.04441
113	-0.08491	1.294392
114	0.007728	0.604952
115	-0.25166	0.337039
116	-0.4184	-1.16931
117	0.026256	0.9348
118	0.267113	-0.41517
119	0.026256	0.659944
120	0.026256	-1.46624
121	-0.4184	0.039362
122	-0.04785	-0.38654
123	-0.58515	-1.35451
124	-0.06638	-0.97105
125	-0.36282	-0.21512
126	0.211531	0.069636
127	-0.14049	0.891325
128	0.285641	0.338614
129	0.155948	-0.1019
130	0.193003	1.001692
131	-0.04785	1.132291
132	-0.10344	-1.81724

40	0.026256	-0.73336
41	0.026256	-0.89831
42	0.044783	1.046713
43	0.081838	-0.30128
44	-0.23313	-0.04704
45	0.100366	-1.49119
46	0.026256	1.058596
47	0.118893	0.425639
48	-0.4184	1.308931
49	0.211531	-1.06045
50	0.063311	0.787698
51	-0.14049	-0.37077
52	-0.0108	-2.30857
53	0.415334	0.267173
54	0.341224	-0.96652
55	-0.04785	0.653997
56	0.174476	0.271882
57	0.044783	-0.83895
58	-0.19607	0.227179
59	0.267113	0.198308
60	0.081838	1.085713
61	0.063311	-1.09984
62	-0.14049	0.149146
63	0.507971	-0.64576
64	0.100366	-0.29379
65	0.026256	0.324377
66	0.415334	1.544521
67	-0.19607	-0.75533
68	0.137421	-0.84453
69	0.267113	0.439993
70	0.026256	-0.73336
71	-0.56663	1.273732
72	0.063311	-1.21572
73	0.026256	0.486962
74	0.322696	0.316494
75	0.248586	1.850431
76	0.007728	-0.56001
77	-0.10344	-0.86128
78	-0.08491	-0.51292
79	0.193003	-1.00932
80	0.007728	0.399895
81	0.137421	0.272825
82	-0.15902	0.173296
83	0.026256	0.968088
84	-0.32577	-0.45466
85	-0.30724	-2.04228
86	-0.10344	-0.66721
87	0.415334	-0.2633
88	0.322696	0.280253
89	0.174476	-0.15706
90	-0.04785	0.146228
91	0.415334	0.322825
92	0.174476	-0.68574
93	-0.25166	0.681799

133	0.267113	0.245075
134	0.193003	-0.76129
135	0.063311	-0.07236
136	-0.19607	1.375973
137	0.044783	0.292264
138	-0.08491	0.553791
139	-0.2146	0.711999
140	0.026256	0.305929
141	0.359751	0.286939
142	0.248586	0.176162
143	-0.30724	-1.8399
144	0.211531	-0.53743
145	0.248586	0.323438
146	0.118893	-0.826
147	-0.15902	0.866126
148	-0.0108	-1.14111
149	0.063311	0.443167
150	0.026256	0.619176
151	0.026256	1.198934
152	-0.02933	-0.19771
153	0.081838	-0.76965
154	0.044783	-1.45051
155	-0.10344	0.066292
156	-0.08491	1.388933
157	0.100366	1.052625
158	-0.19607	-0.25423
159	-0.2146	-0.65958
160	-0.04785	0.069147
161	-0.47399	-1.27323
162	-0.4184	-0.52401
163	-0.4184	0.535253
164	-0.19607	1.179651
165	-0.4184	1.230011
166	-0.02933	0.208084
167	-0.02933	-0.73549
168	0.081838	1.26053
169	-0.4184	-1.40442
170	0.007728	0.994905
171	0.007728	0.001868
172	0.044783	-0.75214
173	0.174476	0.524746
174	0.230058	-0.23754
175	-0.36282	1.189032
176	0.044783	0.304871
177	0.193003	0.173378
178	-0.15902	0.428079
179	-0.14049	0.988325
180	-0.45546	-0.61027
181	0.044783	-1.75545
182	0.193003	0.750465
183	0.063311	-0.77042
184	0.044783	0.662324
185	0.007728	-1.1396
186	-0.06638	0.43444
187	-0.04785	0.811665

Math Teacher Quartile Rankings Over Time Table A5

Teacher Name	Teacher Grd	2006-2007 Math	2007-2008 Math	2008-2009 Math	2009-2010 Math	2010-2011 Math	2011-2012 Math
Teacher 1	3rd				3	4	4
Teacher 29	3rd				2	1	1
Teacher 31	3rd	2	4	3	2		
Teacher 32	3rd					3	4
Teacher 33	3rd	3	4	4	4	3	4
Teacher 7	3rd			1	1	1	2
Teacher 42	3rd		1	2	2	1	2
Teacher 44	3rd	1	3	2	3	3	2
Teacher 45	3rd	2	1	2	3	3	2
Teacher 46	3rd	4	3	4	1	2	3
Teacher 4	4th			1	1	1	3
Teacher 10	4th			2	3	3	3
Teacher 12	4th		4	4	4	4	4
Teacher 15	4th				2	2	1
Teacher 20	4th	3	2	2	3	2	3
Teacher 21	4th	2	1	4	2	2	
Teacher 23	4th			2	2	3	2
Teacher 24	4th	4	4	3	3		
Teacher 35	4th	3	3	3	4	2	3
Teacher 38	4th	2	3	2	2	4	4
Teacher 39	4th	1	1	1	1	1	1
Teacher 8	5th	2	4	4	4	4	4
Teacher 19	5th				2	2	1
Teacher 22	5th		1	3	3	4	3
Teacher 26	5th	1		3	2	3	4
Teacher 27	5th	3	2	1	1	1	1
Teacher 30	5th			1	4	2	2
Teacher 40	5th		2	3	1	3	2
Teacher 6	6th				3	2	3
Teacher 2	6th			2	2	3	3
Teacher 9	6th	3	2			1	2
Teacher 14	6th					4	1
Teacher 15	6th			1	1	3	2
Teacher 18	6th			4	4	4	3
Teacher 28	6th		1	3	4	4	4
Teacher 36	6th		4		1	1	1
Teacher 3	7th	4	3	4	4	4	4
Teacher 34	7th			2	3	2	
Teacher 43	7th	1	2	1	1	1	1
Teacher 47	8th			3	1	1	1
Teacher 24	8th	4	3	4	4	4	
Teacher 37	8th	1	2	1	3	3	4

Reading Teacher Quartile Rankings Over Time Table A6

Teacher Name	Teacher Grd	2006-2007 Reading	2007-2008 Reading	2008-2009 Reading	2009-2010 Reading	2010-2011 Reading	2011-2012 Reading
Teacher 1	3rd				1	1	1
Teacher 29	3rd				4	2	3
Teacher 32	3rd					2	4
Teacher 33	3rd	4	3	3	4	4	4
Teacher 7	3rd			4	3	1	3
Teacher 42	3rd		2	1	4	3	1
Teacher 44	3rd	1	4	2	2	1	1
Teacher 45	3rd	2	1	1	2	4	3
Teacher 46	3rd	3	2	4	3	3	4
Teacher 4	4th			1	1	3	3
Teacher 10	4th			3	3	4	4
Teacher 12	4th		2	4	4	4	3
Teacher 16	4th				4	3	2
Teacher 20	4th	4	3	2	3	3	1
Teacher 21	4th	2	1	4	2	1	
Teacher 23	4th			1	3	2	1
Teacher 25	4th		3	2	3		
Teacher 31	4th	3	4	3	2		
Teacher 35	4th	3	4	2	4	3	2
Teacher 38	4th	2	1	2	1	1	4
Teacher 39	4th	1	2	1	1	1	1
Teacher 8	5th	1	4	4	4	4	4
Teacher 19	5th			3	2	3	1
Teacher 22	5th		2	3	2	4	3
Teacher 26	5th	1		3	1	3	4
Teacher 27	5th	3	1	2		1	2
Teacher 30	5th			1	3	2	3
Teacher 40	5th		3	3	2	2	1
Teacher 6	6th				2	1	2
Teacher 9	6th	2	3		3	2	3
Teacher 14	6th					2	2
Teacher 15	6th				1	3	1
Teacher 18	6th			4	4	4	3
Teacher 28	6th		1	2	3	4	4
Teacher 36	6th		4		1	2	2
Teacher 11	7th				2	4	4
Teacher 13	7th	1	2	3	1	1	2
Teacher 17	7th	3	4	1	4		
Teacher 5	8th		4	4	1	4	4
Teacher 48	8th		1	1	2	2	2
Teacher 41	8th	3	3	2	4	2	2

Top Math Teachers Tracked Over Time 2011-2012 Table A7a

	TOP Scorers Math 2011/2012- Tracked Quartile Ranking for Consistency						Top Scores for Grade Level
Teacher Name	**Teacher Grd**	**2006-2007 Math**	**2007-2008 Math**	**2008-2009 Math**	**2009-2010 Math**	**2010-2011 Math**	**2011-2012 Math**
Teacher 29	3rd				2	1	1
Teacher 39	4th	1	1	1	1	1	1
Teacher 19	5th				2	2	1
Teacher 14	6th					4	1
Teacher 43	7th	1	2	1	1	1	1
Teacher 47	8th			3	1	1	1

Top Math Teachers Tracked Over Time 2011-2012 Table A7b

Consistent same Quart over time	Percentage	Stayed within/moved 1 Quartile over time	Percentage
2/3 years	66%	3/3 years	100%
6/6 years	100%	6/6 years	100%
1/3 years	33%	3/3 years	100%
1/2 years	50%	1/2 years	50%
5/6 years	83%	6/6 years	100%
3/4 years	75%	3/4 years	75%
Avg Consistency over time	**68%**	Avg consistency over time	**88%**

Bottom Math Teachers Tracked Over Time 2011-2012 Table A8a

	BOTTOM Scorers Math 2011-2012-Tracked Ranked Quartiles for Consistency Over Time						Lowest Scores for Grade Level
	Teacher Grade	**2006-2007 Math**	**2007-2008 Math**	**2008-2009 Math**	**2009-2010 Math**	**2010-2011 Math**	**2011-2012 Math**
Teacher 32	3rd					3	4
Teacher 37	4th	2	3	2	2	4	4
Teacher 8	5th	2	4	4	4	4	4
Teacher 28	6th		1	3	4	4	4
Teacher 3	7th	4	3	4	4	4	4
Teacher 37	8th	1	2	1	3	3	4

Bottom Math Teachers Tracked Over Time 2011-2012 Table A8b

Consistently in same Quartile Over Time	Percentage	Stayed within/moved 1 Quartile Over Time	Percentage
1/2 years	50%	2/2 years	100%
2/6 years	33%	3/6 years	50%
5/6 years	83%	5/6 years	83%
3/5 years	60%	4/5 years	80%
5/6 years	83%	6/6 years	100%
1/6 years	17%	3/6 years	50%
Avg consistency over time	**54%**	**Average consistency over time**	**77%**

Top Reading Teachers Tracked 2011-2012 Table A9a

TOP Scorers Reading 2011-2012- Tracked for Consistency							Top Scores for Grade Level
Teacher Name	**Grade**	**2006-2007 Reading**	**2007-2008 Reading**	**2008-2009 Reading**	**2009-2010 Reading**	**2010-2011 Reading**	**2011-2012 Reading**
Teacher 42	3rd		2	1	4	3	1
Teacher 39	4th	1	2	1	1	1	1
Teacher 40	5th		3	3	2	2	1
Teacher 15	6th				1	3	1
Teacher 13	7th	2	2	3	1	1	2
Teacher 41	8th	3	3	2	4	2	2

Top Reading Teachers Tracked 2011-2012 Table A9b

Consistent to same Quartile Over Time	Percentage	Stayed within/moved 1 Quartile over time	Percentage
2/5 years	40%	2/5 years	40%
5/6 years	83%	6/6 years	100%
1/5 years	20%	3/5 years	60%
2/3 years	67%	2/3 years	67%
3/6 years	50%	4/6 years	66%
2/6 years	33%	4/6 years	66%
Average consistency over time	**49%**	**Average consistency over time**	**66.5%**

Bottom Reading Teachers Tracked 2011-2012 Table A10a

BOTTOM Scorers Reading 2011/2012- Tracked for Consistency							Bottom Scores for Grade Level
Teacher Name	**Grade**	**2006-2007 Reading**	**2007-2008 Reading**	**2008-2009 Reading**	**2009-2010 Reading**	**2010-2011 Reading**	**2011-2012 Reading**
Teacher 33	3rd	4	3	3	4	4	4
Teacher 10	4th			3	3	4	4
Teacher 8	5th	1	4	4	4	4	4
Teacher 28	6th		1	4	3	4	4
Teacher 11	7th				2	4	4
Teacher 5	8th		4	4	1	4	4

Bottom Reading Teachers Tracked 2011-2012 Table A10b

Consistent same Quart over time	Percentage	Stayed within/moved 1 Quartile Over Time	Percentage
4/6 years	67%	6/6 years	100%
2/4 years	50%	4/4 years	100%
5/6 years	83%	5/6 years	83%
3/5 years	60%	4/5 years	80%
2/3 years	66%	2/3 years	66%
4/5 years	80%	4/5 years	80%
Average Consistency Over Time	**67%**	**Average Consistency Over Time**	**85%**