CHARTING SUCCESS:
Data Use and Student Achievement in Urban Schools

Council of the Great City Schools
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INTRODUCTION

Overview of the Study

In recent years, interest has spiked in data-driven decision making in education—that is, using various types of data, particularly quantitative assessment data, to inform a range of decisions in schools and classrooms (Marsh, Pane, & Hamilton, 2006). This is a natural result of technological changes, the advent of test-based accountability systems under No Child Left Behind, and the increased availability of quantitative data due to accountability reforms. The increased emphasis on using data is based on the belief that assessment data and other student performance data can be important levers for improved teaching and learning. Many schools, districts, and states have invested resources in tools designed to provide teachers, principals, and other key stakeholders with ready access to (and analysis of) information regarding student performance throughout the school year.

Of particular interest is the development of interim (also known as benchmark) assessments that are often adopted at the district level and are administered at regular intervals throughout the academic year. These assessments are intended to help teachers monitor and improve student learning, both in general and on the high-stakes, end-of-year accountability tests. There is a growing body of research on interim assessments and how they relate to data-driven instruction and decision making. Researchers also have examined the implementation of data practices in school districts and schools that are purportedly making strides in data-driven decision making and instruction or that have undertaken significant initiatives in this area (e.g., Datnow, Park, & Wohlsetter, 2007; Snipes, Doolittle, & Herlihy, 2002). However, the field has yet to produce reliable evidence regarding the relationship between data use and teacher or school effectiveness at raising student achievement. Although the literature includes case studies regarding views about and the use of interim assessments in a particular school district, relatively few studies have attempted to generate specific estimates of the relationship between teacher data-use practices and perceptions and student achievement on end-of-year accountability tests.

In October 2008, the Council of the Great City Schools and American Institutes for Research (AIR) launched a project funded by The Bill & Melinda Gates Foundation that focused on understanding the use of interim assessment data as a lever for instructional improvement. The study was conducted in four urban districts located in geographically distinct areas. The project had two interrelated objectives: (1) to document and understand current data-use practices across urban school districts in terms of the use and availability of data—in particular, the administration and use of interim assessments—and (2) to generate empirical evidence regarding the relationships between student achievement and data-use practices at the school and classroom levels. To address the first objective, we administered surveys to district academic/curriculum coordinators and research directors to obtain a general overview of the state of current practices in using data to inform school- and classroom-level decision making across urban school districts. Following the surveys, we conducted a series of case studies of four urban districts, allowing for a more in-depth look at district data use. For more information on the site visits, please see the published report, titled *Using Data to Improve Instruction in the Great City Schools: Documenting Current Practices*, available at www.cgcs.org.

This report focuses on the second objective: examining the empirical relationships between teacher and principal use of student interim assessment data and achievement on end-of-year accountability tests. In this report, we expand on the existing body of literature on the use of interim assessments by examining the extent to which data-use practices (including perceptions about using data) are related to student achievement. The report is organized in three sections. First, we review the literature on using data from interim assessments and put forth a theory of action that undergirds our investigation. The theory of action identifies a set of key dimensions of data use and hypothesizes that supporting conditions in states, school districts, and schools can facilitate the effective classroom-level use of data to respond to students' instructional needs. Second, we report results of an empirical test of this theory of action. The analyses examined the relationship between teachers' and schools' use of interim assessment data and improvements in student achievement in reading and mathematics at grades 4, 5, 7, and 8. We focused on classroom-level data-use practices as reported by teachers, and school-level data-use practices and perceptions as reported by principals. The analyses include more than 1,500 teachers and 150 school principals and student achievement data from over 60,000 students across four urban districts collected during the 2009–10 school year. In the third and final section of this report, we interpret the study findings and provide recommendations and conclusions.

Policy Context for the Use of Student Achievement Data

Test scores have been used for some time to make instructional decisions, but test-score data have not always been easily available or systematically used to inform such decisions (Abelman, Elmore, Even, Kenyon, & Marshall, 1999). Recent efforts to implement systematic assessments at regular intervals during the school year hold promise for higher student achievement, and some researchers and practitioners suggest that their use may be critical to school improvement. According to Marshall (2006), many schools that serve disadvantaged students who academically "beat the odds" analyze their interim assessment data as part of their overall strategy for improving achievement. Indeed, studies that have examined the characteristics of high-performing schools and school districts have found that data-driven instruction and decision making are common features in many of these organizations (Datnow et al., 2007; Snipes et al., 2002).

The continued advancement of technology and the growing pressure for schools to be data driven have resulted in substantial new funding and research on educational data systems (Hamilton, 2005). With the U.S. Department of Education's desire to close achievement gaps through data use, new policies have been implemented to promote data use in schools and classrooms. The American Recovery and Reinvestment Act of 2009 called on states, school districts, and schools to develop longitudinal data systems to increase their capacity to support students' strengths and identify their weaknesses. This legislation sends a strong message about the importance of using data to inform educational practices and will inform a dialogue among multiple stakeholders on how data should and can be used in the future to improve public education. Other initiatives, such as the Data Quality Campaign (2009), have focused attention and resources on building state longitudinal databases that house student-level information for use by stakeholders at all levels. At the same time, access to student data is clearly growing. According to a nationally representative survey, for example, teacher access to student data systems grew from 48 percent in 2005 to 74 percent in 2007 (U.S. Department of Education, 2009).

Creating the infrastructure to facilitate data-driven instruction has been a federal priority for several years. Since 2005, the State Longitudinal Data System (SLDS) grant program has distributed grants to assist states in developing data systems. In total, 74 grants have been awarded to 42 states. Of note, three of the districts participating in the study reported here were in states that received SLDS grants. These states are Nevada, which received a grant in 2007; Kentucky, which received grants in 2005 and 2007; and Virginia, which received grants in 2007 and 2010.

The focus on data systems continued with the U.S. Department of Education's Race to the Top program. Race to the Top grants required states to describe both their current state data systems and their plans to improve those systems to a common standard. States applying for Race to the Top grants were expected to develop data systems that encompass elements of the America COMPETES Act.[1] Among these elements are a unique student identifier; a teacher identifier system with the ability to match individual teachers to individual students; student-level enrollment, demographics, and participation; student-level information about points at which a student exits, transfers in or out, drops out, or completes PK–16; the capacity to communicate with higher education systems; yearly state assessment records of individual students; student-level transcript information, including course completion and grade earned; student-level college readiness test scores; data on student transition from secondary to postsecondary, including remedial coursework enrollment; and data necessary to address alignment and adequate preparation for success in postsecondary education and the workforce (America COMPETES Act, 2007).

Despite the recent attention and investment in data systems at national, state, and local levels, researchers and practitioners have not reached consensus on what being data driven actually means in practice. Moreover, little evidence connects specific data uses to changes in teaching and actual improvements in student outcomes.

Literature and Previous Research on Assessment Data Use

In this section of the report, we begin by reviewing different types of student assessments available to school districts, schools, and teachers. We next summarize the research on using data, particularly interim assessment data, to guide instructional decisions and improve student outcomes.

The literature on the use of data to inform instruction deals with various types of assessments and assessment strategies, including interim assessments, formative assessment, progress monitoring, and curriculum-based measurement (CBM). Although these types of assessments do not have agreed-on definitions, they overlap somewhat in practice.

Formative assessment, progress monitoring, and CBM each are typically described as part of an ongoing process in which classroom teachers assess students' knowledge and understanding with activity-embedded, brief, small-scale tasks that are linked directly to the current curriculum topic. Formative assessments are not always standardized across schools, classrooms, or even students; therefore, aggregating formative assessment data is not typically done or useful (Perie, Marion, Gong, & Wurtzel, 2007). Several studies on formative assessment suggest that teachers can use classroom-embedded student assessments to elicit achievement gains (Black, Harrison, Lee, Marshall, & Wiliam, 2002; Brookhart, 2001; Christman et al., 2009; Hayward, Priestley, & Young, 2004; Heritage, 2007; Shepard, 2005). Based on a review of the literature on formative assessments, Black and Wiliam (1998a) concluded that formative assessments can increase student achievement. In a related piece, Black and Wiliam (1998b) suggested that formative assessments are effective because—by definition—they use evidence to directly inform teaching practices to meet students' learning needs, unlike summative and other assessments. Drawing from eight studies on the impact of formative assessment on quantitative comparisons of learning gains through quasi-experimental and experimental designs, the authors concluded that increases in formative assessment practices lead to learning gains. None of the eight studies showed that increases in formative assessment practices negatively affected student achievement. However, the magnitude of the increases in student learning varied according to how teachers responded to the information that formative assessments provided and how they used the assessment information to provide feedback to students about their progress. Based on this finding, Black and Wiliam (1998b) called for further research, specifically on how teachers can best use assessment feedback to improve student learning.

[1] The America Creating Opportunities to Meaningfully Promote Excellence in Technology, Education, and Science (COMPETES) Act (20 U.S.C. 9871) aims to improve American competitiveness in science, technology, engineering, and mathematics. Among its provisions are requirements for a statewide PK–16 education data system (see section 6401(e)(2)(D)).

CBM is a type of student progress monitoring characterized by quick (one- to five-minute) student-level assessments that teachers administer weekly to measure student progress in an academic area. The CBM approach to student testing was developed as an alternative or supplement to commercially distributed standardized tests. In the special education literature, several studies on the effects of CBM on learning outcomes of students with disabilities provided early insight into data-driven teacher practices that positively affect student achievement (e.g., Deno, 1985; Deno & Fuchs, 1987; Fuchs, Deno, & Mirkin, 1984). CBM specifies procedures for measuring student proficiency within curricular goals and basic skills. Some key uses of CBM are screening students for special services, developing and monitoring instructional programs, and evaluating program efficacy (Fuchs & Fuchs, 1990). In a study by Fuchs et al. (1984), students with disabilities were randomly assigned to either CBM treatment or a more traditional special education evaluation over a period of 18 weeks. The researchers observed teacher pedagogy and concluded that teachers assigned to use CBM were more responsive to their students' needs and achievements than those in more traditional special education settings. Moreover, their students achieved greater outcome gains than their peers in the control group. Similarly, Fuchs and Fuchs (1990) also demonstrated that CBM increased student learning outcomes, and CBM with additional support (in the form of skills analysis) increased student performance more than using CBM alone. This result emphasizes the focus of CBM on providing teachers with instructional guidance, in addition to providing high-quality tools for ongoing assessment, to impact student learning and understanding.

Another study of classrooms in 24 states found that student achievement increased in classrooms implementing curriculum-based progress monitoring and instructional management systems as part of a mathematics program, as compared to control classrooms, with significantly higher achievement for classrooms where these practices were implemented with high fidelity (Ysseldyke & Tardew, 2007). Other studies of CBM report similar findings, demonstrating that CBM increases student achievement (Davis & Fuchs, 1995; Hintze, Daly, & Shapiro, 1998; Marston et al., 2007; Stecker & Fuchs, 2000), and perhaps more important, when coupled with instruction in effective teaching strategies, it increases student outcomes more than CBM alone (Fuchs, Fuchs, & Hamlett, 2007; Fuchs, Fuchs, Hamlett, & Stecker, 1991).

The existing evidence about formative assessments in general and their use in specific contexts (e.g., special education) provides a basis for using regular, systematic assessment to inform instruction. However, research has yet to clarify whether the widespread use of assessments—commonly known as interim assessments—can produce robust gains in student achievement.

Of particular interest in this study are interim (also known as benchmark) assessments that are typically adopted at the district level. Interim assessments are generally defined as assessments that are administered at regular intervals throughout the school year to help educators gauge student achievement before the annual state exams used to measure adequate yearly progress (AYP; Christman et al., 2009). Interim assessments provide data that can be aggregated to the student, teacher, and school levels and are often designed to predict student performance on end-of-year accountability assessments. Other purposes of interim assessments are to provide information to diagnose student strengths and weaknesses and to provide evaluative information about curricula or instructional programs (Perie et al., 2007). Interim assessments are administered routinely (e.g., every six to eight weeks) across grade levels in particular content areas (e.g., reading and mathematics) within a school or a school district. They may be commercially developed, developed by school districts or states, or a combination of both. Some interim assessments are delivered as fixed form tests, whereas others are delivered as computer-adaptive tests based on large item banks.

Not surprisingly, some evidence suggests that such assessments are not sufficient by themselves to raise student achievement. In a large study of the effectiveness of interim assessments, Henderson, Petrosino, Guckenburg, and Hamilton (2007; 2008) reported that assessments used as part of a pilot program in Massachusetts did not yield improvements in student mathematics achievement. In the study, 22 schools used state-developed quarterly administered assessments. Using a quasi-experimental design, the researchers matched these schools in terms of student population to 44 similar schools. They compared the mathematics achievement scores of eighth-grade students at schools with state quarterly assessments with those of their counterparts in schools without state quarterly assessments. The authors did not observe any statistically significant or substantively important differences between the two groups. However, they noted that other interim assessments may have been in place at the comparison schools, and, perhaps most important, information about how the data from the assessments were used by educators in the treatment schools was beyond the scope of the study (Henderson et al., 2007).

Indeed, other research suggests that the effects of interim assessments on improving student achievement depend on the ways that interim assessments are implemented and used (Marshall, 2006). The use of interim assessment data is the direct focus of the key dimensions of data use and the theory of action that we posit in this study.

Key Dimensions of Data Use

To guide the study, we formulated an integrated theory that hypothesized how data practices at multiple levels (school district, school, principal, teacher, and student) may be related to student achievement.

We began by acknowledging interim assessment data can be used for three general implicit purposes:

- To better understand the academic needs of individual students and respond to these needs by targeting instruction, support, and resources accordingly.
- To better understand the instructional strengths and weaknesses of individual teachers and use this information to focus professional development, peer support, and improvement efforts.
- To support and facilitate conversations among teachers and instructional leaders regarding strategies for improving instruction.

These practices, in turn, are thought to lead to improved and more responsive teaching and, therefore, yield increased student achievement.

From this broad theoretical perspective, our goal was to articulate a theory of action that would undergird our investigation of the relationships among data-use practices and improvements in student achievement over time in large urban districts. Our intention was to ground the specific classroom- and school-level data-use practices that could theoretically improve student achievement in the context of the larger systems in which they occur.

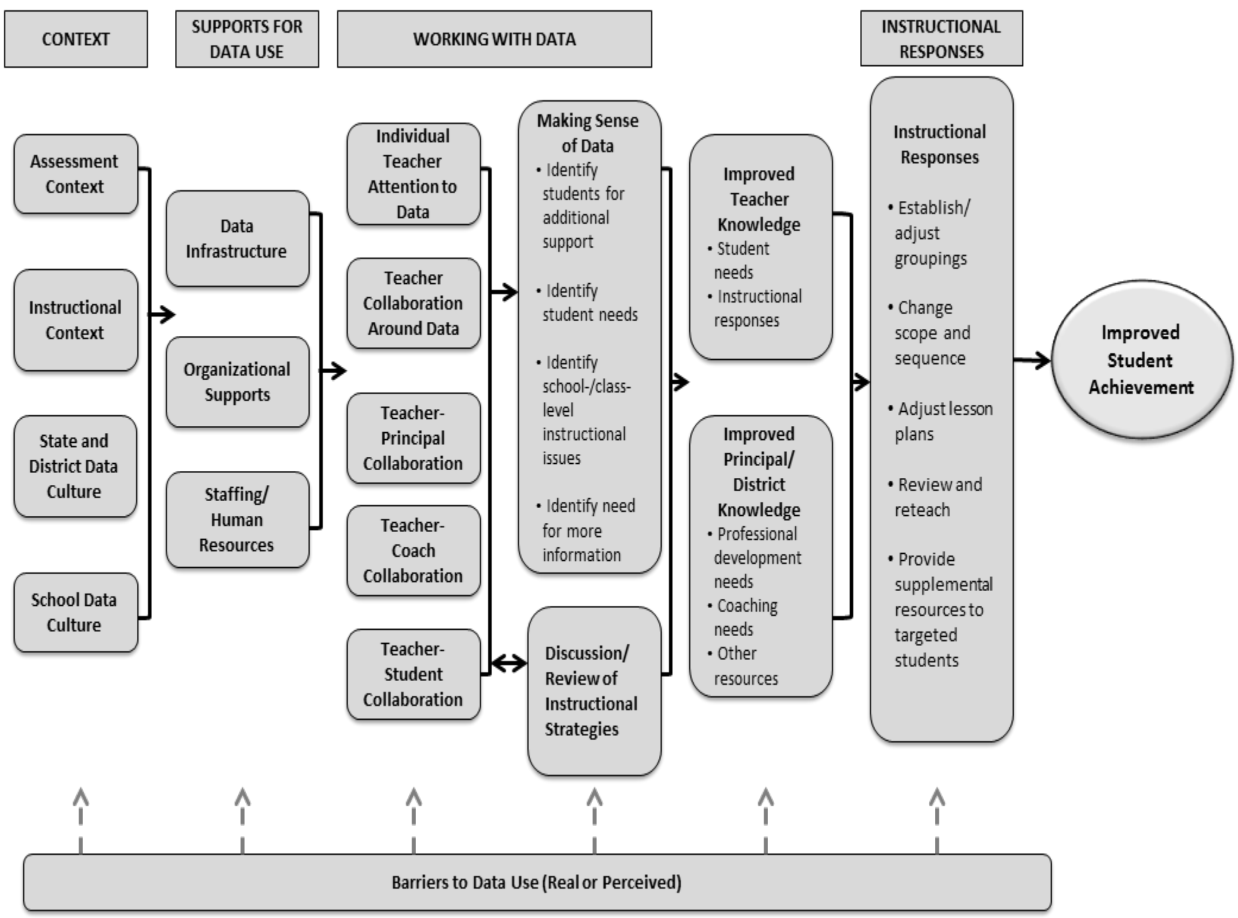
At the outset, we identified four key dimensions of the interim assessment data-use process. In the following sections, we describe the theory of action in terms of these four dimensions.

1. ***Context***. State, school district, and school conditions that facilitate a general emphasis on using data (i.e., a "culture of data use")

2. ***Supports for data use***. Concrete factors that facilitate, enable, and support specific uses of data
3. ***Working with data***. The manner in which teachers and principals work both individually and collaboratively to review data and identify specific ways the data are used to improve knowledge about student needs
4. ***Instructional responses***. The ways that teachers can respond to the knowledge and information generated by their review of student data, which in theory could lead to improved teaching and learning and higher student achievement outcomes

This proposed theory of action is shown in Exhibit 1.1. The broader dimensions and perceptions are on the left side of the diagram, and more specific aspects of data-use practices are on the right, with the ultimate end goal of improved student achievement on the far right. The diagram flows from left to right, with key dimensions on the left leading, in theory, to key dimensions to the right.

Exhibit 1.1. Using Data from Interim Assessments to Improve Student Achievement



In brief, the *Context* factors at the far left are hypothesized to support the establishment of *Supports for Data Use*, which in turn are expected to facilitate teachers and principals *Working with Data*. *Working with Data* hypothetically leads to a change in teaching strategies or *Instructional Responses*, which ultimately leads to improved student achievement. The theory of action also explicitly acknowledges that real or perceived *Barriers to Data Use* can affect the key dimensions and the links among them. *Barriers* are represented in Exhibit 1.1 below the key dimensions, with dashed arrows signifying that real or perceived barriers can interrupt the theoretical process of supporting and using data to improve student achievement at any point.

Along with the left-to-right flow of the key dimensions, we also posited that the ways educators work with data must first result in a change in their knowledge and then lead to a change in instructional responses. That is, to make an instructional change in the classroom with all or some students, a teacher requires an improved understanding of what students do or do not know or understand. However, we did not define teacher knowledge as a key dimension of practice because our focus is on observable, measurable aspects of data use. Nevertheless, in the theory of action, we identify improved knowledge as a mediating step between *Working with Data* and *Instructional Responses*.

Although the arrows in the figure illustrate some of the key relationships, Exhibit 1.1 does not illustrate every important relationship. For example, the elements of practice listed within each key dimension may theoretically contribute to and reinforce one another. For example, although staffing resources and organizational supports both contribute to individual teacher attention to data, staffing resources and organizational supports also may reinforce one another. Moreover, although the theory of action implies that each key dimension is primarily related to the next key dimension to the right, any of the key dimensions might theoretically be linked with student achievement directly or through other unmeasured mediating factors.

In the following sections, we review the literature that informs the theory of action, focusing on the four key dimensions. Under each dimension, we define the key elements within the theory of action in Exhibit 1.1. Following a review of the relevant literature is a list of important components of each key element that provide a framework for the broader study. Finally, we review literature on typically cited barriers to data use—that is, factors that are known or hypothesized to limit the extent to which teachers use data to inform their instruction.

Key Dimension 1: Context

The first key dimension of data use broadly encompasses the contextual and cultural factors that may be related to data use. Key elements of *Context* include the assessment context, the instructional context, the state and district data culture, and the school data culture (see Table 1.1). Although other contextual elements are theoretically relevant (e.g., the political or the economic context), our theory and measurement of data use focus on factors that we hypothesized are most relevant to the use of data in school districts, schools, and classrooms.

Table 1.1. Summary of Aspects of *Context*

Key Elements	Components	Description/Examples of Components
Assessment Context	Purpose of assessment	To improve instruction and predict performance on accountability tests
	Assessment type	Curriculum embedded; external benchmarks; formative and summative assessments; test construction (e.g., externally *versus* internally developed); length and structure; fixed forms *versus* item banks; cumulative *versus* unit based
	Assessment quality	Reliability and validity; appropriate scaling; alignment with state standards, state assessments, curricula, and pacing guides
Instructional Context	Implementation of districtwide curricula and pacing guides	Flexibility of curricula; flexibility and speed of pacing (including time to reteach)
	Centralized *versus* site-based decision making	Decisions related to curriculum and instruction, staffing/human resources, and professional development
	Accountability context	Includes district and school AYP history
	Schoolwide and/or districtwide initiatives	Implementation of other districtwide or statewide instructional initiatives; implementation of systemwide or schoolwide response to intervention (RTI) strategies
State and District Data Culture	Support	Explicit support for the use of data (i.e., as an explicitly stated state or school district priority)
	Clearly articulated goals and expectations	Clearly articulated plan for implementing process and procedures to support and encourage data use; clear goals for using data across the system
	State and district participation	State- and school district-level perceptions of validity, relevance, and quality of assessments; participation in discussions about data integration into state and district reviews, evaluations, and goal setting
School Data Culture	Clearly articulated goals and expectations	Presence and staff awareness of an action plan or clear strategy for data use; level of buy-in for data strategy; shared goals and norms around using data and interim assessments; clearly articulated process for implementing the data system
	Stakeholder knowledge and perceptions	Quality, usefulness, and usability of data and reports; usefulness of training and coaching activities; accountability for data use (e.g., using data is part of job expectations)
	Support and guidance from school- and school district-level leadership	Participation in planned meetings to discuss data; interest in and availability for additional conversations about data

Assessment Context. Assessment context includes goals, expectations, and policies related to developing and implementing interim assessments, including the types of assessments given and their purpose(s). Assessment context also includes the quality (e.g., validity and reliability) of the interim assessments.

Research suggests that the perceived quality of the data is as important as the strength of the data infrastructure and the accessibility and timeliness of the data. The perception that assessments are of poor quality can be a clear barrier to use. Studies have concluded that doubts about the accuracy of data lead to a lack of support for data initiatives and result in decreased data use by teachers (e.g., Feldman & Tung, 2001; Herman & Gribbons, 2001; Herman, Yamashiro, Lefkowitz, & Trusela, 2008; Ingram, Louis, & Schroeder, 2004). One evaluation of districtwide use of data found that concerns about the accuracy of student data were correlated with lower levels of data use (Wayman, Cho, & Johnston, 2007). Similarly, Kerr, Marsh, Ikemoto, Darilek, and Barney (2006) found that the perceived validity of data affected the extent to which teachers used them.

The alignment between the selected assessment and the intended uses of the data is also important. Militello, Schweid, and Sireci (2010) emphasized the importance of a close fit between the characteristics of a formative assessment and the intended use of the data by the school district and teachers to ensure that the data have a meaningful impact on teachers and students.

Indeed, multiple studies have found that the alignment of the interim assessments with standards, state tests, and pacing guides facilitates data use (Kerr et al., 2006; Marshall, 2008; U.S. Department of Education, 2010a). For example, in Philadelphia, researchers found that interim assessment results were viewed as highly relevant to teachers' instructional planning because they were aligned to the curriculum and a six-week instructional cycle. The sixth week of the cycle was designated for remediation and extension of topics that could be designed by teachers on the basis of their review of the interim assessment results (Christman et al., 2009). However, in the same study, teachers' satisfaction with the interim assessments was not significantly related to student achievement growth in reading or mathematics.

Instructional Context. The instructional context includes the curricular and instructional environment in which teachers and principals collect and use data. The uniformity, focus, and history of the instructional program all have the potential to affect how data are used in school districts, schools, and classrooms. As is the case with assessment context, instructional context is primarily meant to capture issues at state and district levels that shape school and classroom data activities.

A key aspect of instructional context is the degree of flexibility in the curriculum and pacing schedule. The literature suggests that school districts and schools must be flexible in their curriculum pacing to allow teachers time to alter instruction on the basis of assessment results (Clune & White, 2008; Datnow, Park & Kennedy, 2008; David, 2008). Marsh et al. (2006) suggested that curriculum pacing pressures—especially in the presence of regimented programs with pacing plans—are an obstacle to teacher data use. Even if pacing pressures are more perceived than real, teachers often follow the pacing plans instead of adjusting their instruction on the basis of the results of their data analyses (Marsh et al., 2006).

State and District Data Culture. State and district data culture includes attitudes, direction, and support at state and district levels regarding using data in general and interim assessments in particular. We hypothesized that the degree and nature of support for data use, as well as the direction of district and state policy in this area, can affect the manner and extent to which data are employed at the school level.

Marsh et al. (2006) found that teachers use data more frequently in school systems whose principals had committed to data-driven decision making and had a clear vision about data use at the school level. These school systems also were characterized by openness and a sense of collaboration around data use, in contrast to school systems in which data analysis was seen as an individual activity.

Clearly articulated and communicated goals for district data use also appear to be related to the extent to which teachers use data. Studies have found that a barrier to teacher data use is the perception—real or imagined—that teachers are going to be blamed for the poor performance of their students (Clune & White, 2008; Ingram et al., 2004; Kerr et al., 2006; Marshall, 2008; Park & Datnow, 2009). Conversely, Park and Datnow (2009) found that school districts can support data use in several ways, including aligning resources and goals, providing professional development, modeling effective data use, and encouraging shared decision making and collaboration. A correlational study by Anderson, Leithwood, and Strauss (2010) reinforced the role of district leadership in setting expectations for data use. They found that district leadership was more strongly related to some of the typical barriers to data use, such as accessibility, timeliness, quality, and capacity for use, than was leadership among school principals.

School Data Culture. This key element of *Context* concerns goals, norms, expectations, processes, attitudes, and leadership for using interim assessment data at the school level.

One study of Philadelphia's interim assessments found that the key supporting factors that facilitated the link between using the interim assessments and academic progress were school-level instructional leadership and collective responsibility for data (Christman et al., 2009). This was true in a context where although teachers expressed satisfaction with the benchmarks and their alignment with the core curriculum, the pacing plan, and the instructional cycle, their satisfaction alone was not predictive of growth in student achievement in reading and mathematics (Christman et al., 2009).

Other research also suggests that school leadership is a key factor in the successful use of data. Kerr et al. (2006) found greater data use in schools that had created data-driven cultures through strong school and district leadership. Murnane, Sharkey, and Boudett (2005) found that teachers' own use of data depends largely on the amount of principal support for data use. Many other studies also highlight this point (e.g., Enright & Witham, 2008; Feldman & Tung, 2001; Lachat & Smith, 2005; Marsh et al., 2006; Mason, 2002). Anderson et al. (2010), however, found that although principals play a key role in influencing data use in their schools, the majority often do not act to change the specific conditions that affect data use that are under their control.

Although the principal often is identified as the leader responsible for several important data supports, case studies by the U.S. Department of Education (2009) suggest that other individuals, including coaches and lead teachers, may also provide important leadership support for data use. Indeed, schools with higher levels of data use often had more widespread data expertise than typical schools because they did not confine the expertise to the principal or a lead teacher (Anderson et al., 2010).

Key Dimension 2: Supports for Data Use

Supports for Data Use involve the specific elements of practice related to logistical and operational support for using data, including the infrastructure, organizational resources, time allocation, and personnel resources necessary to support using interim assessment data to guide and improve instruction. This dimension is related to the amount of investment and support that exist at the district level but is focused on the tools and resources that are available at the school level. It includes both technology-related resources and the content of the data and reporting system itself. In particular, the key elements in *Supports for Data Use* are data infrastructure, organizational supports, and staffing and human resources (see Table 1.2).

The concrete supports that school districts and schools can provide to enhance data use appear to be important factors in whether data are used. In an article summarizing their two studies of interim assessment data use in Philadelphia, Bulkley, Christman, Goertz, and Lawrence (2010) assert that interim assessments can serve an instructional purpose, but critical to such use are the supports provided by the school district, including data systems, useful reports, time for reflection and collaboration, and professional development. Marsh et al. (2006), reflecting on conclusions drawn from four studies conducted by RAND, also suggested that concrete support for data use is critical to encouraging teachers to use data. The concrete supports they emphasize include various infrastructure supports, such as data access, the timeliness of the data reports, and adequate time for teachers and principals to review and discuss data.

Table 1.2. Summary of Aspects of *Supports for Data Use*

Key Elements	Components	Description/Examples of Components
Data Infrastructure	Data access and dissemination	Type of access: availability of direct access into the data system and provision of district-generated reports; level and ease of access by all stakeholders (e.g., school district, school, principal, teacher, student, and parent); availability of computer resources; ability to manipulate data (e.g., disaggregation by item types or student subgroups); frequency and timeline of reports
	Content and capacity of reports and data systems	Identification of student needs and classroom- and school-level needs and challenges; data disaggregation (i.e., student performance by subgroup, content standards, and item types)
Organizational Supports	Allocation of time	Time allocated to access, review, and/or discuss data; time allocated for one-on-one meetings between teacher and principal or data leader to review and discuss assessment data
	Administrative support	Principal participation in data-focused meetings
	Monitoring and implementation support	District- and school-level oversight; evaluation; reporting requirements; tools for reviewing and understanding data
Staffing and Human Resources	Personnel resources	School staff with the role of supporting access and analysis of data; district-level staff available to support data use; the functions and goals of data support staff (e.g., instructional *versus* accountability *versus* progress monitoring); availability of data support staff (i.e., percentage of time dedicated to providing data use support)
	Staff capacity	Prior training and expertise of staff (e.g., assessment literacy, awareness, and experience using available data systems)
	Professional development and training	Professional development focused on how to use data effectively; availability and access to experienced data coaches; ongoing evaluation of the success and effectiveness of training activities; level of participation in training activities

Data Infrastructure. This key element consists of two primary components: the infrastructure for accessing, analyzing, and disseminating data and the content or capacity of the reports and the data system. Several studies have emphasized the importance of system-level infrastructure support (Datnow et al., 2008; Kerr et al., 2006; Murnane et al., 2005; Wayman & Stringfield, 2006). A U.S. Department of Education (2009) study found that data systems are often of limited use to teachers for instruction because of limitations in the data, the user interface, or system tools. For example, only slightly more than one half of teachers with access to a data system also reported having access to their students' diagnostic test performance. However, 79 percent of school districts report having an assessment system that analyzes interim assessment data, suggesting that at least in some districts, there is a disconnect between the actual available infrastructure and teachers' knowledge or perceptions about the available infrastructure.

The quality of the data infrastructure also seems to affect levels of teacher data use. Kerr et al. (2006) found that schools demonstrating greater data use had better data infrastructure systems that included timely reporting of results, online access to data, and an interface that allowed teachers to manipulate data and run specialized reports.

Other studies concur that the timeliness and accessibility of data are particularly important. For example, Clune and White (2008) concluded that out-of-date data significantly impede the ability of teachers to modify their instruction. Specifically, teachers and administrators reported that it would be preferable to receive data within two weeks after assessments were administered. Otherwise, the data were considered too out of date for teachers to modify instruction in the current quarter school year. Similarly, in a study of data-use practices and perceptions in five urban high schools, interviews with teachers and principals revealed that those who had access to timely data were more likely to use them and were more successful at integrating results from their analyses into classroom practice (Lachat & Smith, 2005).

Organizational Supports. This key element refers to logistical and operational supports for data use, including scheduling and allocating time for review and discussion of interim assessment data and their implications for instruction. Although the presence or prevalence of these supports may be a function of the data culture within a school or a school district, the focus in this dimension is on concrete systems that exist apart from norms, expectations, and other soft supports.

A supporting factor for using data in schools is the allocation of time for teachers to work independently and collaboratively with student data. Inversely, the lack of structured time to learn how to use and review data and reflect on instructional responses is often cited as a barrier to effective data use. A report by the U.S. Department of Education (2009) noted that the majority of teachers who use student data report doing so on their own and with colleagues in their departments or grade levels—in grade-level team meetings that are sometimes facilitated by a coach.

A study by Young (2006) also found that data use is more likely to occur when schools and school districts provide structured time to allow teachers to learn how to use data collaboratively. The author used an embedded-systems perspective to explore factors influencing teachers' data use. Specifically, she explored how different factors from the hierarchical structure of school systems—such as grade-level team norms and leadership at the school and district levels—influence how teachers both view and use data. The findings were based on 90 interviews with district principals, school principals, and teachers, as well as 73 observations of grade-level team meetings, staff meetings, and professional development sessions.

In addition, tools such as assessment results linked to model lesson plans, frameworks, and curriculum guides can be developed within the data system to help teachers interpret data and respond instructionally; however, these are not common—even in districts known to be "high data users" (U.S. Department of Education, 2009).

Staffing and Human Resources. This key element refers to a school's capacity to use data to improve instruction. It includes staff positions, the capacity of staff to use data, and professional development available to support data use.

A lack of staff capacity and a lack of training in assessment and data analysis have been reported as important obstacles to teacher data use in numerous studies (Heritage, 2007; Heritage & Bailey, 2006; Herman et al., 2008; Ingram et al., 2004; Lachat & Smith, 2005; Sharkey & Murnane, 2006; U.S. Department of Education, 2009; Wayman et al., 2007). Herman et al. (2008) found that teachers are typically not trained in assessment and are not introduced to the content and pedagogical knowledge required to interpret student performance results and make instructional changes.

Professional development in using data provided by instructional coaches or other data facilitators can increase the likelihood that teachers will use data. Several studies have suggested that trained teachers are more apt to modify their teaching practices appropriately on the basis of the knowledge they have gained from assessment data (Henke, 2005; Marsh et al., 2006; Mason, 2002). Young (2006) conducted observations and interviews with district principals, school principals, and teachers about data use and concluded that effective data use was more likely to occur when districts modeled data use for their teachers.

Based on the 2006–07 National Educational Technology Trends Study (NETTS) teacher survey, 39 percent of teachers self-reported that the training they received about data-driven decision making prepared them to use data to improve student achievement (U.S. Department of Education, 2009). In addition, the NETTS study also found that school districts with high levels of data-driven decision making tend to offer district-funded, school-based data coaches to support teachers' data use. The role of the data coach varies, but the typical responsibilities include helping teachers examine and interpret data and connect results to instructional strategies (U.S. Department of Education, 2009).

Key Dimension 3: Working with Data

Working with Data includes the specific ways in which classroom-, school-, and district-level staff review and understand interim assessment data, interact with one another regarding assessment data, and use these data to inform their knowledge of student needs and decision making regarding instructional strategies. In other words, what do they do with the data they receive? How do they interpret and use the data to inform what they know about student needs? The key elements of *Working with Data* are related to the ways that teachers and principals work individually and together to understand student data, including individual teacher attention to data, collaboration around data, and "making sense of data," which refers to specific ways of reviewing assessment data to understand student performance (see Table 1.3).

Table 1.3. Summary of Aspects of *Working with Data*

Key Elements	Components	Description/Examples of Components
Individual Teacher Attention to Data	Frequency of data review	Interim assessment data and/or reports
	Focus and purpose of review	Understanding the data or reporting system; using data to identify and discuss student-, classroom-, or school-level patterns or needs; reflecting on instructional challenges; identifying potential areas to incorporate into lesson plans
Collaboration Around Data	Teacher collaboration	Frequency of teacher meetings about student data; teachers partnering outside of formal meetings (e.g., one-on-one peer support for interpreting data and developing instructional responses)
		Level of teacher, principal, and other staff (e.g., district liaisons) participation in meetings about data or involving data discussions
		Understanding data systems and interpreting assessment results; using data to identify and discuss student-level issues; discussing classroom- and school-level patterns in data; using data to reflect on instructional challenges and potential solutions
	Teacher-principal collaboration	Recognizing accountability *versus* support; using data to identify and discuss student-level issues; discussing classroom- and school-level patterns in data; using data to reflect on instructional challenges and potential solutions; informal interactions about interim assessment data, student results, and student needs
	Teacher-coach collaboration	Frequency and focus of meetings and discussions about data; using data to identify and discuss student-level issues; identifying classroom- and school-level patterns; using data to reflect on instructional challenges and potential solutions; working on instructional solutions (e.g., lesson planning and modeling)
	Teacher-student collaboration	Providing explicit instruction to students on how to use their own achievement to monitor their progress; motivating students by setting clear, attainable goals; providing students with a clear understanding of the content and skills that will be assessed; providing time for reflection on students' own performance
Making Sense of Data	Identifying students for additional support	Comparing individual student scores with the performance of a larger group (e.g., class or grade level); identifying "bubble" students (students below but close to proficiency); identifying (diagnosing) students with particular needs in foundational skills (e.g., literacy); identifying students for intervention within the classroom; targeting students for intervention outside the classroom (supplemental or pullout)
	Identifying specific student needs	Identifying students with particular needs in specific concepts; grouping students on the basis of similar patterns or trends over time; reviewing scores on individual items to understand patterns of performance and to diagnose areas of misunderstanding (e.g., item analysis); reviewing individual scores by content standards and item types; reviewing student growth over time
	Identifying school- and classroom-level instructional issues	Reviewing average scores to determine class strengths and weaknesses; reviewing classroom-level scores by content standards, item types, subgroups; reviewing student growth over time

We hypothesized that these elements of practice are mutually reinforcing. For example, teacher collaboration around data elicits individual teacher attention to data and vice versa. Specific ways to make sense of data are facilitated by the time spent in collaboration around data (and by individual teacher attention to data), and they are a function of the extent to which collaboration around and individual attention to data emphasize these particular activities. Collaboration around data, individual teacher attention to data, and specific ways to make sense of data can lead to discussion and review of instructional strategies and responses. This entire process leads to improved teacher knowledge of student needs and available instructional responses. This in turn leads to specific instructional responses (our fourth category of practice).

Individual Teacher Attention to Data. Research suggests that simply having interim assessments in place is not enough—knowing how to use data to inform instructional practice is necessary to improving student achievement. Specifically, teachers can use data to identify problems, then to identify reasons behind the problems and further, to determine how to take appropriate actions to solve them (Anderson et al., 2010).

Easy-to-access data-management systems can allow users to analyze data to determine problem areas, but levels of actual usage appear to vary both within and across school districts. In an in-depth study of data system usage, Tyler (2010) found limited use among teachers in the Cincinnati Public Schools. On average in 2008–09, teachers of mathematics, English, social studies, and science in Grades 3–8 spent about seven hours using the system over the course of the year, with the majority of their time being devoted to viewing pages that provide resources for teaching (32 percent of time) and pages that have results for multiple students in their class (27 percent of time). Although higher percentages of teachers logged into the system in the weeks following an interim assessment (from 45 percent to about 70 percent), an average over the year showed that only from 10 percent to 40 percent of teachers logged in during any given week and spent an average of six to eight minutes using the system. Focus groups provided some possible insights into why usage was so low, including a perceived lack of validity of the interim assessment, a lack of time to reteach what the data system identified as weaknesses, and a lack of time provided to use the data system.

Making Sense of Data. When teachers do review student assessment data, multiple research studies have noted some commonly cited uses, including identifying individual or groups of students with particular needs (Henke, 2005; Love, 2004; Niemi, Vallone, Wang, & Griffin, 2007), identifying bubble or at-risk students whose scores fall within particular ranges (Blanc et al., 2010; Christman et al., 2009; Long, Rivas, Light, & Mandinach, 2008; Marsh et al., 2006), and comparing classroom scores with school scores (Niemi et al., 2007).

A study in Philadelphia's public schools revealed that teachers consider a variety of factors when reviewing data (Nabors Oláh, Lawrence, & Riggan, 2010). Most teachers in the study began their review by identifying their classes' weak points. They considered their students' results in light of what they knew about their students' background or performance, their district's curriculum or pacing guide, and their perceptions about the difficulty of the material for their students. They also used a triage method of focusing efforts on the students or topics deemed most in need of attention.

Henke's (2005) case study of three school districts provides examples of how teachers and principals used data from district-level interim assessments in efforts to improve student achievement outcomes. Seven of eight schools in the Lemon Grove School District were ranked underachieving by the California Academic Performance Index. After implementing a new districtwide data system, three of the four schools that received Title I aid were declared high-achieving Title I schools. The author noted that implementation of the data system alone did not increase student achievement. Instead, improvement was attributed to the principals' and teachers' specific and targeted use of data to guide instruction and intervention.

For example, in one school, the principal analyzed state and district assessment results to identify students with particular weaknesses. The principal found that high percentages of fifth-grade students were performing below proficiency in vocabulary and reading comprehension. This knowledge shaped the school's literacy intervention, which in turn was believed to have led to improvements in student reading achievement.

In other cases, however, similar uses of data did not produce increases in student outcomes, or, at best, student progress was unclear. For example, Quint, Sepanik, and Smith (2008) investigated the effects of the Formative Assessments of Student Thinking in Reading (FAST-R) program in the Boston Public Schools (BPS) using comparative interrupted time series analyses that compared student achievement outcomes before and after FAST-R was implemented. A preintervention baseline was constructed using data from the 2001–02 school year through the 2004–05 school year. Outcomes were predicted for the 2005–06 school year using the preintervention baseline, and the differences between actual outcomes and predicted outcomes were measured. Specifically, they examined differences in trends in third- and fourth-grade reading scores on the Massachusetts Comprehensive Assessment System in 21 BPS elementary schools and found that the FAST-R data-use program did not have a statistically significant effect on student achievement. However, the study concluded that the FAST-R program, and, in particular its data coaches, seemed to help teachers better understand how their students were performing, including identifying students who were weaker in certain areas of reading.

Similarly, Herman et al. (2008) explored the relationship between student achievement in 13 Seattle schools and the use of the Seattle Public Schools' Comprehensive Value-Added Assessment System using data from four case studies, district surveys, and student test scores. The results of their latent variable, multilevel analysis suggested that data use did not have a statistically significant effect on student outcomes. The extent to which the lack of impact on student achievement stemmed from variations in data practice, a small sample size, or the lack of effective and widespread data use is unclear, but it appeared that the teachers valued access to student achievement data. The case studies suggest, however, that teachers do use data to inform their teaching practices and improve student outcomes.

Collaboration around Data. Shown in the theory of action as collaboration among teachers, between teachers and principals, coaches, and students, collaboration around data includes the supports and practices related to time that teachers and principals spend examining student data in collaboration with others. Collaboration around data occurs when teachers discuss student achievement data with other teachers, principals, coaches, parents, and students themselves. Herman et al. (2008) found that in at least one of the four case-study schools, the principal reported that most teachers collaborated frequently to compare student data across classrooms and grade levels to better prepare students for the next grade. Another recent study found that principals were more often facilitating teachers' data use than using the data independently, thus supporting collaboration around data within their schools (Anderson et al., 2010). The 2007 National Educational Technology Trends Study also found that teacher collaboration around data was almost as common as teachers' individual use of data systems (U.S. Department of Education, 2009). Marsh, McCombs, and Martorell (2010) found a small but statistically significant link between student achievement and the frequency of meetings between coaches and reading teachers to review assessment data.

Involving students in the review of their own data also has been noted as an important aspect of effective data use. Work conducted in the 1990s documented that interventions that incorporated students analyzing their own data combined with feedback from their teachers seemed to improve student outcomes (Phillips, Hamlett, Fuchs, & Fuchs, 1993). Another more recent study that used random assignment found that granting students access to an online-based feedback system that included students' individual test scores led to increased student achievement (May & Robinson, 2007). According to recommendations from a recent U.S. Department of Education Practice Guide titled *Using Student Achievement Data to Support Instructional Decision Making*, students should be active partners in analyzing their own achievement data. The authors specifically suggest that it is important to explain expectations and assessments to students, including the content and skills that will be assessed (Hamilton et al., 2009). Also, similar to facilitating factors of data use at the teacher and school levels, feedback to students should be timely, clear, and constructive (Black & Wiliam, 1998a; Brunner et al., 2005).

Improved Knowledge

Implicit in the path from making sense of data to implementing instructional responses is a change in educators' knowledge. That is, if data use is to be an effective means for improving instruction, it is likely that it must first yield improved teacher knowledge about student needs and principal and district knowledge about teacher and school needs.

Improved Teacher Knowledge involves improved awareness and understanding of the following:

- Instructional needs and challenges of individual students
- Instructional needs and challenges facing their classrooms as a whole
- Teachers' own strengths and weaknesses
- Strategies and resources for addressing the needs of struggling students
- Different strategies for teaching and reteaching specific concepts

Improved Principal and District Knowledge involves improved awareness and understanding of the following:

- Instructional needs and challenges facing individual classrooms or teachers and the school as a whole
- Teachers' (and schools') strengths and weaknesses
- Strategies and resources for addressing the needs of teachers and schools

Although we identify teacher and principal knowledge explicitly in the theory of action, measuring teacher or principal knowledge (and changes in what they know as a result of reviewing data) was beyond the scope of this study.

Key Dimension 4: Instructional Responses

Instructional Responses are the ways classroom-, school-, and district-level staff translate the improved knowledge they glean from reviewing interim assessment results and use it to change classroom-level instruction. This dimension also includes instructional responses (e.g., interventions) implemented at the school and district levels in response to patterns and trends in student assessment data (Table 1.4).

There is evidence that beyond access to data, knowing how to use data to inform instructional practice is related to improving student achievement. Kerr et al. (2006), in a study of data use in three urban districts, noted that there is anecdotal evidence that data-based decision making can have a positive impact on student achievement. Given that a number of studies have shown that just administering the tests does not appear to yield changes in student achievement, we hypothesize that this process must move beyond using data to diagnosing problems to identifying appropriate actions to solve them (see also Anderson et al., 2010).

Table 1.4. Summary of Important Aspects of *Instructional Responses to Data*

Key Elements	Components	Description/Examples of Components
Teacher Instructional Responses	Establish/adjust groupings	Establishing and/or adjusting student groups on the basis of assessment scores
	Change scope and sequence	Changing the scope and sequence of individual lesson plans or larger curriculum maps
	Adjust lesson plans	Adjusting the approach and materials used in lesson plans
	Review and reteach	Covering material again for all or some students in the classroom, reteaching content that students may have missed during the initial instruction period
	Provide supplemental resources to targeted students	Providing supplemental interventions and support (e.g., tutoring) for struggling students; additional attention to "bubble" students (i.e., students close to reaching proficiency)
School Instructional Responses	School-level instructional response	Providing schoolwide responses such as professional development for teachers or revising the school improvement plan.

Table 1.4 lists a number of instructional responses or changes that teachers and schools make in response to the review of student assessment data. Previous studies document that teachers respond in varied ways to student achievement data, including the components listed in Table 1.4 as *Teacher Instructional Responses*. For example, student data are commonly used to identify certain students for small-group instruction and interventions within and outside the classroom (Blanc et al., 2010; U.S. Department of Education, 2010a). In their study of 10 Philadelphia schools, Blanc et al. (2010) found that regrouping was one of the most common strategies that teachers used after viewing interim assessment results. Teachers identified weaknesses in groups of students and worked with them to address those challenges. Teachers described a flexible system, with groups that changed frequently based on data. In an exploratory case study of three districts and a portion of a fourth district, Snipes et al. (2002) also found that data were used for grouping and providing interventions or tutorials within the classroom.

In an exploratory study using a mix of qualitative and quantitative analyses, Brunner et al. (2005) examined the use of assessments in New York City public schools in grades 3–8 and found that interim assessments were reported to be most useful for making pacing decisions and prioritizing instructional time. Brunner et al. conducted several rounds of interviews and administered surveys in 17 schools across the city. Of the respondents, 89 percent said that assessments were useful in making prioritizing decisions regarding instructional time, and 76 percent said that assessments were important tools when planning lessons. A majority (51 percent) also reported that they use assessments in making year-long pacing plans.

Clune and White (2008) examined how data from the quarterly assessments were used in the Providence Public School District. The assessment program was initiated in 2004, with interim assessments administered in grades 2–8 in language arts and mathematics. The results based on teacher surveys indicated that assessment data were useful in identifying low-performing students for remediation and adjusting the content of lesson plans to improve student learning.

Another common instructional response for teachers is to reteach content to the entire class or groups of students. For example, in the previously described study of Philadelphia's interim assessments, Nabors Oláh et al. (2010) examined the ways that teachers weighed their options for recovering particular content during the district's reteaching week. As noted under Key Dimension 3: *Working with Data*, the teachers used a triage method to identify the topics that were most problematic for students. Teachers in the study most commonly attributed student mistakes to procedural errors; consequently, their reteaching often focused on procedural steps. However, the Philadelphia assessment results appeared to be of little help in guiding teachers in correcting conceptual errors. Teachers often presented material with which students had struggled in a different way; however, the change was not related to an analysis of the assessment items but rather to a belief that being exposed to different methods of teaching was beneficial to students. Goertz, Nabors Oláh, and Riggan (2009) also found that teachers used data to determine what to reteach and to whom, but only half of the teachers in the study changed how they taught the concept, and those changes were not always rooted in the data.

Blanc et al. (2010) similarly found that one of the most common instructional changes based on data was reteaching the information identified on the interim assessments as a class weakness. In this study of 10 elementary schools in Philadelphia, including five detailed case-study analyses and interviews of district staff, the district and school staff reported that some teachers retaught the material using the same instructional strategies, but others felt it was important to change the teaching strategies to provide students with a different way to access the information.

In another study of teachers' instructional responses to student achievement data, Hoover (2009) found that in a suburban Virginia district, the most common instructional responses were differentiating instruction to remediate and/or enhance learning (96.4 percent), reteaching topics or concepts (93.5 percent), and changing the pacing of future instruction (91.7 percent). Many teachers also remediated and retested for a specific unit (82.7 percent), regrouped students within the classroom (80.4 percent), or changed their instruction in some other way (42.9 percent). Sixty-four percent of the teachers reported that pacing prevented them from reteaching, but they incorporated strategies to address assessment results into their next units.

The most commonly cited school-level uses of student achievement data include revising school improvement plans, revising curricular choices (content as well as scope and sequence), and implementing or adapting schoolwide interventions.

For example, in a case study involving interviews with school and district personnel, Henke (2005) described a school district's initiative to use data in targeted and specific ways to improve schools that were in underachieving status. One school conducted an analysis of state and district assessment results to identify students with particular weaknesses. School staff found that high percentages of fifth-grade students were performing below proficiency in vocabulary and reading comprehension. This knowledge shaped the school's intervention, which involved implementing a mandated corrective-reading effort during the school day, a guided reading program after school, and the use of a three-hour support aid. The author attributed the increased academic success of students in this school to these interventions and data-based curriculum changes.

A larger 2010 study from the U.S. Department of Education (2010a) examined 36 case-study schools and found that the most common uses of data at the school level were school improvement planning and curricular decisions. Setting classroom, school, and district goals also has emerged as a prevalent response to interim assessment data in several studies (Clune & White, 2008; Marsh et al., 2006; Marshall, 2008; Niemi et al., 2007; Young, 2006).

Barriers to Data Use

Barriers to Data Use associated with any of the aforementioned key dimensions may disrupt the process at any point in the theory of action, see Exhibit 1.1 (theory of action). That is, real or perceived barriers to data use can interrupt the theoretical progression toward improved student achievement. Several obstacles to effective data use have been described in the review of the key dimensions; this section summarizes often-cited barriers in previous research as follows:

- Lack of time to engage in data exploration and reflection (U.S. Department of Education, 2010a)
- Poor assessment quality or validity (Feldman & Tung, 2001; Herman & Gribbons, 2001; Herman et al., 2008; Ingram et al., 2004; Kerr et al., 2006)
- Lack of data accuracy (Wayman et al., 2007)
- Lack of alignment with standards and pacing (Marsh et al., 2006; U.S. Department of Education, 2009; U.S Department of Education, 2010a)
- Lack of timeliness and accessibility of data (Clune & White, 2008; Lachat & Smith, 2005)
- Limited staff capacity (Heritage, 2007; Heritage & Bailey, 2006; Herman et al., 2008; Ingram et al., 2004; Lachat & Smith, 2005; U.S. Department of Education, 2010a; Sharkey & Murnane, 2006; Wayman et al., 2007)
- Negative perceptions of the use of interim assessment data for teacher evaluation (Clune & White, 2008; Ingram et al., 2004; Kerr et al., 2006; Marshall, 2008)

CHAPTER 2
RESEARCH DESIGN

The following section describes the methods and procedures used to address the research questions posed. The general approach in the study was to link teacher and principal survey data with student achievement data to test the relationships between data-use practices and perceptions and student achievement. The investigation focused on both elementary grades (grades 4 and 5) and middle grades (grades 7 and 8).

The overarching goal of the study was to understand the links between data-driven instruction and student achievement by examining two research questions:

1. What are the relationships between teachers' data-use practices and perceptions and their students' achievement?

2. What are the relationships between school polices, practices, and resources for data-driven instruction and student achievement?

Samples

This section describes the samples of districts, schools, principals, teachers, and students included in the analyses that examine data use and student achievement. Overall sample sizes are shown in Table 2.1; these numbers reflect the number of individuals who were included in analyses of the links between data use and achievement in four analysis samples: (1) elementary grades mathematics, (2) elementary grades reading, (3) middle grades mathematics, and (4) middle grades reading. Schools were randomly selected within districts (described below) and invited to participate. The teachers included were those in participating schools who taught mathematics and/or reading in grades 4, 5, 7, or 8, and completed one or more of the data-use surveys. The students included were those who were in the surveyed teachers' classes in these grade levels during the 2009–10 school year.

Table 2.1. Number of Districts, Schools, Principals, Teachers, and Students in the Four Groups of Analysis Samples

	Elementary Grades		Middle Grades	
	Mathematics	Reading	Mathematics	Reading
Districts	4	4	4	4
Schools	111	110	86	85
Principals	102	101	76	75
Teachers	593	614	471	532
Students	14,354	14,764	38,583	36,169

The principal samples overlap across subjects completely because they were asked to respond to items about data use in both mathematics and reading in their schools. There is considerable overlap (92 percent) between the teachers in elementary grades mathematics and reading samples because most teachers taught both subjects. Teachers who taught both were asked to respond to items about data use in both subjects. Among middle grades teachers, only 7 percent taught both mathematics and reading; most taught one subject or the other. There is also overlap in the student samples across subjects because most students had both reading and mathematics scores. In the next section, we describe the sample of districts, schools, principals, teachers, and students including providing the total number of unique participants. Exhibit C.1 in Appendix C provides a detailed depiction of the sample from the beginning of survey administration to the samples of schools, principals, teachers, and students used in the analyses.

District Sample

The four districts that participated in this study were selected by drawing on data from a district-level survey that we administered to all 67 member districts of the Council of the Great City Schools in June 2009. The survey asked about district interim assessments, data systems, and data use in member districts. One version of the survey was administered to the academic chief/curriculum coordinator and another to the research director of each district. The survey versions were similar in their content and scope but modified to reflect each individual's role within the district to provide a general overview of the state of current practice in using data to inform school- and classroom-level decision making across urban districts in the U.S. A total of 35 curriculum coordinators (52 percent response rate) and 54 research directors (81 percent response rate) completed the surveys. Between the curriculum coordinators and research directors, respondents represented a total of 62 of the 67 districts in the Council's membership (94 percent).

Based on the district survey results and additional supplemental information, we identified four districts that (1) had administered interim assessments continuously for the past three years; (2) planned to continue administering interim assessments for at least the next several school years; (3) administered interim assessments at least three times in a school year; and (4) had a data system with the capacity to meet the requirements of a quantitative study that would link school- and classroom-level data-use practices with student achievement. The selected districts also had to be willing to participate in the in-depth study, which included a series of principal and teacher surveys and a two-day site visit.

To set the context for the study, a brief description of each district as of 2010 follows a general overview of the types of data available in the participating districts *via* the state longitudinal data systems. The following sections briefly describe the participating districts and their data use climates. The study team collected information regarding the latter during site visits conducted in each district during the 2009–10 school year. During these two- to three-day visits, we collected information about the district's history and the background of the interim assessment process through focus groups and interviews.[2]

The four participating districts are each in a different state, with a different emphasis on data use. Three districts are in states with high data capacity—that is, they have in place all or nearly all the required elements for the America COMPETES Act, with plans to improve on them and implement the remaining elements (see Table A.1 in Appendix A).

District 1. As of 2010, District 1 served about 90,000 students in 126 schools with a staff of about 6,500 teachers. The district adopted interim assessments in 2003. The interim assessments initially covered all the content that students were expected to learn during the school year and were administered to determine to what extent students were making progress toward meeting state and district standards in reading and mathematics. However, the district transitioned to a new interim assessment model in 2008, whereby each assessment is intended to reflect the content that has been taught to students up to that time, according to the district curriculum and pacing guide. This transition started with high schools and later was adopted in middle and elementary schools. The mode of administration also has changed, from online administration to paper-based administration.

These changes to the interim assessment occurred concurrently with other significant changes in the district. These included a transition from a site-based management system to a more centralized management model, particularly for curriculum, assessment, school schedules, and budgetary practices. Another change was the adoption of districtwide curriculum maps in 2009. In 2009–10, District 1 administered interim assessments three times in most grades.

[2]More information about the data use and interim assessment-related practices in each district is provided in *Using Data to Improve Instruction in the Great City Schools: Documenting Current Practices,* which is available online (www.cgcs.org).

District 2. District 2 is one of the largest school districts in the country, serving approximately 311,000 students in 324 schools, with a staff of about 14,800 teachers. The district is divided into four areas that vary geographically and demographically. From the district's perspective, each area requires different levels and types of support regarding data use. In this district, schools maintain site-based decision-making autonomy; this autonomy carries over into the interim assessment process.

In District 2, the development of the interim assessments stemmed from the need to determine whether students were meeting benchmarks defined by the district as well as the need for more immediate data regarding student progress during the school year. With the previous testing structure, the district could use only the prior year's state accountability test to plan for the upcoming school year.

In this district, common assessments—generally developed by teachers with some guidance from district principals—also are used in some schools and administered approximately twice a year. The common assessments reportedly compete with the interim assessments, particularly in mathematics, because the teachers believe that the common assessments are better aligned with the curriculum and the pacing guides than the interim assessments. This contextual factor may present some challenges to the district's efforts to achieve a consistent measure of students' strengths and weaknesses across the district. In 2009–10, District 2 administered interim assessments three times in most grades.

District 3. As of 2010, District 3 served close to 98,000 students in 155 schools and employed more than 6,000 teachers. The district's vision for data use is driven by nine broad organizational standards focused on collaborative and data-driven decision making. This district began implementing interim assessments in 2005 to gauge students' academic progress before the end-of-year state exam. The interim assessment program in this district is different from those of other districts in several ways. First, the assessments include open-ended questions. As a result, significant effort is put into training staff on how to score these questions to ensure that the results are consistent from school to school. Second, the district created the data management system in-house, so it has more flexibility to modify the system to meet staff needs.

This district currently operates under a school-based management model; therefore, individual schools have some degree of autonomy in how much they use data as a driving force for instructional changes and whether interim assessments are administered in their schools. Consequently, the understanding of interim assessments and how they can be used varies from school to school. The district has built the capacity to systematically monitor school-based activities through several structures, including the data-management system, district staff collaborations, subject- and grade-based planning, professional development, and leadership meetings. In 2009–10, District 3 administered interim assessments up to seven times in some grades.

District 4. In 2010, District 4 served close to 24,000 students in 53 schools and had a staff of approximately 1,900 teachers. Interim assessments had been in use in the district for more than 10 years. The decision to adopt district interim assessments stemmed from a history of low student performance that had placed the district among the states' lowest performing. Initially, teachers did not see the purpose or potential benefits of interim assessments; however, the district worked to encourage buy-in from the schools and, according to district representatives, has improved engagement with the interim assessment process over the past seven years.

The district's management model includes significant oversight of the interim assessment process. The district described a culture of data use in which teachers understand the expectations for using data and are engaged in the interim assessment process. The district also emphasized collaborative relationships that allow teachers and principals to be part of the decision-making process about the interim assessments. Hiring practices at the administrative level are additional evidence of how District 4 has taken steps to create a more sustainable data-driven culture. Several district-based staff reported that experience in using data was a requirement for their positions, suggesting a commitment to data use in the district. In 2009–10, District 4 administered interim assessments three times in most grades.

School Sample

A total of 193 elementary and middle schools across the four districts were included in the study. To gather a sample of schools that was representative of all elementary and middle schools in the participating districts, we conducted a stratified random sampling procedure within districts.

Based on initial power calculations, we sought a sample of 100 elementary schools and 80 middle schools per district (yielding approximately 800 elementary school teachers and 960 middle school teachers). We also wanted to over-sample by 5 percent to account for attrition/nonresponse, resulting in a total of 107 elementary schools and 85 middle schools that we sought to invite to participate. For the elementary school sample, we simply divided the required number of schools based on the power analyses (107) by the number of districts (4), therefore seeking between 26 and 28 schools per district. For the middle school sample, we sought an uneven number of schools per district because one district had only nine middle schools. To accommodate this, we sampled a larger number of schools from another district.

Stratified random sampling was conducted in each district to select the desired number of elementary and middle schools. Schools within district were stratified by (1) school type (elementary *versus* middle school), (2) percent economically disadvantaged (i.e., percent eligible for the National School Lunch Program), and (3) percent ethnic/racial minority enrollment. The percentage of students served per school who were eligible for the school lunch program and were racial/ethnic minorities was gathered from the U.S. Department of Education's Common Core of Data. We used the median value on percent economically disadvantaged and percent minority for elementary and middle schools, within district, to create groups of schools that were either low or high on economic disadvantage or minority status.[3] Based on these groupings, schools were then assigned to one of six strata (e.g., Stratum 1 included elementary schools with high percent economic disadvantage and high percent minority enrollment).

We then drew a simple random sample from each stratum where the number of schools chosen from each stratum was proportionate to the number of schools in that stratum. For example, if 60 percent of schools were in stratum 1, then 60 percent of the sampled schools were drawn from stratum 1.

[3]Median values were calculated separately for elementary and middle schools; therefore, there were different cutoff scores for high *versus* low economic disadvantage and minority enrollment for elementary and middle schools within and between districts.

Table 2.2. Number of Schools Sampled per District

District	Number of Elementary Schools	Number of Middle Schools
District 1	26	21
District 2	27	34
District 3	26	21
District 4	28	9
Total	***107***	***85***

Note: In District 4, all schools were invited to participate rather than a random stratified sample of schools.

Teacher Sample

Teachers in the sampled schools were invited to participate in the surveys if they taught reading or mathematics in grades 4, 5, 7, or 8.[4] We selected these grade levels because the district survey indicated that most urban districts are especially focused on administering interim assessments in grades 3–8. The entire sample of teachers includes 1,581 elementary and middle grades teachers of reading or mathematics who were linked with students via classroom rosters. For more detailed information about the sample, please see Appendix C.

Elementary School Teachers. Of the 1,581 teachers, 623 taught reading and/or mathematics to students in grades 4 and 5. Of the 623 elementary grade teachers, most (92 percent) taught both reading and mathematics; 2 percent taught mathematics only, and 6 percent taught reading only. Table 2.3 shows the demographic characteristics of the elementary school teachers included in the analytic sample, for whom demographic data were available. A majority of the elementary grade teachers who responded to the surveys were white (69 percent), and most were women (83 percent). Seventy-two percent of the sample had a master's degree or higher. The respondents had, on average, more than 11 years of experience teaching and 6 years in their current schools, although there was a wide range in years of experience ranging from less than 1 year to 44 years (*SD* = 8.67).

[4] In District 3, we sampled teachers within middle schools to attain the target sample size. In this large district, there were many more middle school teachers nested within the sample schools than were necessary based on our power calculations (633 versus 431). Therefore, a random sample of teachers within sampled schools was conducted whereby 68 percent of teachers within each school were randomly selected. Therefore, rather than including all seventh- and eighth-grade teachers within each sample middle school, a range from 14 to 29 teachers per school were invited to participate, based on the size of the school. The total number of teachers invited to participate in District 3 was 431.

Table 2.3. Demographic Characteristics of Fourth- and Fifth-Grade Teacher Sample

	Mathematics		Reading		Total	
	Number	Percentage	Number	Percentage	Number	Percentage
Degrees obtained						
Below bachelor's degree	0	0%	0	0%	0	0%
Bachelor's degree	514	100%	538	100%	547	100%
Master's degree	314	72%	326	72%	332	72%
Educational specialist or professional diploma	80	25%	83	25%	83	25%
Certificate of Advanced Graduate Studies	63	21%	67	22%	68	22%
Doctorate or professional degree (Ph.D., Ed.D.)	9	3%	9	3%	9	3%
Gender (Female)	433	84%	452	84%	459	83%
Race						
White	354	69%	371	70%	376	69%
Black	75	15%	79	15%	82	15%
Asian	6	1%	6	1%	6	1%
American Indian	4	1%	4	1%	4	1%
Multiracial	12	2%	13	2%	13	2%
Ethnicity						
Latino/Latina	59	12%	60	11%	61	11%
Missing race/ethnicity information	77	13%	79	13%	81	13%

Note. Teachers who taught both subjects are included in both the Mathematics and Reading columns. The numbers in these columns do not add up to the numbers in the Total column because of the overlap. Percentages reported in table 2.3 are based on teachers for whom we had complete demographic data.

Middle School Teachers. The middle school sample included 958 teachers; 473 (49 percent) of these respondents taught middle school mathematics, and 552 (58 percent) taught middle school reading. Only 67 (7 percent) of the 958 middle school teachers taught both mathematics and reading. Table 2.4 presents the demographic characteristics of the middle school teachers, for whom demographic data were available. Similar to the elementary school respondents, a majority of the middle school teachers who responded were white (71 percent), and most (78 percent) were women. On average, the middle school respondents had an average of more than 11 years of teaching experience, ranging from less than 1 year to 44 years (*SD* = 8.91). With respect to degrees earned, all but one teacher in the sample had at least a bachelor's degree, and 72 percent had a master's degree.

Table 2.4. Demographic Characteristics of Seventh- and Eighth-Grade Teacher Sample

	Mathematics		Reading		Total	
	Number	Percentage	Number	Percentage	Number	Percentage
Degrees obtained						
Below bachelor's degree	1	< 1%	0	0%	1	< 1%
Bachelor's degree	425	> 99%	482	> 99%	849	> 99%
Master's degree	274	72%	321	73%	551	72%
Educational specialist or professional diploma	79	30%	83	28%	150	29%
Certificate of Advanced Graduate Studies	51	20%	60	21%	104	21%
Doctorate or professional degree (Ph.D., Ed.D.)	6	3%	13	5%	19	4%
Gender (Female)	306	71%	412	85%	671	78%
Race						
White	299	71%	338	72%	597	71%
Black	43	10%	61	13%	97	12%
Asian	9	2%	3	1%	12	1%
American Indian	1	0%	2	0%	3	0%
Multiracial	13	3%	12	3%	23	3%
Ethnicity						
Latino/Latina	57	14%	55	12%	103	12%
Missing race/ethnicity information	51	11%	81	15%	123	13%

Note. Teachers who taught both subjects are included in both the Mathematics and Reading columns. The numbers in these columns do not add up to the numbers in the Total column because of the overlap. Percentages reported in table 2.4 are based on teachers for whom we had complete demographic data.

Principal Sample

All principals (and assistant principals, where appropriate) of the participating schools were asked to complete the surveys. The sample included a total of 212 principals, with 124 principals from elementary schools, 86 principals from middle schools, and 2 principals from K-8 schools (who were considered principals of middle grades for this study). Table 2.5 presents the demographic characteristics of principals for whom demographic data were available. Overall, 76 percent of the principals and assistant principals in the survey sample were women—from elementary schools, the proportion of female principals was 84 percent, and from middle schools, 65 percent. Forty-eight percent of elementary principals and 64 percent of middle school principals were white, and 40 percent of elementary and 23 percent of middle school principals were African American.

All of the elementary and middle school principals and assistant principals had at least a master's degree, and 23 percent of the elementary school principals and 17 percent of the middle school principals had a Ph.D. or Ed.D. In terms of experience, the overall average years of experience for principals were 14 years as teachers and 11 years as principals. Table 2.5 presents the demographic characteristics of the principals included in the analytic sample.

Table 2.5. Demographic Characteristics of Principal Sample

	Elementary Grades		Middle Grades		Total	
	Number	Percentage	Number	Percentage	Number	Percentage
Degrees obtained						
Below bachelor's degree	0	0%	0	0%	0	0%
Bachelor's degree	103	100%	75	100%	178	100%
Master's degree	105	100%	75	100%	180	100%
Educational specialist or professional diploma	37	51%	30	58%	67	54%
Certificate of Advanced Graduate Studies	24	39%	14	31%	38	36%
Doctorate or professional degree (Ph.D., Ed.D.)	13	23%	7	17%	20	21%
Gender (Female)	87	84%	49	65%	136	76%
Race						
White	48	48%	48	64%	96	55%
Black	40	40%	17	23%	57	32%
Asian	2	2%	1	1%	3	2%
American Indian	1	1%	1	1%	2	1%
Multiracial	4	4%	2	3%	6	3%
Ethnicity						
Latino/Latina	6	6%	6	8%	12	7%
Missing race/ethnicity information	23	19%	13	15%	36	17%

Note. Percentages reported in table 2.5 are based on principals for whom we had complete demographic data.

Student Sample

The student sample included 61,798 students across the four districts, of which 14,974 were in grades 4 or 5 and 46,824 were in grades 7 or 8. Their demographics are shown in Table 2.6. The student sample was 34 percent white, 22 percent African American, and 36 percent Hispanic. Sixty-five percent of the elementary grade students and 59 percent of the middle school students were eligible for the National School Lunch Program. Fifteen percent of students in the elementary grades sample and 12 percent in the middle grades sample received special education services. Thirteen percent of the elementary grades sample and 11 percent of the middle grades sample were English language learners.

Table 2.6. Demographic Characteristics of Student Sample

	Elementary Grades		Middle Grades		Total	
	Number	Percentage	Number	Percentage	Number	Percentage
Gender (Female)	6,901	49%	22,420	49%	29,321	49%
Race						
White	9,680	31%	29,634	35%	39,314	34%
Black	3,951	28%	9,001	20%	12,952	22%
Asian, Native Hawaiian, or Pacific Islander	709	5%	2,966	6%	3,675	6%
American Indian	229	2%	557	1%	786	1%
Ethnicity						
Latino/Latina	4,724	33%	17,027	37%	21,751	36%
Missing race/ethnicity information	857	6%	1,115	2%	1,972	3%
Received free or reduced-price lunch	9,603	65%	26,459	59%	36,062	61%
Received special education services	2,244	15%	5,334	12%	7,578	13%
ELL status	1,935	13%	4,908	11%	6,843	12%

Note. Percentages reported in table 2.6 are based on students for whom we had complete demographic data.

Measures

To examine the relationships among the key dimensions of data use to test the hypothesized links in the theory of action, we measured teachers' and principals' data-use practices and perceptions using surveys administered three times over the course of the 2009–10 school year. Our analysis focused on the relationships between the four key dimensions of data use (*Context*, *Supports for Data Use*, *Working with Data*, and *Instructional Responses*) and student achievement on the state assessments in reading and mathematics. We also examined the links between perceived *Barriers to Data Use* and student achievement in both subjects.

Surveys of Teachers' and School Principals' Data-Use Practices and Perceptions

To gather data on data use, we surveyed teachers and school principals about their data-use practices at three points during the 2009–10 school year. The surveys were administered online and measured the key dimensions of data use.

The surveys were designed to measure each of the key dimensions included in the theory of action. To develop the surveys of teacher and principal data-use practices and perceptions, researchers conducted an initial scan of more than 40 previously used surveys that measured some aspect of data use (general or specific). Researchers then narrowed the item pool to the most relevant, reliable, and valid measures of data use—229 items from 22 source surveys. Items from the source surveys were examined for content and psychometric properties. The source surveys included instruments specifically developed to measure data use, such as the online Ohio Department of Education (ODE) School Administrator Survey,[5] as well as surveys that had a broader purpose, such as those used for the National Longitudinal Study of No Child Left Behind (U.S. Department of Education, 2010b).

[5]The ODE survey is available online at, (www.ode.state.oh.us/GD/Templates/Pages/ODE/ODEDetail.aspx?page=3&TopicRelationID=1222&ContentID=57327&Content=94770).

After a pool of possible items was selected, the items were then mapped back onto the theory of action to ensure adequate coverage of each key dimension of data use. There were many available items addressing many of the key dimensions of data use (e.g., issues of staffing/human resources related to data use). However, there was a dearth of items addressing other key dimensions (e.g., instructional responses). To further develop the surveys for the purpose of the study, existing item sets were modified and developed to sufficiently measure all the key dimensions, including *Instructional Responses*. Items included in the survey were mostly five-point Likert-type items but also included frequency count questions to measure teachers' and principals' data-use practices.

In summer 2009, an in-depth cognitive laboratory process to pilot the items with 17 teachers and principals in the Washington, D.C., area was conducted. Fourteen of the cognitive laboratory participants were teachers—four in elementary schools and ten in middle schools; two were principals, and one was a vice principal. Using ThinkAloud techniques, participants answered the questions on the survey while saying everything they were thinking. This process allowed for an investigation into the cognitive processes that teachers and principals employ when thinking about the survey items. In addition, cognitive laboratories provide information about factors other than data-use practices that may have an effect on teachers' responses to the items. This technique allows participants to talk through any possible issues with survey items, including confusing wording, content issues, vocabulary that may not be understood, or confusing response structures. We then refined the survey items on the basis of the feedback provided by the teachers and principals during this process.

Survey items from the data-use surveys were tailored to measure the four key dimensions of data use—including *Context*, *Supports for Data Use*, *Working with Data*, and *Instructional Responses*—as well as the key *Barriers to Data Use* previously noted in the literature on data-driven decision making. The following sections provide descriptive information about the survey items used to measure each construct. The teacher and principal surveys included many common items, with some unique items on each. Also, some survey items for both principals and teachers were subject specific for reading or mathematics instruction. Most items were administered in all three waves; however, some item sets were included in only one wave. For example, questions about data coaches were included only in the second wave. Example survey items used to measure the dimensions of data use among teachers and principals are provided in Appendix B (Table B.3).

Context. The surveys included items that measured assessment/instructional context and state, district, and school data culture. Survey items measuring assessment/instructional context asked teachers and principals about different types of assessments and the alignment of interim assessments with other assessments. State, district, school data culture were measured with items gauging state, district, and school leader supportiveness of and emphasis on data-use practices. There were 36 items on the teacher survey and 32 items on the principal survey that measured constructs related to *Context*.

Supports for Data Use. This key dimension was measured with items representing three constructs: data infrastructure, organizational supports, and staffing and human resources. Survey items asked teachers and principals about the data system, the support they receive from the district and school around data use, and the professional development training they receive to use interim assessment data. Teachers' perceptions of *Supports for Data Use* were measured with 48 survey items; the principal survey had 51 items.

Working with Data. The key dimension of *Working with Data* was measured with 42 items that measured aspects of teachers' and principals' individual attention to data and collaboration around data. Both teachers and principals were asked to report the amount of time they spent individually examining student data. To measure collaboration in the review of data among key actors—including teachers, principals, data coaches, parents, and students—the survey assessed the frequency of collaborative interactions about data, including, specifically, the number and types of interactions between teachers and principals; teachers and instructional coaches; and teachers, principals, and parents.

Instructional Responses. *Instructional Responses* were measured with survey items that asked teachers and principals about changes made in the classroom or school in response to their review and interpretation of interim assessment results. On the teacher survey, 26 items represented four main constructs: adjust lesson plans, establish/adjust groupings, provide supplemental resources to targeted students, and change scope and sequence. On the principal survey, 24 items related to *Instructional Responses* that represented four constructs: adjust lesson plans, establish/adjust groupings, provide supplemental resources to targeted students, and school-level instructional responses. Survey items measuring school-level *Instructional Responses* were asked of principals only, in reference to their perceptions of the influence of interim assessment results on schoolwide issues such as evaluating school initiatives or programs and identifying professional development needs.

Barriers to Using Data. Perceptions of *Barriers to Data Use* were measured with survey items that asked teachers and principals about situational factors that may prevent them from using interim assessment data. For example, survey items asked principals and teachers if inadequate professional development or curriculum pacing pressures interfered with their ability to use interim assessment results. For teachers, *Barriers to Data Use* were measured with 15 survey items; for principals, there were 13 survey items. All survey items measuring *Barriers to Data Use* are Likert-type items.

Data-Use Scale Construction

Survey items measuring the constructs were combined into scale scores to provide a single measure for each of the four key dimensions and barriers. The survey items within each scale varied in response formats, including Likert items, binary response items, and frequency counts (e.g., number of hours spent reviewing data). Therefore, we standardized the item responses to create scale scores. First, each item response was standardized within wave using z-score standardization with a mean of zero and a standard deviation of one. Items were standardized separately for the teacher and principal samples. Next, each standardized item was averaged across the three administration waves to incorporate responses from all available waves of data collection.

Finally, the standardized item responses averaged across waves were used to create the five scales—one for each of the four key dimensions plus one representing barriers. Scale averages were calculated for each survey respondent who responded to at least 50 percent of the survey items within the scale. For example, the *Context* scale score for teachers contains 36 survey items. Eighteen completed survey items were required to compute a scale score for *Context* for any participating teacher.

The internal consistency reliability was moderate to high for all scales on both the teacher and principal surveys. Cronbach's alpha reliability coefficients ranged from 0.74 to 0.97 for the teacher scales, and from 0.76 to 0.97 for the principal scales, indicating adequate internal reliability. For a detailed description of the number of items per scale and individual reliability coefficients, see Tables B.1 and B.2 in Appendix B.

Measures of Teacher and Principal Characteristics

The teacher and principal surveys contained items on respondents' background and demographic characteristics, including education level, race/ethnicity, and gender. The surveys also collected information about teaching experience, including the total number of years teaching and number of years teaching at the current school, for both teachers and principals. Principals were additionally asked to report the total number of years of administrator experience and the number of years they had served as a principal at their current schools.

Student Information

District-provided student data were shared through secure file transfer protocol sites established between AIR and each participating district. Data were collected for a total of 86,837 students across the four districts. These data included individual student data, such as achievement and demographics, as well as student-teacher rosters that connected students with their teachers and classrooms.

Student Characteristics and Demographics. Each district provided demographic data for students in grades 4, 5, 7, and 8 during the 2009–10 school year. Demographic information available in the district administrative records included gender, race/ethnicity, free or reduced-price lunch eligibility, special education services eligibility, and English language learner (ELL) status.

Student Achievement in Mathematics and Reading. The district-provided student records data included state assessment data in mathematics and reading from the two years prior to the study (spring 2008 and 2009) and for the year of the study (spring 2010) for all students in grades 4, 5, 7, and 8 enrolled in the participating schools in the 2009–10 school year. The assessments and the possible range of scores were different in each district, as they are each in different states. For example, District 1 scores ranged from 0 to 999; District 2 scores ranged from 100 to 500; and District 4 scores ranged from 0 to 600. In these three districts, the scale scores were the same across grades; however, District 3 has grade-specific scale scores based on an 80-point scale system (i.e., grade 4 scores ranged from 400 to 480; grade 5 scores ranged from 500 to 580; grade 7 scores ranged from 700 to 780; and grade 8 scores ranged from 800 to 880). Because each state assessment measured student achievement differently, we standardized the student achievement data within state and grade level.

Classroom Rosters (Student-Teacher Assignments). All districts also provided classroom roster data for mathematics and reading classes in grades 4, 5, 7, and 8 that listed the students assigned to each teacher in each class. Specifically, the rosters included course name, teacher name, teacher ID, and student IDs for all students in the class.

Data Collection Procedures

Teacher and Principal Survey Administration

Survey data collection occurred three times over the course of the 2009–10 school year. The surveys were administered online using SurveyMonkey® in fall 2009, winter 2010, and spring 2010. Each survey administration was timed to begin between 7 and 14 days after each district's interim assessments were administered in an effort to obtain accurate measures of teachers' and school principals' use of student data. In the surveys, respondents were asked to respond to items with respect to the latest round of interim assessments. Table 2.7 displays the specific start and end dates in each district. The surveys remained open for approximately 3 weeks.

Table 2.7. Survey Administration Dates by District

	District 1	District 2	District 3	District 4
Wave 1				
Date survey opened	11/16/2009	11/30/2009	11/3/2009	11/18/2009
Date survey closed	12/8/2009	12/18/2009	11/30/2009	12/9/2009
Wave 2				
Date survey opened	2/9/2010	3/1/2010	3/1/2010	3/17/2010
Date survey closed	3/2/2010	3/29/2010	3/29/2010	4/14/2010
Wave 3				
Date survey opened	5/3/2010	5/12/2010	5/10/2010	5/18/2010
Date survey closed	5/25/2010	6/4/2010	6/4/2010	6/14/2010

An initial e-mail was sent to the district e-mail address of every teacher in the sample, inviting them to participate in the survey.[6] E-mail reminders were sent weekly thereafter to nonrespondents. Other follow-up strategies included postcard reminders sent approximately one week after the survey opened and follow-up calls made one week before the end of the survey. Upon completion of the online survey, teachers received a $25 gift card. To further encourage respondents to participate in the second and third waves of administration, those who completed the surveys also were entered into a raffle for an additional $100 gift card.[7]

Survey Response Rates

Detailed information about both the teacher and principal response rates by wave and by district are presented below. In general, the percent of respondents invited to participate that responded to at least one of the three waves of online surveys was 83 percent for teachers and 87 percent for principals.

Teachers. Across the four participating districts, 2,248 teachers were invited to participate in the online survey. Response rates per survey wave ranged from 64 percent to 69 percent (see Table 2.8).

Table 2.8. Teacher Survey Response Rates, by Wave and District

	Wave 1			Wave 2			Wave 3		
District	**Invited**	**Responded**	**Response Rate**	**Invited**	**Responded**	**Response Rate**	**Invited**	**Responded**	**Response Rate**
District 1	643	470	73%	643	472	73%	643	446	69%
District 2	689	496	72%	704	454	64%	706	444	63%
District 3	624	398	64%	620	407	66%	619	389	63%
District 4	273	169	62%	273	176	64%	271	162	60%
Total	*2,229*	*1,533*	*69%*	*2,240*	*1,509*	*67%*	*2,239*	*1,441*	*64%*

To include as many teachers as possible in the final analyses, data were retained if a teacher responded to at least one wave of the survey. A total of 1,855 teachers completed at least one wave of the data-use survey during the 2009–10 school year, for an overall response rate of 83 percent. Table 2.9 displays the response rates for the sample of teachers who responded to at least one of the three waves of survey administration, by district.

[6] One district did not share teacher e-mail addresses; therefore, the online survey invitation and reminders were sent by the school district rather than the study team.

[7] A total of 4,483 $25 gift cards were distributed to survey respondents, and a total of eight $100 gift cards were distributed to lottery winners, accounting for $112,875 spent on incentives designed to boost teacher and principal response rates.

Table 2.9. Percentage of Teachers Responding to at Least One Wave of the Survey, by District

District	Invited	Participated in at least one wave	% Responding to at least one wave
District 1	643	561	87%
District 2	707	587	83%
District 3	624	488	78%
District 4	274	219	80%
Total	*2,248*	*1,855*	*83%*

Survey responses from teachers who could not be linked to individual students *via* classroom rosters (e.g., if they taught electives or supplemental courses that did not have classes with English language arts or mathematics titles) were excluded. Following these exclusions, we had an analytic sample of 1,581 teachers across the four districts. Proportionately, 30 percent of the analytic teacher sample was from District 1, 32 percent was from District 2, 26 percent was from District 3, and 12 percent was from District 4.

Principals. Across the four districts, 244 principals or assistant principals were invited to participate. Response rates by wave ranged from 64 percent to 85 percent (see Table 2.10).

Table 2.10. Principal Survey Response Rates, by Wave and District

	Wave 1			Wave 2			Wave 3		
District	Invited	Responded	Response Rate	Invited	Responded	Response Rate	Invited	Responded	Response Rate
District 1	47	36	77%	47	34	72%	47	35	74%
District 2	63	48	76%	65	34	52%	66	44	67%
District 3[a]	47	40	85%	49	34	69%	48	37	77%
District 4[b]	39	29	74%	81	54	67%	81	56	69%
Total	*196*	*153*	*78%*	*242*	*156*	*64%*	*242*	*172*	*71%*

Note. The increase in the number of invited principals in District 4 between Wave 1 and Waves 2 and 3 represents the inclusion of assistant principals in Waves 2 and 3. This change was made because assistant principals were reported to be more involved than principals in the interim assessment data process in this district.

[a] Across the three waves of data collection, 50 principals from District 3 were invited to take the survey. Between the first wave and the third wave, two principals retired, and three more principals were invited to take the survey.

[b] One principal in District 4 was the principal of two schools.

As with the teachers, principals were retained in the survey sample if they completed a survey for at least one wave of data collection. Table 2.11 displays the principal response rates across any of the three waves of surveys. Of the 244 principals or assistant principals invited to participate, 212 (87 percent) completed one or more of the three online surveys. Of the total respondents, 124 were elementary school principals or assistant principals, 86 were middle school principals or assistant principals, and 2 were principals at K–8 schools and included in the middle school sample.

Table 2.11. Percentage of Principals Responding to at Least One Wave of the Survey, by District

District	Invited	Responded	Response Rate
District 1	47	42	89%
District 2	66	56	85%
District 3	50	45	90%
District 4	81	69	85%
Total	*244*	*212*	*87%*

Linking Teacher Survey Data to Student Achievement

To implement our analysis strategy, it was necessary to link teachers' survey data to their own students' achievement data. This linking process occurred in two stages: We linked teachers' survey responses with their district-provided identifiers; then, we linked teachers with their students using the classroom rosters provided by the district.

One complication with linking the students to their teachers was that some students were enrolled in multiple reading or mathematics courses. For example, a student may be enrolled in both a reading class and a language arts class taught by different teachers; therefore, that student was associated with multiple teachers in the "reading teacher" survey sample. Five percent of the students in the sample were enrolled in multiple reading classes, and 5 percent were enrolled in multiple mathematics classes. Enrollment in multiple mathematics or multiple reading classes was more prevalent in middle grades in Districts 3 and 4 where the percentage of students enrolled in two or more reading classes was as high as 13 percent and 12 percent, respectively. To address this problem, we randomly selected unique student-teacher links to represent the teacher-student mathematics and reading relationships. To do this, we first identified each unique student-teacher link in the four district data files. After the files were cleaned of any duplicate links, each student-teacher link became a row in the data file. Next, a random number generator was used to create lists of numbers associated with each student-teacher link. The file was then sorted by a student identifier and the random number. To randomly select one student-teacher link per student per subject, only the first student-teacher link was retained in the data file, thus randomly selecting one teacher to represent each student's mathematics or reading educator.

When the student-teacher links were established, we created one large analytic file that included teachers' and principals' survey responses reflecting their data-use practices and perceptions and all relevant data for their own students including background characteristics and multiple years of achievement data.

Analytic Strategy

To reiterate the focus of the study, we posed two broad research questions regarding data-driven instruction:

1. What are the relationships between teachers' data-use practices and perceptions and their students' achievement?

2. What are the relationships between schools' policies, practices, and resources for data-driven instruction and student achievement?

To address these research questions, we began with a set of descriptive analyses examining levels of data use in elementary and middle schools and for teaching of reading and mathematics. We also examined the simple correlations among the four dimensions of data use, barriers, and student achievement.

Based on the exploratory descriptive analyses, we then conducted two sets of analyses to examine how teacher- and school-level data-use practices and perceptions were related to student achievement. Because students were nested within teachers, which were in turn nested within schools, a multilevel framework was used for both sets of analyses.

The first set of analyses used structural equation modeling (SEM) to examine the relationship between a global sense of data use and student achievement. The second set used hierarchical linear modeling (HLM) to examine the unique links between each dimension of data use and student achievement, independent of the other dimensions.

CHAPTER 3
RESULTS

This chapter presents the results of analyses that tested whether and how data-use practices and perceptions are linked to student achievement. First, we present descriptive statistics and bivariate correlations among the key variables. Then, we provide the results of the statistical analysis organized by the research questions.

Descriptive Statistics

Descriptive statistics for teacher and principal data-use variables are presented in Table 3.1–3.4. Because data-use scores were standardized, all data-use scale scores have a mean of zero and a standard deviation of one, where higher scores indicate higher levels of data use.

Mean Comparisons of Data Use

In general, scores on the data-use scales were higher in elementary grades than in middle grades. In both reading and mathematics, elementary grade teachers reported higher levels of data use than did middle school teachers. To compare elementary and middle grades teachers' reported data-use practices and perceptions, we conducted independent-samples t-tests with each of the four key dimensions of data use and barriers as the dependent variables. These tests of difference were conducted separately for mathematics and reading teachers. As shown in Table 3.1, elementary grade reading teachers reported higher levels of data use than did middle school reading teachers in terms of *Context*, *Supports for Data Use*, and *Working with Data*. No significant differences on *Instructional Responses* or perceived *Barriers* were detected.

Table 3.1. Elementary and Middle Grades Teachers' Reported Key Dimensions of Data Use in Reading

	Elementary Grades Reading Mean (SD)	Middle Grades Reading Mean (SD)	Mean Difference *(Elementary – Middle)*
Context	0.02 (0.38)	-0.04 (0.44)	0.06**
Supports for data use	0.02 (0.50)	-0.07 (0.47)	0.09**
Working with data	0.07 (0.46)	-0.03 (0.47)	0.10***
Instructional responses	0.06 (0.60)	0.02 (0.66)	0.04
Barriers	0.02 (0.44)	-0.03 (0.50)	0.05

Note. $^{**}p < .01$, $^{***}p < .001$, two-tailed. Means were calculated across the entire sample of schools using standardized scores with a mean of 0 and a standard deviation of 1.

There also were significant differences between elementary and middle grade mathematics teachers on two of the five data-use variables. Elementary mathematics teachers reported higher levels of *Working with Data* and *Instructional Responses* than did middle school mathematics teachers. There was no significant difference between elementary and middle school mathematics teachers on *Context*, *Supports for Data*, or *Barriers* (see Table 3.2).

Table 3.2. Elementary and Middle Grades Teachers' Reported Key Dimensions of Data Use in Mathematics

	Elementary Grades Reading Mean (SD)	Middle Grades Reading Mean (SD)	Mean Difference *(Elementary – Middle)*
Context	0.03 (0.37)	0.00 (0.40)	0.03
Supports for data use	0.01 (0.49)	-0.03 (0.48)	0.04
Working with data	0.08 (0.46)	-0.05 (0.47)	0.13***
Instructional responses	0.06 (0.59)	-0.06 (0.64)	0.12**
Barriers	0.03 (0.44)	0.02 (0.46)	0.01

Note. $^{**}p < .01$, $^{***}p < .001$, two-tailed. Means were calculated across the entire sample of schools using standardized scores with a mean of 0 and a standard deviation of 1.

We saw similar significant differences among principals, where principals in elementary grades had higher scores on *Context* and *Supports for Data Use* than did those in middle grades. Also, principals in elementary grades reported lower levels of perceived *Barrier*s than those in middle grades. Scores on *Working with Data* and *Instructional Responses* were not significantly different among elementary and middle school principals (see Tables 3.3 and 3.4).

Table 3.3. Elementary and Middle Grades Principals' Reported Key Dimensions of Data Use in Reading

	Elementary Reading Mean (SD)	Middle Reading Mean (SD)	Mean Difference *(Elementary – Middle)*
Context	0.02 (0.38)	-0.07 (0.36)	0.09**
Supports for data use	0.04 (0.40)	-0.12 (0.40)	0.16*
Working with data	-0.01 (0.56)	-0.12 (0.45)	0.11
Instructional responses	-0.05 (0.64)	-0.09 (0.57)	0.04
Barriers	-0.06 (0.38)	0.22 (0.40)	-0.28**

Note. *p < .05, **p < .01, two-tailed. Means were calculated across the entire sample of schools using standardized scores with a mean of 0 and a standard deviation of 1.

Table 3.4. Elementary and Middle Grades Principals' Reported Key Dimensions of Data Use in Mathematics

	Elementary Reading Mean (SD)	Middle Reading Mean (SD)	Mean Difference *(Elementary – Middle)*
Context	0.03 (0.37)	-0.07 (0.36)	0.10*
Supports for data use	0.05 (0.41)	-0.11 (0.40)	0.16*
Working with data	0.00 (0.56)	-0.12 (0.44)	0.12
Instructional responses	-0.04 (0.65)	-0.08 (0.56)	0.04
Barriers	-0.07 (0.40)	0.23 (0.39)	-0.30***

Note. *p < .05, ***p < .001, two-tailed. Means were calculated across the entire sample of schools using standardized scores with a mean of 0 and a standard deviation of 1.

Bivariate Correlations

In addition to observing descriptive patterns between elementary and middle grades data-use practices and perceptions, we also examined correlations among the data-use scales as measured by our surveys.

Bivariate Correlations Between Teacher Data-Use Variables

As seen in Tables 3.5–3.8, the four key dimensions—*Context*, *Supports for Data Use*, *Working with Data*, and *Instructional Responses*—all were positively correlated in each analytic sample. These scales all were negatively correlated with teacher-reported *Barriers*, with correlations ranging from -0.09 to -0.39. All the positive correlations were statistically significant. Notably, the correlations between teacher-reported *Working with Data* and *Instructional Responses* were greater than 0.75 in all four analytic samples.

Table 3.5. Bivariate Correlations Among Data-Use Scales for Elementary Grades Mathematics Teachers (*N* = 593)

Teacher Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.49**	—			
Working with data	0.39**	0.64**	—		
Instructional responses	0.41**	0.45**	0.77**	—	
Barriers	-0.34**	-0.34**	-0.17**	-0.09	—

Note. ***p* < .01, two-tailed.

Table 3.6. Bivariate Correlations Among Data-Use Scales for Elementary School Reading Teachers (*N* = 614)

Teacher Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.51**	—			
Working with data	0.38**	0.65**	—		
Instructional responses	0.41**	0.47**	0.76**	—	
Barriers	-0.33**	-0.35**	-0.20**	-0.13**	—

Note. ***p* < .01, two-tailed.

Table 3.7. Bivariate Correlations of Data-Use Scales for Middle School Mathematics Teachers (*N* = 471)

Teacher Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.63**	—			
Working with data	0.54**	0.68**	—		
Instructional responses	0.48**	0.54**	0.80**	—	
Barriers	-0.35**	-0.35**	-0.14**	-0.10*	—

Note. **p* < .05, ***p* < .01, two-tailed.

Table 3.8. Bivariate Correlations of Data-Use Scales Among Middle School Reading Teachers (*N* = 532)

Teacher Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.63**	—			
Working with data	0.58**	0.68**	—		
Instructional responses	0.56**	0.58**	0.80**	—	
Barriers	-0.37**	-0.39**	-0.19**	-0.13**	—

Note. ***p* < .01, two-tailed.

Bivariate Correlations Between Principal Data-Use Variables

Correlations among principal-reported data-use variables followed similar patterns, where *Instructional Responses* were highly and positively correlated with *Working with Data* across the four analytic samples (with correlation coefficients close to or greater than 0.80). *Context*, *Supports for Data Use*, and *Working with Data* were moderately to highly correlated (from 0.41 to 0.70). *Barriers* were negatively correlated with all four variables in elementary schools (ranging from -0.28 to -0.50 for both elementary and middle schools) but were not correlated with *Supports for Data Use* in middle schools (see Tables 3.9–3.12).

Table 3.9. Bivariate Correlations of Data-Use Scales Among Principals in Elementary School Mathematics Sample (*N* = 102)

Principal Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.59**	—			
Working with data	0.50**	0.70**	—		
Instructional responses	0.53**	0.61**	0.85**	—	
Barriers	-0.40**	-0.50**	-0.38**	-0.37**	—

Note. ***p* < .01, two-tailed.

Table 3.10. Bivariate Correlations of Data-Use Scales Among Principals in Elementary School Reading Sample (*N* = 101)

Principal Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.56**	—			
Working with data	0.49**	0.69**	—		
Instructional responses	0.50**	0.59**	0.84**	—	
Barriers	-0.35**	-0.47**	-0.36**	-0.36**	—

Note. ***p* < .01, two-tailed.

Table 3.11. Bivariate Correlations of Data-Use Scales Among Principals in Middle School Mathematics Sample (*N* = 76)

Principal Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.50**	—			
Working with data	0.41**	0.65**	—		
Instructional responses	0.47**	0.55**	0.80**	—	
Barriers	-0.37**	-0.20	-0.31*	-0.34*	—

Note. *p < .05, **p < .01, two-tailed.

Table 3.12. Bivariate Correlations of Data-Use Scales Among Principals in Middle School Reading Sample (*N* = 75)

Principal Data-Use Scales	Context	Supports for Data Use	Working With Data	Instructional Responses	Barriers
Context	—				
Supports for data use	0.51**	—			
Working with data	0.39**	0.64**	—		
Instructional responses	0.47**	0.55**	0.80**	—	
Barriers	-0.37**	-0.20	-0.28*	-0.33*	—

Note. *p < .05, **p < .01, two-tailed.

For both teachers and principals, the scales measuring *Working with Data* and *Instructional Responses* were particularly strongly related, with correlation coefficients greater than r = 0.75 for the teacher samples and 0.80 for the principal samples. This observation led us to consider whether these aspects of data use—defined as distinct in the theory of action (Exhibit 1.1)—are, in fact, too similar to separate, at least as measured by the survey instrument we used. As described in the next sections, we combined *Working with Data* and *Instructional Responses* for some of the analyses.

More information about the implications of the high correlations among the data-use variables (also known as multicollinearity) is provided in Appendix D.

Analyses Used to Test the Research Questions

To test our research questions about the links between data-use practices and student achievement, we conducted two types of analyses. These are described in the next sections.

1. We used structural equation modeling to test the relationship between student achievement and *General Data Use*—a combination of all the data-use variables.

2. We used hierarchical linear modeling to test the relationship between student achievement and each data-use variable separately.

Structural Equation Modeling (SEM)

We used SEM to examine how one large construct of overall data use was related to student achievement at both the teacher and school levels. In this statistical approach, latent variables are created that combine information from multiple scales from the surveys. Although observed variables are directly measured (such as with a survey, observation, or interview), latent variables represent underlying constructs that are measured using multiple observed variables. For example, a latent variable of socioeconomic status may be made up of the observed variables of education, income, and professional status. Our analysis proceeded in a two-step fashion common when using SEM. First, we combined observed variables (i.e., the scale scores from the teacher surveys) to create one latent variable of *General Data Use*. Second, we tested the proposed relationships between the latent variable of data use and student achievement. All SEMs were conducted within a multi-level framework that accounted for the nested nature of the data.

Hierarchical Linear Modeling (HLM)

Next, we specified a series of HLM analyses that examined the unique relationship between each key dimension of data use and student achievement. For these analyses, we combined *Working with Data* and *Instructional Responses* into one scale. Although the theory of action assumes these are distinct aspects of data-use practice, our review of the bivariate correlations among these two scales showed that they were highly correlated for both teachers and principals. We re-named the combined variable *"Attention to Data in the Classroom"* for teachers and *"Attention to Data in the School"* for principals.

Therefore, the four independent variables we tested in separate HLMs were (1) *Context*, (2) *Supports for Data Use*, (3) *Attention to Data in the Classroom/School*, and (4) *Barriers to Data Use*.

HLMs were used to adjust for the nesting of students within teachers within schools. HLM models allow for simultaneous estimates at level 1 (students), level 2 (teachers), and level 3 (schools). This modeling approach yields more accurate standard errors and regression estimates and also allows for including covariates at the student, teacher, and school levels (Raudenbush & Bryk, 2002).

As with the other analyses including the SEMs, we analyzed separate HLMs by grade level (elementary and middle) and subject (reading and mathematics). We began modeling by including all student-, teacher-, and school-level covariates that were significantly related to student achievement (for a list of all possible covariates, see Appendix D, Table D.4). After the control model was developed, we then assessed the relationships between each key dimension of data use and student achievement, controlling for the covariates in multiple sets of three-level models. Centering was used to make the estimates more interpretable (see Appendix D).

Research Question 1: What Are the Relationships Between Teachers' Data-Use Practices and Perceptions and Their Students' Achievement?

Teachers' General Data Use and Student Achievement

We used multi-level SEM to test the hypothesized relationships between teachers' *General Data Use* and student achievement. These were a series of two-level models with students nested within teachers, one each for elementary grades reading, elementary grades mathematics, middle grades reading, and middle grades mathematics.

Our first step was to use the scale scores for each key dimension to create one large latent variable of *General Data Use*. For this, we used the original four scales measuring the key dimensions *Context*, *Supports*, *Working with Data*, and *Instructional Responses*. All four loaded well on the latent variable of *General Data Use*, with factor loadings greater than 0.40,[8] consistent with the finding that the dimensions of data use all were related, and further suggesting that they measured the one underlying construct of *General Data Use* (see Table 3.13).

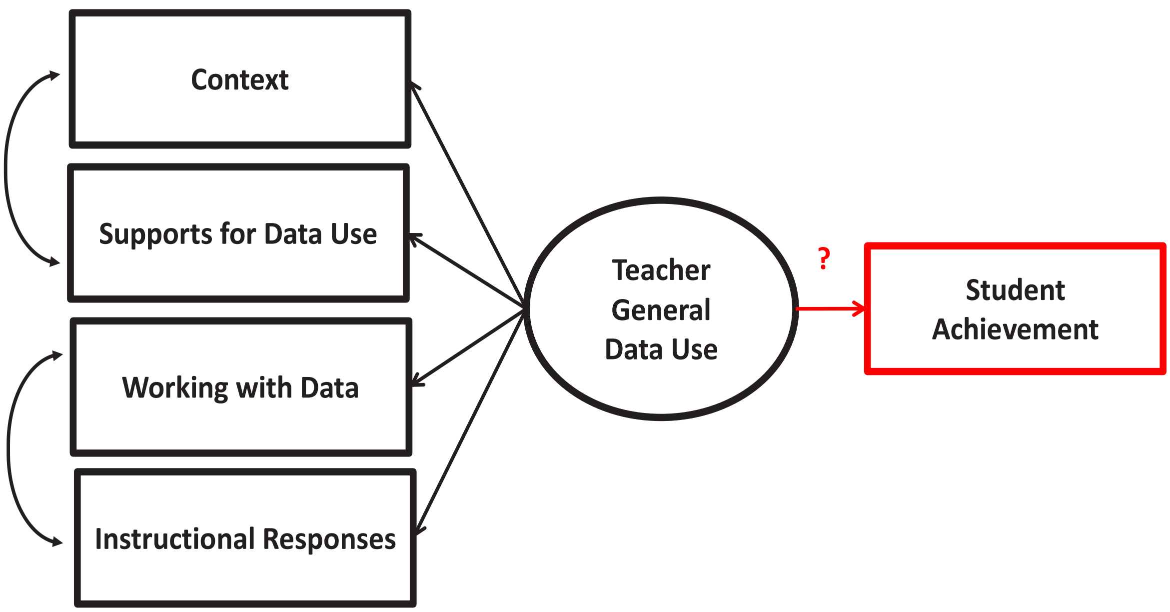
Table 3.13. Factor Loadings for the Latent Variable of Teachers' *General Data Use* in Each Analytic Sample

	Mathematics		Reading	
Teacher Data-Use Scales	**Elementary**	**Middle**	**Elementary**	**Middle**
Context	1.00	1.00	1.00	1.00
Supports for data use	0.72	1.51	2.28	1.30
Working with data	0.54	1.31	3.05	1.74
Instructional responses	0.72	1.58	3.12	2.15

Note. The factor loadings for *Context* were set to be 1.00 in the SEM models to set the metric for the other indicators in the latent variable.

We next added in the path between teachers' *General Data Use* and student achievement, as measured on the state assessments in mathematics and reading, as depicted in Exhibit 3.1.

Exhibit 3.1. Structural Equation Model of the Relationship Between Teachers' *General Data Use* and Student Achievement



[8] A cutoff of 0.40 is the standard acceptable level for factor loadings (Kline, 2005).

Table 3.14 reports the coefficients of the path between teachers' *General Data Use* and student achievement for each grade level and each subject (represented by the question mark in Exhibit 3.1). Full results, including all paths and covariances for each model, are presented in Tables D.1–D.3 in Appendix D.[9]

Table 3.14. Relationships Between Teachers' *General Data Use* and Student Achievement in Elementary and Middle Grades Mathematics and Reading

Grade Level and Content Area	Coefficient
Elementary grades mathematics	0.04
Middle grades mathematics	0.10*
Elementary grades reading	0.17*
Middle grades reading	0.06

Note. **p* < .05, two-tailed.

These results suggest that teachers' *General Data-Use* practices and perceptions are positively related to student achievement in elementary grades reading and middle grades mathematics. However, there was no statistically significant relationship between teacher data use and student achievement in elementary grades mathematics and middle grades reading. These findings in combination partially support the theory of action.

Links Between Each Key Dimension of Teacher Data Use and Student Achievement

To further address the first research question, we estimated the unique associations among each teacher data-use dimension and student achievement using HLM and the methods described previously. These analyses controlled for student background characteristics and prior achievement and teacher demographics.[10]

The results are shown in Table 3.15. They show that teacher reports of *Context and Supports for Data Use* were not significantly associated with student achievement in mathematics in either elementary or middle grades. Teachers' *Attention to Data in the Classroom* was positively associated with mathematics achievement among middle grades students but not elementary grades students. *Barriers* were significantly and negatively correlated with elementary grades students' mathematics achievement but not middle grades students.

These results show that in the middle grades, teachers' *Attention to Data in the Classroom* was correlated with higher student achievement in mathematics. In the elementary grades, teachers' perceived *Barriers* to data use were negatively related with student achievement such that the greater the perceived barriers to using data, the lower the students' achievement.

Different patterns emerged for reading achievement. As shown in Table 3.15, for the elementary and middle grades samples, *Context*, *Supports for Data Use*, and *Barriers* were not significantly related to reading achievement. *Attention to Data in the Classroom* was positively associated with elementary grades student achievement in reading but not in middle grades.

[9] Model fit for both measurement and path models was highly similar and indicated moderate model fit. Comparative Fit Index (CFI) and Tucker Lewis Index (TLI) ranged between 0.80 and 0.95, which are less than the recommended value of 0.95. Root Mean Square Error of Approximation (RMSEA) of 0.08 is borderline, and Standardized Root Mean Square Residual (SRMR) of 0.09 is greater than the recommended value of 0.05. However, the statistically significant R2 value of 0.83 for both the reading and mathematics analyses indicates that the models account for a substantial percentage of variance in the outcome (83 percent).

[10] It is interesting to note that when conducting simple bivariate correlations between the data-use variables and student achievement scores, contrary to the hypothesized positive relationships between data use and student achievement, many of these correlations were negative in direction, suggesting that teachers with higher scores on the data-use scales in 2009–10 taught students with lower achievement in the prior spring (2009) and in the spring of 2010. These bivariate correlations do not control for any other variables, such as student prior achievement or socioeconomic status, nor do they adjust for the nested nature of the data. However, these negative relationships were later shown to be inconsistent with the results of the main analyses that did control for all relevant student, teacher, and principal background characteristics and were conducted in a multi-level framework.

Table 3.15. Relationships Between Teacher Data-Use Scales and Student Achievement in Mathematics and Reading

	Mathematics		Reading	
Teacher Data-Use Scales	Elementary	Middle	Elementary	Middle
Context	0.03	0.04	0.03	0.06
Supports for data use	0.01	-0.01	-0.01	0.01
Attention to data in classroom	0.04	0.09**	0.06*	0.02
Barriers to data use	-0.08*	-0.04	-0.02	0.00

Note. *$p < .05$, **$p < .01$, two-tailed.

Research Question 2: What Are the Relationships Between Schools' Policies, Practices, and Resources for Data-Driven Instruction and Student Achievement?

Principals' General Data Use and Student Achievement

To test the second research question, we drew on the principal surveys to measure school-level data-use practices and perceptions. Similar to the teacher-level analyses, we examined school-level general data use using multilevel SEM[11] and then examined the unique links between each dimension of school-level data use and student achievement with HLM.

The process of creating a measure of principals' *General Data-Use* practices mirrored that described previously for teachers. The principals' scale scores for each of the four original key dimensions (*Context, Supports for Data Use, Working with Data,* and *Instructional Responses)* were used to build one latent variable. As for teachers, the four indicators loaded well on the latent variable of principals' *General Data Use*, with all loadings greater than the 0.40 cutoff, which suggested that the four key dimensions of principal data use were related and measured the same underlying construct of *General Data Use* (see Table 3.16).

Table 3.16. Factor Loadings for the Latent Variable of Principals' *General Data Use* in Each Analytic Sample

	Mathematics		Reading	
Principal Data-Use Scales	Elementary	Middle	Elementary	Middle
Context	1.00	1.00	1.00	1.00
Supports for data use	1.48	1.62	1.46	1.75
Working with data	1.75	4.84	2.79	1.69
Instructional responses to data	1.83	5.73	2.85	1.95

Note. The factor loadings for *Context* were set to be 1.00 in the SEM models to set the metric for the other indicators in the latent variable.

We next added in the path between principals' *General Data Use* and student achievement. Therefore, the four school-level SEM models included one latent variable of principal data use and one observed variable of student achievement, as depicted in Exhibit 3.2.

[11] The SEMs for the second research question were two-level models with students nested within schools.

Exhibit 3.2 Structural Equation Model of Principals' *General Data Use* and Student Achievement

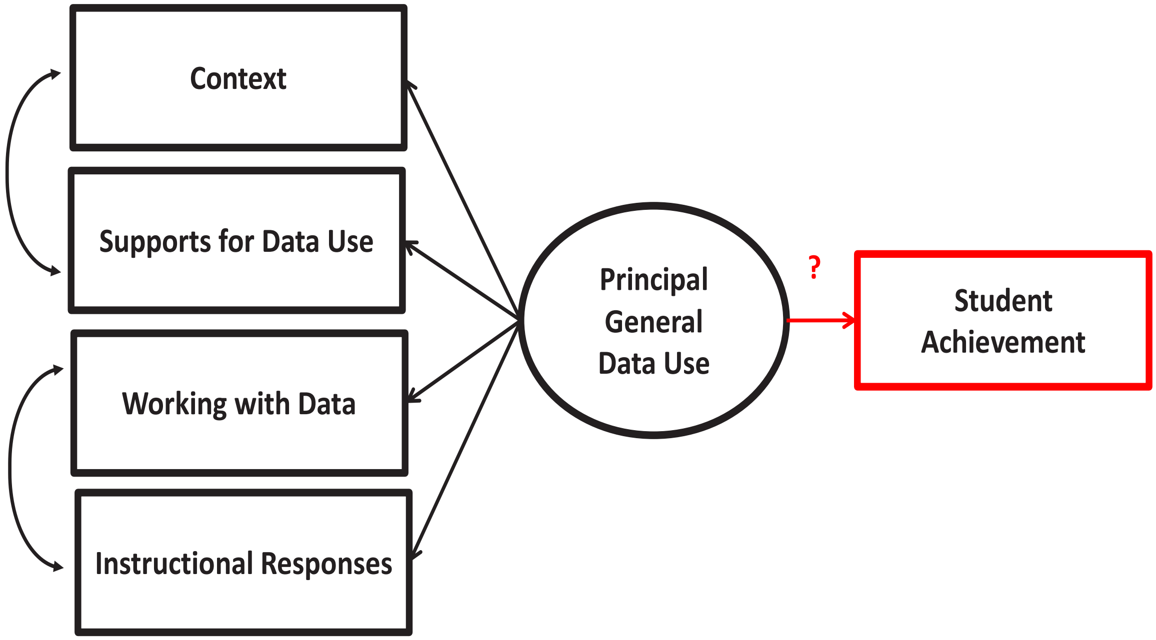


Table 3.17 reports the coefficients of the path between principals' *General Data Use* and student achievement for each grade level and subject (represented by the question mark in Exhibit 3.2). Full results, including all paths and covariances for each model, are presented in Tables D.1–D.3 in Appendix D.[12]

Table 3.17. Relationships Between Principals' *General Data Use* and Student Achievement in Elementary and Middle Grades Mathematics and Reading

Grade Level and Content Area	Coefficient
Elementary grades mathematics	0.17
Middle grades mathematics	0.23*
Elementary grades reading	-0.07
Middle grades reading	0.01

Note. *p < .05, two-tailed.

The results suggest that principals' *General Data-Use* practices are positively related to student achievement in middle grades mathematics. We observed a statistically significant positive relationship between the latent variable of principals' *General Data Use* and student achievement in only this one of the four analytic samples.

[12] Model fit for both measurement and path models in reading and mathematics were highly similar and indicated moderate model fit. CFI and TLI ranged between 0.7 and 0.8, which are less than the recommended value of 0.95. RMSEA of 0.08 is borderline, and SRMR of 0.09 is greater than the recommended value of 0.05. However, the statistically significant R2 value of 0.83 for both the reading and mathematics analyses indicates that the models account for a substantial percentage of variance in the outcome (83 percent).

Links Between Each Key Dimension of Principal Data Use and Student Achievement

For these analyses, we estimated a series of three-level models (level 1, students; level 2, teachers; and level 3, schools) to examine the unique links between each dimension and student achievement. No teacher data-use variables were included in these models; they included principal data-use variables only. All covariates included in the teacher models for the first research question were included in the principal models; these covariates included student background characteristics and prior achievement and teacher demographics. Principal covariates were tested, but none were significant predictors and they were therefore removed from the final models (see Appendix D, Table D.4).[13]

As shown in Table 3.18, principal-reported *Supports for Data Use* and *Attention to Data in the School* were positively correlated with student achievement in mathematics in elementary school. In addition, higher levels of *Supports for Data Use* reported by principals of elementary schools were associated with higher levels of student achievement in reading. *Context* and *Barriers* as reported by principals in elementary schools were not significantly correlated with student achievement in either subject.

Among middle school principals, no significant relationships between the data-use variables and student achievement were observed in either mathematics or reading.

Table 3.18. Relationships Between Principal Data-Use Scales and Student Achievement in Mathematics and Reading

	Mathematics		Reading	
Principal Data-Use Scales	**Elementary**	**Middle**	**Elementary**	**Middle**
Context	0.09	0.03	0.04	-0.06
Supports for data use	0.11*	0.06	0.09*	0.01
Attention to data in the school	0.10*	0.04	0.01	0.00
Barriers to data use	-0.03	-0.02	-0.04	0.10

Note. *$p < .05$, two-tailed.

[13] As with the teacher analyses, bivariate correlations that did not control for any covariates, nor adjust for the nested nature of the data revealed negative and significant correlations between principal data use and student achievement, suggesting that schools with higher scores on the data-use scales in 2009–10 had students with lower achievement in the prior spring (2009) and in the spring of 2010. Again, these negative relationships were later shown to be inconsistent with the results of the main analyses that did control for all relevant student, teacher, and principal background characteristics and were conducted in a multi-level framework.

CHAPTER 4
DISCUSSION AND CONCLUSION

Although there was some prior evidence that using periodic assessments (formative assessments, progress monitoring, and/or CBM) may be positively related to student achievement, research on interim assessment use is limited. At the same time, significant investment has been made in interim assessment systems in school districts across the country. There is a great need for information about whether and how general and specific aspects of teachers' and principals' data-use practices and perceptions are linked to student achievement. This study attempted to fill this gap by measuring multiple aspects of interim assessment data use among teachers and principals, and empirically testing the links between key data-use practices and student achievement on end-of-year state assessments.

Summary of Findings

The study examined the relationships between student achievement and (1) teachers' practices and perceptions related to the use of interim assessment data and (2) school data policies, practices, and resources. We hypothesized that general and specific data-use practices and perceptions would be positively related to student achievement. The findings partially supported this hypothesis. For both teachers' and principals' *General Data Use* was related to student achievement in some grade levels and subjects. With regard to more specific practices and perceptions, teachers' *Attention to Data in the Classroom*, principals' *Attention to Data in the School*, and principals' perceptions of *Supports for Data Use* were related to higher student achievement in some grades and subjects. In other words, the more that teachers and principals reported reviewing and analyzing student data and using this information to make instructional decisions, the higher their students' achievement, at least in some grades and subjects. Moreover for principals, the more they reported having support in the form of an appropriate data infrastructure, adequate time for review and discussion of data, professional development, and the appropriate human resources, the higher their students' achievement. Again, these results varied by grade and content area, with significant links observed in both elementary grades and middle grades, as well as in mathematics and reading. This section of the report considers the findings and their implications.

Mean Differences in Data Use by Grade

Average levels of reported data use and associated data-use-related perceptions were higher in the elementary grades than in the middle grades among both teachers and principals. This difference by grade level also persisted across content areas, where both mathematics and reading teachers reported higher use in the elementary grades than in the middle grades. Specifically, elementary grades teachers reported more positive perceptions of the data culture and supports for data use in their schools and school districts and also reported spending more time reviewing interim assessment data and using this information to make instructional decisions in the classroom than did middle grades teachers. These differences may be due in part to the fact that elementary grades teachers often teach all subjects, have fewer students in total, and interact with their students for more time during the school day than do middle grades teachers. This may promote a more supportive data culture in which teachers and administrators are more likely to work with the data and engage in data-driven decision making. More support may be necessary to facilitate higher levels of data use in middle schools in urban districts.

Correlations Among Key Dimensions of Data Use

The teacher and principal surveys measured the key dimensions of data use as depicted in the theory of action that guides this study (see Exhibit 1.1). As expected, there were positive correlations among all the key dimensions of data use and a negative correlation between each dimension and *Barriers to Data Use*. Most of the positive correlations were moderate to high, suggesting that these dimensions are indeed related as posited by the theory of action. Two of the key dimensions—*Working with Data* and *Instructional Responses*—were so highly correlated that, although we set out to measure them as separate aspects of data use, they were too interconnected to consider them distinct.

What Are the Relationships Between Teachers' Data-Use Practices and Perceptions and Their Students' Achievement?

The hypothesized relationship between teachers' use of interim assessment data and student achievement was partially supported through both of the main analysis strategies used in this study.

Teachers' General Data Use and Student Achievement. Teachers' *General Data Use* (a combination of the four key dimensions in the theory of action) was related to student achievement in elementary grades reading and middle grades mathematics. These findings suggest that the overall interim assessment process—including the *Context* and data culture, concrete *Supports for Data Use*, and actual review and use of the data—may be a promising practice in urban districts in some grade levels and content areas. The magnitude of the relationships was modest, with effect sizes of 0.10 for middle grades mathematics and 0.17 for elementary reading. Shifting a student's test score by 0.17 standard deviations could have a significant effect on his or her academic standing. For example, if a student who was at the 50th percentile at the end of grade 3 had a fourth grade teacher who was at the mean on *General Data Use*, that student would be at the 57th percentile at the end of grade 4. This could be the difference between a student being categorized as below proficient and proficient on a state assessment. Also, if a student were in classrooms for multiple consecutive years with teachers who have strong data-use perceptions and practices, this positive advantage could be cumulative over time, possibly contributing substantially to the student's academic achievement.

However, we did not find a significant relationship between teachers' *General Data Use* and student achievement in elementary grades mathematics or middle grades reading. We conducted district-specific analyses to test whether the nonsignificant relationships were the result of averaging district-specific effects that varied from each other (e.g., some positive and some negative). We found that the district-specific relationships in each subject and grade level appeared to be relatively similar in direction and magnitude. That is, in all four districts, there was no significant relationship between teachers' *General Data Use* and student achievement in elementary school mathematics and middle school reading, and the district-average results reported in the Results section fairly represented each participating district.

Teachers' Specific Data-Use Practices and Perceptions and Student Achievement. The results of analyses testing the unique links between the key dimensions of data use and student achievement also partially supported the theory of action. Specifically, we found that teacher-reported *Attention to Data in the Classroom* was positively associated with student achievement in middle grades mathematics and elementary grades reading. That is, the more teachers reported reviewing interim student data and responding in the classroom, the higher their students' achievement on the end-of-year state assessment.

These findings suggest that teachers' review and response to interim assessment data can potentially act as a lever to improve student achievement in urban districts. Teachers' *Attention to Data in the Classroom* was more strongly related to student achievement than their sense of the assessment and instructional context, data culture, or supports for data use. This key finding is consistent with previous research that suggests that simply having interim assessments in place is not enough, and that to be effective, educators must actually use data to identify problems, identify reasons behind the problem, and then determine how to adjust their teaching to address the problems (Anderson et al., 2010). By linking teachers' data-use practices and perceptions with their own students' achievement, this study extended prior research that suggested that working with data may help teachers understand and identify their students' needs (e.g., Quint et al., 2008).

Our results indicate that teachers' review of data and subsequent instructional responses were the data-related practices and perceptions most strongly linked to improved student achievement and can be a focus for intervention and improvement with teachers in both elementary and middle grades. To consider in a practical sense how *Attention to Data in the Classroom* might be improved or addressed in urban schools, it is useful to break this construct down into its component parts, and further into the specific practices and activities that comprise the component parts.

Attention to Data in the Classroom was a combination of teachers' *Working with Data* and their data-based *Instructional Responses*. There were three subscales included in *Attention to Data in the Classroom*: teachers' **individual attention to data**, **collaboration around data**, and their **instructional responses to data**. Each of these was composed of items reflecting a number of specific practices related to teachers' review of and response to student data. Examples of the specific practices are shown in Table 4.1. Any or all of the practices shown in Table 4.1 may contribute to or drive the significant positive link between *Attention to Data in the Classroom* and student achievement that we found in this study.

Table 4.1. Components and Specific Practices that Comprise *Attention to Data in the Classroom*

Components of Teachers' *Attention to Data in the Classroom*	**Concrete and Specific *Attention to Data* Practices**
Individual Attention to Data	- Teachers' independent review, analysis, and interpretation of their student data, such as: ○ Identifying the number of students per proficiency category ○ Reviewing the percent of students who mastered each separate item or groups of items on the interim assessment ○ Identifying trends in content mastery at the individual student level and classroom level - Includes frequency of review and overall amount of time spent engaging in independent review
Collaboration around Data	- Teachers' review, analysis, and interpretation of data in collaboration with other teachers, administrators, instructional coaches, data coaches, parents, and with students. - Frequency of participation in formal "data meetings" or professional learning communities - Frequency of participation in informal collaborative meetings/discussions
Instructional Responses to Data	- On the basis of gaps and strengths identified in interim assessment data, instructional strategies such as: ○ Adjusting lesson plans (e.g., to spend more or less time on a concept than originally planned, depending on needs identified in the data) ○ Changing scope or sequence of instruction ○ Reteaching missed or misunderstood material or concepts to the whole class, small groups, or individual students ○ Changing teaching methodology (e.g., from lecture to activity-based) ○ Changing or adapting instructional materials ○ Re-grouping ▪ Heterogeneously, to mix students with different skill/mastery levels ▪ Homogeneously, to provide remediation or acceleration to students at similar skill levels ○ Providing targeted interventions for students with poor performance on interim assessments, such as referring students for tutoring within and outside of school.

The positive link between *Attention to Data in the Classroom* and student achievement indicates that the more that teachers engage in the types of practices listed in Table 4.1, the higher their students' achievement. At the component level, this means that the more that teachers engage in independent review of their data, and collaborate with others to review their students' data, and the more they can point to specific instructional responses to data that they use with their students, the higher their students' achievement at the end of the year.

Of course, this study was not designed to determine whether any or all of these data-use practices shown in Table 4.1 cause achievement to increase, but this study does provide evidence to suggest that supports that encourage these practices may hold promise for improving the use of interim assessment data, which in turn may help improve student achievement. That is, our results suggest that teachers' review and response to interim assessment data as described above can potentially act as a lever to improve student achievement in urban districts.

Teachers' perceived *Barriers to Data Use* (such as a lack of time to study and think about data, a lack of time to collaborate with others in analyzing and interpreting data, or a lack of timeliness in receiving students' scores) were negatively related to student achievement—but only in elementary grades mathematics. As depicted in the theory of action, perceived barriers to using data can interrupt the assessment process at any point. For example, if teachers perceive that the test itself is of low quality, they will be unlikely to even examine their students' results closely. If teachers accept the validity and quality of the test but do not receive the data in an easy-to-use format, they still may not be able to review the data with ease and then respond to students' strengths and weaknesses within their classrooms. Perceived *Barriers to Data Use* may be indicative of breakdowns with the interim assessment process specifically or may more generally be an indicator of systemwide or districtwide issues. Additional investigation should examine why barriers have a more negative effect on elementary grades mathematics than the other subjects and grade levels.

What Are the Relationships Between Schools' Policies, Practices, and Resources for Data-Driven Instruction and Student Achievement?

As with the teacher-reported data-use practices and perceptions, the hypothesized relationships between schools' policies, practices, and resources for data-driven instruction and student achievement were partially supported.

Principals' General Data Use and Student Achievement. Principals' *General Data Use* (again, a combination of the four key dimensions of data use in the theory of action) was related to student achievement in middle grades mathematics. However, there was no relationship in middle grades reading, elementary grades mathematics, or elementary grades reading. These findings suggest that the overall interim assessment process may be a promising practice at the school level in urban districts for some students but not all students and subjects. Principal-reported data-use practices and perceptions were related to improvement in student achievement only in middle grades mathematics. Thus, it may be possible that the adoption of an interim assessment process with an emphasis on supporting effective data use may be one area in which urban schools can intervene at the school level and positively impact student achievement, perhaps in middle grades mathematics in particular.

Principals' Specific Data-Use Practices and Student Achievement. The results of analyses testing the unique links between the school-level key dimensions of data use and student achievement also partially supported the theory of action. Principal-reported *Supports for Data Use* and *Attention to Data in the School* were positively associated with student achievement in some grades and subjects.

Principals' reported levels of working with and responding to interim assessment data (i.e., *Attention to Data in the School*) were positively related to elementary school students' mathematics scores. For principals, working with and responding to data were school-level processes, such as targeting teacher professional development on the basis of interim assessment results or adapting school improvement plans on the basis of interim assessment results. Although this study cannot purport a causal link between these school-level processes and student achievement, this finding is consistent with previous research that suggests school-level processes around data use are promising for improving student achievement (Henke, 2005; U.S. Department of Education, 2010a). The magnitude of the link between principals *Attention to Data* and student achievement in elementary mathematics was educationally meaningful, with an effect size of 0.10.

Again, to make this key finding actionable in terms of identifying specific practices on which schools and districts could focus when seeking to improve the use of interim assessment data, it is useful to break *Attention to Data in the School* down into its component parts and further, into the concrete activities that comprise the component parts.

Attention to Data in the School was a combination of principals' review and analysis of data and their data-based responses. The three subscales included in *Attention to Data in the School* were principals' **individual attention to data**, **collaboration around data**, and **school-level responses to data**. Each of these was composed of items reflecting a number of specific practices related to principals' review of and response to student data. Examples of the specific practices are shown in Table 4.2. As with the classroom-level practices for teachers, any or all of the school-level practices shown in Table 4.2 may contribute to or drive the significant positive link between *Attention to Data in the School* and elementary math achievement that we found in this study.

Table 4.2. Components and Specific Practices that Comprise *Attention to Data in the School*

Components of Principals' *Attention to Data in the Classroom*	**Concrete and Specific *Attention to Data* Practices**
Individual Attention to Data	- Principals' independent review, analysis, and interpretation of their student data, such as: ○ Identifying the percentage of students scoring at or above the proficiency level by grade, subject, and classroom ○ Comparing the performance of students in their school versus other schools ○ Examining the performance of student subgroups (e.g., students with disabilities, English learners) ○ Identifying changes or trends in the school's results across years - Includes frequency of review and overall amount of time spent independently reviewing data
Collaboration around Data	- Principals' review, analysis, and interpretation of data in collaboration with other teachers, administrators, instructional coaches, data coaches, parents, and with students. - Frequency of participation in formal "data meetings" and professional learning communities - Frequency of participation in informal collaborative meetings/discussions
Instructional Responses to Data	- On the basis of data review: ○ Making curriculum changes or decisions ○ Developing school improvement plans ○ Seeking professional development for teachers based on identified gaps in either content or pedagogical skills that are revealed in the data ○ Setting schoolwide student achievement goals ○ Evaluating programs (i.e., examining trends over time for students who participate in particular instructional programs/initiatives)

Given the positive relationship between *Attention to Data in the School* and student achievement, the more principals engage in the types of activities shown in Table 4.2, the higher the math achievement of students in their schools (at the elementary level). Specifically, independent review of interim assessment data may represent a set of promising principal or school-level data-use practices. Moreover, collaboration that includes administrators—either principals or assistant principals, or both where appropriate—may be a key feature of an effective data-use process in urban schools. If supported, this type of collaboration may potentially help drive improvements in student achievement. Finally, the specific examples of school-level responses shown in Table 4.2 may be promising data-use activities.

Our final key finding was that principals' perceptions of *Supports for Data Use* were also positively related to student achievement in both elementary grades reading and mathematics. The literature on school-level data use emphasizes the importance of organizational supports—such as common meeting times to discuss data, the presence of a data coach, the quality of the data infrastructure, and professional development around data use—as promising dimensions of effective data use (Bulkley et al., 2010; Clune & White, 2008; Henke, 2005; Marsh et al., 2006; Young, 2006). Our results further indicate that these are aspects of using data most strongly related to student achievement at the principal/school level, with effect sizes ranging from 0.09 to 0.11.

As with teachers' *Attention to Data in the Classroom* and principals' *Attention to Data in the School,* it is useful to break down *Supports for Data Use* into its component parts and the concrete and specific aspects of these components in order to consider ways that schools and school districts can improve their data supports to be more effective.

The three subscales included in *Supports for Data Use* were **organizational supports**, **staffing and human resources**, and **data infrastructure**. In general, the more positive principals' perceptions of these supports, the higher their students' achievement (at the elementary school level). Table 4.3 shows the specific aspects of each of these three components. Any or all of the aspects shown in Table 4.3 may contribute or drive the significant positive link between *Supports for Data Use* and student achievement that we found in this study.

Any or all of these specific aspects in Table 4.3 may be key school-level supports that helped drive the link between principals' perceptions of their *Supports for Data Use* and student achievement. Further research is needed to examine the finer grained relationships, but the results of this study suggest that the concrete and specific *Supports* described above are potentially promising aspects of interim assessment data use.

The observed findings for principals were in contrast to the results focused on teachers, where *Supports for Data Use* were not a significant predictor of student achievement at either grade level or subject. Principal-reported *Supports for Data Use* included both the support that they themselves provide in an administrative role as well as supports principals and teachers receive from the school district. Our findings suggest that these school and district supports hold promise as levers for change in urban schools to improve student achievement in elementary grades reading and mathematics.

However, contrary to our hypotheses, principals' data-use practices and perceptions were not significantly correlated with middle grades students' achievement in either mathematics or reading. These differences between elementary and middle grades should be examined in future research.

Table 4.3. Components and Specific Aspects of *Supports for Data Use*

Components of *Supports for Data Use*	**Concrete and Specific *Supports for Data Use***
Organizational Supports	- Structured time for review and discussion of interim assessment results built into the school day for teachers and administrators ○ Sometimes conducted with the whole staff, subject area teams or departments, or at grade level data meetings - Data coaches who conducted such activities as: ○ Providing feedback on school improvement plans that incorporate student achievement data ○ Making recommendations about curricular or instructional changes based on student scores ○ Emphasizing the link between instructional practices and student interim assessment scores
Staffing and Human Resources	- Principals' perceptions of the quantity and quality of the professional development offered to their teachers that is specifically about using data to inform instruction - Training on how to access student data electronically, how to generate different types of reports, and how to analyze and respond to student data.[14] - Staff capacity to use data including principal perceptions of the ability of their teachers to use data in multiple ways, such as ○ Translating data into knowledge about student strengths and weaknesses ○ Analyzing trends in individual student- and classroom-level performance over time ○ Making data-based instructional changes
Data Infrastructure	- Quality, timeliness, and ease of use of the data system including: ○ The ways that principals access student interim assessment data (e.g., electronically or on paper-based reports) ○ Lag-time to gain access to student data after administration of assessments

[14] It is important to note that both principals and teachers indicated needing more support and training in how best to respond to student data.

Study Limitations

This study used rigorous statistical modeling to explore the relationships between the key dimensions of data use and student achievement, but it is important to note some limitations. First, the study relied on self-report survey data rather than observations of actual data use and instructional practices. Based on the teacher and principal survey results, the four key dimensions of data use were highly correlated. Although these correlations provide some basic support for the study's theory of action, they may be at least partially explained by measurement error due to the fact that the variables were measured using the same survey. If the key dimensions were measured separately with different techniques (e.g., a combination of survey and observations), we may have been able to obtain more refined measures of each dimension and the key elements and components within each dimension. These constructs in the theory of action provided a roadmap for designing the surveys used for this study; however, as measured, the scales (and subscales) derived from the surveys did not appear to represent highly distinct aspects of data-use practices and perceptions. Future studies may benefit from a mixed-methods approach to measuring teacher and principal data use.

A related limitation is that the analysis does not identify whether certain practices within these dimensions are more promising than others. Future work also should continue to refine the measurement strategy to allow for analyses of the links between more specific data-use practices and student achievement than could be tested in this foundational study.

A third limitation of the study is that it was not designed to provide information about the implementation quality of the interim assessment process in the participating districts. For example, a teacher may report regularly attending team data meetings, but the quality or relevance of the content of those meetings is not captured in the survey responses. The survey data also do not provide information about the quality of the actual interim assessments used in the participating districts. Although we collected data about perceived alignment with the curriculum, pacing guides, and state assessments, a measure of the true degree of this alignment was beyond the scope of this study. To partially address this limitation, we conducted a follow-up study of the alignment between the interim assessments and the state standards and pacing guides in one subject (mathematics) in one of the participating districts. A brief report on this alignment study is provided in Appendix A. The results suggest that in this one district, the interim assessments were well aligned with the state assessment. Similar alignment studies in the other participating districts would help to further ground the results of the main study.

A fourth limitation involves the generalizability of the findings. The school-based samples of principals, teachers, and students were sufficiently large in size, but there were only four districts. It is not clear whether the findings from these four districts can be generalized to other urban districts or districts in other localities (e.g., suburban or rural).

Finally, although this study provides evidence of a relationship between some key dimensions of data use and student achievement, it is essential to understand that no causal claims about the nature of these relationships can be made on the basis of this correlational study. Interim assessments and the use of their data are just one of a number of policies, practices, and interventions being implemented within schools and school districts. It is not our claim that supports for data use and attention to data use in the classroom or school *cause* improved student achievement in certain grades and subjects. Rather, this study provides foundational evidence that as some aspects of data use increase, so too does student achievement. This study does not rule out the possibility that something else caused both the level or degree of data use and the improvement in achievement.

Future Directions

Future research can help provide additional evidence of whether and how interim assessments can be used as a tool to increase student achievement. The ultimate goal would be to develop a set of standards or strategies that districts and schools can use as a guide for effective data use.

Self-report measures of data use have provided valuable information on how interim assessments are used at classroom and school levels in the selected urban districts. As already noted, these data could be further enhanced through observations of actual data-use practices. These could include observations of data meetings where staff discuss the results of interim assessments or plan instructional responses and professional development on data use. Deeper study could also include a review of lesson plans that stem from a review of the interim assessment data, along with classroom observations to explore how these plans are implemented.

As we learn more about specific data-use practices that are associated with student achievement, another next step is to develop a more refined theory of action and set of measures designed to tap into it. This could involve the suggestions already mentioned, followed by developing specific data-use interventions intended to improve teachers' instructional responses and student achievement that can be systematically tested in the schools.

Of the six significant relationships between data-use practices/perceptions and student achievement that emerged in this study's analyses, five were found in the elementary grades. This finding suggests that something about the structure of the elementary grades may be more conducive to the successful use of interim assessments, compared with the middle grades. Further research is needed to identify key factors in the elementary grades that could be adopted or adapted in the middle grades to potentially increase the utility of interim assessments for older students. Similarly, further exploration can help achieve a better understanding of data-use differences in mathematics and reading that were revealed in this study.

Conclusion

With the current increase in the use of interim assessments, the need for a more comprehensive body of literature on effective use of data for instructional improvement is critical. Supporters of interim assessments believe that using this type of measure on a periodic basis can lead to improved student achievement. However, despite the widespread use of these assessments, few studies actually document the relationship between data-use-related perceptions and practices and student achievement. This study attempted to shed light on this issue by examining the relationship between key dimensions of data use and student achievement in two major content areas (reading and mathematics) and in the two grade levels (elementary and middle) in which interim assessments most often are used. The results across content areas and grade levels were mixed but suggest that some aspects of classroom- and school-level interim assessment data use are related to improvements in student achievement. The results also appear to be in line with previous research that suggests that having interim assessments may be helpful but not sufficient to produce positive changes in student achievement.

This study sought to begin to understand the connection between different aspects of interim assessment data use and student achievement. Given that school districts and schools are facing significant budget challenges and must make important decisions about resource allocation, it is imperative that we identify the specific dimensions of data use that are most important for improving student outcomes. Many school districts are increasingly using various types of assessments and data in an effort to engage in data-driven decision making. Although the study focused primarily on the use of data from interim assessments, some of the study results may extend beyond interim assessments to provide a glimpse into the overall data culture of participating districts. As such, this study provides a foundation for the future exploration of the relationships between student achievement and other types of data that can be used for instructional and school improvement.

Finally, these findings have implications for data-use policies and practices in school districts and schools. The findings suggest that, at the very least, if schools adopt interim assessments to produce changes in student achievement, schools and districts should provide adequate support for using the data, and teachers should actively use data in the classroom—both by spending time individually and collaboratively reviewing the student data and by responding instructionally.

This is particularly important as the nation moves toward Common Core State Standards and the assessment systems that will accompany them. Although these findings do not identify the specific aspects of each dimension that are most important, it appears that data use by principals, particularly in elementary school, may be as important as teacher data use. This is in line with the findings from our site visits (as well as prevailing wisdom) that suggest that leadership and support from the administration are critical. The findings of this three-year project revealed that schools are better able to work with data when they have the appropriate data infrastructure, organizational supports for the analysis and productive discussions about data, human resources (e.g., data coaches) and professional development. In addition, there are important uses for interim assessment data by stakeholders at all levels. These include use by district leaders to identify professional development needs and evaluate district initiatives, use by school leaders to develop and evaluate school and staff improvement plans, and perhaps most importantly, use by teachers to inform instructional strategies. It is there in the classroom that student needs are met most effectively.

APPENDICES

Appendix A: District and State Context

State Data-Use Capacity: America COMPETES Act

The states of three of the participating districts have previously submitted Race to the Top grants that, as of fall 2011, have not been funded. In their Race to the Top grant applications, the states described their plans to adopt formative and summative assessments, monitor student growth, improve data systems, and make data more widely available. These states also described their status regarding the 12 America COMPETES Act elements (see Table A.1). Information on the status of data systems in the fourth district, in Virginia, was collected through the Virginia Statewide Longitudinal Data Systems (SLDS) grant application, which was submitted in 2010. Three of the four participating districts have in place all or nearly all the required elements at the state level, with plans to improve on them and implement the remaining elements.

Table A.1. Data Elements in the Four Participating Districts

	District			
America COMPETES Act Elements	**1**	**2**	**3**	**4**
1. Unique student ID	P	C	C	C
2. Student-level enrollment, demographics, and participation	C	C	C	C
3. Student-level information about points at which a student exits, transfers in/out, drops out, or completes PK–16	P	C	C	C
4. Capacity to communicate with higher education system	C	C	C	P
5. State data audit assessing data quality, validity, and reliability	C	C	C	P
6. Yearly state assessment records of individual students	C	C	C	C
7. Information on students not tested by grade and subject	C	C	C	C
8. Teacher identifier system with ability to match individual teachers to individual students	C	C	C	—
9. Student-level transcript information including course completion and grade earned	C	C	C	—
10. Student-level college readiness test scores	C		C	C
11. Data on student transition from secondary to post-secondary, including remedial coursework enrollment	C	C	C	P
12. Data necessary to address alignment and adequate preparation for success in post-secondary	C	C	C	P

Note. Elements marked with a C are complete or operational but undergoing improvements. Elements marked with a P are partially completed.

District 3: In-Depth Site Visit Evaluation Examining Alignment of the Interim Assessment Process With the State Standards

In July 2011, an independent third-party analyzed the degree to which the interim assessments in District 3 in grades 5 and 8 were aligned with the state Core Content for Mathematics expectations as delineated by the State Department of Education and the district pacing guides. All 143 items from the grade 5 and grade 8 interim assessments were analyzed individually to reveal if they were appropriately aligned to a state expectation and the instructional units in the pacing guide. The analysis revealed an extremely high degree of alignment between the grades 5 and 8 interim assessments and both the state's Core Content in Mathematics and the county's pacing guide (see Table A.2). Although data use can be impeded by the perception that assessments are not aligned to pacing guides and curricula, the independent reviewer concluded that the interim assessments are connected with both the curriculum expectations and unit pacing.

Table A.2. Summary of Alignment Study Findings

	Grade 5		Grade 8	
	n	**%**	***n***	**%**
Number of proficiency assessments analyzed	3	-	8	-
Total number of items analyzed	39	-	104	-
Items appropriately aligned with the core context expectations	38	97%	102	98%
Items appropriately placed within pacing guide	39	100%	101	97%
Items aligned with current unit(s)	33	85%	69	68%
Items aligned with prior unit	6	15%	32	32%

Appendix B: Measures and Data-Use Survey Items

This appendix includes the reliability statistics of each subscale and scale used to measure the key dimensions of data use for teachers and principals. A list of example data-use survey items administered to teachers and principals also is provided.

- Tables B.1 and B.2 present the reliability of each teacher subscale and scale (Table B.1) and each principal subscale and scale (Table B.2).

- Table B.3 presents example survey items from the teacher and principal surveys of data use.

Teacher and Principal Data-Use Survey Reliability

The reliability statistics of each scale and the number of survey items in each scale are shown in Table B.1 for the four samples of teachers, including elementary grades reading teachers, elementary grades mathematics teachers, middle grades reading teachers, and middle grades mathematics teachers. The alpha statistics for all key dimensions of the data-use scales and subscales measuring teachers' data use are greater than 0.70, which suggests adequate reliability. The number of survey items that measure the key dimensions of data use for teachers range from 15 to 48 survey items. For example, among elementary grades reading teachers, the *Supports for Data Use* scale is internally consistent with a Cronbach's alpha of 0.95 and is measured with 48 teacher survey items.

Table B.2 provides reliability coefficients (Cronbach's alpha) for scales and subscales measuring the key dimensions of data use for principals and the number of survey items that measure each subscale and scale. Each principal scale and subscale has a Cronbach's alpha greater than 0.70, which suggests that each scale and subscale is internally consistent. The number of survey items from the principal data-use survey used to measure the key dimensions of data use ranged from 13 to 51. For instance, the principal *Supports for Data Use* scale is internally consistent with a Cronbach's alpha of 0.92 and is measured with 51 survey items.

Table B.1. Reliability of Data-Use Scales and Subscales (Teacher Survey)

			Cronbach's Alpha			
Key Dimension Scale	**Subscales Within Each Key Dimension Scale**	**Survey Item *N***	**Elementary Grades Reading Teachers**	**Elementary Grades Math Teachers**	**Middle Grades Reading Teachers**	**Middle Grades Math Teachers**
Context		**36**	**0.86**	**0.86**	**0.91**	**0.88**
	Assessment/Instructional Context	23	0.79	0.78	0.86	0.81
	State, District and School Data Culture	13	0.85	0.86	0.89	0.88
Supports for Data Use		**48**	**0.95**	**0.95**	**0.95**	**0.94**
	Data Infrastructure	9	0.80	0.80	0.79	0.81
	Organizational Supports	31	0.95	0.94	0.94	0.94
	Staffing/Human Resources	8	0.96	0.95	0.95	0.94
Working with Data		**42**	**0.94**	**0.94**	**0.95**	**0.95**
	Individual Teacher Attention to Data	16	0.89	0.88	0.91	0.90
	Teacher Collaboration Around Data	10	0.87	0.88	0.89	0.88
	Teacher-Principal Collaboration	3	0.75	0.75	0.77	0.67
	Teacher-Coach Collaboration	4	0.78	0.79	0.79	0.77
	Teacher-Parent Collaboration	4	0.74	0.74	0.77	0.74
	Teacher-Student Collaboration	5	0.89	0.89	0.89	0.88
Instructional Responses		**26**	**0.96**	**0.97**	**0.97**	**0.97**
	Establish/Adjust Groupings	6	0.84	0.85	0.86	0.86
	Change Scope and Sequence	5	0.84	0.84	0.89	0.87
	Adjust Lesson Plans	10	0.93	0.93	0.95	0.94
	Provide Supplemental Resources to Targeted Students	5	0.82	0.82	0.85	0.84
Barriers to Data Use		**15**	**0.74**	**0.74**	**0.79**	**0.76**

Sample Size: Elementary Reading Teachers *N* = 612; Elementary Mathematics Teachers *N* = 587; Middle School Reading Teachers *N* = 552; Middle School Mathematics Teachers *N* = 473

Table B.2. Reliability of Data-Use Scales and Subscales (Principal Survey)

Key Dimension Scale	Subscales Within Each Key Dimension Scale	Survey Item *N*	Cronbach's Alpha: General Principal Responses	Cronbach's Alpha: Reading Instruction Specific	Cronbach's Alpha: Math Instruction Specific
Context		**32**	**--**	**0.87**	**0.87**
	Assessment/Instructional Context	23	--	0.82	0.81
	State, District and School Data Culture	9	0.84	--	--
Supports for Data Use		**51**	**0.92**	**--**	**--**
	Data Infrastructure	8	0.82	--	--
	Organizational Supports	31	0.90	--	--
	Staffing/Human Resources	12	0.93	--	--
Working with Data		**42**	**--**	**0.97**	**0.97**
	Individual Principal Attention to Data	17	--	0.93	0.93
	Principal Collaboration Around Data	3	0.79	--	--
	Principal-Teacher Collaboration	9	0.86	--	--
	Principal-Coach Collaboration	4	0.83	--	--
	Principal-Parent Collaboration	3	--	0.75	0.75
	Principal-Student Collaboration	6	0.87	--	--
Instructional Responses		**24**	**--**	**0.96**	**0.97**
	Establish/Adjust Groupings	4	--	0.80	0.80
	Adjust Lesson Plans	6	--	0.88	0.88
	Provide Supplemental Resources to Targeted Students	3	--	0.81	0.81
	School-Level Instructional Response	11	--	0.92	0.93
Barriers to Data Use		**13**	**0.76**	**--**	**--**

Note. -- denotes that the reliability coefficient was not calculated because the items included in the scale or subscale were either content specific (generating Reading Instruction Specific and/or Mathematics Instruction Specific coefficients, but *not* general principal responses) or were content general (generating a coefficient for general principal responses, but *not* content specific reading or mathematics coefficients). School-Level Instructional Response is a subscale specific to the principal survey.

Data-Use Survey Items

Table B.3 presents a series of example survey items and response options from the data-use surveys distributed to teachers and principals. The teacher survey was administered to teachers of reading or mathematics in grades 4, 5, 7, and 8, and the principal survey was administered to principals and, where appropriate, assistant principals of participating elementary and middle schools. The example survey items are linked with the subscale and scale it measured. Each scale measured a key dimension of data use as depicted in the theory of action, including *Context*, *Supports for Data Use*, *Working with Data*, *Instructional Responses,* and *Barriers* to data use.

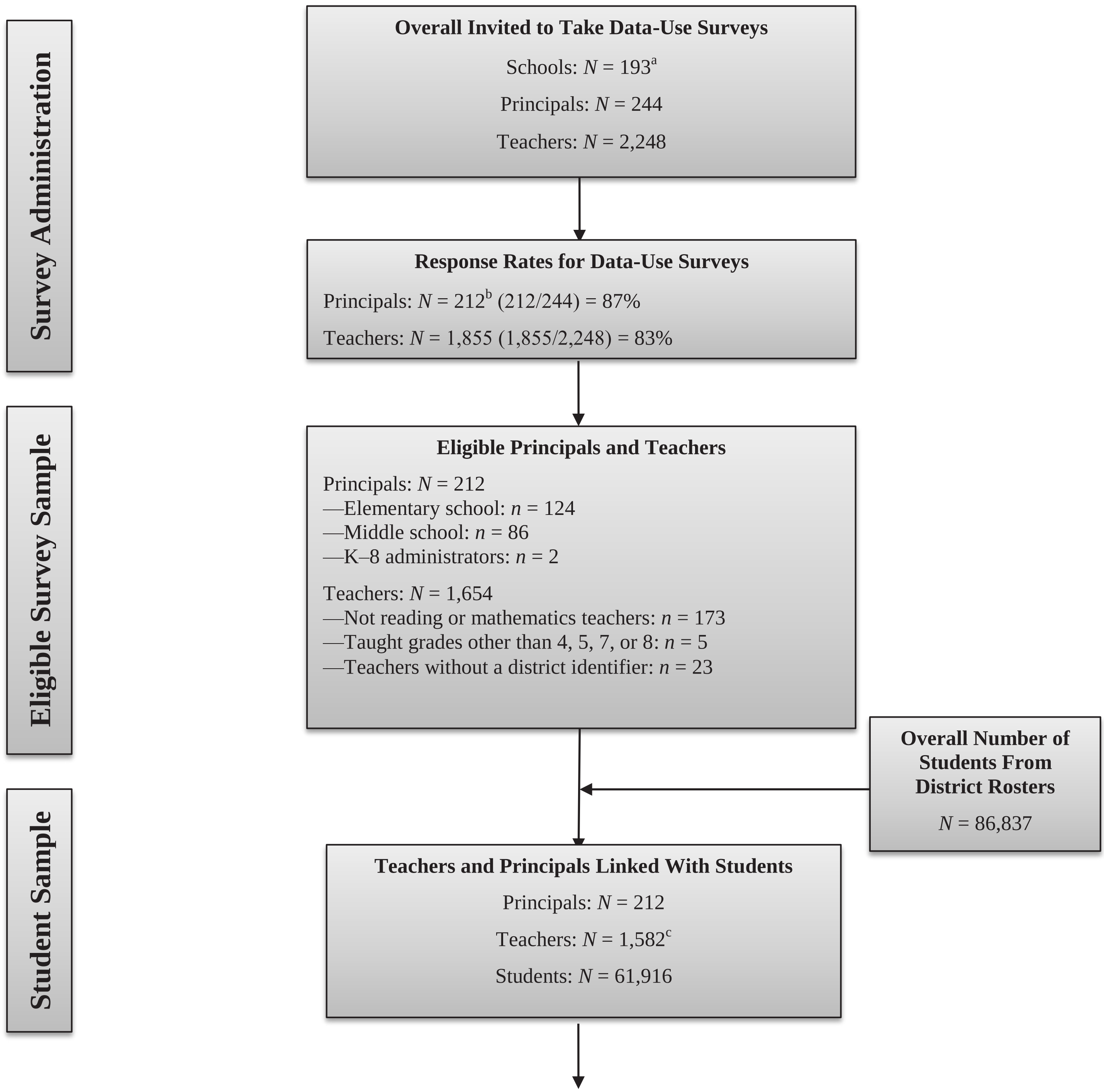
Table B.3. Example Items from the Teacher and Principal Surveys of Data Use

Scale	Subscale	Survey Item	Response Scale
Context	Assessment/Instructional Context	How much do you agree or disagree with the following statement? The district interim assessments are well aligned with state and district standards.	1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree
Context	State, District, and School Data Culture	How much do you agree or disagree with the following statement about your district's priorities about using data? The district sets clear, consistent goals for schools to use data for school improvement.	1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree
Supports for Data Use	Data Infrastructure	How much do you agree or disagree with the following statement about using district interim assessment data? Interim assessment results are reported to me in a timely manner.	1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree
Supports for Data Use	Data Infrastructure	How much do you agree or disagree with the following statement about using district interim assessment data? Interim assessment data are easy to use.	1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree
Working With Data	Teacher Collaboration Around Data	How frequently do you review student interim assessment data with classroom teachers?	0 = Never; 1 = 1 or 2 times a quarter; 2 = 1 or 2 times a month; 3 = 1 or 2 times a week
Working With Data	Teacher-Coach Collaboration	How frequently do you review student interim assessment data with instructional coaches?	0 = Never; 1 = 1 or 2 times a quarter; 2 = 1 or 2 times a month; 3 = 1 or 2 times a week
Working With Data	Teacher-Parent Collaboration	How frequently do you review student interim assessment data with parents/guardians?	0 = Never; 1 = 1 or 2 times a quarter; 2 = 1 or 2 times a month; 3 = 1 or 2 times a week
Working With Data	Teacher-Student Collaboration	How frequently do you review student interim assessment data with students?	0 = Never; 1 = 1 or 2 times a quarter; 2 = 1 or 2 times a month; 3 = 1 or 2 times a week
Working With Data	Individual Teacher Attention to Data	How much have you used the latest interim assessment results to identify individual students who need remedial assistance?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Working With Data	Individual Teacher Attention to Data	How much have you used the latest interim assessment results to identify areas where you need to strengthen your content knowledge or teaching skills?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Instructional Responses	Adjust Lesson Plans	How much have you used the latest interim assessment results to tailor instruction to individual students' needs?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Instructional Responses	Change Scope and Sequence	How much have you used the latest interim assessment results to identify and correct gaps in the curriculum for all students?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Instructional Responses	Provide Supplemental Resources to Targeted Students	How much have you used the latest interim assessment results to recommend tutoring or other educational services for students?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Instructional Responses	Establish/Adjust Groupings	How much have you used the latest interim assessment results to assign or reassign students to classes or groups?	0 = Did not use in this way; 1 = Used minimally; 2 = Used moderately; 3 = Used extensively
Barriers to Data Use	Barriers to Data Use	To what extent has lack of time to study and think about available data hindered your ability to use data to make instructional decisions?	0 = Not at all; 1 = To a minor extent; 2 = To a major extent; 3 = To a great extent

Appendix C: Information on Samples

This appendix includes information on the number of schools, principals, teachers, and students involved in the study, from those invited to participate to the final analytic sample.

Exhibit C.1. Sample Tracking Flowchart



After Random Selection

After Random Selection of Student-Teacher Links

Principals: *N* = 212[d]

Teachers: *N* = 1,581[e]

Students: *N* = 61,798[f]

Elementary Grades Reading

Schools: *n* = 110
Principals: *n* = 101
Teachers: *n* = 614
Students: *n* = 14,764

Elementary Grades Mathematics

Schools: *n* = 111
Principals: *n* = 102
Teachers: *n* = 593
Students: *n* = 14,354

Middle Grades Reading

Schools: *n* = 85
Principals: *n* = 75
Teachers: *n* = 532
Students: *n* = 36,169

Middle Grades Mathematics

Schools: *n* = 86
Principals: *n* = 76
Teachers: *n* = 471
Students: *n* = 38,583

Teacher Analytic Samples

Elementary Grades Reading[g]

Context Key Dimension:
—Schools: *n* = 107
—Teachers: *n* = 518
—Students: *n* = 10,761

Supports for Data Use Key Dimension:
—Schools: *n* = 107
—Teachers: *n* = 510
—Students: *n* = 10,598

Working With Data/ Instructional Responses Key Dimension:
—Schools: *n* = 107
—Teachers: *n* = 523
—Students: *n* = 10,892

Barriers to Data Use:
—Schools: *n* = 107
—Teachers: *n* = 508
—Students: *n* = 10,557

Elementary Grades Mathematics[g]

Context Key Dimension:
—Schools: *n* = 108
—Teachers: *n* = 489
—Students: *n* = 10,429

Supports for Data Use Key Dimension:
—Schools: *n* = 108
—Teachers: *n* = 488
—Students: *n* = 10,421

Working With Data/ Instructional Responses Key Dimension:
—Schools: *n* = 108
—Teachers: *n* = 499
—Students: *n* = 10,642

Barriers to Data Use:
—Schools: *n* = 108
—Teachers: *n* = 486
—Students: *n* = 10,379

Middle Grades Reading[g]

Context Key Dimension:
—Schools: *n* = 85
—Teacher *n* = 448
—Students: *n* = 27,580

Supports for Data Use Key Dimension:
—Schools: *n* = 85
—Teachers: *n* = 433
—Students: *n* = 26,634

Working With Data/ Instructional Responses Key Dimension:
—Schools: *n* = 85
—Teachers: *n* = 450
—Students: *n* = 27,697

Barriers to Data Use:
—School *n* = 85
—Teachers: *n* = 436
—Students: *n* = 26,710

Middle Grades Mathematics[g]

Context Key Dimension:
—Schools: *n* = 84
—Teachers: *n* = 412
—Students: *n* = 30,378

Supports for Data Use Key Dimension:
—Schools: *n* = 84
—Teachers: *n* = 391
—Students: *n* = 28,902

Working With Data/ Instructional Responses Key Dimension:
—Schools: *n* = 84
—Teachers: *n* = 412
—Students: *n* = 30,368

Barriers to Data Use:
—Schools: *n* = 84
—Teachers: *n* = 387
—Students: *n* = 28,402

Principal Analytic Samples

Elementary Grades Reading[g]

Context Key Dimension:
—Principals: *n* = 99
—Students: *n* = 10,175

Supports for Data Use Key Dimension:
—Principals: *n* = 92
—Students: *n* = 9,365

Working With Data/ Instructional Responses Key Dimension:
—Principals: *n* = 96
—Students: *n* = 9,788

Barriers to Data Use:
—Principals: *n* = 82
—Students: *n* = 8,430

Elementary Grades Mathematics[g]

Context Key Dimension:
—Principals: *n* = 100
—Students: *n* = 10,073

Supports for Data Use Key Dimension:
—Principals: *n* = 93
—Students: *n* = 9,266

Working With Data/ Instructional Responses Key Dimension:
—Principals: *n* = 97
—Students: *n* = 9,690

Barriers to Data Use:
—Principals: *n* = 83
—Students: *n* = 8,373

Middle Grades Reading[g]

Context Key Dimension:
—Principals: *n* = 74
—Students: *n* = 23,632

Supports for Data Use Key Dimension:
—Principals: *n* = 68
—Students: *n* = 21,686

Working With Data/ Instructional Responses Key Dimension:
—Principals: *n* = 74
—Students: *n* = 23,809

Barriers to Data Use:
—Principals: *n* = 55
—Students: *n* = 18,348

Middle Grades Mathematics[g]

Context Key Dimension:
—Principals: *n* = 74
—Students: *n* = 26,708

Supports for Data Use Key Dimension:
—Principals: *n* = 67
—Students: *n* = 23,241

Working With Data/ Instructional Responses Key Dimension:
—Principals: *n* = 73
—Students: *n* = 26,085

Barriers to Data Use:
—Principals: *n* = 54
—Students: *n* = 20,931

[a] Schools across the four districts were oversampled, and 193 schools were invited to participate in the data use surveys. Based on power analyses, only 180 schools were needed to detect an effect size of 0.18. [b] Out of the 212 administrators, 174 were principals, and 38 were assistant principals. [c] Across the four districts, 72 teachers who completed data-use surveys could not be linked with students. [d] Principal data were aggregated to the school level because some schools had multiple principals respond to the data-use survey. As a result, principal data for 174 schools are linked with teacher data use and student achievement. [e] One teacher who taught 23 students was dropped during the random selection process. [f] One district had 118 students who were each linked with two teachers who taught both reading and mathematics. However, the teacher responsible for each student's reading and mathematics instruction could not be determined because roster course information was not provided for either teacher. These students were dropped from the student sample. [g] Three teachers and 94 students were excluded from the analytic samples because these teachers changed schools or grade levels within the same academic year. The data for these teachers and students were retained for descriptive statistics only.

Appendix D: Estimation Methods and Hypothesis Testing

This appendix presents intra-class correlations (ICCs), a discussion of potential multi-collinearity, the results for the structural equation models (SEMs), and the results for the hierarchical linear models (HLMs).

- Table D.1 shows the variance in student achievement at the student, teacher, and school levels. Tables D.2 and D.3 show the variance in teacher data use at the teacher and school levels.
- Exhibits D.1–D.8 present the full model results for the SEM models of general data use and student achievement.
- Table D.4 presents the covariates examined in developing the HLM model and includes a list of all control variables included in the final model for HLM analyses.
- Tables D.5–D.36 present the full model results for the HLM models for each data use dimension and student achievement.

Intraclass Correlations

Tables D.1–D.3 present ICCs based on unconditional HLM models. Table D.1 shows the ICC based on an unconditional three-level model for student achievement (with students nested in teachers[15] nested in schools), which were estimated separately for elementary and middle grades and for reading and mathematics. These ICCS were examined to understand the percentage of variance in student achievement at each level (the student, teacher, and school level). The majority of variance in student achievement was at the student level (between 54 and 81 percent), with more teacher-level variance in middle grades (33 to 37 percent in middle grades *versus* 9 and 10 percent in elementary grades). Finally, school-level variance ranged from 6 to 10 percent.

Table D.1. Partitioning of Variance in Student Achievement at the Student, Teacher, and School Level

	Dependent Variable: Student-Level Academic Achievement			
	Elementary Grades Reading	Elementary Grades Mathematics	Middle Grades Reading	Middle Grades Mathematics
Student-level variance	81.15	78.84	54.08	60.39
Teacher-level variance	9.68	10.70	37.56	33.17
School-level variance	9.17	10.46	8.36	6.44

ICCs were also calculated to determine the variance in teachers' data-use surveys. Specifically presented in Tables D.2 and D.3 is the percent of variance in teachers' data use at the teacher and school level. These ICCs were calculated on the basis of the results of unconditional two-level models (level 1 teachers, level 2 schools) with each teacher data-use scale as the outcome. The majority of variance in teachers' data use was at the teacher level, with less variance at the school level (ranging from 7 to 26 percent) depending on grade and subject.

[15] The second level of the HLM analyses represents teachers, not classrooms. Each teacher is linked with the students in their class(es). Students are linked with only one reading and one mathematics teacher.

Table D.2. Partitioning of Variance (ICCs) in Reading Teachers' Data Use at the Teacher and School Level

	Dependent Variable: Reading Teacher Data Use				
	Context	Support	Instructional Responses	Working with Data	Barriers
Teacher level variance	82.39	81.90	76.34	77.65	88.23
School level variance	17.61	18.10	23.66	22.35	11.77

Table D.3. Partitioning of Variance (ICCs) in Mathematics Teachers' Data Use at the Teacher and School Level

	Dependent Variable: Mathematics Teacher Data Use				
	Context	Support	Instructional Responses	Working with Data	Barriers
Teacher level variance	78.95	80.65	73.21	74.07	92.77
School level variance	21.05	19.35	26.79	25.93	7.23

Addressing Multicollinearity

Following a review of the descriptive statistics and bivariate correlations among the data-use variables, we further specified the HLM and SEM analysis strategy to be used to address the potential issues with multicollinearity. There is currently no direct diagnostic test for multicollinearity in multilevel models. Therefore, we carried out multicollinearity diagnostics in a multiple regression framework, where data-use variables were independent variables, and classroom/school averages of student achievement were dependent variables. We used three collinearity diagnostics: VIF (variance inflation factor), TOL (tolerance), and COLLINOINT (which displays several different measures of collinearity). The large VIF values (greater than 4.0) suggest that there was a high degree of collinearity among these data-use variables.

We then took several steps to address the potential multicollinearity in our subsequent analyses. First, we used all four key dimensions of data to create one latent variable of general data use to adjust for the correlations between each of the dimensions of data use in the SEM analyses.[16] Second, we estimated each dimension of data use separately for teachers and administrators in the HLM analyses, rather than using a model that simultaneously estimated the relationship between all key dimensions of data use and student achievement (which could be plagued by multicollinearity problems). Third, because the two scales *Working with Data* and *Instructional Responses* were consistently the most highly correlated and thus could be considered largely redundant, we combined them into a new variable: *"Attention to Data in the Classroom"* for teachers and *"Attention to Data in the School"* for principals. We used these combined attention to data variables as the predictors in the HLM analyses.

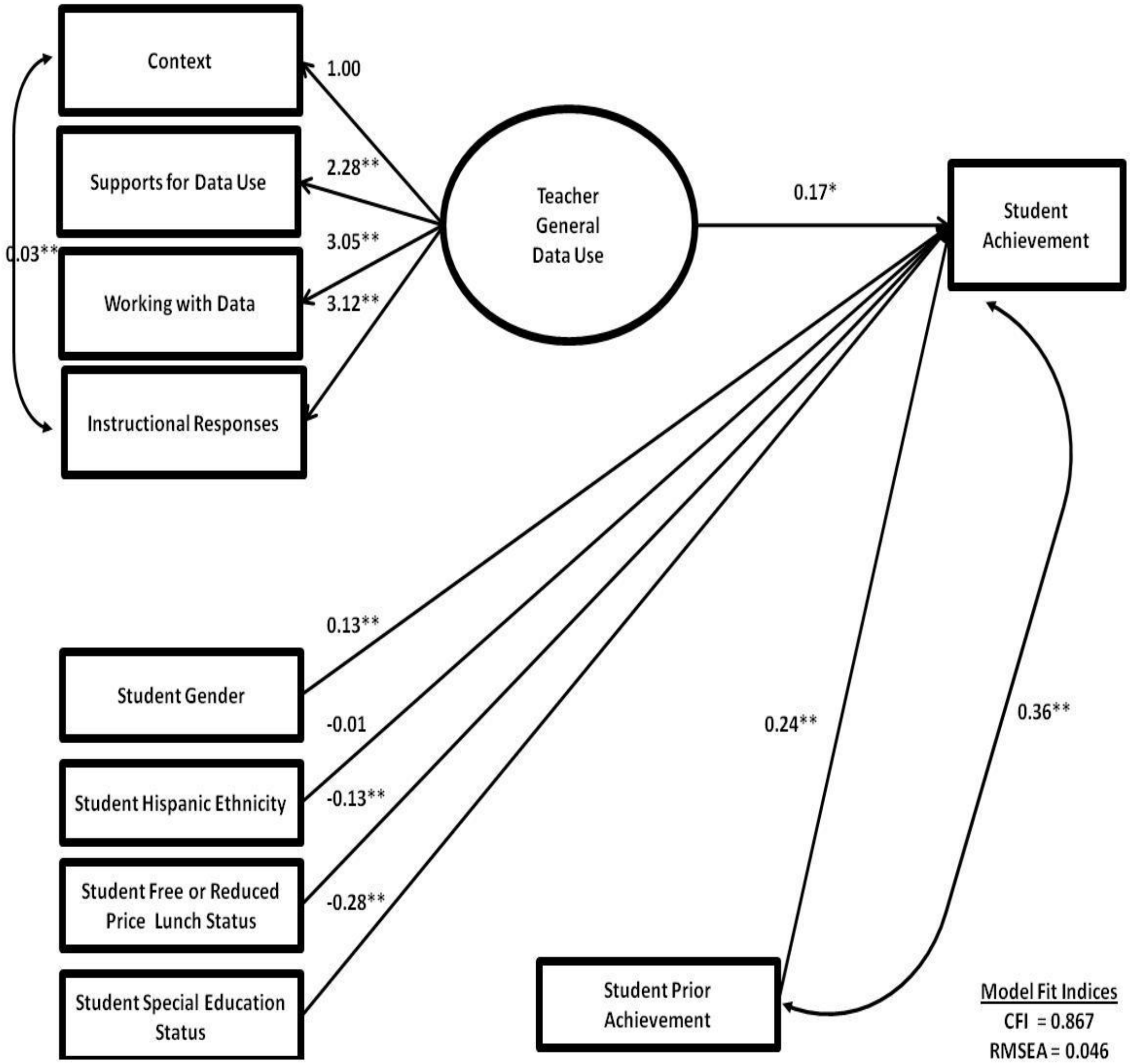
Structural Equation Models (SEMs)

Exhibits D.1–D.8 present the path coefficients for all paths tested in the SEMs of interim assessment data use. Each exhibit is a separate analysis conducted with a different sample of principals, teachers, and students. Exhibits D.1–D.4 present teacher models of general data use, and Exhibits D.5–D.8 present principal models of general data use.

[16] The *Barriers* variable was kept separate, given that its correlations with the other four data-use variables were significant but low or moderate (all below 0.50).

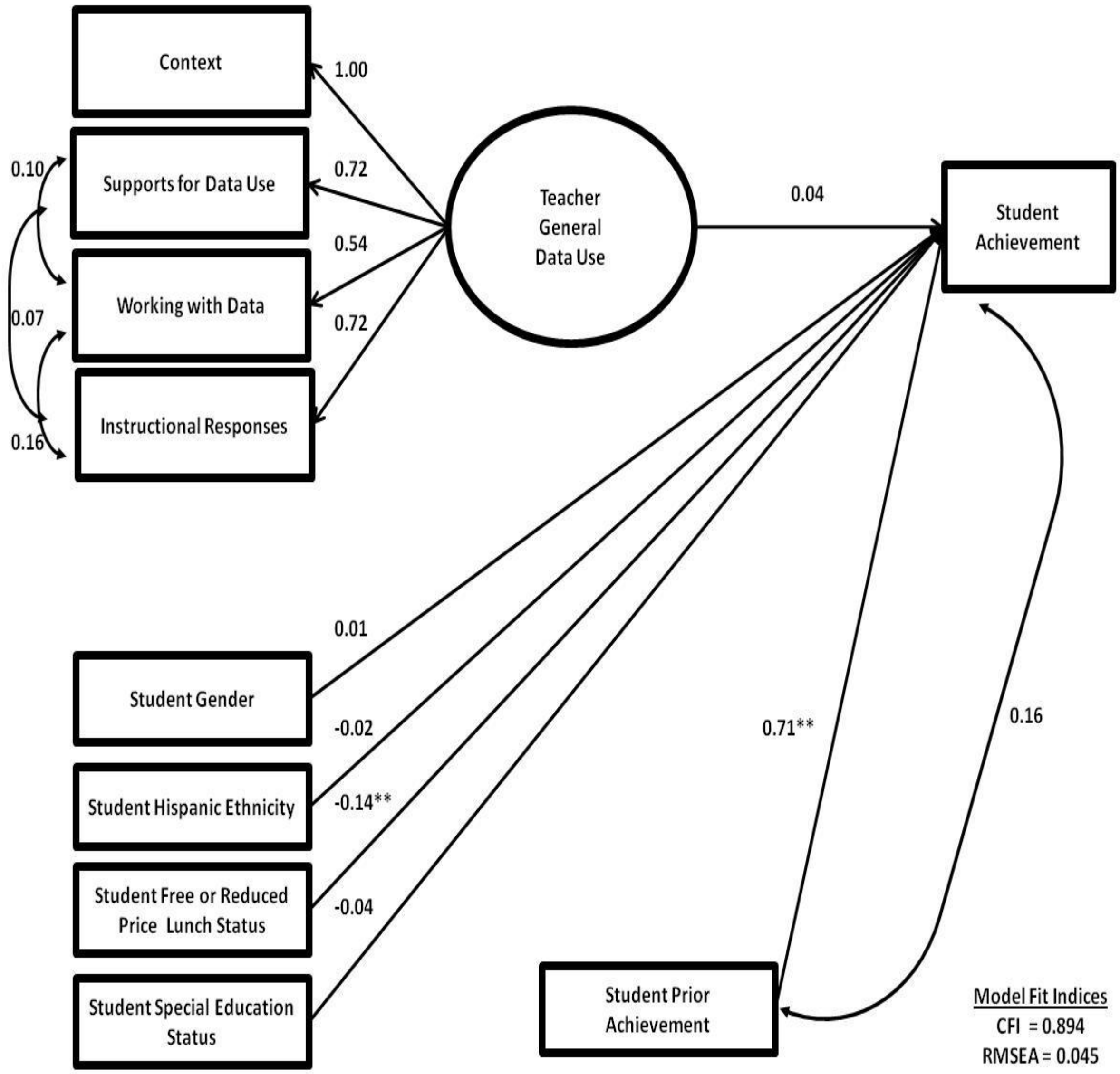
In structural equation modeling, rectangular boxes represent indicators or observed variables, and large circles or ovals represent latent variables. In the following sets of models, each has 10 observed variables (represented by square boxes) and one latent variable for "Teacher/Principal General Data Use" (represented by a large oval). Correlated errors of latent variables and covariances between observed variables are represented by double arrowed lines. Factor loadings and regression paths are represented using lines with only one arrow.

Exhibit D.1. Structural Equation Model of the Relationship Between Teachers' *General Data Use* and Student Achievement in Elementary Grades Reading



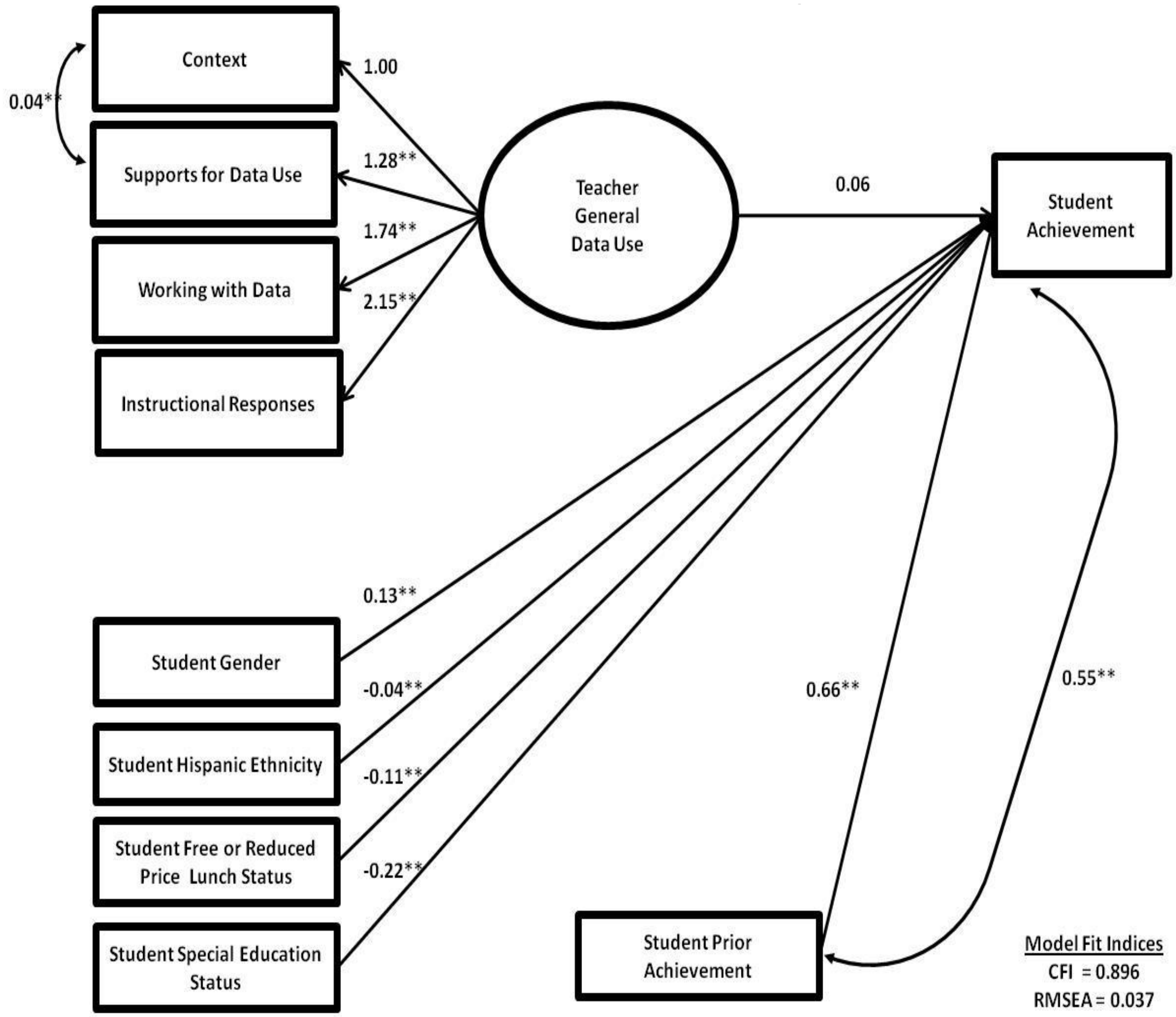
Note. ** $p < .01$, two-tailed; * $p < .05$, two-tailed.

Exhibit D.2. Structural Equation Model of the Relationship Between Teachers' *General Data Use* and Student Achievement in Elementary Grades Mathematics



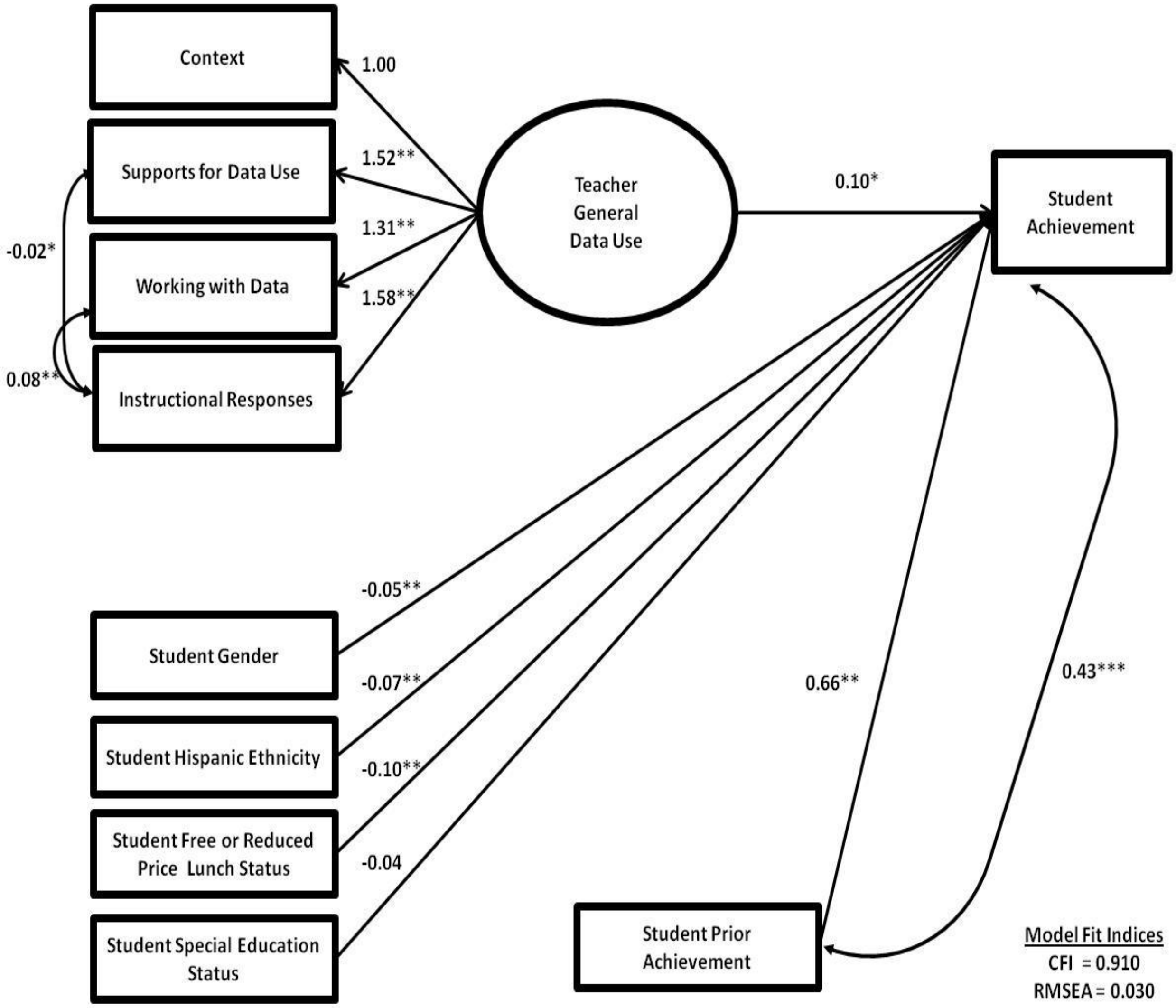
Note. ** p < .01, two-tailed.

Exhibit D.3. Structural Equation Model of the Relationship Between Teachers' *General Data Use* and Student Achievement in Middle Grades Reading



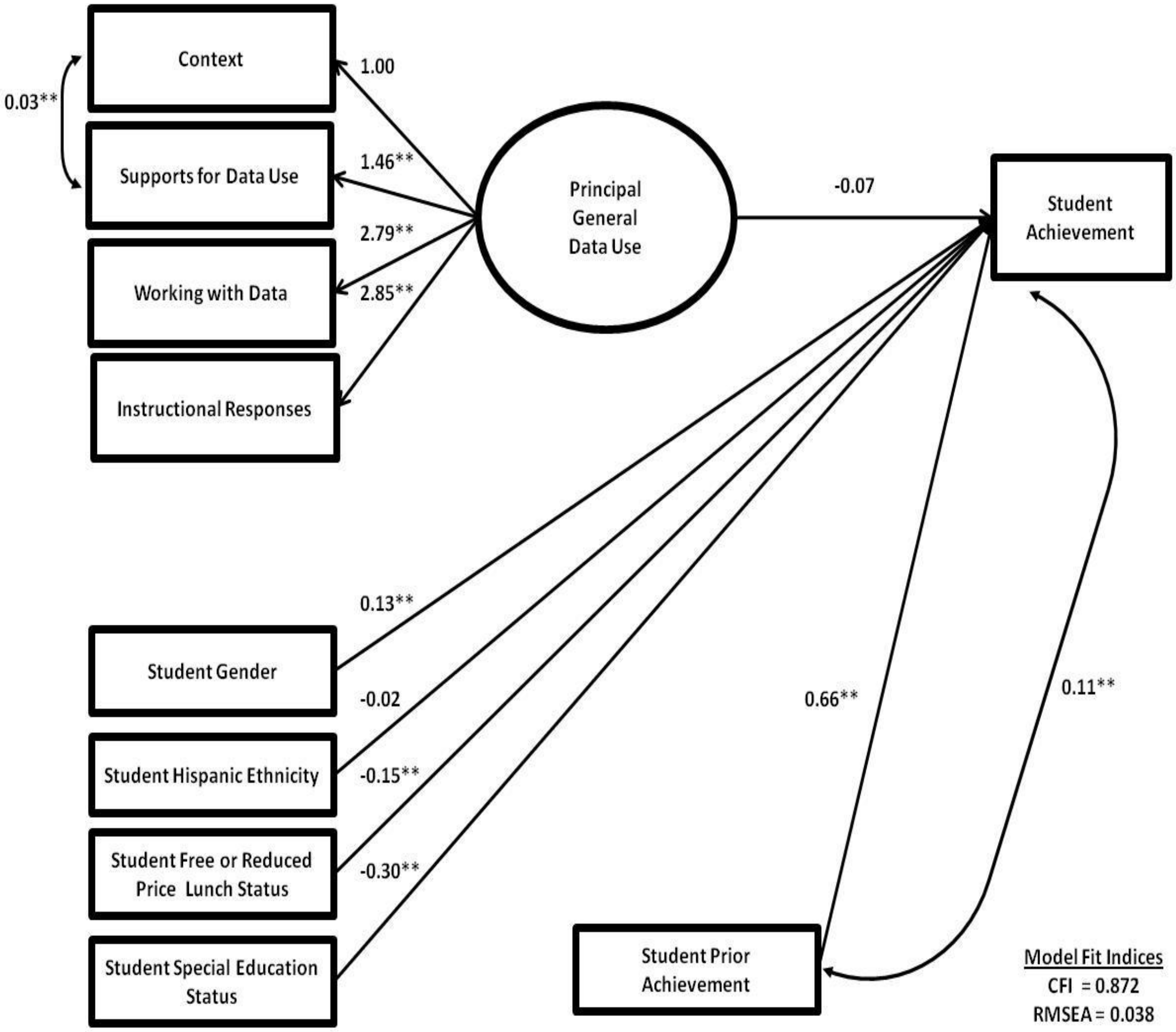
Note. ** p < .01, two-tailed.

Exhibit D.4. Structural Equation Model of the Relationship Between Teachers' *General Data Use* and Student Achievement in Middle Grades Mathematics



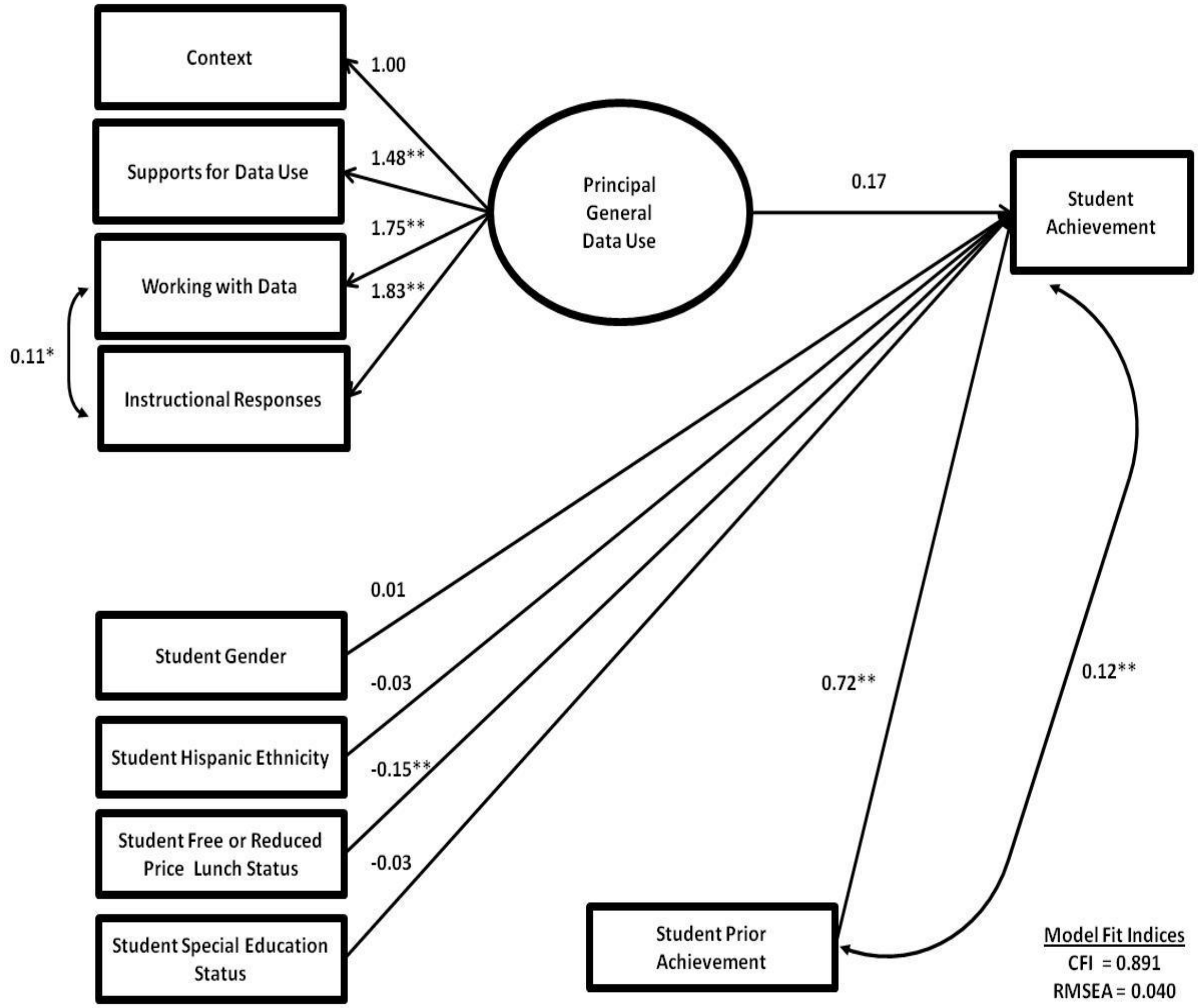
Note. ** p < .01, two-tailed; * p < .05, two-tailed.

Exhibit D.5. Structural Equation Model of the Relationship Between Principals' *General Data Use* and Student Achievement in Elementary Grades Reading



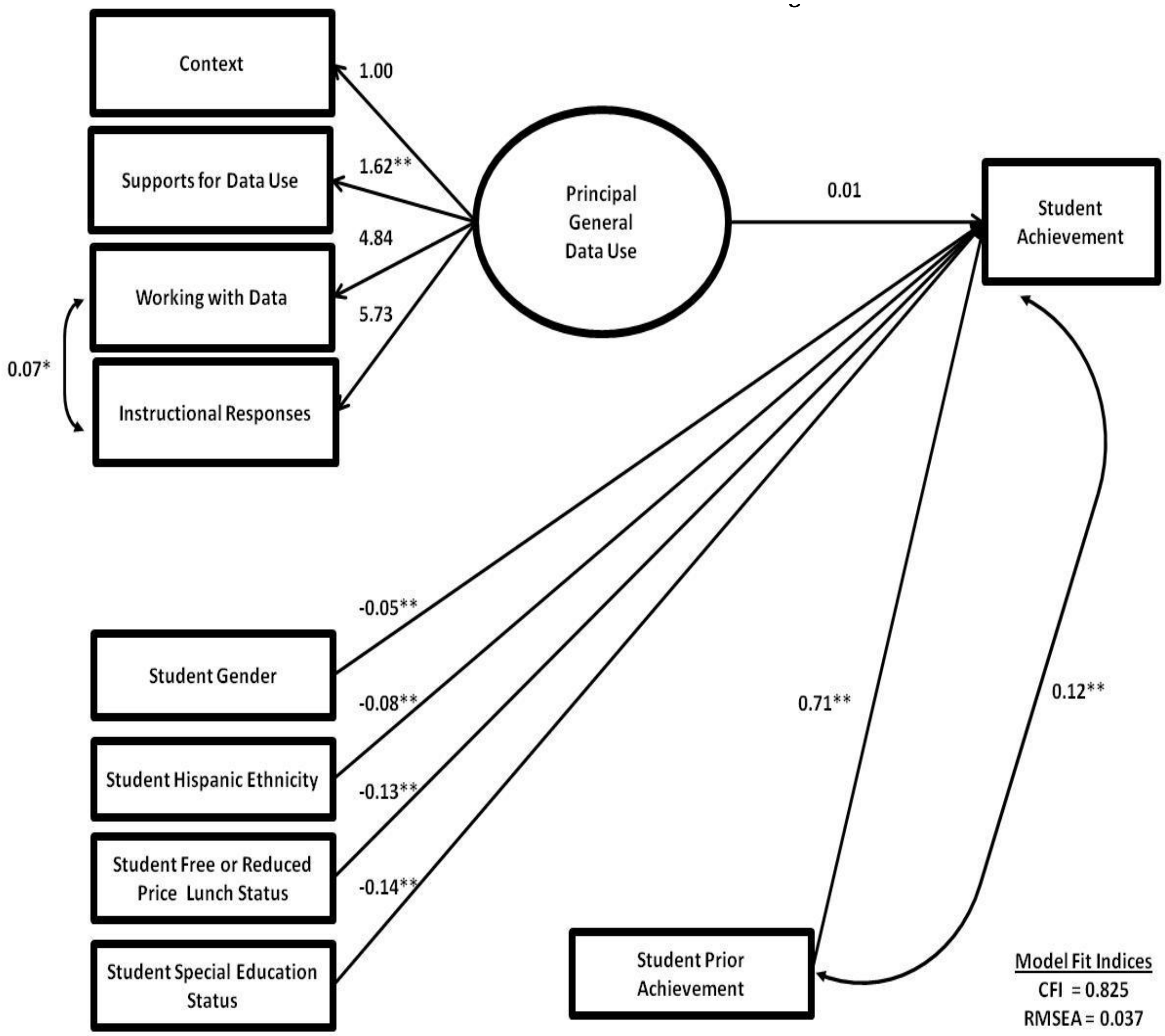
Note. ** p < .01, two-tailed.

Exhibit D.6. Structural Equation Model of the Relationship Between Principals' *General Data Use* and Student Achievement in Elementary Grades Mathematics



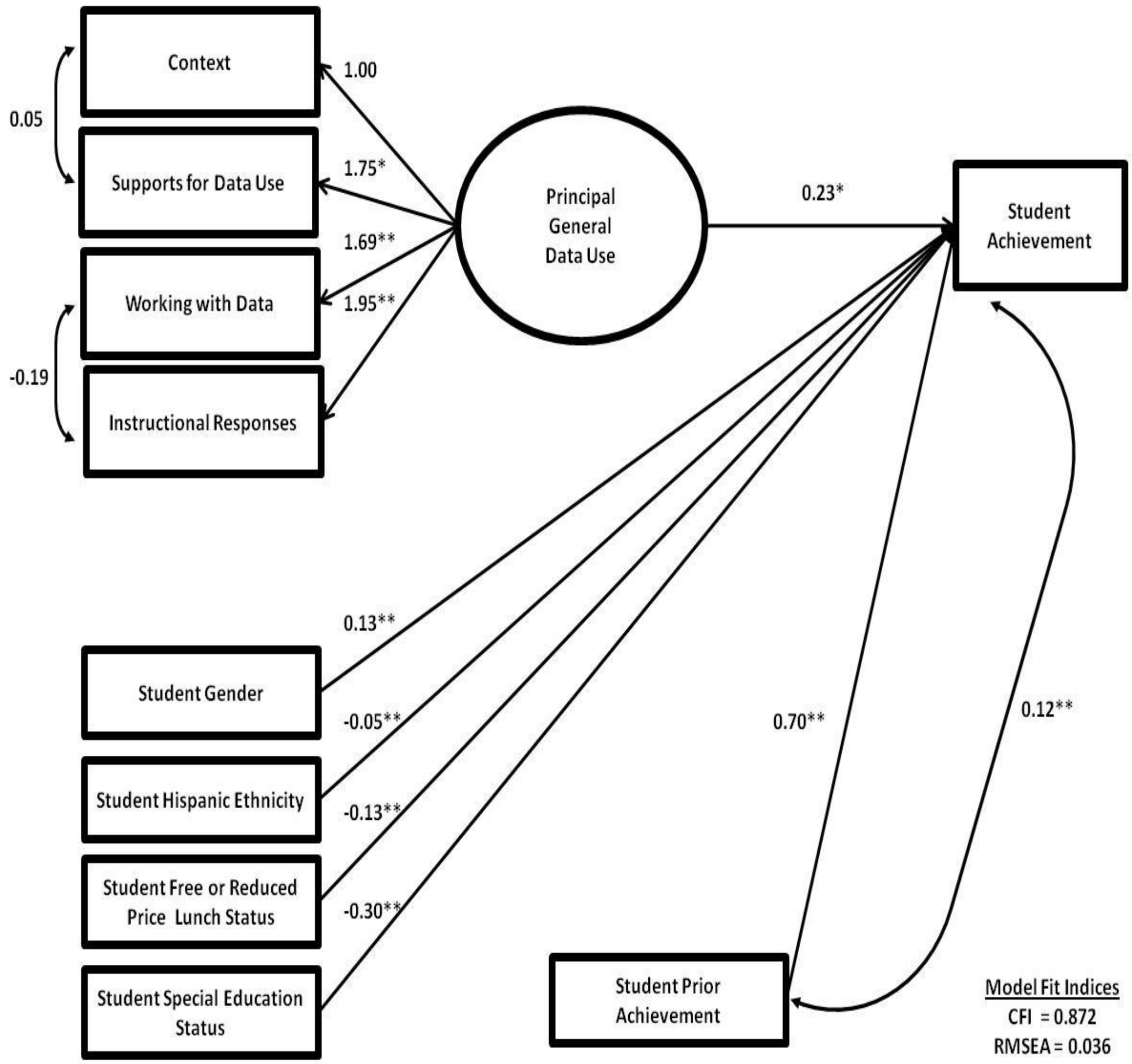
Note. ** p < .01, two-tailed; * p < .05, two-tailed.

Exhibit D.7. Structural Equation Model of the Relationship Between Principals' *General Data Use* and Student Achievement in Middle Grades Reading



Note. ** p < .01, two-tailed; * p < .05, two-tailed.

Exhibit D.8. Structural Equation Model of the Relationship Between Principals' *General Data Use* and Student Achievement in Middle Grades Mathematics



Note. ** p < .01, two-tailed; * p < .05, two-tailed.

Hierarchical Linear Models (HLMs)

Centering of Variables

The measures of data use and student achievement used in the study, like many psychological and educational constructs, are expressed on arbitrary metrics that lack a meaningful zero point. In such situations, centering is often used in estimating hierarchical models, to facilitate interpretation of the intercept (Enders & Tofighi, 2007). We used grand-mean centering for student prior achievement, student demographics, and teacher and principal demographic and teaching experience covariates (Luke, 2004). In other words, all student-level variables and teacher and principal covariates were centered to have a mean of zero across the full sample. Teacher data-use variables were group-mean centered (i.e., centered on the school averages). Principal data-use variables were centered at the grand mean because their scores are constant for each school. These centering decisions are consistent with the guidelines proposed by Enders and Tofighi (2007).

Examining and Selecting Covariates

Before estimating the HLM models to address the research questions, we estimated a set of exploratory three- and two-level models that included student-, teacher-, and school-level covariates to develop a model of important covariates that should be included in the final model. To estimate the control model, we tested each set of covariates separately, beginning with level 1 covariates (student-level variables), followed by level 2 covariates (teacher-level variables), and finally adding level 3 covariates (principal-/school-level variables). All control models also included district indicators, grade-level indicators, prior achievement, and their two-way or three-way interactions. The final control model contains the set of district, grade-level indicators, and all significant covariates from among those listed. Variables tested in the control model and those kept in the final control model are presented in Table D.4.

HLM Final Model Results

Tables D.5–D.36 present the full results for the HLM models of the relations of each data-use dimension and student achievement. These tables all are organized into two main sections, with the first one for fixed effects and the second one for random effects. The Fixed Effect section summarizes unstandardized regression coefficients and standard errors corresponding to the data-use variable and control variables (e.g., district-, school-, teacher-, and student-level covariates, and the interaction terms).

Tables D.5–D.12 present the results for the HLM models of teacher data use and student achievement in mathematics and reading at the elementary grade level. Tables D.13–D.20 present the HLM results of teacher data use and student achievement in mathematics and reading in middle school grades. Tables D.21–D.36 present results of principal data use and student achievement in the two subject matters at both middle and elementary schools.

Table D.4. Covariates Tested in Developing and Included in the Final Control Model

	Variables Tested	Variables Included in the Final Control Model
Covariates		
District indicators	√	√
Grade level	√	√
Prior achievement (reading and mathematics)	√	√
District by grade interactions	√	√
District by prior achievement interactions	√	√
Student Demographics		
Gender	√	√
Hispanic	√	√
Asian (including Pacific Islander)	√	√
African American	√	√
Native American	√	√
Multiracial	√	√
Prior reading achievement	√	√
Free or reduced-price lunch status	√	√
Special education status	√	√
	Variables Tested	**Variables Included in the Final Control Model**
Teacher Covariates		
Gender	√	√
Hispanic	√	
Asian (including Pacific Islander)	√	
African American	√	
Native American	√	
Other racial	√	
Level of education	√	√
Years of teaching	√	√
Classroom average student achievement scores	√	√[a]
Principal Covariates		
Gender	√	
Hispanic	√	
Asian (including Pacific Islander)	√	
African American	√	
Native American	√	
Other racial groups	√	
Level of education	√	
Years of teaching	√	
Years of administration	√	
School average student achievement scores	√	√[b]

[a]Classroom average of student achievement was included in the HLM models only when teacher data use was the predictor.
[b]School average of student achievement was included in the models only when principal reported data use was the predictor.

Table D.5. Estimated Relationship Between *Context for Data Use* Among Elementary School Teachers and Student Achievement in Mathematics (*N*=10,429)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.022	.048	.652
Context for Data Use[a]	.034	.044	.435
District covariates			
District 1 (*versus* District 3)	-.017	.066	.792
District 2 (*versus* District 3)	-.035	.063	.581
District 4 (*versus* District 3)	.090	.068	.186
Teacher-level covariates			
Total years of teaching experience	.002	.002	.299
Education above a bachelor's degree (*versus* bachelor's degree)	.068	.029	.018
Female	.022	.036	.545
Classroom-level prior mathematics achievement[b]	.063	.032	.052
Student-level covariates			
Prior mathematics achievement[c]	.714	.020	< .0001
Grade 5 (*versus* Grade 4)	.008	.047	.861
Hispanic (*versus* white)	-.055	.018	.002
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.092	.030	.002
African American (*versus* white)	-.139	.020	< .0001
American Indian (*versus* white)	-.111	.051	.029
Multiracial (*versus* white)	-.108	.093	.243
Eligible for free or reduced-price lunch	-.120	.016	< .0001
Female	.014	.012	.226
IEP	-.035	.018	.061
Interaction terms			
District 1 × Grade 5	-.032	.065	.622
District 2 × Grade 5	-.046	.064	.473
District 4 × Grade 5	-.033	.077	.671
District 1 × prior mathematics achievement	-.086	.027	.001
District 2 × prior mathematics achievement	-.023	.025	.353
District 4 × prior mathematics achievement	-.166	.031	< .0001
Grade 5 × prior mathematics achievement	.200	.028	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.212	.038	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.129	.035	0
District 4 × Grade 5 × prior mathematics achievement	-.151	.045	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.364	.005	< .0001
Level 2	.053	.005	< .0001
Level 3	.020	.006	0
Total variance	.438		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May, Perez-Johnson, Haimson, Sattar, & Gleason, 2009).

Table D.6. Estimated Relationship Between *Supports for Data Use* Among Elementary School Teachers and Student Achievement in Mathematics (*N*=10,421)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.018	.046	.693
Supports for Data Use[a]	.008	.031	.790
District covariates			
District 1 (*versus* District 3)	-.011	.064	.863
District 2 (*versus* District 3)	-.034	.062	.582
District 4 (*versus* District 3)	.103	.066	.123
Teacher-level covariates			
Total years of teaching experience	.002	.002	.246
Education above a bachelor's degree (*versus* bachelor's degree)	.076	.029	.008
Female	.024	.036	.494
Classroom-level prior mathematics achievement[b]	.068	.032	.032
Student-level covariates			
Prior mathematics achievement[c]	.718	.020	< .0001
Grade 5 (*versus* Grade 4)	.017	.045	.701
Hispanic (*versus* white)	-.058	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.089	.030	.003
African American (*versus* white)	-.143	.019	< .0001
American Indian (*versus* white)	-.120	.051	.018
Multiracial (*versus* white)	-.125	.087	.151
Eligible for free or reduced-price lunch	-.118	.017	< .0001
Female	.011	.012	.346
IEP	-.039	.018	.036
Interaction terms			
District 1 × Grade 5	-.051	.063	.414
District 2 × Grade 5	-.045	.063	.471
District 4 × Grade 5	-.049	.075	.516
District 1 × prior mathematics achievement	-.089	.026	.001
District 2 × prior mathematics achievement	-.023	.024	.353
District 4 × prior mathematics achievement	-.160	.031	< .0001
Grade 5 × prior mathematics achievement	.194	.027	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.208	.037	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.128	.034	0
District 4 × Grade 5 × prior mathematics achievement	-.155	.044	0
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.360	.005	< .0001
Level 2	.051	.005	< .0001
Level 3	0020	.006	0
Total variance	.431		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.7. Estimated Relationship Between *Attention to Data in the Classroom* Among Elementary School Teachers and Student Achievement in Mathematics (*N*=10,642)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.010	.047	.831
Working with Data/Instructional Response[a]	.036	.030	.235
District covariates			
District 1 (*versus* District 3)	-.004	.064	.955
District 2 (*versus* District 3)	-.014	.062	.825
District 4 (*versus* District 3)	.093	.066	.166
Teacher-level covariates			
Total years of teaching experience	.002	.002	.335
Education above a bachelor's degree (*versus* bachelor's degree)	.069	.029	.015
Female	.012	.035	.726
Classroom-level prior mathematics achievement[b]	.064	.031	.038
Student-level covariates			
Prior mathematics achievement[c]	.718	.019	< .0001
Grade 5 (*versus* Grade 4)	.018	.045	.688
Hispanic (*versus* white)	-.056	.018	0002
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.091	.029	.002
African American (*versus* white)	-.144	.019	< .0001
American Indian (*versus* white)	-.117	.050	.020
Multiracial (*versus* white)	-.126	.088	.152
Eligible for free or reduced-price lunch	-.119	.016	< .0001
Female	.013	.012	.266
IEP	-.030	.018	.096
Interaction terms			
District 1 × Grade 5	-.041	.063	.515
District 2 × Grade 5	-.061	.062	.330
District 4 × Grade 5	-.044	.075	.564
District 1 × prior mathematics achievement	-.090	.026	.001
District 2 × prior mathematics achievement	-.027	.024	.264
District 4 × prior mathematics Achievement	-.170	.030	< .0001
Grade 5 × prior mathematics achievement	.195	.027	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.207	.037	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.125	.034	0
District 4 × Grade 5 × prior mathematics achievement	0.147	.044	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.361	.005	< .0001
Level 2	.053	.005	< .0001
Level 3	.020	.006	0
Total variance	.434		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.8. Estimated Relationship Between *Barriers to Data Use* Among Elementary School Teachers and Student Achievement in Mathematics (N=10,379)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.017	.046	.718
Barriers to Data Use[a]	-.079	.032	.014
District covariates			
District 1 (*versus* District 3)	-.007	.064	.914
District 2 (*versus* District 3)	-.037	.062	.552
District 4 (*versus* District 3)	.113	.067	.094
Teacher-level covariates			
Total years of teaching experience	.002	.002	.213
Education above a bachelor's degree (*versus* bachelor's degree)	.080	.028	.004
Female	.018	.035	.604
Classroom-level prior mathematics achievement[b]	.077	.031	.014
Student-level covariates			
Prior mathematics achievement[c]	.716	.020	< .0001
Grade 5 (*versus* Grade 4)	.016	.044	.721
Hispanic (*versus* white)	-.062	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.086	.030	.004
African American (*versus* white)	-.145	.019	< .0001
American Indian (*versus* white)	-.123	.051	.015
Multiracial (*versus* white)	-.132	.088	.135
Eligible for free or reduced-price lunch	-.116	.017	< .0001
Female	.012	.012	.299
IEP	-.040	.018	.028
Interaction terms			
District 1 × Grade 5	-.052	.062	.398
District 2 × Grade 5	.040	.061	.513
District 4 × Grade 5	-.091	.074	.219
District 1 × prior mathematics achievement	-.088	.026	.001
District 2 × prior mathematics achievement	-.022	.024	.366
District 4 × prior mathematics achievement	-.159	.031	< .0001
Grade 5 × prior mathematics achievement	.195	.027	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.210	.037	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.131	.034	0
District 4 × Grade 5 × prior mathematics achievement	-.144	.044	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.360	.005	< .0001
Level 2	.048	.005	< .0001
Level 3	.021	.006	< .0001
Total variance	.429		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate scores into a common metric. All scores were standardized to Z-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using Z-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.9. Estimated Relationship Between *Context for Data Use* Among Elementary School Teachers and Student Achievement in Reading (*N*=10,761)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.019	.039	.640
Context for Data Use[a]	.031	.037	.398
District covariates			
District 1 (*versus* District 3)	-.009	.055	.876
District 2 (*versus* District 3)	-.052	.052	.324
District 4 (*versus* District 3)	.045	.056	.424
Teacher-level covariates			
Total years of teaching experience	.002	.001	.115
Education above a bachelor's degree (*versus* bachelor's degree)	.025	.025	.328
Female	-.015	.031	.633
Classroom-level prior reading achievement[b]	.158	.030	< .0001
Student-level covariates			
Prior reading achievement[c]	.652	.020	< .0001
Grade 5 (*versus* Grade 4)	-.005	.044	.910
Hispanic (*versus* white)	-.061	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.008	.031	.783
African American (*versus* white)	-.137	.020	< .0001
American Indian (*versus* white)	-.284	.052	< .0001
Multiracial (*versus* white)	-.101	.091	.267
Eligible for free or reduced-price lunch	-.107	.017	< .0001
Female	.132	.012	< .0001
IEP	-.254	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.017	.060	.781
District 2 × Grade 5	.002	.059	.974
District 4 × Grade 5	-.006	.067	.933
District 1 × prior reading achievement	-.032	.027	.240
District 2 × prior reading achievement	.039	.025	.113
District 4 × prior reading achievement	-.108	.030	0
Grade 5 × prior reading achievement	.247	.028	< .0001
District 1 × Grade 5 × prior reading achievement	-.320	.038	< .0001
District 2 × Grade 5 × prior reading achievement	-.203	.035	< .0001
District 4 × Grade 5 × prior reading achievement	-.275	.044	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.386	.005	< .0001
Level 2	.040	.005	< .0001
Level 3	.010	.004	.004
Total variance	.437		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.10. Estimated Relationship Between *Supports for Data Use* Among Elementary School Teachers and Student Achievement in Reading (*N*=10,598)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.016	.039	.681
Supports for Data Use[a]	-.008	.028	.764
District covariates			
District 1 (*versus* District 3)	-.007	.054	.896
District 2 (*versus* District 3)	-.049	.052	.348
District 4 (*versus* District 3)	.065	.056	.248
Teacher-level covariates			
Total years of teaching experience	.002	.001	.083
Education above a bachelor's degree (*versus* bachelor's degree)	.033	.025	.198
Female	-.014	.031	.656
Classroom-level prior reading achievement[b]	.163	.030	< .0001
Student-level covariates			
Prior reading achievement[c]	.654	.020	< .0001
Grade 5 (*versus* Grade 4)	-.004	.043	.927
Hispanic (*versus* white)	-.058	.019	.002
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.013	.031	.683
African American (*versus* white)	-.135	.020	< .0001
American Indian (*versus* white)	-.283	.052	< .0001
Multiracial (*versus* white)	-.107	.091	.243
Eligible for free or reduced-price lunch	-.106	.017	< .0001
Female	.131	.012	< .0001
IEP	-.255	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.019	.059	.747
District 2 × Grade 5	.004	.059	.944
District 4 × Grade 5	-.024	.067	.715
District 1 × prior reading achievement	-.035	.027	.198
District 2 × prior reading achievement	.048	.025	.056
District 4 × prior reading achievement	-.115	.031	0
Grade 5 × prior reading achievement	.250	.027	< .0001
District 1 × Grade 5 × prior reading achievement	-.323	.038	< .0001
District 2 × Grade 5 × prior reading achievement	-.216	.035	< .0001
District 4 × Grade 5 × prior reading achievement	-.273	.044	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.386	.005	< .0001
Level 2	.039	.005	< .0001
Level 3	.010	.004	.004
Total variance	.435		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.11. Estimated Relationship Between *Attention to Data in the Classroom* Among Elementary School Teachers and Student Achievement in Reading (*N*=10,892)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.005	.039	.901
Working with Data/Instructional Response[a]	.063	.026	.014
District covariates			
District 1 (*versus* District 3)	.008	.054	.885
District 2 (*versus* District 3)	-.028	.052	.600
District 4 (*versus* District 3)	.039	.056	.486
Teacher-level covariates			
Total years of teaching experience	.002	.001	.165
Education above a bachelor's degree (*versus* bachelor's degree)	.026	.025	.300
Female	-.021	.031	.494
Classroom-level prior reading achievement[b]	.164	.030	< .0001
Student-level covariates			
Prior reading achievement[c]	.653	.020	< .0001
Grade 5 (*versus* Grade 4)	-.008	.043	.850
Hispanic (*versus* white)	-.062	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.010	.030	.751
African American (*versus* white)	-.137	.019	< .0001
American Indian (*versus* white)	-.284	.051	< .0001
Multiracial (*versus* white)	-.104	.090	.249
Eligible for free or reduced-price lunch	-.106	.016	< .0001
Female	.134	.012	< .0001
IEP	-.247	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.010	.059	.868
District 2 × Grade 5	.002	.058	.972
District 4 × Grade 5	.001	.067	.988
District 1 × prior reading achievement	-.032	.027	.227
District 2 × prior reading achievement	.035	.024	.154
District 4 × prior reading achievement	-.108	.030	0
Grade 5 × prior reading achievement	.252	.027	< .0001
District 1 × Grade 5 × prior reading achievement	-.326	.037	< .0001
District 2 × Grade 5 × prior reading achievement	-.204	.034	< .0001
District 4 × Grade 5 × prior reading achievement	-.280	.043	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.385	.005	< .0001
Level 2	.039	.004	< .0001
Level 3	.010	.004	.003
Total variance	.434		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.12. Estimated Relationship Between *Barriers to Data Use* Among Elementary School Teachers and Student Achievement in Reading (N=10,557)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.016	.039	.681
Barriers to Data Use[a]	-.019	.029	.524
District covariates			
District 1 (*versus* District 3)	-.006	.054	.906
District 2 (*versus* District 3)	-.049	.052	.346
District 4 (*versus* District 3)	.068	.056	.223
Teacher-level covariates			
Total years of teaching experience	.002	.001	.082
Education above a bachelor's degree (*versus* bachelor's degree)	.033	.025	.192
Female	-.015	.031	.631
Classroom-level prior reading achievement[b]	.162	.030	< .0001
Student-level covariates			
Prior reading achievement[c]	.654	.020	< .0001
Grade 5 (*versus* Grade 4)	-.003	.043	.942
Hispanic (*versus* white)	-.060	.019	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.015	.031	.636
African American (*versus* white)	-.136	.020	< .0001
American Indian (*versus* white)	-.284	.052	< .0001
Multiracial (*versus* white)	-.112	.092	.223
Eligible for free or reduced-price lunch	-.106	.017	< .0001
Female	.131	.012	< .0001
IEP	-.255	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.019	.059	.752
District 2 × Grade 5	.001	.059	.983
District 4 × Grade 5	-.042	.067	.535
District 1 × prior reading achievement	-.034	.027	0204
District 2 × prior reading achievement	.046	.025	.063
District 4 × prior reading achievement	-.115	.031	0
Grade 5 × prior reading achievement	.252	.027	< .0001
District 1 × Grade 5 × prior reading achievement	-.325	.038	< .0001
District 2 × Grade 5 × prior reading achievement	-.218	.035	< .0001
District 4 × Grade 5 × prior reading achievement	-.266	.044	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.387	.005	< .0001
Level 2	.039	.005	< .0001
Level 3	.009	.004	.005
Total variance	.435		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to Z-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using Z-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.13. Estimated Relationship Between *Context for Data Use* Among Middle School Teachers and Student Achievement in Mathematics (*N*=30,378)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.013	.039	.745
Context for Data Use[a]	.035	.040	.382
District covariates			
District 1 (*versus* District 3)	.007	.048	.893
District 2 (*versus* District 3)	.002	.046	.958
District 4 (*versus* District 3)	.290	.072	.000
Teacher-level covariates			
Total years of teaching experience	.000	.002	.749
Education above a bachelor's degree (*versus* bachelor's degree)	.024	.029	.405
Female	.015	.029	.599
Classroom-level prior mathematics achievement[b]	.298	.021	< .0001
Student-level covariates			
Prior mathematics achievement[c]	.750	.012	< .0001
Grade 8 (*versus* Grade 7)	.065	.045	.149
Hispanic (*versus* white)	-.103	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.079	.015	< .0001
African American (*versus* white)	-.125	.011	< .0001
American Indian (*versus* white)	-.096	.033	.003
Multiracial (*versus* white)	-.047	.079	.552
Eligible for free or reduced-price lunch	-.094	.009	< .0001
Female	-.036	.007	< .0001
IEP	.002	.013	.881
Interaction terms			
District 1 × Grade 8	-.230	.052	< .0001
District 2 × Grade 8	-.108	.049	.027
District 4 × Grade 8	-.086	.076	.258
District 1 × prior mathematics achievement	-.305	.016	< .0001
District 2 × prior mathematics achievement	-.017	.014	.237
District 4 × prior mathematics achievement	-.195	.031	< .0001
Grade 8 × prior mathematics achievement	.054	.017	.002
District 1 × Grade 8 × prior mathematics achievement	-.093	.023	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.113	.020	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.108	.049	.028
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.055	.005	< .0001
Level 3	.002	.002	.204
Total variance	.404		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.14. Estimated Relationship Between *Supports for Data Use* Among Middle School Teachers and Student Achievement in Mathematics (*N*=28,902)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.019	.040	.629
Supports for Data Use[a]	-.005	.035	.892
District covariates			
District 1 (*versus* District 3)	0	.049	.998
District 2 (*versus* District 3)	-.003	.047	.941
District 4 (*versus* District 3)	.286	.075	0
Teacher-level covariates			
Total years of teaching experience	.001	.002	.672
Education above a bachelor's degree (*versus* bachelor's degree)	.024	.030	.419
Female	.011	.030	.704
Classroom-level prior mathematics achievement[b]	.298	.021	< .0001
Student-level covariates			
Prior mathematics achievement[c]	.752	.012	< .0001
Grade 8 (*versus* Grade 7)	.058	.045	.206
Hispanic (*versus* white)	-.106	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.074	.016	< .0001
African American (*versus* white)	-.126	.012	< .0001
American Indian (*versus* white)	-.093	.034	.006
Multiracial (*versus* white)	-.052	.083	.532
Eligible for free or reduced-price lunch	-.094	.009	< .0001
Female	-.035	.007	< .0001
IEP	.008	.013	.557
Interaction terms			
District 1 × Grade 8	-.241	.053	< .0001
District 2 × Grade 8	-.097	.049	.048
District 4 × Grade 8	-.097	.078	.212
District 1 × prior mathematics achievement	-.313	.017	< .0001
District 2 × prior mathematics achievement	-.019	.014	.192
District 4 × prior mathematics achievement	-.212	.032	< .0001
Grade 8 × prior mathematics achievement	.043	.018	.014
District 1 × Grade 8 × prior mathematics achievement	-.101	.024	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.105	.021	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.033	.053	.532
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.346	.003	< .0001
Level 2	.056	.005	< .0001
Level 3	.002	.003	.210
Total variance	.404		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.15. Estimated Relationship Between *Attention to Data in the Classroom* Among Middle School Teachers and Student Achievement in Mathematics (*N*=30,368)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.011	.039	.776
Working with Data/Instructional Response[a]	.093	.026	.000
District covariates			
District 1 (*versus* District 3)	.012	.047	.793
District 2 (*versus* District 3)	.024	.045	.593
District 4 (*versus* District 3)	.257	.072	.001
Teacher-level covariates			
Total years of teaching experience	.000	.002	.794
Education above a bachelor's degree (*versus* bachelor's degree)	.020	.028	.491
Female	.025	.029	.377
Classroom-level prior mathematics achievement[b]	.306	.020	< .0001
Student-level covariates			
Prior mathematics achievement[c]	.750	.012	< .0001
Grade 8 (*versus* Grade 7)	.065	.045	.147
Hispanic (*versus* white)	-.103	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.079	.015	< .0001
African American (*versus* white)	-.125	.011	< .0001
American Indian (*versus* white)	-.095	.033	.003
Multiracial (*versus* white)	-.047	.079	.551
Eligible for free or reduced-price lunch	-.095	.009	< .0001
Female	-.036	.007	< .0001
IEP	.003	.013	.813
Interaction terms			
District 1 × Grade 8	-.226	.052	< .0001
District 2 × Grade 8	-.108	.049	.027
District 4 × Grade 8	-.089	.076	.238
District 1 × prior mathematics achievement	-.306	.016	< .0001
District 2 × prior mathematics achievement	-.017	.014	.230
District 4 × prior mathematics achievement	-.194	.031	< .0001
Grade 8 × prior mathematics achievement	.053	.017	.002
District 1 × Grade 8 × prior mathematics achievement	-.092	.023	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.113	.020	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.108	.049	.027
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.054	.005	< .0001
Level 3	.001	.002	.253
Total variance	.403		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.16. Estimated Relationship Between *Barriers to Data Use* Among Middle School Teachers and Student Achievement in Mathematics (*N*=28,402)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.023	.040	.565
Barriers to Data Use[a]	-.037	.033	.267
District covariates			
District 1 (*versus* District 3)	-.006	.050	.906
District 2 (*versus* District 3)	-.005	.047	.922
District 4 (*versus* District 3)	.281	.075	.000
Teacher-level covariates			
Total years of teaching experience	.001	.002	.665
Education above a bachelor's degree (*versus* bachelor's degree)	.017	.030	.559
Female	.003	.030	.926
Classroom-level prior mathematics achievement[b]	.303	.021	< .0001
Student-level covariates			
Prior mathematics achievement[c]	.752	.012	< .0001
Grade 8 (*versus* Grade 7)	.055	.045	.222
Hispanic (*versus* white)	-.104	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.074	.016	< .0001
African American (*versus* white)	-.126	.012	< .0001
American Indian (*versus* white)	-.102	.034	.003
Multiracial (*versus* white)	-.051	.082	.532
Eligible for free or reduced-price lunch	-.094	.009	< .0001
Female	-.037	.007	< .0001
IEP	.011	.013	.397
Interaction terms			
District 1 × Grade 8	-.235	.053	< .0001
District 2 × Grade 8	-.101	.049	.041
District 4 × Grade 8	-.094	.077	.223
District 1 × prior mathematics achievement	-.303	.017	< .0001
District 2 × prior mathematics achievement	-.018	.014	.217
District 4 × prior mathematics achievement	-.213	.031	< .0001
Grade 8 × prior mathematics achievement	.043	.018	.016
District 1 × Grade 8 × prior mathematics achievement	-.110	.024	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.103	.021	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.031	.053	.555
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.345	.003	< .0001
Level 2	.054	.005	< .0001
Level 3	.003	.003	.152
Total variance	.401		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.17. Estimated Relationship Between *Context for Data Use* Among Middle School Teachers and Student Achievement in Reading (*N*=27,580)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.083	.040	.041
Context for Data Use[a]	.057	.031	.067
District covariates			
District 1 (*versus* District 3)	-.081	.052	.121
District 2 (*versus* District 3)	-.076	.048	.121
District 4 (*versus* District 3)	.010	.073	.888
Teacher-level covariates			
Total years of teaching experience	.001	.001	.608
Education above a bachelor's degree (*versus* bachelor's degree)	-.023	.027	.379
Female	.048	.032	.135
Classroom-level prior reading achievement[b]	.285	.018	< .0001
Student-level covariates			
Prior reading achievement[c]	.695	.012	< .0001
Grade 8 (*versus* Grade 7)	-.020	.041	.630
Hispanic (*versus* white)	-.076	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.002	.015	.921
African American (*versus* white)	-.125	.012	< .0001
American Indian (*versus* white)	-.144	.033	< .0001
Multiracial (*versus* white)	-.073	.082	.371
Eligible for free or reduced-price lunch	-.091	.009	< .0001
Female	.114	.007	< .0001
IEP	-.224	.014	< .0001
Interaction terms			
District 1 × Grade 8	-.071	.049	.143
District 2 × Grade 8	.047	.046	.315
District 4 × Grade 8	.034	.067	.614
District 1 × prior reading achievement	-.206	.018	< .0001
District 2 × prior reading achievement	.017	.015	.238
District 4 × prior reading achievement	-.093	.029	.001
Grade 8 × prior reading achievement	-.006	.019	.758
District 1 × Grade 8 × prior reading achievement	-.043	.025	.087
District 2 × Grade 8 × prior reading achievement	.011	.022	.630
District 4 × Grade 8 × Prior reading achievement	-.045	.040	.259
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.342	.003	< .0001
Level 2	.039	.004	< .0001
Level 3	.010	.003	.001
Total variance	.392		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.18. Estimated Relationship Between *Supports for Data Use* Among Middle School Teachers and Student Achievement in Reading (*N*=26,634)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.086	.040	.032
Supports for Data Use[a]	.010	.030	.751
District covariates			
District 1 (*versus* District 3)	-.082	.051	.115
District 2 (*versus* District 3)	-.088	.048	.070
District 4 (*versus* District 3)	.005	.073	.944
Teacher-level covariates			
Total years of teaching experience	0	.001	.806
Education above a bachelor's degree (*versus* bachelor's degree)	-.024	.027	.370
Female	.062	.033	.059
Classroom-level prior reading achievement[b]	.285	.018	< .0001
Student-level covariates			
Prior reading achievement[c]	.695	.012	< .0001
Grade 8 (*versus* Grade 7)	-.024	.041	.553
Hispanic (*versus* white)	-.078	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.003	.016	.828
African American (*versus* white)	-.128	.012	< .0001
American Indian (*versus* white)	-.153	.034	< .0001
Multiracial (*versus* white)	-.074	.082	.364
Eligible for free or reduced-price lunch	-.087	.010	< .0001
Female	.115	.007	< .0001
IEP	-.221	.014	< .0001
Interaction terms			
District 1 × Grade 8	-.070	.049	.153
District 2 × Grade 8	.067	.047	.151
District 4 × Grade 8	.027	.068	.697
District 1 × prior reading achievement	-.195	.018	< .0001
District 2 × prior reading achievement	.015	.015	.299
District 4 × prior reading achievement	-.088	.030	.003
Grade 8 × prior reading achievement	-.004	.019	.842
District 1 × Grade 8 × prior reading achievement	-.062	.026	.016
District 2 × Grade 8 × prior reading achievement	.016	.022	.473
District 4 × Grade 8 × prior reading achievement	-.069	.041	.091
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.343	.003	< .0001
Level 2	.041	.005	< .0001
Level 3	.009	.003	.003
Total variance	.393		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.19. Estimated Relationship Between *Attention to Data in the Classroom* Among Middle School Teachers and Student Achievement in Reading (*N*=27,697)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.081	.040	.047
Working with Data/Instructional Response[a]	.017	.023	.467
District covariates			
District 1 (*versus* District 3)	-.077	.051	.141
District 2 (*versus* District 3)	-.072	.049	.143
District 4 (*versus* District 3)	.005	.072	.941
Teacher-level covariates			
Total years of teaching experience	.001	.001	.586
Education above a bachelor's degree (*versus* bachelor's degree)	-.024	.027	.364
Female	.052	.032	.104
Classroom-level prior reading achievement[b]	.283	.018	< .0001
Student-level covariates			
Prior reading achievement[c]	.695	.012	< .0001
Grade 8 (*versus* Grade 7)	-.021	.041	.610
Hispanic (*versus* white)	-.076	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.002	.015	.895
African American (*versus* white)	-.124	.012	< .0001
American Indian (*versus* white)	-.144	.033	< .0001
Multiracial (*versus* white)	-.073	.082	.374
Eligible for free or reduced-price lunch	-.091	.009	< .0001
Female	.115	.007	< .0001
IEP	-.225	.014	< .0001
Interaction terms			
District 1 × Grade 8	-.072	.048	.137
District 2 × Grade 8	.048	.046	.295
District 4 × Grade 8	.038	.067	.572
District 1 × prior reading achievement	-.205	.018	< .0001
District 2 × prior reading achievement	.017	.015	.241
District 4 × prior reading achievement	-.094	.029	.001
Grade 8 × prior reading achievement	-.004	.019	.828
District 1 × Grade 8 × prior reading achievement	-.046	.025	.066
District 2 × Grade 8 × prior reading achievement	.009	.022	.679
District 4 × Grade 8 × prior reading achievement	-.047	.040	.242
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.342	.003	< .0001
Level 2	.040	.004	< .0001
Level 3	.010	.003	.001
Total variance	.392		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.20. Estimated Relationship Between *Barriers to Data Use* Among Middle School Teachers and Student Achievement in Reading (*N*=26,710)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.087	.040	.034
Barriers to Data Use[a]	-.002	.028	.957
District covariates			
District 1 (*versus* District 3)	-.086	.052	.102
District 2 (*versus* District 3)	-.088	.049	.074
District 4 (*versus* District 3)	.015	.074	.838
Teacher-level covariates			
Total years of teaching experience	0	.001	.890
Education above a bachelor's degree (*versus* bachelor's degree)	-.027	.027	.331
Female	.063	.033	.059
Classroom-level prior reading achievement[b]	.284	.018	< .0001
Student-level covariates			
Prior reading achievement[c]	.695	.012	< .0001
Grade 8 (*versus* Grade 7)	-.024	.041	.557
Hispanic (*versus* white)	-.077	.010	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.005	.016	.749
African American (*versus* white)	-.128	.012	< .0001
American Indian (*versus* white)	-.146	.034	< .0001
Multiracial (*versus* white)	-.074	.082	.365
Eligible for free or reduced-price lunch	-.089	.010	< .0001
Female	.116	.007	< .0001
IEP	-.224	.014	< .0001
Interaction terms			
District 1 × Grade 8	-.071	.049	.153
District 2 × Grade 8	.068	.047	.149
District 4 × Grade 8	.026	.069	.709
District 1 × prior reading achievement	-.208	.018	< .0001
District 2 × prior reading achievement	.015	.015	.301
District 4 × prior reading achievement	-.094	.030	.002
Grade 8 × prior reading achievement	-.004	.019	.845
District 1 × Grade 8 × prior reading achievement	-.050	.025	.049
District 2 × Grade 8 × prior reading achievement	.015	.022	.481
District 4 × Grade 8 × prior reading achievement	-.060	.041	.145
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.344	.003	< .0001
Level 2	.042	.005	< .0001
Level 3	.010	.003	.002
Total variance	.395		

[a]The key dimensions of data use for teachers were group-mean centered. [b]Values are standardized classroom-level aggregates of students' prior achievement. Each teacher has one unique value for the average of their students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.21. Estimated Relationship Between *Context for Data Use* Among Elementary School Principals and Student Achievement in Mathematics (*N*=10,073)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.014	.048	.777
Context for Data Use[a]	.086	.060	.152
District covariates			
District 1 (*versus* District 3)	.016	.069	.818
District 2 (*versus* District 3)	-.007	.064	.915
District 4 (*versus* District 3)	.111	.067	.103
School-level covariates			
School-level prior mathematics achievement[b]	.084	.054	.123
Teacher-level covariates			
Total years of teaching experience	.002	.002	.177
Education above a bachelor's degree (*versus* bachelor's degree)	.070	.029	.016
Female	.021	.036	.560
Student-level covariates			
Prior mathematics achievement[c]	.724	.020	< .0001
Grade 5 (*versus* Grade 4)	.008	.047	.868
Hispanic (*versus* white)	-.060	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.087	.031	.005
African American (*versus* white)	-.147	.020	< .0001
American Indian (*versus* white)	-.047	.050	.350
Multiracial (*versus* white)	-.107	.090	.236
Eligible for free or reduced-price lunch	-.110	.016	< .0001
Female	.008	.012	.504
IEP	-.028	.018	.129
Interaction terms			
District 1 × Grade 5	-.021	.065	.740
District 2 × Grade 5	-.042	.065	.519
District 4 × Grade 5	-.046	.077	.552
District 1 × prior mathematics achievement	-.038	.027	.163
District 2 × prior mathematics achievement	-.022	.025	.378
District 4 × prior mathematics achievement	-.163	.031	< .0001
Grade 5 × prior mathematics achievement	.187	.028	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.167	.038	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.130	.036	0
District 4 × Grade 5 × prior mathematics achievement	-.147	.045	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.352	.005	< .0001
Level 2	.055	.006	< .0001
Level 3	.018	.005	.001
Total variance	.425		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and standard deviation of test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful, efficient way to combine results from assessments (May et al., 2009).

Table D.22. Estimated Relationship Between *Supports for Data Use* Among Elementary School Principals and Student Achievement in Mathematics (*N*=9,266)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.018	.048	.706
Supports for Data Use[a]	.109	.052	.036
District covariates			
District 1 (*versus* District 3)	-.003	.067	.961
District 2 (*versus* District 3)	.006	.066	.924
District 4 (*versus* District 3)	.085	.068	.210
School-level covariates			
School-level prior mathematics achievement[b]	.099	.057	.086
Teacher-level covariates			
Total years of teaching experience	.003	.002	.077
Education above a bachelor's degree (*versus* bachelor's degree)	.056	.030	.061
Female	.035	.038	.362
Student-level covariates			
Prior mathematics achievement[c]	.725	.021	< .0001
Grade 5 (*versus* Grade 4)	.007	.046	.878
Hispanic (*versus* white)	0.065	.019	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.087	.033	.009
African American (*versus* white)	-.134	.021	< .0001
American Indian (*versus* white)	-.045	.053	.399
Multiracial (*versus* white)	-.102	.091	.263
Eligible for free or reduced-price lunch	-.114	.017	< .0001
Female	.013	.012	.303
IEP	-.030	.019	.126
Interaction terms			
District 1 × Grade 5	-.055	.066	.399
District 2 × Grade 5	-.032	.067	.634
District 4 × Grade 5	-.045	.076	.554
District 1 × prior mathematics achievement	-.047	.028	.099
District 2 × prior mathematics achievement	-.024	.026	.352
District 4 × prior mathematics achievement	-.164	.031	< .0001
Grade 5 × prior mathematics achievement	.189	.029	< .0001
District 1 × Grade 5 × prior mathematics achievement	0.173	.040	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.128	.037	0.001
District 4 × Grade 5 × prior mathematics achievement	-.149	.045	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.355	.005	< .0001
Level 2	.051	.006	< .0001
Level 3	.018	.006	.001
Total variance	.424		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.23. Estimated Relationship Between *Attention to Data in the School* Among Elementary School Principals and Student Achievement in Mathematics (*N*=9,690)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.023	.048	.634
Working with Data/Instructional Response[a]	.096	.045	.033
District covariates			
District 1 (*versus* District 3)	0	.067	.995
District 2 (*versus* District 3)	.023	.067	.731
District 4 (*versus* District 3)	.069	.070	.321
School-level covariates			
School-level prior mathematics achievement[b]	.135	.058	.022
Teacher-level covariates			
Total years of teaching experience	.003	.002	.049
Education above a bachelor's degree (*versus* bachelor's degree)	.054	.029	.062
Female	.043	.036	.236
Student-level covariates			
Prior mathematics achievement[c]	.723	.021	< .0001
Grade 5 (*versus* Grade 4)	.009	.046	.839
Hispanic (*versus* white)	-.062	.018	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.092	.031	.004
African American (*versus* white)	-.144	.020	< .0001
American Indian (*versus* white)	-.042	.051	.412
Multiracial (*versus* white)	-.105	.091	.248
Eligible for free or reduced-price lunch	-.112	.017	< .0001
Female	.010	.012	.431
IEP	-.023	.019	.216
Interaction terms			
District 1 × Grade 5	-.045	.065	.482
District 2 × Grade 5	-.028	.065	.662
District 4 × Grade 5	-.048	.076	.525
District 1 × prior mathematics achievement	-.043	.028	.126
District 2 × prior mathematics achievement	-.029	.026	.262
District 4 × prior mathematics achievement	-.163	.031	< .0001
Grade 5 × prior mathematics achievement	.189	.029	< .0001
District 1 × Grade 5 × prior mathematics achievement	-170	.039	< .0001
District 2 × Grade 5 × prior mathematics achievement	-.122	.036	.001
District 4 × Grade 5 × prior mathematics achievement	-.148	.045	.001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.353	.005	< .0001
Level 2	.050	.005	< .0001
Level 3	.019	.006	0
Total variance	.422		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.24. Estimated Relationship Between *Barriers to Data Use* Among Elementary School Principals and Student Achievement in Mathematics (*N*=8,373)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.031	.053	.562
Barriers to Data Use[a]	-.031	.060	.608
District covariates			
District 1 (*versus* District 3)	.010	.077	.898
District 2 (*versus* District 3)	-.037	.069	.591
District 4 (*versus* District 3)	.140	.072	.057
School-level covariates			
School-level prior mathematics achievement[b]	.098	.059	.101
Teacher-level covariates			
Total years of teaching experience	.004	.002	.031
Education above a bachelor's degree (*versus* bachelor's degree)	.047	.031	.128
Female	.055	.039	.156
Student-level covariates			
Prior mathematics achievement[c]	.730	.022	< .0001
Grade 5 (*versus* Grade 4)	-.015	.047	.749
Hispanic (*versus* white)	-.048	.020	.017
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.087	.033	.008
African American (*versus* white)	-.150	.021	< .0001
American Indian (*versus* white)	-.022	.059	.707
Multiracial (*versus* white)	-.147	.093	.116
Eligible for free or reduced-price lunch	-.110	.018	< .0001
Female	.012	.013	.340
IEP	-.035	.021	.088
Interaction terms			
District 1 × Grade 5	-.018	.070	.798
District 2 × Grade 5	-.003	.065	.961
District 4 × Grade 5	-.076	.077	.322
District 1 × prior mathematics achievement	-.057	.031	.068
District 2 × prior mathematics achievement	.028	.027	.296
District 4 × prior mathematics achievement	-.175	.033	< .0001
Grade 5 × prior mathematics achievement	.192	.030	< .0001
District 1 × Grade 5 × prior mathematics achievement	-.116	.043	.008
District 2 × Grade 5 × prior mathematics achievement	-.133	.037	0
District 4 × Grade 5 × prior mathematics achievement	-.143	.046	.002
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.346	.005	< .0001
Level 2	.047	.005	< .0001
Level 3	.021	.006	.001
Total variance	.414		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.25. Estimated Relationship Between *Context for Data Use* Among Elementary School Principals and Student Achievement in Reading (*N*=10,175)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.002	.042	.960
Context for Data Use[a]	.036	.048	.447
District covariates			
District 1 (*versus* District 3)	.004	.059	.941
District 2 (*versus* District 3)	-.029	.055	.602
District 4 (*versus* District 3)	.086	.057	.136
School-level covariates			
School-level prior reading achievement[b]	.104	.046	.028
Teacher-level covariates			
Total years of teaching experience	.003	.001	.032
Education above a bachelor's degree (*versus* bachelor's degree)	.037	.026	.156
Female	-.007	.032	.839
Student-level covariates			
Prior reading achievement[c]	.653	.021	< .0001
Grade 5 (*versus* Grade 4)	.002	.045	.973
Hispanic (*versus* white)	-.063	.019	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.016	.032	.620
African American (*versus* white)	-.142	.020	< .0001
American Indian (*versus* white)	-.240	.052	< .0001
Multiracial (*versus* white)	-.070	.094	.456
Eligible for free or reduced-price lunch	-.095	.017	< .0001
Female	.131	.012	< .0001
IEP	-.257	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.017	.061	.775
District 2 × Grade 5	-.010	.061	.865
District 4 × Grade 5	-.046	.069	.505
District 1 × prior reading achievement	.033	.028	.244
District 2 × prior reading achievement	.050	.026	.052
District 4 × prior reading achievement	-.105	.031	.001
Grade 5 × prior reading achievement	.247	.029	< .0001
District 1 × Grade 5 × prior reading achievement	-.313	039	< .0001
District 2 × Grade 5 × prior reading achievement	-.204	0.036	< .0001
District 4 × Grade 5 × prior reading achievement	-.270	.045	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.376	.005	< .0001
Level 2	.041	.005	< .0001
Level 3	.009	.004	.007
Total variance	.426		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.26. Estimated Relationship Between *Supports for Data Use* Among Elementary School Principals and Student Achievement in Reading (N=9,365)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.000	.041	.996
Supports for Data Use[a]	.091	.043	.036
District covariates			
District 1 (*versus* District 3)	.008	.058	.895
District 2 (*versus* District 3)	-.004	.056	.940
District 4 (*versus* District 3)	.072	.058	.217
School-level covariates			
School-level prior reading achievement[b]	.124	.050	.014
Teacher-level covariates			
Total years of teaching experience	.004	.001	.011
Education above a bachelor's degree (*versus* bachelor's degree)	.023	.026	.391
Female	.011	.034	.752
Student-level covariates			
Prior reading achievement[c]	.646	.021	< .0001
Grade 5 (*versus* Grade 4)	.005	.045	.908
Hispanic (*versus* white)	-.064	.019	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.017	.034	.625
African American (*versus* white)	-.142	.021	< .0001
American Indian (*versus* white)	-.246	.054	< .0001
Multiracial (*versus* white)	-.062	.094	.510
Eligible for free or reduced-price lunch	-.100	.017	< .0001
Female	.130	.013	< .0001
IEP	-.262	.020	< .0001
Interaction terms			
District 1 × Grade 5	-.037	.062	.554
District 2 × Grade 5	-.020	.062	.753
District 4 × Grade 5	-.047	.068	.488
District 1 × prior reading achievement	.049	.029	.094
District 2 × prior reading achievement	.058	.026	.028
District 4 × prior reading achievement	-.098	.031	.002
Grade 5 × prior reading achievement	.256	.029	< .0001
District 1 × Grade 5 × prior reading achievement	-.344	.041	< .0001
District 2 × Grade 5 × prior reading achievement	-.223	.037	< .0001
District 4 × Grade 5 × prior reading achievement	-.279	.045	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.373	.006	< .0001
Level 2	.038	.005	< .0001
Level 3	.010	.004	.006
Total variance	.421		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to Z-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using Z-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.27. Estimated Relationship Between *Attention to Data in the School* Among Elementary School Principals and Student Achievement in Reading (*N*=9,788)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.002	.041	.963
Working with Data/Instructional Response[a]	.007	.037	.856
District covariates			
District 1 (*versus* District 3)	.007	.058	.908
District 2 (*versus* District 3)	-.021	.057	.714
District 4 (*versus* District 3)	.085	.059	.150
School-level covariates			
School-level prior reading achievement[b]	.109	.050	.031
Teacher-level covariates			
Total years of teaching experience	.003	.001	.020
Education above a bachelor's degree (*versus* bachelor's degree)	.026	.026	.310
Female	.008	.032	.793
Student-level covariates			
Prior reading achievement[c]	.645	.021	< .0001
Grade 5 (*versus* Grade 4)	.006	.044	.891
Hispanic (*versus* white)	-.062	.019	.001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.013	.032	.682
African American (*versus* white)	-.143	.020	< .0001
American Indian (*versus* white)	-.238	.052	< .0001
Multiracial (*versus* white)	-.062	.095	.514
Eligible for free or reduced-price lunch	-.096	.017	< .0001
Female	.130	.012	< .0001
IEP	-.262	.019	< .0001
Interaction terms			
District 1 × Grade 5	-.028	.061	.639
District 2 × Grade 5	-.018	.060	.762
District 4 × Grade 5	-.047	.067	.483
District 1 × prior reading achievement	.046	.029	.113
District 2 × prior reading achievement	.054	.026	.037
District 4 × prior reading achievement	-.097	.031	.002
Grade 5 × prior reading achievement	.255	.029	< .0001
District 1 × Grade 5 × prior reading achievement	-.333	.040	< .0001
District 2 × Grade 5 × prior reading achievement	-.216	.037	< .0001
District 4 × Grade 5 × prior reading achievement	-.278	.045	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.374	.006	< .0001
Level 2	.037	.005	< .0001
Level 3	.010	.004	.004
Total variance	.422		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.28. Estimated Relationship Between *Barriers to Data Use* Among Elementary School Principals and Student Achievement in Reading (N=8,430)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.009	.045	.845
Barriers to Data Use[a]	-.037	.049	.448
District covariates			
District 1 (*versus* District 3)	-.030	.064	.647
District 2 (*versus* District 3)	-.023	.058	.689
District 4 (*versus* District 3)	.066	.061	.277
School-level covariates			
School-level prior reading achievement[b]	.108	.050	.034
Teacher-level covariates			
Total years of teaching experience	.004	.002	.012
Education above a bachelor’s degree (*versus* bachelor’s degree)	.030	.027	.277
Female	.008	.034	.807
Student-level covariates			
Prior reading achievement[c]	.675	.023	< .0001
Grade 5 (*versus* Grade 4)	-.010	.047	.825
Hispanic (*versus* white)	-.058	.021	.005
Asian/Native Hawaiian /Pacific Islander (*versus* white)	-.004	.034	.899
African American (*versus* white)	-.129	.022	< .0001
American Indian (*versus* white)	-.250	.061	< .0001
Multiracial (*versus* white)	-.100	.099	.316
Eligible for free or reduced-price lunch	-.113	.019	< .0001
Female	.123	.013	< .0001
IEP	-.249	.022	< .0001
Interaction terms			
District 1 × Grade 5	.015	.067	.820
District 2 × Grade 5	-.014	.062	.827
District 4 × Grade 5	-.041	.070	.553
District 1 × prior reading achievement	.013	.033	.693
District 2 × prior reading achievement	.022	.028	.418
District 4 × prior reading achievement	-.136	.033	< .0001
Grade 5 × prior reading achievement	.234	.031	< .0001
District 1 × Grade 5 × prior reading achievement	-.261	.046	< .0001
District 2 × Grade 5 × prior reading achievement	-.185	.038	< .0001
District 4 × Grade 5 × prior reading achievement	-.252	.047	< .0001
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.374	006	< .0001
Level 2	.035	.005	< .0001
Level 3	.010	.004	.007
Total variance	.419		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students’ prior achievement. Each school has one unique value for the average of its students’ prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to Z-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using Z-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.29. Estimated Relationship Between *Context for Data Use* Among Middle School Principals and Student Achievement in Mathematics (*N*=26,708)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	-.014	.046	.758
Context for Data Use[a]	.031	.048	.518
District covariates			
District 1 (*versus* District 3)	-.015	.057	.799
District 2 (*versus* District 3)	.002	.054	.977
District 4 (*versus* District 3)	.282	.083	.001
School-level covariates			
School-level prior mathematics achievement[b]	.220	.050	< .0001
Teacher-level covariates			
Total years of teaching experience	.002	.002	.269
Education above a bachelor's degree (*versus* bachelor's degree)	-.027	.037	.466
Female	.050	.037	.174
Student-level covariates			
Prior mathematics achievement[c]	.760	.012	< .0001
Grade 8 (*versus* Grade 7)	.048	.052	.360
Hispanic (*versus* white)	-.104	.011	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.093	.016	< .0001
African American (*versus* white)	-.127	.012	< .0001
American Indian (*versus* white)	-.104	.035	.003
Multiracial (*versus* white)	-.019	.080	0.810
Eligible for free or reduced-price lunch	-.090	.010	< .0001
Female	-.033	.007	< .0001
IEP	.002	.014	0.895
Interaction terms			
District 1 × Grade 8	-.248	.060	< .0001
District 2 × Grade 8	-.079	.056	0.159
District 4 × Grade 8	-.082	.082	0.315
District 1 × prior mathematics achievement	-.318	.017	< .0001
District 2 × prior mathematics achievement	-.011	.015	0.453
District 4 × prior mathematics achievement	-.200	.031	< .0001
Grade 8 × prior mathematics achievement	.054	.018	0.002
District 1 × Grade 8 × prior mathematics achievement	-.099	.024	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.120	.021	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.110	.049	0.025
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.086	.008	< .0001
Level 3	0	0	0
Total variance	.433		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.30. Estimated Relationship Between *Supports for Data Use* Among Middle School Principals and Student Achievement in Mathematics (*N*=23,241)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	-.028	.050	.569
Supports for Data Use[a]	.062	.055	.261
District covariates			
District 1 (*versus* District 3)	.000	.062	.997
District 2 (*versus* District 3)	.018	.062	.769
District 4 (*versus* District 3)	.303	.088	.001
School-level covariates			
School-level prior mathematics achievement[b]	.223	.055	0
Teacher-level covariates			
Total years of teaching experience	.002	.002	.310
Education above a bachelor's degree (*versus* bachelor's degree)	-.015	.041	.715
Female	.047	.041	.251
Student-level covariates			
Prior mathematics achievement[c]	.767	.013	< .0001
Grade 8 (*versus* Grade 7)	.047	.055	.393
Hispanic (*versus* white)	-.108	.012	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.110	.018	< .0001
African American (*versus* white)	-.138	.013	< .0001
American Indian (*versus* white)	-.103	.037	.005
Multiracial (*versus* white)	-.042	.086	.621
Eligible for free or reduced-price lunch	-.100	.011	< .0001
Female	-.034	.008	< .0001
IEP	.029	.015	.047
Interaction terms			
District 1 × Grade 8	-.252	.063	< .0001
District 2 × Grade 8	-.097	.061	.108
District 4 × Grade 8	-.086	.085	.311
District 1 × prior mathematics achievement	-.327	.018	< .0001
District 2 × prior mathematics achievement	-.016	.016	.316
District 4 × prior mathematics achievement	-.209	.031	< .0001
Grade 8 × prior mathematics achievement	.055	.019	.003
District 1 × Grade 8 × prior mathematics achievement	-.100	.025	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.120	.023	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.108	.050	.030
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.353	.003	< .0001
Level 2	.096	.009	< .0001
Level 3	0	0	0
Total variance	.449		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.31. Estimated Relationship Between *Attention to Data in the School* Among Middle School Principals and Student Achievement in Mathematics (*N*=26,085)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	-.014	.046	.765
Working with Data/Instructional Response[a]	.040	.037	.283
District covariates			
District 1 (*versus* District 3)	-.015	.057	.787
District 2 (*versus* District 3)	.018	.056	.753
District 4 (*versus* District 3)	.266	.085	.003
School-level covariates			
School-level prior mathematics achievement[b]	.218	.051	< .0001
Teacher-level covariates			
Total years of teaching experience	.002	.002	.329
Education above a bachelor's degree (*versus* bachelor's degree)	-.025	.038	.509
Female	.050	.038	.185
Student-level covariates			
Prior mathematics achievement[c]	.760	.012	< .0001
Grade 8 (*versus* Grade 7)	.048	.053	.365
Hispanic (*versus* white)	-.106	.011	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.098	.017	< .0001
African American (*versus* white)	-.129	.012	< .0001
American Indian (*versus* white)	-.110	.035	.002
Multiracial (*versus* white)	-.020	.080	.805
Eligible for free or reduced-price lunch	-.095	.010	< .0001
Female	-.032	.007	< .0001
IEP	.008	.014	.585
Interaction terms			
District 1 × Grade 8	-.250	.061	< .0001
District 2 × Grade 8	-.091	.057	.109
District 4 × Grade 8	-.083	.082	.313
District 1 × prior mathematics achievement	-.318	.017	< .0001
District 2 × prior mathematics achievement	-.014	.015	.352
District 4 × prior mathematics achievement	-.200	.031	< .0001
Grade 8 × prior mathematics achievement	.054	.018	.002
District 1 × Grade 8 × prior mathematics achievement	-.099	.024	< .0001
District 2 × Grade 8 × prior mathematics achievement	-.120	.021	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.109	.049	.026
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.088	.008	< .0001
Level 3	0	0	0
Total variance	.435		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.32. Estimated Relationship Between *Barriers to Data Use* Among Middle School Principals and Student Achievement in Mathematics (N=20,931)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	-.005	.056	.935
Barriers to Data Use[a]	-.021	.055	.708
District covariates			
District 1 (*versus* District 3)	-.030	.066	.656
District 2 (*versus* District 3)	.023	.065	.725
District 4 (*versus* District 3)	.310	.101	.003
School-level covariates			
School-level prior mathematics achievement[b]	.153	.062	.018
Teacher-level covariates			
Total years of teaching experience	.001	.002	.584
Education above a bachelor's degree (*versus* bachelor's degree)	-.022	.046	.626
Female	.053	.045	.240
Student-level covariates			
Prior mathematics achievement[c]	.780	.014	< .0001
Grade 8 (*versus* Grade 7)	.078	.060	.192
Hispanic (*versus* white)	-.094	.012	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.093	.018	< .0001
African American (*versus* white)	-.129	.014	< .0001
American Indian (*versus* white)	-.104	.038	.006
Multiracial (*versus* white)	-.064	.093	.490
Eligible for free or reduced-price lunch	-.102	.011	< .0001
Female	-.027	.008	.001
IEP	-.003	.016	.832
Interaction terms			
District 1 × Grade 8	-.323	.068	< .0001
District 2 × Grade 8	-.100	.064	.118
District 4 × Grade 8	-.151	.094	.108
District 1 × prior mathematics achievement	-.392	.019	< .0001
District 2 × prior mathematics achievement	-.032	.017	.059
District 4 × prior mathematics achievement	-.231	.034	< .0001
Grade 8 × prior mathematics achievement	.045	.019	.020
District 1 × Grade 8 × prior mathematics achievement	-.055	.026	.036
District 2 × Grade 8 × prior mathematics achievement	-.116	.023	< .0001
District 4 × Grade 8 × prior mathematics achievement	-.127	.053	.016
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.339	.003	< .0001
Level 2	.097	.010	< .0001
Level 3	0	0	0
Total variance	.436		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state mathematics assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.33. Estimated Relationship Between *Context for Data Use* Among Middle School Principals and Student Achievement in Reading (*N*=26,632)

Fixed Effect	**Coefficient**	**Std Error**	***p* value**
Intercept	.078	.049	.112
Context for Data Use[a]	-.064	.056	.257
District covariates			
District 1 (*versus* District 3)	-.119	.064	.069
District 2 (*versus* District 3)	-.140	.060	.023
District 4 (*versus* District 3)	-.032	.086	.713
School-level covariates			
School-level prior reading achievement[b]	.313	.055	< .0001
Teacher-level covariates			
Total years of teaching experience	.000	.002	.912
Education above a bachelor's degree (*versus* bachelor's degree)	-.024	.038	.535
Female	.135	.045	.003
Student-level covariates			
Prior reading achievement[c]	.708	.013	< .0001
Grade 8 (*versus* Grade 7)	-.042	.052	.416
Hispanic (*versus* white)	-.075	.011	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.003	.017	.868
African American (*versus* white)	-.131	.013	< .0001
American Indian (*versus* white)	-.146	.037	< .0001
Multiracial (*versus* white)	-.012	.084	.886
Eligible for free or reduced-price lunch	-.093	.010	< .0001
Female	.114	.008	< .0001
IEP	-.239	.016	< .0001
Interaction Terms			
District 1 × Grade 8	-.044	.061	.467
District 2 × Grade 8	.101	.058	.082
District 4 × Grade 8	.063	.077	.414
District 1 × prior reading achievement	-.236	.019	< .0001
District 2 × prior reading achievement	0014	.016	.390
District 4 × prior reading achievement	-.089	.030	.003
Grade 8 × prior reading achievement	-.015	.020	.465
District 1 × Grade 8 × prior reading achievement	-.025	.027	.358
District 2 × Grade 8 × prior reading achievement	.027	.023	.244
District 4 × Grade 8 × prior reading achievement	-.049	.041	.232
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.078	.008	< .0001
Level 3	.009	.004	.018
Total variance	.434		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.34. Estimated Relationship Between *Supports for Data Use* Among Middle School Principals and Student Achievement in Reading (*N*=21,686)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.062	.052	.239
Supports for Data Use[a]	.007	.060	.912
District covariates			
District 1 (*versus* District 3)	-.085	.067	.212
District 2 (*versus* District 3)	-.127	.066	.059
District 4 (*versus* District 3)	-.006	.089	.942
School-level covariates			
School-level prior reading achievement[b]	.345	.061	< .0001
Teacher-level covariates			
Total years of teaching experience	0	.002	.938
Education above a bachelor's degree (*versus* bachelor's degree)	-.030	.041	.453
Female	.151	.049	.002
Student-level covariates			
Prior reading achievement[c]	.705	.013	< .0001
Grade 8 (*versus* Grade 7)	-.029	.054	.588
Hispanic (*versus* white)	-.079	.012	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.011	.017	.532
African American (*versus* white)	-.141	.014	< .0001
American Indian (*versus* white)	-.130	.039	.001
Multiracial (*versus* white)	-.052	.088	.559
Eligible for free or reduced-price lunch	-.098	.011	< .0001
Female	.120	.008	< .0001
IEP	-.244	.016	< .0001
Interaction terms			
District 1 × Grade 8	-.060	.063	.343
District 2 × Grade 8	.079	.061	.193
District 4 × Grade 8	.051	.079	.518
District 1 × prior reading achievement	-.236	.019	< .0001
District 2 × prior reading achievement	.015	.017	.358
District 4 × prior reading achievement	-.089	.030	.003
Grade 8 × prior reading achievement	-.009	.020	.673
District 1 × Grade 8 × prior reading achievement	-.030	.028	.270
District 2 × Grade 8 × prior reading achievement	.030	.024	.215
District 4 × Grade 8 × prior reading achievement	-.055	.041	.184
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.347	.003	< .0001
Level 2	.084	.009	< .0001
Level 3	.010	.005	.020
Total variance	.440		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.35. Estimated Relationship Between *Attention to Data in the School* Among Middle School Principals and Student Achievement in Reading (*N*=23,809)

Fixed Effect	**Coefficient**	**Std Error**	***p* Value**
Intercept	.075	.049	.130
Working with Data/Instructional Response[a]	.005	.045	.915
District covariates			
District 1 (*versus* District 3)	-.099	.063	.122
District 2 (*versus* District 3)	-.142	.061	.024
District 4 (*versus* District 3)	-.025	.088	.775
School-level covariates			
School-level prior reading achievement[b]	.312	.056	< .0001
Teacher-level covariates			
Total years of teaching experience	.000	.002	.999
Education above a bachelor's degree (*versus* bachelor's degree)	-.024	.038	.517
Female	.139	.045	.002
Student-level covariates			
Prior reading achievement[c]	.707	.013	< .0001
Grade 8 (*versus* Grade 7)	-.043	.052	.408
Hispanic (*versus* white)	-.080	.011	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.004	.016	.808
African American (*versus* white)	-.135	.013	< .0001
American Indian (*versus* white)	-.152	.037	< .0001
Multiracial (*versus* white)	-.014	.083	.871
Eligible for free or reduced-price lunch	-.092	.010	< .0001
Female	.117	.008	< .0001
IEP	-.242	.016	< .0001
Interaction terms			
District 1 × Grade 8	-.044	.061	.470
District 2 × Grade 8	.104	.058	.073
District 4 × Grade 8	.064	.077	.405
District 1 × prior reading achievement	-.235	.019	< .0001
District 2 × prior reading achievement	.017	.016	.271
District 4 × prior reading achievement	-.089	.030	.003
Grade 8 × prior reading achievement	-.014	.020	.466
District 1 × Grade 8 × prior reading achievement	-.025	.027	.356
District 2 × Grade 8 × prior reading achievement	.033	.023	.159
District 4 × Grade 8 × prior reading achievement	-.049	.041	.230
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.345	.003	< .0001
Level 2	.078	.008	< .0001
Level 3	.010	.004	.014
Total variance	.433		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

Table D.36. Estimated Relationship Between *Barriers to Data Use* Among Middle School Principals and Student Achievement in Reading (*N*=18,348)

Fixed Effect	Coefficient	Std Error	*p* Value
Intercept	.043	.059	.472
Barriers to Data Use[a]	.104	.064	.104
District covariates			
District 1 (*versus* District 3)	-.157	.072	.033
District 2 (*versus* District 3)	-.154	.071	.034
District 4 (*versus* District 3)	.046	.100	.646
School-level covariates			
School-level prior reading achievement[b]	.288	.068	< .0001
Teacher-level covariates			
Total years of teaching experience	.001	.002	.642
Education above a bachelor's degree (*versus* bachelor's degree)	-.021	.048	.658
Female	.168	.058	.004
Student-level covariates			
Prior reading achievement[c]	.720	.014	< .0001
Grade 8 (*versus* Grade 7)	-.061	.062	.319
Hispanic (*versus* white)	-.085	.013	< .0001
Asian/Native Hawaiian /Pacific Islander (*versus* white)	.011	.018	.559
African American (*versus* white)	-.130	.015	< .0001
American Indian (*versus* white)	-.143	.040	.000
Multiracial (*versus* white)	.015	.098	.882
Eligible for free or reduced-price lunch	-.093	.012	< .0001
Female	.114	.009	< .0001
IEP	-.238	.018	< .0001
Interaction terms			
District 1 × Grade 8	-.008	.071	.906
District 2 × Grade 8	.169	.069	.015
District 4 × Grade 8	.082	.086	.340
District 1 × prior reading achievement	-.268	.021	< .0001
District 2 × prior reading achievement	-.017	.018	.342
District 4 × prior reading achievement	-.120	.033	.000
Grade 8 × prior reading achievement	-.023	.022	.292
District 1 × Grade 8 × prior reading achievement	-.036	.030	.224
District 2 × Grade 8 × prior reading achievement	.049	.026	.063
District 4 × Grade 8 × prior reading achievement	-.014	.044	.753
Random Effect	**Variance**	**Std Error**	***p* Value**
Level 1	.343	.004	< .0001
Level 2	.099	.011	< .0001
Level 3	.005	.005	.154
Total variance	.447		

[a]The key dimensions of data use for principals were group-mean centered. [b]Values are standardized school-level aggregates of students' prior achievement. Each school has one unique value for the average of its students' prior achievement from the 2009 state reading assessment. [c]Because all four participating districts use different state tests, it was necessary to translate the scores into a common metric. All scores were standardized to *Z*-scores using the mean and the standard deviation of the test scores within each district and grade. Standardizing (using *Z*-scores) across grades and states is the most powerful and efficient way to combine results from different assessments (May et al., 2009).

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The Council of the Great City Schools is a coalition of 67 of the nation's largest urban public school systems. The organization's Board of Directors is composed of the Superintendent, CEO or Chancellor of Schools, and one School Board member from each member city. An Executive Committee of 24 individuals, equally divided in number between Superintendents and School Board members, provides regular oversight of the 501 (c)(3) organization. The composition of the organization makes it the only independent national group representing the governing and administrative leadership of urban education and the only association whose sole purpose revolves around urban schooling.

The mission of the Council is to advocate for urban public education and assist its members in their improvement and reform. The Council provides services to its members in the areas of legislation, research, communication, curriculum and instruction, and management. The group convenes two major conferences each year; conducts studies of urban school conditions and trends; and operates ongoing networks of senior school district managers with responsibilities for areas such as federal programs, operations finance, personnel, communications, research and technology. Finally, the organization informs the nation's policymakers, the media, and the public of the successes and challenges of schools in the nation's Great Cities. Urban school leaders from across the country use the organization as a source of information and an umbrella for their joint activities and concerns. The Council was founded in 1956 and incorporated in 1961, and has its headquarters in Washington, D.C.

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