Published in final edited form as:

Educ Finance Policy. 2013 ; 8(2): 168–207. doi:10.1162/EDFP_a_00089.

IF YOU BUILD IT WILL THEY COME? TEACHERS' ONLINE USE OF STUDENT PERFORMANCE DATA

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Abstract

Testing of students and computer systems to store, manage, analyze, and report the resulting test data have grown hand-in-hand. Extant research on teacher use of electronically stored data are largely qualitative and focused on the conditions necessary (but not sufficient) for effective teacher data use. Absent from the research is objective information on how much and in what ways teachers use computer-based student test data, even when supposed precursors of usage are in place. This paper addresses this knowledge gap by analyzing the online activities of teachers in one mid-size urban district. Utilizing Web logs collected between 2008 and 2010, I find low teacher interaction with Web-based pages that contain student test information that could potentially inform practice. I also find no evidence that teacher usage of Web-based student data are related to student achievement gains, but there is reason to believe these estimates are downwardly biased.

1. INTRODUCTION

Schools and teachers are increasingly being called upon to utilize student performance data in making decisions about policy and practice. Indeed, actors in the K–12 arena are likely to be seen as out of touch and behind the times if they are not engaging in “data-driven decision making” or do not claim to be “data-driven schools” or “data-driven teachers.” As recently as 2005, however, Wayman reported that “the use of student data for educational improvement has not been widespread. Until only recently, examining student data was a difficult chore for most educators” (Wayman 2005, p. 235). The recent proliferation of Web-based tools to present and assist in the analysis of student performance data has eased this concern and so the questions now turn to how schools and teachers are using the new tools to improve student outcomes.¹

This paper provides some answers to this question by examining how teachers in one mid-size urban district use a Web-based tool designed to provide them with student achievement

information that can potentially improve their practice. In particular I seek to answer three questions: how much do teachers in the district use the Web tool interactively, what types of information do teachers access when they do use the tool, and is there any evidence that interactive usage of Web-based student data is related to student achievement gains? In addressing these questions this paper is primarily a descriptive study. Nevertheless, solid answers to these questions are critical as the field moves forward in trying to better utilize the vast amounts of student performance data that are now collected every year.

This descriptive study is the first that captures and analyzes, at the individual teacher–student level, objective information on interactive teacher usage of student performance data presented through a Web-based tool. Data for the study come from Web logs that are generated each time a teacher logs in to the district’s Web-based tool that is designed to present student data to teachers in user-friendly formats. This system, a data “Dashboard” system, was developed in-house and brought online at the beginning of the 2005–6 school year in the district under study. The analysis in this paper is based on Web log data from the 2008–9 and 2009–10 school years, data that allow me to link teachers to both their individual click patterns at each login and to the students whose data the teachers are viewing.² For these years I analyze teacher logins to the Dashboard system, the types of pages in Dashboard that teachers view when logged in, the amount of time teachers spend on the different kinds of pages, and whether this activity is related to student test score growth.

A simple theory of action for the way in which teacher usage of student performance data could affect student achievement would have the following sequential components:

1. Test students to gather performance information.
2. Provide the test results to the teacher in a manner and in formats that foster meaningful analysis.
3. The teacher accesses the test data.
4. The teacher spends time analyzing the test data.
5. The teacher draws knowledge from that analysis that can inform her practice.
6. The teacher knows how and has the ability to alter practice based upon the new knowledge.
7. The teacher acts on the new knowledge and classroom practice is altered.
8. The altered practice has a positive impact on student achievement.

Because each step is conditional on the success of previous steps, a breakdown in any one would prevent the effective use of student test data as in input to instructional improvement and eventual student achievement gains. This project examines the third and fourth steps in the model: do teachers access student performance data and how much time do they spend online with the data when it is provided to them? In particular, using data from a mid-sized,

²For narrative simplicity in the remainder of the paper, I will refer to the 2008–9 school year as the 2009 school year and the 2009–10 school year as the 2010 school year.

midwestern school district I analyze the extent to which core-subject (math, English, social studies, and science) teachers in grades 3 through 8 accessed the performance data of their students via the Dashboard Web tool during the 2009 school year. I then use 2010 data to examine changes in usage over a two-year period and to explore the relationship between usage and student performance as measured by scores on various tests.

In a preview of the findings, the average teacher targeted in the study logged into the Dashboard system just less than once per week during the 2009 school year, and 43 percent of these teachers spent a total of one hour or less during the year viewing Dashboard pages containing test data information on their students (17 percent spent 20 minutes or less during the year on these pages). I also find very little change in usage between the 2009 and 2010 school years and no evidence that usage is related to student achievement growth. These relatively low usage levels leave one concerned about the extent to which the average teacher is using Dashboard-presented student test data to inform practice, and the low usage levels also hamper our ability to effectively study the usage-student performance linkage.

The remainder of this paper is organized as follows. In the next section I discuss the literature on teacher use of student performance data. This is followed by a discussion of the data used for this project in section 3 and a presentation and discussion of the results of the analyses of the data in section 4. Section 5 summarizes and concludes.

The district in this study is a typical mid-sized urban school district, and it has much in common with larger urban districts. There are approximately 35,000 K–12 students in the district and like most urban districts the students tend to come from low income and minority families, and student achievement in the district lags behind that of the state as a whole. In the most recent year for which data are available, about 70 percent of the students are eligible for free or reduced-price lunch, about 70 percent of the students are African American, and 25 percent of the students are white.

2. PRIOR RESEARCH

The push for schools and teachers to use student test data as inputs to decision making rests on a relatively recent and thin research base. Studies of how districts, schools, and teachers utilize data began only about a decade ago, with much of the early knowledge resting on case studies that described the many ways in which data were being used to support education decisions (Pardini 2000; Feldman and Tung 2001; Protheroe 2001; Lachat 2002).³ Following this early optimistic assessment regarding the role data could play in assisting school improvement efforts, Ingram, Louis, and Schroeder (2004) used interviews and focus group data from nine schools to caution against assuming that the mere presence of data from standardized tests would translate into the use of that data by schools and teachers. Nevertheless, the increased testing of students combined with the falling price of computing and data storage and the proliferation of data management and analysis tools meant that districts would be awash in student performance data, would have increasing access to

³This work is summarized in Wayman, Stringfield, and Yakimowski (2004).

technological tools for analyzing that data, and would be under steady pressure to use those data in ways that might increase student achievement.

One can get a sense of the rapid growth of the use of education data that occurred in the early years of these developments by the growth in revenue from data management and analysis software and services in the K–12 sector between 2000 and 2003. According to one report, vendor revenues in this area grew from \$98.8 million to \$145 million over this three-year period (Stein 2003). This same report ventured that the (then) recent passage of the No Child Left Behind Act meant that school districts were facing new data reporting challenges that few were prepared to meet, thus suggesting a market ripe for additional investments in data management and analysis tools.

Spurred by both the testing and the reporting requirements of No Child Left Behind, and the desire to use student test data for school improvement and student achievement gains, the push was on to develop systems that could store, manage, present, and help practitioners analyze student data. The resulting development and proliferation of software and Web-based tools designed to make data analysis both cheaper for districts and more user-friendly for teachers and administrators, helped foster a series of studies of how the field was using data and a focus on the factors that seemed to promote or hinder effective data use. District and school-level surveys, interviews, case studies, focus groups, and ethnographic studies were all used to better understand what made schools and teachers “data-driven” (e.g., Brunner et al. 2005; Chen, Heritage, and Lee 2005; Kerr et al. 2006; Marsh, Pane, and Hamilton 2006; Datnow, Parker, and Wohlstetter 2007; Crawford et al. 2008).

A summary of the mostly qualitative research from this era suggests lessons in three areas. First, the probability of data use by teachers taking hold in a school is increased when (1) a “culture of data use” is developed in the school, (2) when the school has strong leadership that is supportive of teacher use of data, (3) when there is sufficient professional development around data use, (4) when there is allotted time for data use, (5) when teachers believe that there is valid information in the test data, and (6) when teachers are provided with data systems that are easy to navigate. Second, factors that affect self-reported levels of teacher data use include the timeliness of data that is turned back to teachers, the perceived validity of the test data, and flexibility in the ability to alter instructional practice and pace, particularly vis-à-vis curriculum pacing guides. Third, the most prevalent ways in which teachers use data are: using data to learn about their new students at the beginning of the year, discerning student needs in order to group students for instruction, and determining class-wide strengths and weaknesses for instructional planning.

Nationally representative data on teacher data use come from a series of studies sponsored by the U.S. Department of Education. In survey data from the National Educational Technology Trends Study (NETTS) the percentage of teachers reporting having access to district student data systems went from 48 percent in 2005 to 74 percent in 2007 (Gallagher, Means, and Padilla 2008). NETTS respondents also reported a greater likelihood of access to grades and attendance data than to student achievement data in 2007, and they expressed a desire for more professional development around data use.

A separate NETTS-based study found that of the 74 percent of teachers who report having access to student data in 2007, 3 percent reported using data at least once a week for the purpose of identifying skills gaps of individual students so that instruction could be individually tailored according to student needs. Another 15 percent reported engaging in this type of activity at least once or twice a month (Means et al. 2009). In the most recent research from NETTS, 55 percent of the surveyed teachers reported using a student data system “at least a few times a year” to identify skill gaps for individual students so that instruction can be tailored to student needs (Means, Padilla, and Gallagher 2010).

These types of interaction between a teacher and the data of individual students are what many have in mind when they think of using data to improve instruction and increase student achievement. An increasingly common source of student data comes from benchmark testing, periodic assessments that are usually designed to provide information on how well students are expected to perform on end-of-the-year state exams. In their analysis of the 2007 NETTS data, Means, Padilla, and Gallagher (2010) found 79 percent of the responding districts reported having an assessment system that could organize and analyze benchmark assessment data and 77 percent report having a data warehouse that can provide access to current and historical student performance data. Meanwhile, over 90 percent of districts reported they had given at least some of their staff training designed to enhance the district’s ability to use data to improve instruction. These same districts, however, also report that training aimed at supporting *teachers* in efforts to use the data system to analyze student achievement or to change their instructional practices are the two types of training least likely to have been given to every school in the district (53 percent of districts report giving both types of training to all schools). And, responding districts reported that the greatest perceived area of need is for models of how to connect student data to instructional practice (37 percent said this was a “great need” and 47 percent identified this as an area of “some need”). Given these results it is perhaps not surprising that in 36 case study districts that were a part of the NETTS study, researchers found that school staff could provide relatively few examples of teachers using data to diagnose areas in which they could improve the way they teach—even in districts that were identified as active promoters of the use of data. In summary the report authors stated, “A good data system is not enough: Use of data to inform instruction requires leadership and systemic realignment” (Means, Padilla, and Gallagher 2010, p. 83).

Supplementing the information from NETTS, Goertz, Olah, and Riggan (2009) rely on case studies in two districts to provide some of the most recent information on how teachers use benchmark testing data and how they interact and use information from these assessments that is provided via a Web-based tool. Regarding use of the assessment data, they find that 90 percent of the teachers in their study begin their use of benchmark data by looking for student weaknesses. Most of these (67 percent) were looking for weak content areas exposed on the benchmark, whereas 21 percent began by looking for low-performing students. When it came to using the Web-based student information system in each district to analyze benchmark data, it was found that in the district whose Web-tool was more complicated and had more functionality—the type of student information system that could theoretically

inform practice—teachers used the complex functions much less frequently than the basic functions available on the tool.

While information from case studies, interviews, and surveys continue to update our knowledge about how teachers use data and, in particular, the Web-based student information systems that increasingly deliver student data to teachers, there remains a dearth of quantitative information on teacher usage of Web-based student performance data. At this point there are only two papers in the literature that analyze objective measures of teacher usage, both from the same project and district. Wayman, Cho, and Shaw (2009) and Wayman, Shaw, and Cho (2011) analyze usage report data from a commercially available tool used by the district in their study to look at teacher usage and the linkage between teacher usage and student achievement. Focusing on the portion of this work related to teacher analysis of student data, the first (2009) report from this project showed that 93 percent of the teachers accessed the “Reports” section of the tool, the section that contains student performance data. Given the availability of information from different levels contained in the “Reports” section (e.g., district, school, class, and student), however, we do not know what percentage of the teachers viewed report data at the individual student level, and importantly, we do not know how much time teachers spent viewing student level data. In the second year study (2011) it was shown that teacher experience was not related to either prevalence of use (total number of times the system was accessed during the year by a teacher) or consistency of use (number of weeks during the year that a teacher accessed the system). It was found that elementary teachers accessed the system 3.3 more weeks during the year than did junior high teachers.

In studying the relationship between use of the data system and student achievement, the second year study (2011) found a statistically significant relationship between system use and student achievement, controlling for prior student achievement and other student covariates. Although statistical relationships were found, the effect sizes were not substantial. For example, whereas the prevalence measure on the system was statistically associated with student achievement gains in reading, the point estimated implied that even a 200-action difference in prevalence (number of times the system was accessed during the year) would be associated with only about 0.04 of a standard deviation difference in test score. Although lacking the kind of detailed, teacher-level click-stream data⁴ that allow for an in-depth look at how much and in what ways teachers interact with computerized student data, the very fact that this study collected and analyzed objective usage measures is a notable step forward in the field.

Although it is not informative about teacher usage of data in particular, there is one randomized study of a district-level data-driven reform that offers some promise regarding the potential for teacher data use to impact student achievement. Carlson, Borman, and Robinson (2011) studied 500 schools in 59 districts across the nation to determine whether there were first-year impacts of a data-driven reform initiative implemented by the Johns Hopkins Center for Data-Driven Reform in Education. The treatment in this study consisted

⁴The term *click-stream data* refers to information associated with every mouse click in an open Web browser including the page being viewed, the time of the click, the query initiated with a click, and so forth.

of (1) quarterly benchmark assessments given to students in grades 3–8 (grades 3–11 in some schools in the study), (2) consultants who used analysis of district test results to provide information to districts on areas where they were at risk of adequate yearly progress failure, and (3) training for district and building leaders in interpreting and using data. Actual teacher use of data, the topic of this current study, is but one part of this district level initiative. Nevertheless, this study found statistically significant and substantive positive impacts on student achievement, some of the first hard evidence that data-driven reform can live up to its promise.

At the same time there is reason to be cautious about the ability of data-driven reform to influence teacher practice and ultimately student achievement. First, as Cohen (1990) detailed in a case study of one teacher's response to mathematical reform, teachers can thwart the best of reform efforts, even if unintentionally. The importance of teachers as the ultimate agents of, or barriers to, education reform is reinforced in work by McLaughlin (1987), Spillane, Reiser, and Reimer (2002), Young (2006), and others. Thus, studies that fail to focus on teachers as the end users of data-driven reform efforts may be less informative than we would hope when it comes to understanding the extent to which those efforts will result in changed instructional practice.

Second, work by Shiffman et al. (2008) suggests that technical barriers to the use of data should not be underestimated. In their qualitative study across three high schools of teacher use of a Web-based tool not dissimilar from Dashboard, they found teachers who lacked the basic computer skills to be able to access the data, and who instead asked colleagues to access the data for them. They also found that among teachers who could access the data, some lacked the ability to analyze the data in ways that could inform their instruction. Only a decade ago, in the nascent stages of data-driven reform efforts, results such as these would not necessarily surprise. At this point, they are, at the least, a sobering account of how far we have come. It is perhaps not surprising that these same researchers report that in two of the three high schools “many teachers remained unconvinced that using the [Web-based data analysis] system was an efficient or necessary step in evaluating student performance and future planning” (p. 59).

Third, as Payne (2008) points out, even when education reform links seemingly good ideas with supportive resources, social and political barriers in the school, district, or community can severely hinder or block the reform efforts. At the teacher level these barriers can range from a “narrow base of [teacher] support” to a lack of time “for training, for planning, [and] for reflection” to “a tendency of teachers to comply in [only] a minimal way” (p. 172). All of these factors and behaviors could be relevant barriers in data-driven reform efforts.

The literature on the implementation of education reform efforts is humbling at best. Like the sequential steps that have to fall into place if student test data are going to be used by teachers in ways that eventually influence student achievement, there are stars that have to align in order for education reform, including data-driven reform, to take root in ways that desired and hypothesized results on instructional practice will actually occur.

In summary, the availability of student performance data and the tools for using that data have both grown substantially in the last decade, along with research regarding the structures, processes, technologies, and behaviors that must be in place if teachers are to intelligently use data to inform practice. Noticeably absent from the research, however, is objective information on *how much* teachers actually use student achievement data, most particularly student data that are presented via Web-based technology. This descriptive study is the first to provide detailed information on how much teachers in a given setting actually use computer-resident student test data interactively, how they spend their time when they do access the data, and whether time spent interacting with computerized individual student data is related to student achievement gains.

3. BENCHMARK TESTING, THE DASHBOARD SYSTEM, AND THE RESULTING DATA

The district in this study has made substantial investments in a system that regularly tests their students in grades 3–8 on Benchmark formative assessments and feeds this test information back to teachers and administrators via the Dashboard tool. For a subset of schools that I will call Targeted Assistance (TA) schools, the district also provides ongoing professional development to teachers on Dashboard use. The fifteen TA schools were low-performing schools targeted to receive extra resources beginning in the 2009 school year. All teachers in the district were provided with the opportunity for voluntary, initial training when the Dashboard system was first brought online. In addition to the end-of-year state level assessments, during the period under study district students in grades 3–8 took four Benchmark assessments through the course of the school year, and students in the fifteen TA schools also took a pre-test in September and a post-test in January. The Benchmark tests are designed to provide feedback regarding the extent to which district students are making satisfactory progress toward mastering material that will be on the end-of-year state exams. Using Dashboard, a teacher can access his students' data on the Benchmark exam within 24 hours from the time the teacher turns in test results to the district assessment office. Each teacher has access to the complete testing record, current and historical, of every student he or she is teaching in a given year. Teachers cannot view information on students they are not teaching that year.⁵

The Dashboard tool was developed in-house during 2004 and brought online in September 2005. Although the district seems to realize the importance of providing training and support to teachers around Dashboard use, teachers in focus group discussions that I conducted to provide context for this paper reported uneven amounts of training and support.⁶ Some teachers in the focus groups reported they felt the district had provided sufficient levels of support for them to use Dashboard effectively, whereas others reported little support and training on how to navigate and use Dashboard. The primary source of training and

⁵Dashboard also provides teachers with student-level information in areas such as number of absences, number of detentions, and so on. I do not analyze teacher usage of this information in this paper.

⁶In December 2008 four elementary schools were chosen at random, and 12 randomly chosen core-subject, grade 3–8 teachers from each school were invited to participate in a focus group to discuss the data Dashboard. Teachers were incentivized to participate in the focus group with a \$20 gift card to a local bookstore. Each of the four school-based focus groups had from six to eight teachers participate.

professional development around Dashboard usage during the period under study came from the district's professional development support teams, seven teams of (usually) six individuals—a former principal, a math coach, a language arts coach, a science coach, a social studies coach, and an individual who specializes in special education. The role of the support teams is to “audit schools and assist with academic improvement.”⁷ Prior to 2009 the support teams worked with all schools and teachers in the district. Beginning in 2009 all five of the teams working at the elementary level were assigned to the fifteen TA schools where one of their primary responsibilities was to help the teachers in these schools utilize Dashboard in ways that would inform and improve their classroom instruction.

The district has worked to put in place a connected system of regular student testing, the ability to turn that test data back to teachers in a timely manner via a tool that provides relatively easy access and usability, and district support and encouragement around teacher data use for instructional improvement. Information used in this study to address questions of how much, in what ways, and to what effect teachers use this system derive from the Web logs that are generated every time a teacher logs in to the Dashboard system. These Web logs capture, among other things, the employee identification number of the teacher who has logged in, the day and time of the login, the pages that are viewed during each Dashboard session, the sequencing of the teacher's journey through the pages, and information that allows for the construction of the amount of time the teacher spent on each page during the session. Because certain student-related pages also have an associated student identification number, the Dashboard Web logs identify the instances when teachers are viewing the test data of individual students.

After stripping the data of all personally identifiable information, district administrators supplied me with the universe of raw Web log files that were generated from every teacher login that occurred between 3 August 2008 and 31 May 2010. In converting these Web logs into analytic data files a key task was coding the Dashboard pages into common groups. Individual pages were grouped into the following page-type categories:

- *Class* level pages that have information on a given class of a given teacher.
- *Students-in-class* level pages that have information on multiple students in a teacher's class.
- *Individual-student* level pages that have information on an individual student in a teacher's class.
- *Item* pages that have information on particular test items.
- *Resource* pages that have resource information for teachers such as model lesson plans.

A teacher viewing a “class” level page might, for example, be provided with graphical information on the percentage of questions her class answered correctly on a given Benchmark test, as compared with the percentage of correct answers on that test for all students in the school, and all students in the district.

⁷Taken from the district's 2006–7 Strategic Plan.

A teacher could then burrow down to the next level to a “students-in-class” level to see performance statistics on the students in her class. Figure 1 is an example of a typical “students-in-class” page from Dashboard, so categorized because it has disaggregated information on all the students in the class.⁸ Information at the top of this example page indicates the data on this page pertain to the fourth Benchmark assessment in math at the sixth-grade level. This particular class got 51 percent of the answers correct whereas sixth graders across the district got 61 percent correct on this Benchmark assessment. The link (“Graphs showing all district, school, class averages”) located below the class and district averages would take the teacher back to “class” level information showing graphical information in grade 6 for each of the core subject areas of math, language arts, science, and social studies.

Each row in the chart of figure 1 provides information on an individual student in the class, giving the student’s name (blanked out in this example except for one fictional student, “Suzie R.”), the percentage of correct answers by the student on this test, and whether this percentage placed the student in a “Reteach,” “Practice,” or “Enrichment” group. For example, Suzie R. received a grade of 67 percent correct which placed her in the “Practice” group on the math material tested on this Benchmark.

A teacher could drill down further by clicking on a student’s name. In our example, clicking on Suzie R. would take the teacher to the page pictured in figure 2. This “individual student” page tells the teacher which questions on the math test Suzie answered correctly, which she answered incorrectly, and, for the incorrect responses, it compares Suzie’s answer to the correct answer. On this particular math test questions 1–8 are multiple choice questions with bubble-in responses, and questions 9 and 10 require the student to both write an answer to the question and provide an explanation of how she arrived at that answer.⁹

There are two sets of links on this “individual student” page. One, the “Click here to see all scores and mastery for this student” link, brings up a page with the complete Benchmark and testing history of the given student, across all grades and subjects—another example of what is categorized as an “individual student” level page in this analyses. A second set of links are the links associated with each test question pictured in figure 2. A click on one of these links takes the teacher to an “item” page where she can view the content and structure of the test question she has selected. Additional information for the teacher on each test item page is the grade level indicator and the state standard associated with a given test item.

In addition to pages associated with student test information, the Dashboard system houses various types of “resource” pages, many of which are linked to test items, grade level indicators, and state standards. Examples of resource pages are pages that offer the teacher model lesson plans and intervention strategies for particular indicators.

⁸Figures 1 and 2 are screen shots from the “demo” version of Dashboard to which I have been given access. Even though student names are anonymized in the demo version, I take the extra step of blanking out names and the class section number, and using an alias for the one student, Suzie R., who is used as an example.

⁹Apparently the open-ended responses in 9 and 10 are weighted differently from the multiple choice questions given that Suzie R. got 6 of 10 correct and received a grade of 67.

The pages in figures 1 and 2 are meant to be examples of the page type groupings that were created for this analysis. Under each of the groupings (class, students-in-class, individual student, item, and resource) there are many different pages that can be accessed on Dashboard.

In addition to the coding of pages as to page type, other variables that were necessary or desirable for the analyses in this study were created from the raw Web logs in the process of converting the Web logs into data suitable for analysis. Following this data processing, information from district personnel files, course files, and student test files were merged into the processed Web log files to create the analytic data files for this study.¹⁰

The resulting data files have complete Dashboard usage information on 429 core subject grade 3–8 teachers in 2009 and 359 teachers in 2010. The 2009 data set is a teacher by Dashboard-page panel with 214,779 lines of data that were generated from 14,228 separate logins between August 2008 and May 2009. Similarly, the 2009–10 Web logs produce a data set that has 230,323 lines of data generated from 15,655 logins between August 2009 and May 2010. Throughout the study only these core subject grade 3–8 teachers are used. It is in these grades and subjects where students are tested regularly on the Benchmark exams and thus where teachers are expected to use Dashboard on a relatively regular basis to access the performance data of their students.

4. RESULTS AND DISCUSSION

Teacher Use of Dashboard

A first look at interactive teacher Dashboard usage as captured in the Web logs indicates that the average teacher in the targeted group logged into the Dashboard system 33 times during the 2009 school year (median = 28 logins during the year) and spent a total of about 7 hours logged in to Dashboard over the course of the school year (median = 3.5 hours). The average teacher apportioned her seven hours during the year on Dashboard in the following ways:

- 3.2 percent on class level pages,
- 26.8 percent on students-in-class pages,
- 9 percent on individual student pages,
- 6.6 percent on item pages,
- 31.6 percent on resource pages,
- 5.2 percent entering student test data information,¹¹ and
- 17.4 percent of the time on login, password, or navigational pages containing decision nodes (links) for users, but no information beyond the potential destination pages.

¹⁰I thank Eric Taylor for his assistance in the student–teacher matching process and in helping to write the Web log conversion code.

¹¹Some of the grade 3–8 teachers also teach in grades K–2 and teachers of these grades enter student test scores directly into Dashboard.

Table 1 gives a more detailed view of how teachers spent time on Dashboard during the 2009 school year. In this table and much of the analysis that follows the focus is on weekly use of Dashboard. Usage statistics at the annual level do not take advantage of the detailed usage information contained in the Dashboard Web logs and would provide no information on any patterns of usage during the year. Months of the year do not naturally denominate school semesters or testing periods, and daily Dashboard usage is too fine-grained for meaningful analysis. Thus, a study of weekly use of Dashboard is not only an analytically convenient level of aggregation, but there is a substantive rationale for weekly usage study as teachers tend to organize their work and planning (e.g., lesson plans) in weekly increments of time.

Panel A of table 1 presents weekly Dashboard login information, with the first row indicating that on average the 429 district teachers logged into Dashboard slightly less than one time per week during the 2009 school year. The second column in the first row indicates that conditional on ever logging in during a week, the average number of logins is about two times per week. The mean time logged in per week across all teachers is about 10 minutes per week, and conditional on having logged in at least once during a week the mean time logged in per week is almost 30 minutes.¹²

Panel B provides statistics on the extent to which teachers are viewing student test data during the time they are logged into the Dashboard site. Of particular interest is teacher usage of students-in-class and individual student pages, because these are the pages that provide teachers with test data and test item information at the student level. The average teacher spends about 2.3 minutes per week on students-in-class pages and slightly over half a minute per week on individual student pages. Among teachers who spend any time on these pages during the week, the mean times are 7.6 minutes on students-in-class pages and 6.33 minutes on individual student pages. The average teacher accesses (hits) a students-in-class page about 2.5 times per week and an individual student page only about once every two weeks (0.58 times per week).

Panel C of the table provides similar statistics for item and resource pages. It is notable that among teachers who ever looked at a resource page during a week, the mean time on these pages that provide teaching resources such as model lesson plans and intervention strategies for given topics was almost an hour. Also, among teachers who ever looked at a test item page during a week, they tended to look at ten test items over a total time of about 13 minutes.

As reported earlier, Wayman, Cho, and Shaw (2009) found that 93 percent of the teachers in their study district accessed the Reports section of the student data tool, the section containing information on student performance. A comparable measure on Dashboard is the percent of teachers who accessed a class, students-in-class, or individual student page at least once during the year. That figure in this study, 98 percent, is comparable to what Wayman, Cho, and Shaw found.

¹²Note the 30 minutes online could be accumulated in one or more Dashboard sessions during the week.

Another comparison that can be made is to the previously cited figures from NETTS of 3 percent of the surveyed teachers who reported using individual student data at least once weekly and 15 percent who reported doing so at least once a month (Means et al. 2009). I, too, find that about 15 percent of the teachers were observed accessing individual student pages on Dashboard at least once a month. A close examination of the Web logs, however, reveals no teachers in the Dashboard data who accessed individual student pages at least once a week throughout the year.

There are two ways teachers can use Dashboard to access student test data. They can view the information online and interactively, or they can use Dashboard to print out student test data. The primary focus of this study is the online, interactive use of the Dashboard tool by teachers. The rationale for studying interactive usage is two-fold. First, the Web logs that form the basis of this study are most informative about interactive usage, with only limited information about print usage. Second and more substantively, interactions with administrative personnel in the district under study make it clear that Dashboard was developed with the intention that teachers would take advantage of the interactive features associated with the Web-based tool, such as the ability to relatively easily and quickly identify consistently incorrect student responses on a given test, examine the test items under question, and then be linked to resource material that can address the content under question.

There is, however, some information in the Web logs on how teachers use Dashboard to gather and print student test information. Panels D and E of table 1 summarize information on this method of interacting with Dashboard. On average teachers went to pages that print students-in-class information only about once every three weeks (0.35 times per week), and they went to pages that print individual student information only once every six weeks (0.16 times per week). These print statistics suggest that teachers used Dashboard more as an interactive tool in 2009 than as a tool for printing off student test data. Of course, it may well be the case that even though teachers print material from Dashboard relatively infrequently, they may spend substantial time viewing and using the student data once it is in paper form. There is, of course, no information in the Web logs on offline usage of Dashboard-based information.

The average weekly statistics of table 1 may obscure potential patterns of usage that may occur during the course of the academic year. Figures 3–6 provide information on weekly usage patterns across various dimensions by teachers during the 2009 school year. In these figures key test dates are marked with vertical lines: with the relevant assessment noted immediately to the right of each vertical line (e.g., “Fall Pretest,” “Benchmark 1”). Whereas four Benchmark assessments are administered to students in all schools each year, students in the fifteen TA schools were also administered a Fall pre-test and a January post-test in the school year under study. Although any individual teacher will see results posted to Dashboard within 24 hours of submitting the exams to central office, teacher delays in submitting exams for scoring means that it often takes up to two weeks before results for all classes appear on Dashboard.¹³

Figure 3 shows variation through the year in the percentage of teachers who log in to Dashboard during the week. In particular, there is evidence in figure 3 that teacher logins to Dashboard tended to spike in the two weeks after the administration of a Benchmark assessment. Except for a spike in Dashboard logins in the last week of December when about 52 percent of the teachers logged in, all of the spikes in usage during the year occurred after Benchmark assessments, ranging from about 45 percent on the Fall pre-test and the first Benchmark to slightly over 70 percent immediately after the last Benchmark in March. This 70-percent spike may be related to the fact that the March exam is the last Benchmark-based measure of student learning before the end-of-year state tests. This general pattern of increasing Dashboard usage is what one might expect in a system where teachers are expected to use regular test results as inputs to instructional practice.

Figure 4 show weekly patterns throughout the year on the median time logged in per week among teachers who ever logged in during that week. These patterns of time spent on Dashboard—conditional on logging in that week—roughly mirror the login patterns of figure 3, with observable spikes in time spent immediately following a Benchmark. Again, we see the highest usage after the March Benchmark that precedes the state exams.¹⁴

Figures 3 and 4 provide information on the weekly patterns associated with *how much* teachers use Dashboard, and a glance at these figures suggests that on any given week somewhere around 10 to 40 percent of the district teachers in the study logged in to the system that week and that the “average” teacher who logged in spent somewhere around six to eight minutes online with Dashboard during the week. One way to think about whether this represents substantial usage of student data is to consider two elementary school teachers who each have self-contained classrooms of, say, 21 students. Assume that one-third of each teacher’s students are struggling and that Benchmark tests have just been administered. According to figure 3, around 45 to 60 percent of the teachers logged in to Dashboard following a Benchmark (except for the 70 percent spike on the March Benchmark), so further assume that only one of the two hypothetical teachers would go to Dashboard to get information that might help her with her seven struggling students. Figure 4 suggests the teacher who did turn to Dashboard for information spent about one minute per struggling student logged into the system (seven struggling students and a median login time of around seven minutes per week for those who ever logged in that week). Although only a rough barometer, this back-of-the-envelope estimation at least raises the question of whether or not usage at this level—spending one minute logged in per week for each struggling student—is characteristic of what the district has in mind in terms of using Dashboard for information that can assist teachers with their struggling students.

In addition to *how much* teachers use Dashboard, a second question pursued in this project is *how* do teachers use Dashboard while they are online? In particular, we are interested in the

¹³Following a Benchmark test the teacher turns the test sheets into district central office where they are scanned for scoring and posted to Dashboard within 24 hours. Teachers are responsible for scoring the relatively few open-response test items of their students and this can sometimes cause a delay in getting the tests in to central office. Also, a teacher may delay turning in test sheets to allow a student who was absent a chance to take the Benchmark test upon return to school. Results from the end-of-year state test take much longer because they are scored by the state. These tests are not available until later in the summer.

¹⁴Mean login times range from close to zero during the middle of October to about 40 minutes in the week following the last Benchmark.

extent to which teachers use Dashboard interactively to view student test data information and whether or not there are predictable patterns of this type of usage during the school year. Because all student-level test data are presented on either students-in-class pages or individual student pages, the focus on Dashboard usage will now turn to those pages. Figure 5 displays information on the mean amount of time teachers spent each week viewing Dashboard students-in-class pages. Averaged across all teachers, including those who never logged on during the week, figure 5 indicates that the average teacher spent from one to four minutes per week viewing students-in-class pages, with the exceptions of six and nine minutes per week spikes after the second and fourth Benchmark tests.

Figure 6 presents weekly information on teacher time on individual student level pages. If one were to hypothesize that the most intensive and informative use of Dashboard data is represented by teachers who “burrow” down to where test data on individual students is presented, the information in figure 6 is somewhat discouraging. In figure 6 the average teacher in the sample spent less than two minutes per week viewing individual student pages, even during peak weeks around Benchmark assessments. As we learned earlier in table 1, the mean time per week spent on individual student pages is only 0.6 minutes per week for all teachers, and 6.33 minutes per week for all teachers who viewed an individual student page in a given week. There is a long right-hand tail to the conditional distribution, however, as the median time on individual student pages among those with non-zero values in a given week is only 1.4 minutes, and the 25th percentile is half a minute. These statistics and figure 6 suggest that the bulk of teachers rarely spend substantive amounts of time on Dashboard viewing performance data at the individual student level.

In an analysis not shown here but available upon request, I examined how teachers apportion their time on Dashboard between viewing student level information and using the Web-based tool for other purposes such as looking at lesson plans or reviewing state standards. In that analysis, teachers who logged in to Dashboard spent from 20 to 50 percent of their time looking at student performance data, figures that seem reasonably high given all of the other types of information a teacher can access on Dashboard. Thus, concerns about how much teachers are using student performance data on Dashboard to inform and improve their practice should focus more on whether they login at all and how much time they spend while logged in, rather than in what they are doing while they are on Dashboard.

Figure 7 summarizes the information thus far about the extent to which teachers use Dashboard to view and analyze student performance data. That figure displays the distribution of total time during the year spent by teachers on students-in-class and individual student pages combined. According to this figure 17 percent of the core-subject grade 3–8 teachers in 2009 (73 of 429 teachers) spent a total of twenty minutes or less during the entire school year viewing both of these types of pages and 43 percent of the teachers (187 out of 429) spent an hour or less during the year on these student level pages. There is a long right-hand tail to this distribution, however, and a third of the teachers spent more than two hours during the year on these pages and 20 percent spent more than three hours.

Correlates of Dashboard Use

The ability to link other district data sources to the Dashboard Web log information allows for an examination of the correlates of Dashboard use. District personnel files are used to obtain information on teacher characteristics such as gender, race/ethnicity, years of experience, education level, and salary.¹⁵ District student and course files are used to match students and their test scores to teachers and construct value-added measures of teacher effectiveness, as well as measures of average class achievement at the beginning of the year.¹⁶ To explore potential correlates of Dashboard use, equation 1 is fit to the data:

$$Y_i = a + \partial * Baseline_i + \beta_1 * VA_i + \beta_2 * Exp_i + \beta_3 * Grade_i + \beta_4 * Educ_i + \varepsilon_i \quad (1)$$

In this equation i indexes teachers and

- Y is the natural log of the sum of total time spent during the year on students-in-class and individual student pages,
- $Baseline$ is the baseline mean achievement level of the teacher's students at the beginning of the year along with an indicator for whether the baseline level was imputed,¹⁷
- VA is teacher i 's value-added score,
- Exp is years of teaching experience,
- $Grade$ is an indicator for whether a teacher taught in grades 3 through 6 relative to grades 6 through 8,¹⁸ and
- $Educ$ is a vector of indicators capturing the education level of each teacher.

The log of time use is used for the dependent variable in equation 1 and in subsequent analyses in this study for two reasons, one statistical and one substantive. As figure 7 shows, the total time spent on students-in-class and individual student pages is decidedly non-normal and highly skewed. The log of this variable, however, is approximately normal (though slightly left-skewed), making the log of total time a more desirable dependent variable from a statistical standpoint. From a substantive standpoint it is more intuitive to relate changes in the independent variables to percentage changes in total time spent rather than changes in the levels.¹⁹

¹⁵Even though annual salary is in the data, because it is essentially determined by years of experience and education level, we use these other variables in regression models instead of salary.

¹⁶Value-added measures (VAMs) for teachers were based on math test scores for teachers who had value-added math scores and reading scores for teachers who had reading but no math value-added scores. In each case the measures were constructed using all available teachers in tested grades and subjects in the district during the 2009 and 2010 school years. Classes where fewer than five students could be linked to a teacher were excluded, and student covariates in the model included the prior year's test score in the subject of interest, an indicator for whether that score was missing and imputed, gender, race/ethnicity, special education classification, indicator for English language learner, indicator for participation in a gifted and talented program, and an indicator for ever being retained in a grade. The specification also included grade by year fixed effects. Empirical Bayes estimates from a multi-level, teacher random effects model were used as the VAM for each teacher.

¹⁷This baseline measure was computed by averaging, for each student, the prior year's state exam math score and state exam reading score (both mean zero, standard deviation one variables), and then averaging these scores across the students in a teacher's class.

¹⁸The dummy variable indicator equaled one for the 311 teachers who taught in any configuration of grades 3 through 6, zero for the nine teachers who taught in a grade 6 through 8 configuration, and zero for the 89 teachers who taught in grades 7 or 8 or a grades 7 and 8 combination.

¹⁹I further note that using logs will eliminate only seven teachers who have a zero value for total annual time in levels.

In the model the baseline achievement level of the teacher's class is included as a control variable because a teacher with a high achieving class may have little need to use data from Dashboard to help with struggling students. The value-added score of the teacher is included to ascertain whether more effective teachers, as measured by value added, use Dashboard more intensively conditional on the baseline achievement level of the class. Years-of-experience is included as a covariate to determine whether younger teachers are perhaps more intensive users of Dashboard than older teachers who may be less comfortable with computers. Similarly, the indicators for the education level of the teacher are included because teachers with more advanced degrees may have been exposed to training that would better prepare them to use Web-based student data. There is no hypothesized relationship between the grade level in which the individual is teaching and Dashboard use.

Again using data from the 2009 school year, estimates in table 2 are based on the 325 teachers who have non-missing values on all of the variables in the model.²⁰ Estimates in the first column of the table are from fitting equation 1 with ordinary least squares (OLS) and clustering standard errors at the school level. In this column the only statistically significant predictors of total time spent viewing student level pages are the prior achievement level of the class and the grade level indicator. Teachers in lower-performing classes tended to view student level Dashboard pages more frequently, and teachers in grades 3–6, traditional elementary grades, viewed student data on Dashboard at lower rates than teachers in middle school grades.

To explore the extent to which teacher correlates in Dashboard usage are explained by the school where a teacher works, a fixed-effects version of equation 1 is fit to the data. Estimates from the school fixed-effects model are in the second column of table 2. Within schools it is no longer the case that the data of students in lower-performing classrooms are viewed at higher rates, but it is the case that within schools teachers in grades 3–6 spend less time viewing student level pages than teaches in the same school who teach in grades 6–8.

We can explore the extent to which variation in teacher usage can be explained at the school level by fitting the multi-level

$$Y_{is} = \alpha + \beta_0 * Baseline_{is} + \beta_1 * VA_{is} + \beta_2 * Exp_{is} + \beta_3 * Grade_{is} + \beta_4 * Educ_{is} + u_s + \varepsilon_{is} \quad (2)$$

where now s indexes school and u_s is the random school effect. The estimates from this model are in the third column, with estimates of the ratio of the level two variance (τ^2) to total variance ($\tau^2 + \sigma^2$) at the bottom of the table. Estimates of the correlates of usage in this model are similar to those estimated using OLS, and of particular interest here is that about 10 percent of the total (unexplained) variation in teacher usage is attributable to between-school variation in usage.

²⁰Four hundred nine teachers have non-missing values on all variables except for value added. When the models in table 2 are fit over these 409 teachers and value added is excluded as a predictor, the results, available from the author, are essentially unchanged. I note the results, also available from the author, are also qualitatively very similar if the model is fit over the levels of time use rather than the log of time use.

In summary, the only teacher level covariate with any explanatory power in terms of Dashboard usage is the indicator for teaching in grades 3–6, with teachers in these grades spending less time on Dashboard. Unfortunately, at this point we do not know what it is about these teachers or the grades in which they teach that might explain this result. Nor do we have school level information that might explain some of the between-school variation in usage that is estimated.

The analysis now turns from examining potential teacher correlates of usage to a study of the time-related correlates of Dashboard usage. Following up on the time dependence of Dashboard usage depicted in figures 3–6, table 3 presents estimates from fitting variations of equation 1 to a teacher-week panel that includes indicator variables for whether a given week in the school year was a week before a Benchmark or state test, within two weeks after a Benchmark or state test, or the week when the Benchmark or state test was administered. The excluded time category is any “off test” week that is not in one of the before-, during-, or after-test intervals.

Estimates in column 1 indicate that teachers are not spending more time per week viewing student level pages in Dashboard in the week just prior to a Benchmark test than during the “off test” weeks. In fact they spend about 13 percent less time in any week before a Benchmark than they do during any “off test” week. Teachers do, however, spend more time viewing student level pages in the two weeks after a Benchmark test. They spend about 50 percent more time per week in the two weeks just after a Benchmark test than during the “off test” weeks.²¹ The estimates in the first column also indicate that teachers spend less time during and after the state exams than during “off test” weeks.

The second and third columns of table 3 explore the extent to which the timing of teachers’ use of Dashboard to view student level pages can be explained by average class ability and teacher characteristics (column 2), and by whether the timing exits within schools (column 3). The estimates from these specifications are very similar to those of the basic model in column 1.²² The increased usage immediately following Benchmark assessments is, again, what one would expect as teachers view the Benchmark data of their students as it becomes available. The robust negative coefficients in the weeks immediately prior to the Benchmark exams can be understood—teachers are likely spending their time preparing students for the upcoming Benchmark. On the other hand, one could also imagine a scenario where teachers turn increasingly to Dashboard data in the weeks just prior to a Benchmark as a tool to help them prepare their students; the data do not support this scenario.

Change Over Time in Usage

The evidence thus far is that teachers spent relatively little time in 2009 viewing student-level performance data on Dashboard. To examine whether these patterns of usage changed between 2009 and 2010 the Web-log data from 2010 are utilized. Summary statistics for the 359 core-subject grade 3–8 teachers in 2010 are similar to those in table 1 that are based on

²¹Calculated as $\exp(0.436) - 1$.

²²I note that the low viewing rates during and following the state exams is not surprising because this is the end of the school year and teachers will not have yet received the state exam results.

the 2009 teachers. The only difference is evidence that teachers in 2010 spent some more time viewing students-in-class pages than did teachers in 2009. On average, 2010 teachers spent 117.3 minutes looking at students-in-class pages versus the 97.4 minutes teachers spent on these pages in 2009 (p -value of the difference is .022). There is no statistical difference in the mean total time for the year viewing individual-student pages (27.1 minutes for 2010 teachers versus 25.2 minutes for 2009 teachers, $p = .611$). Similarly, the 2010 teachers printed out more students-in-class pages than did the earlier teachers (23.1 pages for the year versus 14.7, $p = .000$), but there was no difference in the printing of individual-student pages (8.5 versus 6.7, $p = .173$).

In addition to these aggregate statistics, there are 243 teachers who are observed in both years in the data. Using these teachers we can examine within-teacher changes over time in Dashboard usage of student-level data. The results in table 4 are from teacher fixed effects models that control for any changes across the years in class size and average class ability as measured by the average class scores on the previous year's state exams. The dependent variables in models 1 and 2 measure log teacher time spent on students-in-class (column 1) and individual-student pages (column 2), and the dependent variables in models 3 and 4 measure log number of times students-in-class or individual-student data were printed. Results in the first two columns reinforce the aggregate statistics and suggest that the observed changes in mean time viewing students-in-class pages is primarily a within-teacher change rather than a compositional change in teachers across the years. On the other hand, the marginally significant estimates on the 2010 indicator in column 4 suggest that the aggregate statistics may mask within-teacher increases in the number of times individual-student level pages were printed out between 2009 and 2010. Also, column 3 indicates that teachers in TA schools tended to print out students-in-class information at higher rates in 2010 than in the previous year and at higher rates than teachers in non-TA schools. This suggests the additional training teachers in TA schools received may have resulted in more data usage via printed material, but did not result in more interactive usage of Dashboard data.

The fixed effects estimates in table 4 show some areas where teachers increased Dashboard usage between 2009 and 2010. Overall, however, there is no robust evidence of systematic increases in Dashboard usage across the years.

Dashboard Usage and Student Test Score Gains

Ultimately we are interested in the extent to which online teacher usage of student performance data is related to student achievement gains. I use the 2010 data that have both state exam and Benchmark score data to explore this question, and because the interaction that matters occurs when a teacher views the data of a particular student, I first use these data to examine the predictors of that happening.

In the 2010 data, 309 of the 359 teachers viewed the Dashboard data of one or more of their students at least once during the year. Of these 309 teachers, 271 of them can be matched to the value-added distribution in the district, have non-missing information in the personnel files, and have at least one student who can be matched to the test score file. These teachers

are matched to 4,106 unique students in fitting the following models that explore the correlates of teacher usage of individual student data:

$$Y_{ij} = \beta * pre-test_{ij} + f(X_{ij}) + g(W_j) + \varepsilon_{ij} \quad (3)$$

$$Y_{ij} = \beta * pre-test_{ij} + f(X_{ij}) + \alpha_j + n_{ij} \quad (4)$$

where i indexes students and j indexes teachers and the dependent variable is the log of the total time teacher j viewed the data of student i on Dashboard during 2010. As before, the student pre-test score is the average of the previous year's state exam scores in math and English language arts (ELA). For the few students who did not have both scores to average, the available math or the ELA score was used.²³ The vector X contains student characteristics that might be predictive of Y and in this case include indicators for eligibility in the district's gifted and talented programs, whether a special education student, and whether designated as an English language learner.²⁴ The vector W is composed of teacher characteristics including value-added score, gender, race, years of experience in the district, grade taught in 2010, education level, and whether or not a national board certified teacher. Equation 4 replaces the teacher characteristics with a teacher fixed effect.

Results from estimating equations 3 and 4 are in table 5. The only variables that are consistently predictive of teacher use of a student's Dashboard data are the prior year's state test score and special education status, with teachers viewing the data of students who started the year at lower achievement levels at higher rates, and also viewing the data of special education students at higher rates. Estimates from the teacher fixed effects model in column 3 indicate that given two students in the same teacher's class who were one standard deviation apart in terms of their pre-test scores, the teacher viewed the Dashboard data of the lower achieving student about 5 percent more than the data of the higher achieving student. That same teacher also viewed the data of her special education students at a 21 percent higher rate.²⁵ In this model it is also the case that the data of English language learners were also viewed at a higher rate. Although statistically significant, these estimates should be viewed in context. The mean total time spent viewing a random individual student in 2010 was about 2 minutes, 20 seconds. Thus, even the 16 percent higher rate of viewing the data of special education students translates into only about an extra 20 seconds per year on average that teachers spent on special education versus non-special education students. Nevertheless, these results—more time spent on lower-achieving and special-education students—are consistent with how we might predict a teacher would spend time on Dashboard viewing student data.²⁶

²³There were 22 students with only prior test scores in math and 30 students with only prior ELA scores.

²⁴The data also contain information on gender and race/ethnicity but these are not included in the model because conditional on pre-test score they should not be theoretically linked to a teacher's use of student data. Also, these variables are never statistically important when they are included.

²⁵Calculated as $\exp(0.158) - 1$.

²⁶Similar results available from the author are obtained in models where the dependent variable is an indicator for ever printing out Dashboard data on student i during the year.

The study now turns from exploring what predicts teacher usage of individual student data to whether that usage is related to increased student achievement. Absent exogenous variation in the amount of time teachers spend viewing student Dashboard data, developing a satisfactory model relating teacher Dashboard usage to student achievement growth is not a straightforward exercise. To see this consider the following model:

$$A_{ijt} = \beta * A_{ij,t-1} + \delta * (T_{ijt}) + f(X_{ijt}) + g(W_{jt}) + \varepsilon_{ijt} \quad (5)$$

where i, j , and t index students, teachers, and time, respectively. A is a measure of achievement and, as before, X and W (from equation 5) are vectors of student and teacher characteristics, though the X vector in these achievement equations also contains information on the gender and race/ethnicity of the student. T is a measure of the amount of time that teacher j spent viewing the Dashboard data of student i between period $t - 1$, when a prior measure of achievement was gathered, and time t . As before, we could also consider a model such as equation 6 where the vector of teacher characteristics is replaced with a teacher fixed effect, α .

$$A_{ijt} = \beta * A_{ij,t-1} + \delta' * (T_{ijt}) + f(X_{ijt}) + \alpha_j + \varepsilon_{ijt} \quad (6)$$

The parameters of interest in equations 5 and 6 are δ and δ' , measures of the relationship between time spent viewing a student's data and student achievement growth.

A priori, one would expect δ to be non-negative because viewing a student's Dashboard data should not lead to a decrease in achievement. A concern in estimating δ in this model, however, is that teachers likely use information unavailable to the researcher in making decisions about the use of student performance data on Dashboard. In particular, consider two observationally similar students who have equal levels of prior achievement. If one of these students is having more academic problems during the year than the other and these unobserved (in the data) problems are positively correlated with a teachers' time viewing that student's data, then estimates of δ would be downwardly biased. Nevertheless, lacking suitable instruments for T , I estimate equations 5 and 6 with OLS using the available data.

Equations 5 and 6 are first estimated using the end-of-year state exams as measures of prior and final student achievement. In these models $t - 1$ is the end of the 2009 school year and time t is the end of the 2010 school year. Thus, T represents the total time that teacher j spent on student i 's Dashboard data during the 2010 school year. When the state exams are used as the measures of A_t and A_{t-1} , I can report that the estimate of δ based on equation 5 is essentially zero, 0.0008 (standard error = 0.001), and the estimate from the fixed effects model of equation 6 is even closer to zero.²⁷ From these estimates we would conclude that either teacher usage of Dashboard is unrelated to student achievement growth as measured by the state exams or that the estimates are biased toward zero.

²⁷ Estimates on the other variables in the models are generally as expected (e.g., eligibility for gifted and talented programs is positively related to achievement growth, special education designation is negatively related, and prior achievement is the strongest predictor of current achievement). None of the observed teacher characteristics in W are statistically significant. Full regression results available from the author.

A more proximate measure of student achievement available in the data comes from student test scores on the quarterly Benchmark assessments. In models using Benchmark test scores the immediately prior Benchmark test is used as the measure of prior achievement for each subsequent Benchmark except in the case of the first Benchmark of the year, where prior achievement is measured by the previous year's state exam score. In the Benchmark test model the measure of T is teacher time on the Dashboard data of student i in the interval between the current Benchmark exam and the prior measure of achievement.²⁸ When fitting the Benchmark test models only students in grades 3, 4, and 5 who are observed as having only one teacher are used. With this subsample of students and teachers one can be more certain that all of the activity that is occurring between a teacher and a given student's Dashboard data is being captured. In this sample there are 1,535 students across 149 grade 3–5 teachers with at least one math Benchmark score and 1,530 students across 150 teachers with at least one ELA Benchmark score.

Before turning to estimates of equations 5 and 6 where Benchmark tests are used as measures of achievement, figure 8 displays the scatter plot of the Benchmark scores in math versus teacher time on Dashboard. Each point on either graph represents the Benchmark score of an individual student graphed against the time spent by the teacher viewing the data of that student in the interval between the prior and current Benchmark test. Any given student will be represented by from one to four data points depending upon the number of Benchmark tests for that student in the data.²⁹

Figure 8 certainly does not suggest a relationship between Dashboard usage and Benchmark scores on the math exam.³⁰ Moreover, these figures also highlight yet again the limited usage of Dashboard by teachers for viewing student data. The great bulk of the data is massed at very low levels of time spent on Dashboard. Although the mean of time spent on a student in any given interval between Benchmark tests is just less than half a minute (0.45, standard deviation = 2.07), 74 percent of the 6,279 student-Benchmark-interval data points have a value of zero for the time spent by the teacher viewing student-level data.

Estimates of equations 5 and 6 using Benchmark test scores as the achievement level are presented in table 6, and they bear out the graphical information in figure 8. As with the state test score estimates, in none of the models is the time spent on Dashboard in a Benchmark-interval related to the subsequent Benchmark test score.³¹ The poorly estimated negative point estimates of δ suggest the possible presence of downward bias due to unobserved heterogeneity. In any case, there is no evidence in any of the models used to estimate equations 5 and 6 that Dashboard usage of student performance data leads to student achievement gains.

²⁸In the case of the first Benchmark T is measured by teacher Dashboard use between the beginning of school and the first Benchmark.

²⁹For example, among the observations that will be used in the estimates, there are 1,540 students with math scores in the first Benchmark interval, 1,539 in the second, 1,542 in the third, and 1,367 in the fourth. The numbers are very similar for ELA scores.

³⁰The corresponding figure for Benchmark assessments in reading (available upon request from the author) looks very similar.

³¹In addition to fitting versions of equations 5 and 6, I also use the fact that there are up to four Benchmark exams for each student to fit a student fixed effects model. The results in these models, available from the author upon request, are very similar to the estimates in table 6.

There is a notable pattern of Dashboard usage in the district that may help explain some of the null results in table 6. If teachers were using Dashboard throughout the year as a tool for promoting student achievement, we would expect to observe teachers viewing the data of their students at various times during the year. Instead, it is the case that one of every three teachers used in the just-discussed Benchmark test analysis spent all of their time viewing individual student data in *one* of the four possible Benchmark test intervals, and they spent *no time* during any of the other intervals.³² Also, across teachers who concentrate all of their time in one interval, no interval tends to have more teachers than other intervals. These patterns suggest something other than data use for instructional purposes is driving teacher usage of Dashboard, at least when it comes to viewing data on individual students. For example, it may be that teachers only look at the data of their individual students when prompted by campus principals or district professional development staff, or as a function of the district's teacher evaluation system. Unfortunately, these data have no information that would allow us to better understand this pattern.

5. SUMMARY AND CONCLUSIONS

This paper has drawn upon unique data to present some of the first detailed objective estimates of how much and in what ways teachers actually use Web-based student performance data interactively, and the extent to which such use might be related to student achievement. Though primarily descriptive in nature, the information in this paper should help to fill a void in our understanding regarding the extent to which we might expect teachers to use Web-based student performance data to inform and improve classroom practice. It is obvious that teachers must first access student performance data if these data are to be used in ways that can influence student achievement. To date there has been limited information on this critical step, a knowledge gap this paper addresses.

Although there is no other district against which to compare the teacher usage statistics from the district used in this study, it is fair to say that the results from this district are less than encouraging. Three years after the launching of the Dashboard system, and well into a substantial district effort encouraging teacher use of Dashboard, measures of teacher usage of student data are relatively low. Among the teachers targeted by the district as the primary group to use student performance data (core-subject teachers in grades 3–8) the median time spent during the entire school year viewing pages with any student level information is about 1 hour, 20 minutes. Furthermore, if the goal is to have teachers use a tool like Dashboard to learn about and help individual students, the six minutes per year median time teachers spent on data at the individual student level is particularly disconcerting, as is the mere 36 seconds per-week average spent viewing individual student level pages during the course of the school year. Furthermore, a close examination of the data indicates that one in three teachers spent all of their limited time viewing data on their individual students at only one point during the year, never visiting their student data on Dashboard at any other time. The levels and patterns of observed usage from this study offer little indication of systematic use of student performance data on Dashboard by district teachers.

³²Also, 51 percent of the teachers spent 75 percent or more of their time in just one of the intervals.

The aforementioned focus group research conducted in the district during the two years of this study suggests some reasons that online teacher usage of Dashboard may be suboptimal. Teachers in these meetings were quite candid in expressing their opinions about and experiences with Dashboard. One factor that arose with relative frequency was an expressed concern that the Benchmark tests lacked some validity because they often tested material the teachers had yet to cover in class. A second factor that was supported across the focus group discussions was a perceived lack of instructional time to act on information a teacher might gain from Dashboard data. In particular, teachers expressed frustration with the lack of time to re-teach topics and concepts to students that had been identified on Dashboard as in need of re-teaching. A third concern was a lack of training in how to use Dashboard effectively and efficiently. A fourth common barrier to Dashboard use cited by teachers was a lack of time for Dashboard-related data analysis.

In summary, many factors have to fall into place if teachers are going to become regular and effective users of Web-based student performance data. Teachers must either learn effective data use in their pre-service training, or districts must be prepared to provide that training.³³ There should be training and support in how to translate lessons learned from data analysis into instructional practice that can influence student achievement. The student assessments that generate the data must be tightly aligned with the district curriculum. Time needs to be allocated for teachers to access and analyze student data on a regular basis, and there needs to be space in the curriculum for the re-teaching of concepts that are not learned the first time.

None of these steps is easy and they all require resources and attention to detail. As the logic model discussed at the beginning makes clear, however, if any one link in the chain from testing to altered classroom practice is broken, no amount of investment on a Dashboard-like system will pay off in terms of improved student outcomes.

This study should provide a cautionary note to districts that are investing in Web-based student information systems designed to bring student performance data to teachers. The evidence presented here suggests that teachers' online examination of student test data may be lower than some districts anticipate, and even districts with a well-designed Web tool should not assume that if you build (or buy) it they will come.

Acknowledgments

I would like to thank Ben Zhang, Miriam Joelson, and David Stern of Brown University for their research assistance; Amy Wooten of the Harvard Graduate School of Education for her intellectual contributions and assistance; Eric Taylor of the Center for Education Policy Research at Harvard for assistance with data construction; and Jason Snipes of the Academy for Educational Development and Jeffrey Wayman of the University of Texas at Austin for helpful conversations in the early stages of this project. I also want to thank the Council of Great City Schools for their generous support for this project. Finally, a particular debt of gratitude is owed to the Director of Research, Evaluation, and Test Administration and the Academic and Assessment System Administrator at the study school district for their assistance in this project.

³³I thank an anonymous reviewer for pointing out the potential role that undergraduate and graduate teacher training programs could play and the burden that districts must shoulder if these programs do not prepare teachers to be data users.

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Percentage Correct

Public Schools Dashboard

School: [REDACTED]

Teacher: Demo Teacher

Section: [REDACTED]

Test: Benchmark Assessment 4 Grade 6 Math (7079)-01/15/12

Avg % Correct: 51%

District Avg % Correct: 61%

Graphs showing all district, school, class averages

Student and Score	Assessment Mastery
[REDACTED] (17%)	Reteach
[REDACTED] (17%)	Reteach
[REDACTED] (25%)	Reteach
[REDACTED] (25%)	Reteach
[REDACTED] (25%)	Reteach
[REDACTED] (33%)	Reteach
[REDACTED] (33%)	Reteach
[REDACTED] (33%)	Reteach
[REDACTED] (42%)	Reteach
[REDACTED] (42%)	Reteach
[REDACTED] (42%)	Reteach
[REDACTED] (42%)	Reteach
[REDACTED] (42%)	Reteach
[REDACTED] (50%)	Reteach
[REDACTED] (50%)	Reteach
[REDACTED] (50%)	Reteach
[REDACTED] (50%)	Reteach
[REDACTED] (67%)	Practice
[REDACTED] (67%)	Practice
[REDACTED] (67%)	Practice
Suzie R. (67%)	Practice
[REDACTED] (67%)	Practice
[REDACTED] (67%)	Practice
[REDACTED] (67%)	Practice
[REDACTED] (75%)	Practice
[REDACTED] (83%)	Enrichment
[REDACTED] (83%)	Enrichment
[REDACTED] (92%)	Enrichment

Figure 1.

Example of a Students-in-Class Page from Dashboard

Student Results

Public Schools Dashboard

School: [REDACTED]

Teacher: Demo Teacher

Section: [REDACTED]

Test: Benchmark Assessment 4 Grade 6 Math (7079)-01/15/12

Student: Suzie R.

Question	Correct Answer	Student Response	
1	D	D	Correct
2	A	A	Correct
3	C	A	Incorrect
4	D	B	Incorrect
5	A	D	Incorrect
6	B	B	Correct
7	B	B	Correct
8	B	B	Correct
9	2	2	Correct
10	2	1	Incorrect

[Click here to see all scores and mastery for this student](#)
Figure 2.

Example of an Individual Student Page from Dashboard

Figure 3.
Percentage of Teachers Who Logged in to Dashboard by Week

Figure 4.
Median Time Logged in among Teachers Who Ever Logged in to Dashboard during a Week, by Week

Educ Finance Policy. Author manuscript; available in PMC 2015 January 13.

Figure 6.
Mean Time Spent on Individual Student Pages, by Week

Figure 7.
Distribution of Total Time Spent on Student Level Pages during the Year

Figure 8.
Benchmark Math Test Score for Individual Students by Teacher Time on that Student on Dashboard

Table 1**Descriptive Statistics on Various per-Week Dashboard Usage Measures**

	All Teachers	Conditional on Having a Non-zero Value
Panel A: Dashboard logins		
Average # logins	0.79 (1.60)	2.22 (2.01)
Mean time logged in	9.99 (115.38)	28.29 (192.78)
Panel B: Performance information pages		
Mean time on class pages	0.25 (2.03)	2.84 (6.20)
Mean time on student pages	2.31 (8.37)	7.64 (13.83)
Mean time on individual student page	0.60 (5.14)	6.33 (15.58)
Mean hits on class pages	0.28 (1.31)	2.97 (3.19)
Mean hits on student pages	2.52 (6.70)	8.22 (9.98)
Mean hits on individual student pages	0.58 (4.32)	5.69 (12.41)
Panel C: Resource-type pages		
Mean time on item pages	0.57 (6.05)	12.90 (25.85)
Mean time on resource pages	3.17 (96.96)	51.86 (388.82)
Mean hits on item pages	0.49 (3.76)	10.48 (14.08)
Mean hits on resource pages	0.33 (2.11)	4.83 (6.51)
Panel D: Printing performance information pages		
Mean hits on print class pages	0.04 (0.46)	2.66 (2.42)
Mean hits on print students-in-class pages	0.35 (1.56)	4.04 (3.63)
Mean hits on print individual student pages	0.16 (1.71)	3.77 (7.56)
Panel E: Printing resource-type pages		
Mean hits on print item pages	0.13 (3.41)	10.83 (29.36)
Mean hits on print resource pages	0.00 (0.14)	4.00 (4.82)

Note: These data are for all teachers and conditional on teachers who have non-zero values of the measure under consideration. All time is in minutes. Standard deviations in parentheses.

Table 2

Estimated Relationships between Log Total Time during the Year Spent on “Students” and/or “Individual Student” Level Pages and Various Teacher Level Covariates

	OLS	School Fixed Effects	School Random Effects
Baseline average student achievement	−0.496* (0.241)	−0.112 (0.087)	−0.402* (0.187)
Value-added estimate	−0.054 (0.598)	−0.190 (0.212)	−0.188 (0.604)
Years of experience	−0.006 (0.010)	0.000 (0.003)	−0.004 (0.010)
Elementary grade teacher	−0.425* (0.199)	−0.199** (0.061)	−0.397* (0.175)
Bachelors degree plus	−0.280 (0.336)	−0.104 (0.130)	−0.286 (0.367)
Master’s degree	−0.170 (0.332)	−0.148 (0.122)	−0.154 (0.352)
Master’s degree plus	−0.301 (0.357)	−0.201 (0.134)	−0.313 (0.377)
Ratio of random effects parameters: $\tau^2/(\sigma^2 + \tau^2)$	NA	NA	0.103
R-squared	0.070	0.169	—
N	325	325	325

Note: Robust standard errors (in parentheses) clustered at the school level.

*
 $p < .05$,

**
 $p < .01$.

Table 3

OLS Estimates from Regressions with Log Total Time during the Week Spent on “Students” and/or “Individual Student” Level Pages as the Dependent Variable

	(1)	(2)	(3)
1 week before a Benchmark exam	−0.131* (0.063)	−0.150* (0.063)	−0.155* (0.063)
The week during a Benchmark exam	0.014 (0.072)	−0.043 (0.071)	−0.042 (0.071)
2 weeks after a Benchmark exam	0.436*** (0.058)	0.412*** (0.057)	0.417*** (0.058)
1 week before the state exams	0.022 (0.103)	0.016 (0.103)	0.014 (0.102)
2 weeks during the state exams	−0.281 [†] (0.145)	−0.262 [†] (0.145)	−0.263* (0.145)
2 weeks after the state exams	−0.489*** (0.127)	−0.478*** (0.127)	−0.464** (0.124)
Teacher and Class Variables ^a	No	Yes	Yes
School fixed effect	No	No	Yes
Number of teachers	325	325	325
Number of observations	4,385	4,385	4,385
R-squared	0.027	0.062	0.080

Note: Robust standard errors clustered at the school level in parentheses.

^aIncluding beginning of year average class achievement level, teacher value-added estimate, years of teaching experience, and indicators for whether average student ability was imputed and for the education level of the teacher.

*
 $p < .05$,

**
 $p < .01$,

 $p < .001$,

[†]
 $p < .10$.

Table 4
Within Teacher Estimates of the Change in Dashboard Usage between 2008–09 and 2009–10

	(1) Log Minutes on Students-in-Class Level Data	(2) Log Minutes on Individual- student Level Data	(3) Log Number of Times Students-in- Class Level Data Printed	(4) Log Number of Times Individual- student Level Data Printed
2010 indicator	0.234* (0.0966)	0.0124 (0.201)	0.197 (0.102)	0.322** (0.194)
Targeted Assistance (TA) School	0.0535 (0.319)	–0.378 (0.616)	0.171 (0.321)	–0.565 (0.671)
TA School in 2009–10	–0.239 (0.160)	–0.338 (0.324)	0.383* (0.153)	0.0726 (0.284)
Number of students in class	–0.00425* (0.00182)	–0.00655 (0.00377)	–0.000810 (0.00216)	–0.00165 (0.00366)
Average class achievement	–0.00643 (0.172)	–0.132 (0.344)	–0.334 (0.175)	–0.447 (0.298)
Teacher fixed effects	Yes	Yes	Yes	Yes
Number teachers	243	243	243	243
Adjusted R-sq	0.615	0.286	0.709	0.381

Note: Standard errors in parentheses.

*
 $p < .05$,

**
 $p < .10$.

Table 5

Student and Teacher Predictors of How Much Teachers View the Data of Individual Students in Dashboard

	(1)	(2)	(3)
	Log Minutes on Individual Student Data	Log Minutes on Individual Student Data	Log Minutes on Individual Student Data
Prior year test score	−0.0914* (0.0460)	−0.0659 [†] (0.0380)	−0.0479 [†] (0.0245)
Eligible for gifted and talented	0.174 (0.124)	0.180 (0.113)	0.0599 (0.0824)
English language learner	0.264 (0.172)	0.204 (0.155)	0.186 [†] (0.109)
Special education	0.171* (0.0708)	0.192** (0.0681)	0.158*** (0.0471)
Teacher characteristics	No	Yes	—
Teacher fixed-effects	No	No	Yes
Number of student observations	4,106	4,106	4,106
Number of teachers	271	271	271
Adjusted R-sq	0.007	0.017	0.302

Note: Standard errors (in parentheses) clustered at the teacher level.

*
 $p < .05$,

**
 $p < .01$,

 $p < .001$,

[†]
 $p < .10$.

Table 6

Estimates of the Relationship between Benchmark Test Scores in Math and ELA and the Amount of Time Spent by the Teacher Viewing the Student's Data in the Just Prior Interval between the Last and the Current Benchmark Test

	(1)	(2)	(4)	(5)
	Math Benchmark	Math Benchmark	ELA Benchmark	ELA Benchmark
Minutes of teacher Dashboard time on student in just prior Benchmark test interval	-0.00640 (0.005667)	-0.00862 (0.00472)	-0.00339 (0.00351)	-0.00403 (0.00406)
Prior test score	0.627** (0.0151)	0.583** (0.0141)	0.618** (0.0172)	0.588** (0.0140)
Eligible for gifted and talented	0.225** (0.053)	0.276** (0.0378)	0.240** (0.0343)	0.294** (0.0343)
English language learner	0.0405 (0.0552)	0.0671 (0.0596)	0.0450 (0.0749)	0.0720 (0.0617)
Special education	-0.144** (0.0346)	-0.132** (0.0308)	-0.156** (0.0271)	-0.1868** (0.0304)
Students in class	0.001080 (0.000652)	—	0.000734 (0.000738)	—
Average class achievement	0.067* (0.034)	—	0.162** (0.0263)	—
Student gender and race/ethnicity	Yes	Yes	Yes	Yes
Teacher characteristics	Yes	—	Yes	—
Teacher fixed effects	No	Yes	No	Yes
Number of student-interval observations	5,652	5,652	5,644	5,644
Number of teachers	149	149	150	150
Adjusted R-sq	0.4923	0.505	0.494	0.497

Note: Standard errors (in parentheses) clustered at the teacher level.

* $p < .01$,

** $p < .001$.