



Managing The Teacher Workforce in Austere Times: The Implications of Teacher Layoffs *

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Abstract – Over 2000 teachers in the state of Washington received reduction-in-force (RIF) notices in the past two years. We link data on these RIF notices to a unique dataset that includes student, teacher, school, and district variables to determine the factors that predict the likelihood of a teacher receiving a RIF notice. Not surprisingly, we find that a teacher’s seniority is the greatest predictor, but we also find (all else equal) that teachers with a master’s degree and teachers credentialed in the “high-needs areas” of math, science, and special education were less likely to receive a RIF notice. Value-added measures of teacher effectiveness can be calculated for a subset of the teachers and these show no relationship between effectiveness and the likelihood of receiving a RIF notice. Finally, simulations suggest that a very different group of teachers would be targeted for layoffs under an effectiveness-based layoff scenario than under the seniority-driven system that exists today.

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Budget cuts have resulted in “*the most rampant layoffs of teachers and other government employees in decades,*” as “*72,700 education jobs were eliminated in September (2010) on a seasonally adjusted basis.*”

-*Washington Post and New York Times*, October 8, 2010

I. Background

Tough economic times portend tight school budgets, possibly for years to come. Stories abound about the staffing cuts that will have to be made today and in the next couple of years, as the ripple effects of the economic crisis impact local and state education budgets (Lewin and Dillon, 2010; Westneat, 2009). Education is a labor-intensive industry with most districts devoting well over 50 percent of expenditures toward teacher compensation.¹ Consequently, major budget cuts have resulted in the first significant teacher layoffs in recent times. In fact, the number of layoffs likely would have been larger over the past couple of years in the absence of federal stimulus money (AP 2010). Moreover, while the recently passed Education Jobs and Medicaid Assistance Act (widely known as the “Edujobs bill”) may save hundreds of thousands of teacher jobs nationwide this year (Klein 2010), education budgets do not look like they will be improving in the next couple of years as state-expenditures are expected to drop again in 2011 (Adams, 2010; Hess and Downs, 2010) and many pundits expect that this is the last time the federal government will step in to avert widespread teacher layoffs (AP 2010).

There is a growing body of literature that uses value-added models (VAMs) to identify the contribution that *individual* teachers make toward student learning gains (e.g. Aaronson et al., 2007; Goldhaber and Hansen, 2010; McCaffrey et al., 2009), and this

¹ According to the U.S. Department of Education, for instance, in 2005-06 about 54 percent of aggregate educational expenditures were devoted to instructional salaries and benefits (U.S. Department of Education, 2009).

literature demonstrates that teacher quality is the most important *schooling* factor influencing student achievement.² Estimates suggest, for example, that a one standard deviation increase in teacher quality raises student achievement in reading and math by 10 (Rivkin et al., 2005; Rockoff, 2004) to 26 (Koedel and Betts, 2007) percent of a standard deviation.³ Thus, for districts facing the prospect of layoffs, determining which teachers are laid off has profound implications for student achievement. This fact has not gone unnoticed as calls to reform teacher layoff policies have begun to appear with regularity in newspaper editorials and policy briefs (e.g. Daly and Ramanathan, 2010; NCTQ, 2010, The New Teacher Project, 2010).

In this paper we describe the findings from a study on the factors that predict teacher layoffs and present some speculative evidence on the implications of layoff policies on student achievement. For the analyses we utilize a unique dataset from Washington State that links teachers to schools and students and includes information on those teachers who received layoff notices in the 2008-09 and 2009-10 school years.

We find strong evidence that seniority plays an outsized role in determining the teachers who are targeted for layoffs, but it is not the sole factor as teachers who are in high-needs subjects are less likely to receive a layoff notice than those who are not. Measures of teacher effectiveness, however, appear to be entirely unrelated to which teachers receive layoff notices. Finally, simulations suggest that a very different group of teachers would be targeted for layoffs under an effectiveness-based layoff scenario than under the seniority-driven system that exists today.

² We use the term “teacher quality” to mean the *ability of teachers to contribute in measurable ways to student gains on standardized tests*, and treat this as synonymous with the terms “teacher performance” and “teacher effectiveness”.

³ Moreover, other estimates (Hanushek, 1992) show that the difference between having a very effective versus a very ineffective teacher can be as much as a full year’s learning growth.

II. Seniority-Based Layoff Policies: Background and Implications

It is a relatively rare event to have teachers laid off because of school budget shortages given that per pupil spending has risen every year since 1993 (Digest of Education Statistics 2010).⁴ But layoffs do on occasion happen, so it is not surprising that the layoff process is addressed in collective bargaining agreements (CBAs). And, in the overwhelming majority of these agreements, “last hired, first fired” provisions make seniority the determining factor for which teachers are laid off first. For example, all of the 75 largest school districts in the nation use seniority as *a* factor in layoff decisions, and seniority is the *sole* factor that determines the order of layoffs in over 70 percent of these districts.⁵

There are notable examples of districts that do not rely solely on seniority. Chicago Public Schools, for instance, recently changed policies to allow layoffs for untenured teachers that are performance-based (judged by principals’ evaluations of teachers) (Rossi 2010)—but performance-based exceptions to the seniority-based rule are relatively rare, occurring in only 20 percent of the 75 largest districts. The situation in Washington State—the focus of this study—looks similar. A review of the collective bargaining agreements currently operating in the ten largest school districts in Washington shows that *all* use seniority as a basis for determining layoffs within

⁴ In fact, per pupil spending in the United States has increased every year since 1970 with the exceptions of 1979-80, 1980-81, 1991-92, and 1992-93, and has more than doubled in that time (\$10,041 in 2006-07 compared to \$4489 in 1970-71, as measured in 2007-08 dollars).

⁵ These figures are compiled based on information from the NCTQ TR3 database (NCTQ 2009). Notably, however, some of these districts are trying to move away from seniority-based layoffs despite the language in collective-bargaining agreements. In addition to Chicago, Los Angeles Unified recently settled a lawsuit brought by the ACLU and agreed to limit the use of seniority in teacher layoffs (Felch and Song 2011).

certificated categories⁶, and eight of these districts use seniority as the *only* determinant of which teachers get laid off.

The use of seniority as a determining factor in layoffs is not unique to public education. In a study of the history of layoffs beginning with railroad employees after the American Civil War and continuing with the auto industry in the early 1900s, Lee (2004) finds (as of 1994) that 88 percent of union contracts specified seniority as a factor in the layoff decision. The Bureau of National Affairs also reports that 46 percent of industries (as of 1989) used seniority as the sole factor for layoffs. Among union contracts, the use of seniority-based layoff provisions varies somewhat by industry, though the majority of both manufacturing and non-manufacturing union contracts include these provisions. For instance, over 90 percent of contracts in the manufacture of transportation equipment and communications industries include these seniority provisions, but only about 10 percent of contracts in construction specify seniority as a factor in layoffs (Bureau of National Affairs 1989). Nor are seniority rules limited to unionized sectors of the economy; in a survey of 429 non-construction and non-agricultural firms, Abraham and Medoff (1984) found that 24 percent of non-union hourly workers were subject to some sort of written seniority policy regarding layoffs.

While much of the empirical focus of economic analysis of employment termination has been on its effect on future labor market outcomes, the interest here lies in understanding what predicts employment separation in the case of downsizing. This subset of the literature has explored the role of various factors, including discrimination (Wolpin 1992), macroeconomic cyclicalities (Moser 1986), and institutional structures,

⁶ Certificated categories include teachers (grouped by subject area taught), nurses, speech therapists, and any other credentialed employees.

such as firm-specific human capital (Parsons 1972) and unemployment insurance (Topel 1983). More pertinent to the discussion here, there are some studies that look generally at the characteristics of workers and firms associated with layoffs. Farber et al. (1997) provides a comprehensive look at differences in job loss rates by gender, age, education, as well as across different occupations and industries for US workers. Farber finds that younger and less educated workers tend to have relatively higher rates of job loss. In terms of industry and occupation, Manufacturing and Laborers had the highest rates of job loss, respectively.

To our knowledge, there is no research on the determinants of *layoffs* in education, though there is a small body of literature on teacher *dismissals*. In a recent working paper, Jacob (2010) explores the relationships between various teacher, school, and student characteristics and teacher dismissal probabilities among non-tenured teachers in the Chicago Public Schools. Among others, the findings of the paper include an increased likelihood of dismissal for teachers with frequent absences, poorer credentials (measured by competitiveness of the college attended, failure on previous certification exams, and highest degree completed), and certain demographic characteristics, particularly older and male teachers. Jacob considers several measures of teacher effectiveness as well, including an estimate of the teacher's value-added. He finds a statistically significant negative relationship between a teacher's value-added and the probability of being dismissed.

While the literature has paid little attention to the *determinants* of teacher layoffs, there has been a great deal of recent attention on the *implications* of these layoffs. This is because seniority-based layoff policies may have negative consequences for student

achievement for at least three reasons. The first is obvious: to achieve a given budget reduction target⁷, school districts would need to lay off relatively more junior teachers than senior teachers (as junior teachers have lower salaries), meaning that a seniority-based layoff policy will cause class sizes to rise more than they otherwise would.⁸

The second reason is intuitive, but somewhat less obvious: the most senior teachers, protected under a seniority-based system, may not be the most effective teachers. As a result, school systems may be forced to cut some of their most promising new talent, rather than dismissing teachers who have not demonstrated an ability to raise student achievement, if the latter have more seniority in the system. Boyd et al. (2010) explore the implications of seniority-based layoffs using data from elementary school teachers in New York City. In particular, they *simulate* seniority-based layoffs and compare the resulting teacher workforce to the workforce that results from simulated effectiveness-based (measured by value-added methods) layoffs.⁹ Consistent with Roza (2009), they find that reducing expenditures on teacher salaries by 5 percent requires terminating about 5 percent of teachers under an effectiveness-based system and about 7 percent under a seniority based system (since the teachers laid off earn less), and there is little overlap in the teachers who are laid off under each scenario. Moreover, the typical teacher laid off under an effectiveness-based system is 26 percent of a standard deviation in *student* achievement less effective than the typical layoff under a seniority-based

⁷ The school funding formula in the state of Washington compensates districts for a given number of teachers *regardless* of their seniority, so it is actually the state (rather than individual districts) who would have to set this budget reduction target.

⁸ For instance, Roza (2009) calculates that if layoffs are done solely on the basis of seniority, a district needing to reduce salary expenditures by 5 percent must instead lay off 7.5 percent of its workforce.

⁹ A key distinction between our analysis and that of Boyd et al. is that we use data on *actual* teacher layoff notices, while Boyd et al. rely on simulations of seniority-based layoffs.

system.¹⁰ Given the findings on the impact of teacher effectiveness described in Section I, this implies the differential between the two types of layoffs is quite large, over a standard deviation of *teacher* effectiveness.

A final reason that seniority-based systems may have consequential impacts on student achievement is that strict adherence to seniority would require at least some districts to lay off teachers in high-demand subject areas, like math and special education. **Table 1**, for instance, demonstrates that teachers in these high-demand areas tend to be less senior than other teachers, and there may well be greater costs associated with recruiting teachers in these areas in the future.

Beyond the effects of seniority-based layoffs on the teacher workforce overall is the potential for distributional consequences. For instance, a recent report on the Los Angeles school district (UCLA/IDEA 2009) concluded that seniority-based layoffs will disproportionately affect schools with high proportions of at-risk students because these schools employ more first- and second-year teachers than other schools in the district. This was not born out in the case of the Boyd et al. work from New York, nor in work by Plecki et al (2010), who present summary statistics for the Washington State teachers laid off in the first cycle of layoffs in 2008-09 and find “little variation by student poverty level or race/ethnicity” at the district level.¹¹ But, ultimately the distributional effects depend on which teachers (in terms of seniority and effectiveness) are teaching in which schools and that may differ from district to district.

¹⁰ This somewhat overstates the true impact of the difference in teacher layoff systems since some portion on measured teacher effectiveness is measurement error (Goldhaber and Hansen, 2010; McCaffrey et al., 2009), but the authors account for this by comparing teachers under the two regimes in the future. In these estimates they still find a differential of 12 percent of a standard deviation of student achievement.

¹¹ Note that they do not look at the distributional consequence of teacher layoffs within districts, which where the disparities, like those referenced in Los Angeles, are likely to arise.

III. Data, and Analytic Approach

Data

The analyses here are based on a unique dataset from Washington State that links teachers to their schools and, in some cases, their students; the dataset also includes information on those teachers who received reduction-in-force (“RIF”) notices in the 2008-09 and 2009-10 school years (we use the terms “RIF notice” and “layoff notice” interchangeably).

Information on RIF notices was collected in each year by Washington State’s Professional Education Standards Board (PESB). In the 2008-09 school year, 2144 employees received a layoff notice and in 2009-10 450 employees received a notice. Employees receiving these notices can be linked with administrative records that include information about their credentials, school assignments, degrees, and compensation. Information on employment is derived from the S-275 administrative database, which is an annual personnel-reporting process that provides a record of certificated and classified employees working in Washington State’s school districts including information such as their places of employment, experience and degree, gender and race, and annual compensation levels.¹² We restrict the sample to employees whose duty root indicates they were in a teaching position that year, and further restrict the sample of teachers receiving a layoff notice to teachers who appear in this database, meaning that we only consider teachers who were hired by October 1 of the year they received a layoff notice.¹³

¹² Technically, the database contains the amount apportioned to the district to pay each teacher. However, most (if not all) districts pay teachers the apportioned amount in the database.

¹³ Several teachers who received a layoff notice were not in the S-275 database, meaning they were hired after October 1 of that school year. However, it is not possible to include teachers who were hired after

These restrictions leave a sample of 1717 teachers who received a layoff notice in 2008-09 and 407 teachers who received a layoff notice in 2009-10, with 130 teachers who received a layoff notice in both school years. Overall, about 2 percent of teachers in the state received a layoff notice in either year.

The S-275 includes a measure of cumulative teaching experience in the state, but does not include a direct measure of teacher seniority in the teacher's current district—an important variable to consider since some collective bargaining agreements specify seniority, as opposed to experience, as a factor in determining which teachers are dismissed in the event of necessary downsizing. Given this, we calculate a rough measure of seniority by tracing each teacher through S-275 databases going back to 1994-95 and recording how many years (up to 14 in 2008-09 and 15 in 2009-10) the teacher has been employed by his or her current school district. We impute seniority values for teachers who have taught in the same district since 1994-95 to reflect the expected spread of values beyond 14 or 15 years of seniority.¹⁴ **Figure 1** shows the distribution of teachers who received layoff notices in 2008-09 or 2009-10 by experience and seniority, and clearly shows that most of the teachers receiving RIF notices are junior (approximately 60 percent of RIFed teachers have two or fewer years of experience, and approximately 80 percent have two or fewer years of seniority). It is interesting, however, that some teachers are actually well into their careers, implying that there are districts in the state that are making judgments about which teachers should be laid off

October 1 who did *not* receive a layoff notice, so we restrict the sample to teachers who appear in the S-275. Note that our sample also includes teachers who left before the end of the school year for reasons other than receiving a RIF notice.

¹⁴ The number of years of in-district experience is, on average, 75 percent of the number of years of in-state experience (for teachers who have taught fewer than 15 years). So, for teachers with the maximum number of years of in-district experience, the in-district experience value was imputed using the formula $\text{seniority (imputed)} = 15 + [(\text{experience} - \text{seniority}) * .75]$.

based on criteria other than seniority alone.

In addition to the S-275, the PESB personnel database includes information about teacher credentials, such as where each teacher was trained and in what areas each teacher holds endorsements.¹⁵ The database includes an entry for each new and renewed credential a teacher has received in his or her career, and we use this database in two different ways to calculate measures of teacher training and endorsements. First, we restrict the database to include each teacher's *oldest* credential that came from a college or university, and use the institution that issued the credential as the teacher's college.¹⁶ We code each teacher's college using the 2008 NCES/Barrons Admissions Competitiveness Index¹⁷ (1 = most competitive, 7=least competitive) to create a measure of the selectivity of each teacher's college. The database also includes the endorsement area of each credential, so we include indicators for the number of endorsements and whether teachers hold endorsements in any one of ten areas: math, science, English/reading, social studies, elementary education, special education, health/PE, arts, languages, and other (including agriculture/technology, office staff, administration, etc.)¹⁸.

Though we focus on a teacher's endorsement areas, we recognize that a teacher's endorsements do not necessarily align with his or her actual placement. For example,

¹⁵ This database has missing data for both very old teachers—who began teaching before the state started to require and track teaching credentials—and very new teachers who have either not finalized their credentials or whose paperwork has not been processed yet. We discuss our approach to missing data in the analytic approach section.

¹⁶ A large proportion of teachers have received all their credentials directly from the state's Office of the Superintendent for Public Instruction, meaning they either received their credential from out of state or through an alternative certification route. This means we have college selectivity data for 39,261 of the 55,656 teachers in the 2008-09 sample. We discuss our approach to missing data in the analytic approach section.

¹⁷ For more information, see <http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2010331>

¹⁸ For the summary statistics presented in the next section, we restrict the database to include only each teacher's *most recent* credential, so each teacher also has a single dummy variable for the area in which he or she is most recently endorsed.

Ingersoll (2003) reports that in 1999-2000, 29% of secondary math teachers did not have a credential to teach mathematics. Nonetheless, our objective is to assess the determinants of teacher layoffs, and we believe a teacher's endorsements are more important *in the layoff process* than his or her actual placement. Under No Child Left Behind, a teacher's endorsements determine the positions for which he or she is "highly qualified", and most collective bargaining agreements in the state of Washington specify that teachers should be considered for retention only in positions for which they are highly qualified.¹⁹ Thus the endorsements a teacher holds actually take precedence in layoff decisions over the teacher's actual placement.

Information about the schools in which teachers are employed is derived from two sources: the Washington State Report Card, which includes school-level achievement data on the Washington Assessment of Student Learning (WASL), as well as student and teacher demographics; and the Common Core of Data, which provides school- and district-level information for all public elementary and secondary schools in the United States, such as school location, school level, and district spending. We use the Washington State Report Card to measure the racial composition, student-teacher ratio, percent of students enrolled in the free or reduced meals program, total enrollment, and percent of students who passed the reading and math WASL exams in each teacher's school. We use the Common Core of Data to create a dummy variable for whether each teacher teaches in an urban area²⁰, dummy variables for the level of each teacher's

¹⁹ Of 75 CBAs from the state of Washington we have coded as part of a separate project, 81% require a teacher to hold a valid credential to be considered for retention in a particular position in the event of layoffs. The Seattle CBA, for example, specifies that layoffs are done by seniority within subject matter areas, but to qualify for consideration within a subject area, "teachers must provide information proving they meet the NCLB Highly Qualified criteria in addition to holding the appropriate endorsement."

²⁰ For the purposes of this paper, we define "urban" as an urbanized area within a city of 100,000 people or

school, and the per pupil expenditure on instruction by each teacher's district.

Panel A of **Table 2** provides sample statistics for teachers who either did or did not receive a RIF notice in 2008-09. We chose to use only the 2008-09 year because some teachers received a layoff notice in both years of the data, but the results are very similar whether or not the averages are for 2008-09 as in the table, 2009-10, or aggregated across years.²¹ Not surprisingly, in each year, teachers receiving RIF notices ("RIFed teachers") are less experienced and less senior, by about 10 and 8 years respectively. RIFed teachers are also far less likely to hold an advanced degree. Consequently, there is an average difference of about \$15,000 in salary between the average RIFed and non-RIFed teacher.

Had all 1717 teachers who received RIF notices in 2008-09 actually been laid off, the direct salary savings in the state would have been \$5,521,238. As noted above, one of the prevailing critiques of seniority-based layoffs is that it is necessary to lay off more teachers in order to attain a specified budget objective than would have been laid off using alternative criteria. Based on the actual salaries of teachers in each school district, we calculate the number of teacher layoffs that would be necessary to achieve the same (or slightly greater) budgetary savings in each district if the teachers laid off in each district were earning the district-average salary. Based on this, and aggregating to the state-level, it is estimated that it would only be necessary to lay off 1349 teachers in order to attain the same (or greater) budgetary savings; this is approximately 20 percent less

more.

²¹ Teachers who received layoff notices in 2009-10 were more experienced on average by about a year and a half than teachers who received layoff notices in 2008-09, and there's less evidence that high-needs subjects (defined below) were protected.

than the actual number of teachers (1717) who received layoff notices.²² In the final section we explore more explicitly the question of the budgetary implications of layoffs that are based on teacher effectiveness.

According to the 2006 report “Educator Supply and Demand in Washington State” (OSPI 2006), there are 14 endorsement areas for which there are “high degrees of shortage,” all of which fall into math, science, or special education areas. Thus, we classify any teacher with an endorsement in one of these areas as *high-needs*. Based on this aggregation across endorsements, there is some evidence to suggest that school districts are protecting teachers in high-needs subjects; 13.33 percent of RIFed teachers fell into a high-needs category while 15.10 percent of non-RIFed teachers also did.²³

Teachers receiving a notice tended to be in smaller schools, but contrary to existing research (UCLA/IDEA 2009; Sepe and Roza 2010), RIFed teachers were not, in general, more likely to be teaching in schools with high proportions of minority students or lower WASL achievement levels.

School-level measures can mask a significant degree of teacher sorting across classrooms within schools. Fortunately, a subset of teachers and students can be linked together through the proctor on each student’s state assessment.²⁴ This allows for aggregation of student data to the classroom level from two additional student-based administrative datasets: the Core Student Record System (CSRS) and WASL databases.

²² The actual number of layoffs necessary to meet a budgetary target under the assumption that teachers with the average salary in each district are laid off is somewhat overstated given that the number of teachers necessary to achieve a budgetary target for each district is rounded up in cases where the estimate is not a whole number.

²³ An alternative measure of high-needs subjects, based on the federal TEACH grant program’s definition of “high-need subjects”, presents a similar picture.

²⁴ The proctor of the state assessment was used as the teacher-student link for at least some of the data used for analysis. The ‘proctor’ variable was not intended to be a link between students and their classroom teachers so this link may not accurately identify those classroom teachers.

It also allows for the estimation of value-added models (VAMs) of teacher effectiveness. The CSRS database includes information on student's race/ethnicity, free and/or reduced-price meal eligibility status, and status in the following programs: LAP reading/math, Title I reading/math, Title I Migrant, Gifted/Highly Capable, State Transitional Bilingual Program, and Special Education. The WASL database includes information on students' achievement on the Washington State Assessment of Student Learning (WASL)—a regular annual statewide assessment test for 3rd through 8th, and 10th grades.

Although we do not have student achievement data for the 2009-10 school year, there are over 10,000 teachers in the 2008-09 school year that can be directly linked to student-level information, and we can calculate VAM teacher effectiveness estimates for about 6,600 of them²⁵ (this is approximately 12 percent of all teachers employed in the state). One hundred forty-five of these teachers received a RIF notice in the 2008-09 school year. Panel B of **Table 2** reports the classroom level sample statistics for this subset of teachers in 2008-09.²⁶ These classroom level characteristics present a slightly different picture of the differences between RIF and non-RIF teachers than do the school-level characteristics. For instance, compared to the school-level aggregates, the classroom level measures for percentage of poor students are relatively higher for RIFed teachers and the percentage of white students is relatively lower. Also, the average student achievement in classrooms with RIFed teachers is lower than the average

²⁵ We cannot calculate VAM teacher effectiveness estimates for a third-grade teacher because we do not have prior test scores for that teacher's students. We further restrict the sample of teachers by only assuming that the proctor is the student's teacher when: the proctor is in a "self-contained" classroom; the proctor's certificate issued by the Washington State Professional Educator Standards Board (PESB) is for a 'Teacher'; at least 50% of the proctor's time is spent in the school where they proctored a test; the proctor taught no more than one grade in a given year; and the proctor's class size is within reasonable limits (i.e., not smaller than 10 nor larger than 29).

²⁶ The classroom-level statistics include all the students in the teacher's class, not just the students whose test scores are used to generate the teacher's VAM estimate.

achievement in other classrooms. The dichotomy of findings between the school- and classroom-levels suggests within school inequities in the distribution of teachers.

Panel B of Table 2 also includes the average value-added estimate of teacher effectiveness of RIFed and non-RIFed teachers, and the results demonstrate that the average teacher who received a RIF notice was about 5 percent of a standard deviation less effective (in both reading and math) than the average teacher who did not receive a RIF notice.²⁷ This result is not surprising given that teachers who received RIF notices included many first- and second-year teachers, and many studies (Clotfelter et al., 2006; Goldhaber and Hansen, 2010; Rivkin et al., 2005; Rockoff, 2004) have shown that, on average, effectiveness improves substantially over a teacher’s first few years teaching. That said, **Figure 2** demonstrates there is tremendous overlap in the effectiveness of RIFed and non-RIFed teachers²⁸. Importantly, Figure 2 shows that a significant proportion of the RIFed teachers were more effective than the average teacher in the state.

Since all models we run that include VAM estimates are necessarily restricted to the subset of teachers for whom we can calculate VAM estimates, an important question is whether the teachers in our “VAM sub-sample” are representative of all teachers in similar placements. We do not have data on the grades taught by teachers not in our VAM sub-sample, but we can compare the characteristics of teachers in the VAM sub-sample—again, teachers in grades 4-6 who are matched to student data through the proctor on student exams—with other teachers in the state who hold an endorsement in elementary education but do not appear in our VAM sub-sample. **Table 3** reports

²⁷ These estimates of effectiveness are based on the models described below (equations 2 and 3) and are “shrunk” using Empirical Bayes techniques.

²⁸ We present the *density* of each distribution to highlight the differences in the two distributions.

summary statistics for teachers with an endorsement in elementary education who do and do not appear in our VAM sub-sample. We see from Table 3 that there are statistically significant differences between the sample of teachers who appear in the VAM sub-sample and the sample of teachers who hold an elementary school endorsement but do not appear in the sub-sample.²⁹ Specifically, the average teacher in our VAM sub-sample has a higher salary, more years of in-district experience, and is more likely to hold a master's degree than the average teacher with an elementary endorsement who is not in our sample. There are further significant differences in school-level variables, also reported in Table 3. So, an important caveat to all our results that use the VAM sub-sample is that they may only apply to the specific subset of teachers we were able to match to student-level data.

A final concern is about the validity of the proctor/teacher matches themselves. While there are no other datasets that would allow us to cross-check these matches, we can report that fitting a teacher production function to this data—reported in Goldhaber, et al (2010c)—produces similar results to those found elsewhere in the literature. For example, our model explains about 70 percent of the variation in students' mathematics achievement on the standardized tests, and this figure is fairly typical of the literature (Jackson and Bruegmann, 2009; Jacob, Lefgren, and Sims, 2008). Teacher effectiveness is found to be an important factor in explaining student achievement, and we see similar returns to early teaching experience as elsewhere in the literature (Clotfelter et al 2007). Finally, teacher characteristics and credentials do little to predict what makes teachers

²⁹ These differences could reflect differences between teachers in different grade levels rather than differences between teachers who are in our sample and teachers who should be in our sample but who are not. For example, our sample is necessarily restricted to teachers in grades 4-6, so the differences in Table 3 could simply reflect the differences between 4th-6th grade teachers and teachers at other grade levels. It is not possible to know from our data.

effective or ineffective; this too is consistent with the educational productivity literature (Hanushek, 1997).

Analytic Approach

In order to provide a more contextualized picture of the factors influencing teacher RIF notices, we estimate binary logit models where the dependent variable, Y_{ijkt} , is an indicator of whether or not teacher i in school j in year t received a RIF notice:

$$\text{Logit}(P(Y_{ijkt} = 1)) = \ln\left(\frac{P(Y = 1)}{P(Y = 0)}\right) = \alpha + T_{it}\beta_1 + S_{jt}\beta_2 + D_{kt}\beta_3 + \phi_t. \quad (1)$$

In the baseline, we model the probability of receiving a RIF notice as a function of individual teacher characteristics T_{it} , including: seniority in district³⁰, degree level (MA or higher), gender, race, college selectivity, and endorsement area; the characteristics of the teacher's school, S_{jt} , including urbanicity, grade level (e.g., high school), enrollment, student-teacher ratio, the percentage of students who are eligible for the free/reduced-price lunch program, the percentage of minority students, and measures of student achievement in reading and math; the characteristics of a teacher's district, D_{kt} , including enrollment, per pupil expenditures, and percent of funding that comes from local, state, and federal sources; and a year effect, ϕ_t .³¹

Seniority is clearly a significant factor in determining which teachers receive RIF notices in many school districts throughout the state. Not all districts, however, are

³⁰ Experience and seniority are highly correlated (a bivariate correlation of about .85) so we only include seniority in the models. The results are very similar if experience is used in place of seniority.

³¹ In each model, we also include missing value dummies to test whether teachers with missing values in each area differ significantly from other teachers. The only variable for which the missing value dummy was ever significant was endorsement area, which is not surprising since this data is missing mostly for very experienced teachers who were unlikely to receive a RIF notice.

required by their bargaining agreements to only consider seniority. Some agreements, for instance, give districts the discretion to retain more junior teachers if they are in high-demand subjects so variables identifying teachers' endorsement areas are of interest. To get an idea of what observable teacher characteristics are associated with the probability of receiving a RIF notice, we first run variants of (1) that only include teacher covariates (T_{it}) as predictors. We run several parameterizations of this model to capture the different ways teacher endorsement area and seniority could be associated with the probability of a RIF notice. Different parameterizations include a dummy for whether the teacher's most recent endorsement is in a "high-needs" area, dummies for the subject area of the teacher's most recent endorsement, a dummy for whether the teacher has *any* endorsement in a high-needs area, and dummies for *every* endorsement a teacher has received. We also include interactions between endorsement areas and the number of additional endorsements that teacher holds to account the possible effect of a teacher who holds multiple endorsements. We repeat all these parameterizations with models that treat seniority as a categorical variable to account for the possibility that the effect of seniority could be non-linear.

Whether student characteristics predict a teacher being RIFed is also of interest. Which teachers lose their jobs as a result of budget constraints is likely to be a politically contentious issue; teacher layoffs in large districts from Los Angeles (Daly and Ramanathan, 2010) to Charlotte (Frazier, 2009) have sparked fierce public debate—both in the press and in public rallies—about the distribution of layoffs across the district. On one side, proponents of the seniority-driven system argue that without clearly delineated rules for layoffs, teachers in schools and districts with more politically active and

powerful constituencies will receive preferential treatment.³² On the other side, opponents point to the three potential negative consequences of seniority-driven layoffs outlined in the previous section: higher layoff rates, distributional consequences across endorsement areas, and distributional consequences across a district. Either way, any teacher layoff policy has potential student equity consequences given that there are achievement consequences associated with the churn of teachers.

To capture the association between school and district covariates and the probability of RIF notices, we add observable school (S_{jt}) and district (D_{kt}) variables to the model. We parameterize this model to treat school demographics as either continuous (percent of each race within the school) or categorical (quintiles of minority composition) to account for possible non-linear effects of this variable. Importantly, the coefficients on the teacher covariates in this model should be interpreted as the marginal effects of these teacher characteristics *relative to teachers at comparable schools within comparable districts*.

The reality, though, is that decisions regarding RIF notices are most likely to happen at the district level, and district covariates cannot capture all the variation in RIF policies due to district-level factors. Thus, our final model substitutes a district fixed-effect (not shown in (1)) for district covariates. In this model, the coefficients on teacher and school covariates now represent the marginal effect of these variables *measured relative to other teachers and schools within the same district*.

These variants of (1) give a full picture of *observable* teacher, school, and district

³² For instance, as the California Teachers Association Handbook states: “The seniority system should be encouraged. The seniority system has demonstrated its equity and validity in protecting the rights of all employees. All personnel begin vesting in the system from the first day of service, and modification of the seniority system imperils job security for all employees.” (CTA 2009)

characteristics that are associated with RIF notices, but perhaps of greatest interest is the relative effectiveness of teachers who are RIFed. As mentioned above, a subset of teachers can be linked to students. For these teachers, we experiment with including value-added measures of teacher effectiveness in (1) above to see whether job performance (at least this measure of it) influences which teachers receive a layoff notice. This, of course, requires the estimation of teachers' job performance.

There is a growing body of literature that uses value-added models (VAMs) to measure the average difference between the actual and predicted performance of a teacher's students (e.g. Aaronson et al., 2007; Goldhaber and Hansen, 2010; McCaffrey et al., 2009), but there is no universally accepted method for calculating a teacher's value-added contribution and research shows that methodology and context can influence the measure (Ballou, Sanders, & Wright, 2004; McCaffrey et al., 2004; Rothstein, 2010; Rubin, Stuart, & Zanutto, 2004; Tekwe et al., 2004). The baseline specification is run separately for each grade and year:

$$A_{ijkst} = \alpha A_{is(t-1)} + X_{it}\beta + \tau^n_{jt} + \varepsilon_{ijkst} \quad (2)$$

In (2), i represents students, j represents teachers, k represents schools, n represents the years of teacher experience, s represents subject area (math or reading), and t represents the school year. Student achievement normed within grade and year, A_{ijkst} , is regressed against: prior student achievement, $A_{ijks(t-1)}$, and a vector of student and family background characteristics (for example, age, race and ethnicity, disability, free or reduced-price lunch status, and parental education level), X_{it} . The remaining teacher fixed-effect (τ^n_{jt}) is the VAM estimate for teacher j in year t , who is in her n^{th} year of teaching. The error term, ε_{ijkst} associated with a particular student is assumed to be

normally distributed with a mean of zero.³³

The advantage of model (2) is that it produces a separate VAM estimate for each teacher in each school year. This allows us, for example, to calculate a teacher's value-added performance the year (or the year before) she received a RIF notice. However, the flexibility of model (2) comes with significant costs. First, the teacher-year effect is confounded with classroom and school contributions to student learning, meaning that we cannot control for class- and school-level variables that may also affect student test score gains. Second, model (2) necessarily uses only single years of matched teacher-student data, while research shows that basing teacher effect estimates on multiple years decreases the relative magnitude of sampling error in the estimates, providing a more precise (Goldhaber and Hansen, 2010; McCaffrey et al., 2009), and potentially less biased (Koedel and Betts, forthcoming) estimate of teacher quality. For this reason, when we do *not* need VAM estimates that vary by year, we use the time-variant VAM estimate from model (2) to produce a *time-invariant* VAM estimate for each teacher, controlling for classroom and school covariates:

$$\tau^n_{jt} = C_{jt}\gamma + G_t + \phi_t + n\eta + \lambda^y_j \quad (3)$$

In model (3), the time-variant VAM estimate for teacher j in year t (τ^n_{jt}) is regressed against: the student's class size that year, C_{jt} ³⁴; year, ϕ_t , and grade, G_t , effects;

³³ Note that we plan to focus on self-contained classrooms so that subject area does not vary by teacher, class, or school. However, the annual class grouping of students implies shared (and potentially unobservable) environmental factors that will influence the performance of the entire class, contributing to positive intra-class correlation among students in the same classroom that should be accounted for by clustering students at the classroom level.

³⁴ Many time-invariant models include an entire vector of classroom and school covariates. However, we found that there was insufficient mixing of students between schools and insufficient variation in classroom characteristics across years, so the standard errors of the VAM estimates were significantly larger when we included these covariates. Given that we need accurate standard errors to produce Empirical Bayes shrinkage estimates (Aaronson et al 2007), we chose only to include class size in the time-invariant model, as it varied sufficiently from year to year.

and (for an *experienced-adjusted* estimate) the teacher’s years of experience (n). The remaining teacher fixed-effect (λ^y_j) is the time-invariant VAM estimate based on y years of data for teacher j , and can be interpreted as the teacher’s contribution to student test score gains *over all y years included in the model*. This model is less accurate for teachers who have short careers (i.e. those more likely to receive a RIF notice) than teachers with more years of data.

The VAM estimate produced by model (3) is appropriate when we want to measure the effectiveness of a teacher *relative to other teachers with the same teaching experience*. However, we also want to produce estimates of teacher effectiveness that do not control for experience, so we can compare the effectiveness of, say, a first-year teacher to a fifth-year teacher. In this case, we drop the n term to produce a *non-experience-adjusted* VAM estimate:

$$\tau^n_{jt} = C_{jt}\gamma + G_t + \varphi_t + \lambda^y_j \quad (4)$$

When we substitute model (4) into model (2), we see that this results in a model that controls for student background and class size, and can include multiple years of data:

$$A_{ijkst} = \alpha A_{is(t-1)} + X_{it}\beta + C_{jt}\gamma + \lambda^y_j + G_t + \phi_t + \varepsilon_{ijkst} \quad (5)$$

We utilize model (5) to produce teacher effectiveness estimates that are pooled across all three years ($y = 3$) of student performance data.³⁵ We also experiment with variants of model (5) to test the robustness of our results, including a model that substitutes a school fixed-effect for school-level covariates and a model that substitutes student fixed-effect for student-level covariates. In theory this final approach controls for individual-level student time-invariant factors that are not captured by the student

³⁵ In the case where teachers are in the workforce in all those years, the effectiveness estimates for many junior teachers are, of course, based on fewer years of data.

covariates. However, it is worth noting that student fixed-effects generally have low power on the estimation of the student fixed-effects themselves (due to data limitations from observing students in just a few years), and tests of the joint hypothesis that all student effects are non-zero commonly fail to reject.³⁶ Finally, we adjust the teacher effect estimates using empirical Bayes (EB) methods.³⁷ We find that the unadjusted teacher effect is 0.24 (i.e., a one standard deviation change in teacher effectiveness corresponds with a 0.24 standard deviation change in student performance) in both math and reading, and the EB shrunken estimates suggest effect sizes of 0.19 in math and 0.18 in student reading.

We use the various estimates of teacher effectiveness estimated by (2) and (5) in modeling the likelihood that teachers receive a RIF notice (1). The assumption is that if teacher effectiveness is considered—and more specifically, if more effective teachers are less likely to be RIFed—then the coefficient on the VAM estimate should be negative. Since we do not have student achievement data for the 2009-10 school year, we only use the RIF data from 2008-09 for this part of the analysis.

IV. Results

Table 4 provides the estimated marginal coefficients from logit models

³⁶ Moreover, a recent paper by Kane and Staiger (2008) not only finds that a student fixed-effects specification understates teacher effects in a VAM levels specification (where the dependent variable is the achievement of students in year t and the model includes a control for prior student achievement in year $t-1$), but also that the student fixed-effects were insignificant in a VAM gains specification (where the dependent variable is the gain in student achievement from one year to the next). By contrast, they find a specification that includes a vector of prior student achievement measures produces teacher effects quite similar to those produced under conditions where teachers are randomly matched to their classrooms.

³⁷ The standard empirical Bayes method shrinks estimates back to the grand mean of the population. Note, however, that standard empirical Bayes adjustment does not properly account for the uncertainty in the grand mean, suggesting the estimates are shrunk too much (McCaffrey et al., 2009). We use the standard approach that's been commonly estimated in the literature (an appendix on empirical Bayes shrinkage is available from the authors by request).

identifying if teachers received a RIF notice in 2008-09 or 2009-10.³⁸ The first column presents a model with only teacher characteristics, including a dummy variable for whether a teacher's most recent endorsement falls into a high-needs category; in the second column a teacher's endorsement area is broken out. Columns 2 and 3 substitute dummy variables for *every* area in which a teacher is endorsed, again first considering just whether a teacher has *any* credential in a high-needs area, and then breaking out all teacher endorsement areas. Column 4 adds in a vector of school and district characteristics, and in the final column, district characteristics are replaced by a district fixed-effect.³⁹

As expected, experience/seniority play an important role in determining whether teachers receive a layoff notice ("are RIFed").⁴⁰ The significant negative coefficients on a teacher having an advanced degree or an endorsement in a high-needs area⁴¹ provides evidence that districts are also protecting teachers thought to have advanced or hard-to-recruit skills. In fact, the magnitudes of these coefficients suggest relatively large differences in the likelihood of receiving a layoff notice for teachers who fall into one of these categories: having a master's degree or an endorsement in a high-needs area lowers

³⁸ The results are found to be qualitatively similar when the models are estimated separately for each school year. The only major difference is that fewer of the variables are statistically significant in 2009-10, which is not surprising given the smaller sample of RIFed teachers in that year.

³⁹ The logit coefficients represent the expected change in the log odds of a teacher receiving a RIF notice per one-unit change in the predictor. For a more straightforward interpretation, however, we transform the coefficients into marginal effects and present the results in terms of the marginal probability of receiving a RIF notice. With the exception of the district fixed-effect model, we calculate the marginal effects at the individual level (as recommended in Greene 2000, p. 816) and then take the sample mean of those effects to calculate the overall marginal effect of each variable. The significance levels are $p < 0.1$ (*), $p < 0.05$ (**), and $p < 0.01$ (***)

⁴⁰ The effect of seniority is unlikely to be linear: the difference between years 1 and 2 of seniority should be different than the difference between years 21 and 22, for example. Thus, we interpret the marginal effects of seniority later in this section when we discuss non-linear effects (Table 5).

⁴¹ Note that having an endorsement in a high-needs area is significantly negatively associated with the probability of receiving a RIF notice whether it is the teacher's most recent endorsement or *any* of the teacher's endorsements.

the probability of being RIFed by about .6 percentage points each. Non-white teachers (not shown in Table 4) are marginally less likely to receive a RIF notice, although this significance disappears in models that control for school and district characteristics.

The results presented in column 2 break out the high-needs variable into different endorsement areas. These findings appear to suggest that the significant negative effect of the high-needs endorsements on the probability of receiving a layoff notice is largely driven by having an endorsement in special education. Interestingly, there is only marginal evidence in this model that the jobs of teachers with math and science endorsements are being protected from layoffs more than teachers with other specialties, but subsequent models will demonstrate that this result is sensitive to model specification. Also, there is a significant positive effect of a teacher's most recent endorsement being in health and PE or arts (music, art, theater, etc.) on the probability of receiving a RIF notice.⁴²

Column 3 also presents the marginal effects of different endorsement areas, but now we are considering *every* endorsement a teacher has and we interact each endorsement area with the number of additional endorsements (other than that area) a teacher has. The coefficients in this model can be interpreted as follows: the coefficient on each endorsement area represents the marginal effect of having an endorsement *only* in that area, and the coefficient on each interaction term represents the average marginal effect of *each additional endorsement* for teachers who hold an endorsement in that

⁴² The reference category for endorsement area is elementary education (the most common endorsement in Washington State), meaning that each coefficient represents the marginal effect of being most recently endorsed in that area relative to elementary education. As discussed in the analytic approach section, the dummy variable for missing endorsement area was also significant, but by including it in the model we ensure that the reference category is elementary teachers only. We control for missing endorsement area in each model in Tables 4 and 5.

area.⁴³

Now that we are considering all teacher endorsements, the coefficients on math, science, and special education are all significantly negative⁴⁴, indicating that (all else equal) teachers holding an endorsement in any high-needs area are less likely to receive a layoff notice. However, there is a question of the mechanism through which this takes place. Many of the collective bargaining agreements we reviewed stipulate that seniority-based layoffs should take place within credentialing area, and with good reason; **Table 1** presents the distribution of the seniority of Washington teachers within each credentialing area, and demonstrates that there is significant variability in seniority across credentialing areas. In particular, teachers endorsed in math, elementary education, and special education are, on average, considerably less senior than teachers in other areas.⁴⁵ Because of this variability, it is conceivable that the negative marginal effects of teachers being credentialed in math, science, or special education is solely a product of the relative seniority of teachers within those areas.⁴⁶

In this model, the marginal effects of holding an endorsement in either health and PE or arts remain significant and positive. Further, the marginal effect on nearly every

⁴³ In this model, the reference category is teachers who *only* have an endorsement in elementary education, meaning that all coefficients should be interpreted relative to this group.

⁴⁴ Running this model with a dummy variable indicating whether a teacher has *any* endorsement in a high-needs area produces similar results to column 1.

⁴⁵ The 10th percentile of seniority for both math and special education is 0, meaning that over 10 percent of math and special education teachers in the state are in their first year in the district.

⁴⁶ Specifically, our logit models estimate the probability of a teacher receiving a layoff notice relative to other teachers *of the same seniority*. Since math teachers are significantly less senior than PE teachers, for example, in a system that gives layoff notices by seniority *within credentialing areas*, a third-year math teacher may be less likely to receive a layoff notice solely because she is relatively more senior within her credentialing area. We test this possibility by running a model that does not control for seniority, and find that the coefficients on several endorsement areas are still negatively correlated with the probability of receiving a RIF notice: special education, science, and social studies are all significantly negative, while arts is significantly positive. This suggests that our results reflect a combination of administrators protecting hard-to-staff areas, such as special education, and giving RIF notices by seniority within endorsement areas.

interaction term is negative, and often significant. This lends credence to the notion that school districts are behaving strategically to protect teachers who have endorsements in multiple areas and therefore provide flexibility in terms of the classes they can teach.

The specification in column 4 adds vectors of district and school covariates to the model (not shown). An F-test shows that each of these vectors significantly improves the fit of the model⁴⁷, but the addition of these variables has little effect on most of the estimated teacher coefficients with the exception of non-white, which is no longer statistically significant. However, many of the school-level variables identifying student demographics are statistically significant. Teachers in schools with fewer students receiving free and reduced price lunch and greater percentages of students passing the state assessment are marginally less likely to be RIFed; this is as might be expected if there is a correlation between poverty, student achievement, and the political activism of parents. But, contrary to at least some of the rhetoric around layoffs (UCLA/IDEA 2009; Sepe and Roza 2010), it appears that, all else equal, teachers in urban schools and in schools with more black and Hispanic students are less likely to be RIFed. Note that this does not necessarily mean that minority students are not disproportionately affected by teacher layoffs since schools with high-minority enrollments might also share other characteristics, (e.g. the seniority level of teachers) that influence layoffs. We explore the implications of this in greater detail in the next section of the paper.

Of the district-level variables, the marginal effect of district size is negative, while the marginal effect of the percent of a district's funding that comes from local sources (like property taxes) is significantly positive. This last finding also runs contrary to

⁴⁷ The F-statistic was 24.52 for school variables and 10.89 for district variables, each with a p-value of less than .0001.

conventional wisdom, as it indicates (all else equal) that teachers in districts with a greater proportion of local funding—traditionally districts with high property values and active parents groups⁴⁸—were more likely to receive RIF notices.⁴⁹

The final specification, reported in column 5 of the table, presents the results of a district fixed-effect specification. This model is particularly important because the coefficient on each teacher characteristic is calculated relative to *other teachers in the district*, and since layoffs decisions are made at the district level, this model may give the most insight into the characteristics that drive these decisions. That said, the results for the teacher covariates in this specification are qualitatively similar to those without district fixed-effects: greater seniority, having a master’s degree, and being endorsed in math, science, or special education are negatively associated with the probability of receiving a RIF notice, while the associations for having an endorsement only in health/PE, or arts are positive.

The inclusion of a district fixed-effect also means we compare the characteristics of schools that have layoffs to other schools in the same district, and the marginal effects of many school-level covariates drastically change in this specification; urbanicity, percent Hispanic students,⁵⁰ percent free/reduced lunch, and measures of student achievement are no longer statistically significant. Under this model, both the magnitude and significance of the negative marginal effects of a teacher being credentialed in math,

⁴⁸ The correlation between these variables is well established, although causality is open to interpretation; the basis of dozens of school finance court cases, including *Seattle School District v. State, 1977* (Fraser 2005), is that districts with higher property values and more politically active parents tend to receive more local funding, but papers in the economics literature (e.g., Megdal 1984) argue that in districts that receive a higher proportion of their funding from local sources, voters and parents have an incentive to pay higher property taxes and be more politically active.

⁴⁹ An intriguing explanation for this result (suggested by Katharine Strunk) is that these districts may be using the threat of teacher layoffs as a tool to get parents to give more money.

⁵⁰ Many districts that have a high proportion of Hispanic students did not issue any RIF notices, so it is not surprising that this variable is not significant under a district fixed-effect model.

science, or special education grow significantly.⁵¹

The specifications reported in **Table 5** relax the assumption of linearity in the effect of seniority and school composition. Specifically, in each specification seniority is broken into seven categories: teachers with 1 year or less, 1–2 years, 2–3 years, 3–4 years, 4–6 years, 7–11 years, and 12 or more years of seniority.⁵² Looking across the columns, it is apparent that the addition of categorical variables identifying student characteristics and/or the inclusion of school fixed-effects has little impact on the estimates of the effects of seniority on the likelihood of receiving a RIF notice. The magnitudes of the seniority coefficients indicate that a first-year teacher is over twice as likely (all else equal) to receive a RIF notice than a teacher in her 4th–6th years in the district.⁵³

In column 2 of the table, we add categorical measures of school- and district-level covariates: whether the teacher teaches in a school that falls in the first, second, third, fourth, or fifth quintile of schools in terms of percent of Hispanic of black students.⁵⁴

⁵¹ As a hypothetical example of how effects can change under a district fixed-effect model, consider two large districts, District A and District B, each of which has 1000 teachers. Suppose 20 percent of District A's teachers are credentialed in "high-needs" areas, while only 10 percent of teachers in District B have such a credential. Further suppose that District A sends RIF notices to 100 teachers, 18 of whom are in "high-needs areas", while District B sends RIF notices to 25 teachers, 2 of whom are in "high-needs" areas. Then for each district, the proportion of RIF notices given to "high-needs" teachers is less than the proportion of high-needs teachers in the district (18 percent vs. 20 percent in District A, 8 percent vs. 10 percent in District B,) but if we aggregate across districts we see that 16 percent of all teachers who received a RIF notice were in a high-needs area, while high-needs teachers only account for 15 percent of the teachers across the two districts. Without a district fixed-effect, we might conclude that districts are sending RIF notices to a higher proportion of teachers in high-needs areas, while within each district the opposite is true (this phenomenon is known as Simpson's Paradox).

⁵² Twelve or more years of seniority is used as the reference category for this variable, so all coefficients should be interpreted relative to teachers who have taught 12 or more years in the district. Separate specifications that use other levels as the reference category demonstrate that these marginal effects are significantly different *from each other* as well as from the 12 years and over group.

⁵³ This parameterization of seniority does not significantly change the marginal effects of the endorsement areas presented in Table 4, so we have omitted them from Table 5.

⁵⁴ The reference category for these variables is the first quintile, so coefficients should be interpreted as relative to teachers who teach in school whose percent of minority students falls in the lowest 20 percent of the state.

The results indicate that teachers in schools that fall in the top two quintiles of percent minority students were significantly less likely (all else equal) to receive a layoff notice, which again runs counter to some of the rhetoric about layoffs. As with seniority, this parameterization of racial composition does not significantly alter the marginal effect of any other teacher, school, or district covariate.

Column 3 adds a district fixed-effect, and here the statistical significance of the top two quintiles disappears.⁵⁵ In other words, while teachers at schools with a high percentage of minority students are less likely (all else equal) to receive RIF notices, this effect does not persist when the percent of minority students is measured relative to other schools in the same district.

Columns 4 and 5 repeat the same exercise, this time including categorical variables for whether the teacher teaches in a school that falls in the first, second, third, fourth, or fifth quintile of schools in terms of percent of students in the Free or Reduced Meal Program.⁵⁶ The results of the model that includes school and district covariates (column 4) suggest that teachers in school in the top quintile of free/reduced meal participation are significantly less likely to receive a layoff notice, but this significance disappears under the district fixed-effect model (column 5). Again, the interpretation is that while teachers at schools with a high percentage of low-income students are less likely (all else equal) to receive RIF notices, this effect does not persist when the percent of low-income students is measured relative to other schools in the same district.

⁵⁵ An F-test indicated that including a district fixed-effect significantly improved the fit of the model ($F = 20.40$), which is not surprising since RIF decisions were made at the district level.

⁵⁶ We do not run models with both percent minority and percent free and reduced priced meals due to high bivariate correlation (0.72).

Is Teacher Effectiveness Considered in RIF Decisions?

In **Table 6** we report selected findings on models estimating the probability of receiving a RIF notice in 2008-09 for models that include various estimates of teacher effectiveness. Prior to discussing our main findings on teacher effectiveness, it is worth noting that, while we do not report them in the model, the inclusion of the teacher effectiveness variables do little to change the estimated effects of the district and school-level covariates or those teacher characteristics not reported in the table.

We include a variety of different teacher effectiveness measures in the RIF models in order to test the robustness of our findings. It is conceivable that judgments about teachers may be made based on a teacher's performance in the year in which layoffs occur so column 1 of the table includes teacher-year value-added effect estimates.⁵⁷ Of course it is also possible that administrators' judgments are based on a teacher's prior year of performance given that value-added estimates (or more simple means of calculating the academic growth of the students in a teacher's classroom) are unlikely to be available at the time that layoff notices are sent out. So, in column 2 we include teacher-year effect estimates based on the year prior to the year in which teachers received a layoff notice.⁵⁸

Research clearly shows a degree of intertemporal instability in VAM estimates of teacher effectiveness (Aaronson et al., 2007; Goldhaber and Hansen, 2010; McCaffrey et al., 2009) but estimates that are based on multiple years of teacher-student data are both more stable and less noisy. Given this, we report results for models that include as much

⁵⁷ Note that the teacher-year effect estimates are from model specifications that do not include classroom or school covariates.

⁵⁸ We also might imagine a difference in the results if teachers anticipating a layoff notice exerted less effort (an "Ashenfelter dip").

matched student-teacher data as is available for each teacher in column 3.⁵⁹

Administrators may wish to protect the jobs of teachers who show a great deal of potential even if they are less effective than more senior teachers. Thus, in column 4 we report the results of a specification that includes teacher effect estimates that are adjusted for teacher experience. Finally, there is disagreement in the literature about whether it is appropriate to include school or student fixed-effects in VAMs designed to estimate teacher performance so we report the results for models using effect estimates based on these specification in Columns 5 and 6 respectively.⁶⁰

There is little point in going into great detail about the magnitude of the coefficient estimates on estimated teacher effectiveness. In all cases we see that the marginal effects on the VAM estimates from math and reading are not even close to being statistically significant, implying that effectiveness plays little or no role in determining which teachers are targeted for being laid off.⁶¹

V. Policy Implications and Conclusions

Our findings largely comport with what one would expect given seniority provisions in collective bargaining agreements. As we noted above, all of the collective bargaining agreements governing policy in the ten largest school districts in Washington (during the years of our study) mention that seniority must be used as a factor in

⁵⁹ This model is limited in that most teachers receiving a layoff notice are quite junior so have few years of matched data informing the estimates of effectiveness.

⁶⁰ The standard errors in the models that include school or student fixed-effects were very imprecise so we opted to use teacher effect estimates for these specifications that are not adjusted using Empirical Bayes methods.

⁶¹ This is not surprising given that the correlation of the effect estimates are generally pretty high: the correlations between the various VAM specifications we use are all greater than 0.75, with the exception of the estimates for 2008-09 (the year of the RIF notices) and 2007-08 (the year before the RIF notices), which have a bivariate (intertemporal) correlation of 0.37. This correlation is consistent with year-to-year correlations of 0.3 to 0.5 found elsewhere in the value-added literature (Goldhaber and Hansen, 2010).

determining layoffs and none of these mention teacher effectiveness at all. Given this, the surprise is that factors other than seniority do appear to influence which teachers are targeted for layoffs.

To get a more concrete sense of the extent to which various factors play into the targeting of teachers for layoffs, we run simulations based on the marginal effects reported in Table 5.⁶² Specifically, in **Table 7**, we report the expected probability of a teacher with each combination of endorsement area and seniority level receiving a layoff notice.⁶³ **Table 7** clearly demonstrates that while a teacher's endorsement area does affect the likelihood of being laid off, the effect is far smaller than the influence of seniority. For instance, we estimate the probability that a first-year special education teacher receives a layoff notice is 6.2 percent, compared to 17 percent for a first-year health/PE teacher. This difference is significant, but it pales in comparison to the difference in probabilities for a first-year teacher compared to a teacher with 12 or more years of seniority; the estimated probability of a teacher with 12 or more years of seniority receiving a layoff notice is less than a quarter of a percent for every endorsement area.

Next we examine the implications of using an effectiveness-based layoff system by comparing *simulated* effectiveness-based layoffs to the *actual* layoff notices that were largely driven by seniority. First, we estimate teacher effectiveness in both math and reading (teachers at the elementary level are typically teaching both subjects to students)

⁶² We use the results from columns 3 and 5 of Table 5. The choice of specification does have an impact on estimates of schooling variables on the likelihood of receiving a layoff notice, but very little impact on the magnitude of the effect of teacher seniority.

⁶³ For each combination of endorsement and seniority level, we do a simulation on the individual level, using the actual covariates for each teacher and the marginal effects from the district fixed-effect model in Table 5 to predict the likelihood of that teacher receiving a layoff notice *if that teacher had that endorsement/seniority level*. The average of these probabilities gives the simulated probability that a teacher with that combination of endorsement and seniority level would receive a layoff notice.

across all years of data. Next, for simplicity, the value-added measures are averaged across the two subjects in order to obtain a single estimate of effectiveness for each teacher.⁶⁴ Teachers in each school district are then ranked according to their value-added.⁶⁵ Finally, starting with the least effective teachers in each district and moving up the effectiveness ladder, enough teachers are assigned to a hypothetical layoff pool to achieve a budgetary savings for each district that is at least as great as each district's budgetary savings that would have resulted were all the teachers who received a RIF notice in 2008-09 actually laid off.⁶⁶

The overlap between the subgroup of teachers who *actually* received a RIF notice and the subgroup of teachers laid off in our simulation is relatively small—only 23 teachers (or 16 percent of teachers who received a RIF notice)⁶⁷. Moreover, since the teachers who received RIF notices in our simulation were more senior (and have higher salaries) than the teachers who actually received RIF notices by an average of

⁶⁴ This is not necessarily the most sophisticated way of generating a cross-subject estimate of teacher effectiveness—for example, it is possible to use both math and reading scores in the same model to generate a single measure of effectiveness—but we believe the simplicity of this method might be the best reflection of how districts would be likely to implement such a policy.

⁶⁵ The specification used to generate the value-added estimates and ranking is the pooled-year estimate from Column 3 of Table 6. The aggregated simulation results are similar regardless of the specification we use, although the overlap in teachers laid off under each specification varies widely. For example, 82% of the teachers who receive a layoff notice when we use the pooled-year estimates also receive a layoff notice when we use the experience-adjusted estimates (Column 4, Table 6), but this number drops to 63% when we use a school fixed-effect estimates (Column 5, Table 6) and 41% when we use the student fixed-effect estimates. So, although our aggregate results are robust to the VAM specification we use, the specific population of teachers receiving a layoff notice under an effectiveness-based system is quite sensitive to this specification. This has obvious policy implications.

⁶⁶ In doing this calculation we are restricted to the sample of teachers for whom we can estimate value-added. We do not control for the changes in average class size that result from the layoffs, but a one student increase in class size is associated with a drop of only .0014 standard deviations of student performance, meaning that the expected change in student achievement resulting from any change in average class size is negligible.

⁶⁷ This overlap is relatively robust to the VAM specification we use in the simulation. The overlap is 24 teachers (17%) using experience-adjusted estimates, 21 teachers (14%) using school fixed-effect estimates, and 34 teachers (23%) using student fixed-effect estimates.

approximately eight years⁶⁸, the simulation results in far fewer layoffs: we conservatively calculate that districts would only have to layoff 132 teachers under an effectiveness-based system in order to achieve the same budgetary savings they achieved with 145 RIF notices under today's seniority-driven system, a difference of about 10 percent of the RIFed workforce.⁶⁹

Figure 3 shows the kernel distribution of teacher effectiveness under the simulated effectiveness-based RIF versus the actual effectiveness of teachers who received RIF notices. Clearly, the setup of our simulation guarantees that there will be a difference between the average effectiveness of the two groups, so the true question is how great the difference is. Like Boyd et al. (2010), we find that the difference in average effectiveness is substantial: 20 percent of a standard deviation of student achievement in math and 19 percent of a standard deviation of student achievement in reading.⁷⁰ These are EB shrunken estimates, but as Boyd et al. show, the findings are still likely to somewhat overstate the differential given that performance in year $t+1$ is likely to differ from that estimated in year t .⁷¹ Still, the magnitude of the differential is striking,

⁶⁸ The average seniority of teachers who actually received RIF notices was 1.78 years, while the average seniority of RIFed teachers in our simulation was 9.69 years.

⁶⁹ As in our first simulation, this 10 percent estimate is very conservative because we required that districts achieve *at least* the same savings in our simulation as they did in reality. Had we ignored districts and simulated effectiveness-based RIF notices across the state, only 117 teachers (20 percent fewer) needed to get a RIF notice. Since 10 percent is very conservative, and 20 percent ignores the reality that layoffs occur within districts, the true reduction in RIFs under an effectiveness-based system is likely to be between 10 percent and 20 percent.

⁷⁰ These estimates are somewhat smaller than the estimate in Boyd et al (2010) that the difference is 0.26 standard deviations in student achievement. This is likely due to two reasons. First, our simulations are based on *actual* teacher layoff notices rather than the simulated seniority-based layoffs in Boyd et al., so our results reflect *all* the factors that appear to drive teacher layoff decisions. Further, we are interested in simulating a state-wide policy/practice that operates within districts. Our findings on differences in effectiveness between the two different systems would have been even larger had we ignored district boundaries (because there are some teachers who would not be RIFed based only on within district comparisons, but would be based on teacher comparisons between districts).

⁷¹ Boyd et al., for instance, show that the 26 percent of a standard deviation difference between teachers is reduced to 12 percent when teachers are judged in the year following a hypothetical layoff.

roughly equivalent to the differential between students having a teacher who is at the 16th percentile of effectiveness rather than the 50th percentile. And, given estimates that students in the upper elementary grades typically gain a standard deviation from one grade to the next (Schochet and Chiang, 2010), the differences we are detecting between RIF systems are on the order of magnitude of 2 ½ to 3 ½ months of student learning.

Keep in mind, though, that our calculations are only based on a partial equilibrium analysis. There is, of course, a question of whether a change in layoff policy might have far-reaching consequences for who opts to enter the teacher labor force and how teachers in the workforce behave. Teaching jobs have traditionally been very secure and changes to the security of the occupation might shift the number or quality of prospective teachers. All of this suggests that we cannot know the full impact of using VAM-based reforms without conducting assessments of actual policy variation. Nonetheless, the results presented here indicate that teacher effect estimates are far superior to observable teacher variables as predictors of student achievement, suggesting that these estimates are a reasonable metric to use as a factor in layoff decisions.

Lastly, given that there is little overlap between the samples under these different scenarios, we investigate the likelihood that different types of students might be disproportionately affected by one type of RIF system. For the subset of teachers who can be linked to student-level data, we consider the characteristics of the *students* whose teachers received a RIF notice under the actual system or in our simulation. Columns 1 and 2 of **Table 8** present the probability that a student in various subgroups would have his or her teacher laid-off under the two systems. Column 1 presents the probabilities under the actual RIF system, and demonstrates that the probability that students in a

particular subgroup have a teacher who is RIFed varies considerably from one subgroup to the next. In particular, black students are far more likely than other students to have been in a classroom of a teacher who received a RIF notice. This result could be partly driven by the fact that black students are more likely to be taught by more junior teachers,⁷² but could also be driven by the racial composition of districts that gave RIF notices in the 2008-09 school year.⁷³ In column 2, we repeat the calculations for the simulated effectiveness-based layoffs. The effectiveness-based layoffs result in fewer RIFs, and are much more equitably distributed across student subgroups; black students in particular are only marginally more likely to have been in a classroom with a teacher who received a RIF notice under this system.

Finally, we explore the student achievement consequences of the two layoff systems by calculating the average effectiveness of the RIFed teachers of different subgroups of students under the actual layoffs (column 3) and under the effectiveness-based layoffs (column 4). The differences are similar across all subgroups, as teachers RIFed in our simulation are approximately 20 percent of a standard deviation in student performance less effective than teachers RIFed in reality.

Our findings are not terribly surprising to anyone who is familiar with seniority provisions in collective bargaining agreements: seniority clearly matters for teacher job security. In fact, while our results show that districts are protecting teachers in high-needs areas, the simulations illustrate that having more seniority in a district is far more

⁷² Specifically, the average white student in Washington has a teacher who is one year more senior than the teacher of an average black student.

⁷³ For example, the likelihood of a Hispanic student's teacher receiving a RIF notice is much lower than the other groups under both layoff systems. This is because (as discussed in the previous section) many districts with a high proportion of Hispanic students did not give any RIF notices, so no teachers in these districts received RIF notices in our simulation either.

important than having an endorsement in a hard to recruit or retain area.

The simulations comparing layoffs from an effectiveness-based system to the actual layoff notices given in our seniority-driven system clearly show that these two systems would result in a very different distribution of teachers targeted for layoffs and layoffs that impact different segments of the student population. Further, the differences in the estimated effectiveness of teachers laid off under each type of system would have consequential effects on student achievement, as evidenced by the significant difference in the effectiveness of teachers laid off under the two systems. Districts have not had to face the prospect of widespread teacher layoffs until recently, so the fact that seniority layoff provisions exist in most CBAs used to be irrelevant. This is clearly not the case today, nor is it likely to be the case in the near future as school systems wrestle with tighter budgets.

Districts across the country are now re-thinking layoff strategies. This is sensible, because while the simplicity and transparency of a seniority-based system certainly has advantages, it is hard to argue that it is a system in the best interest of student achievement.

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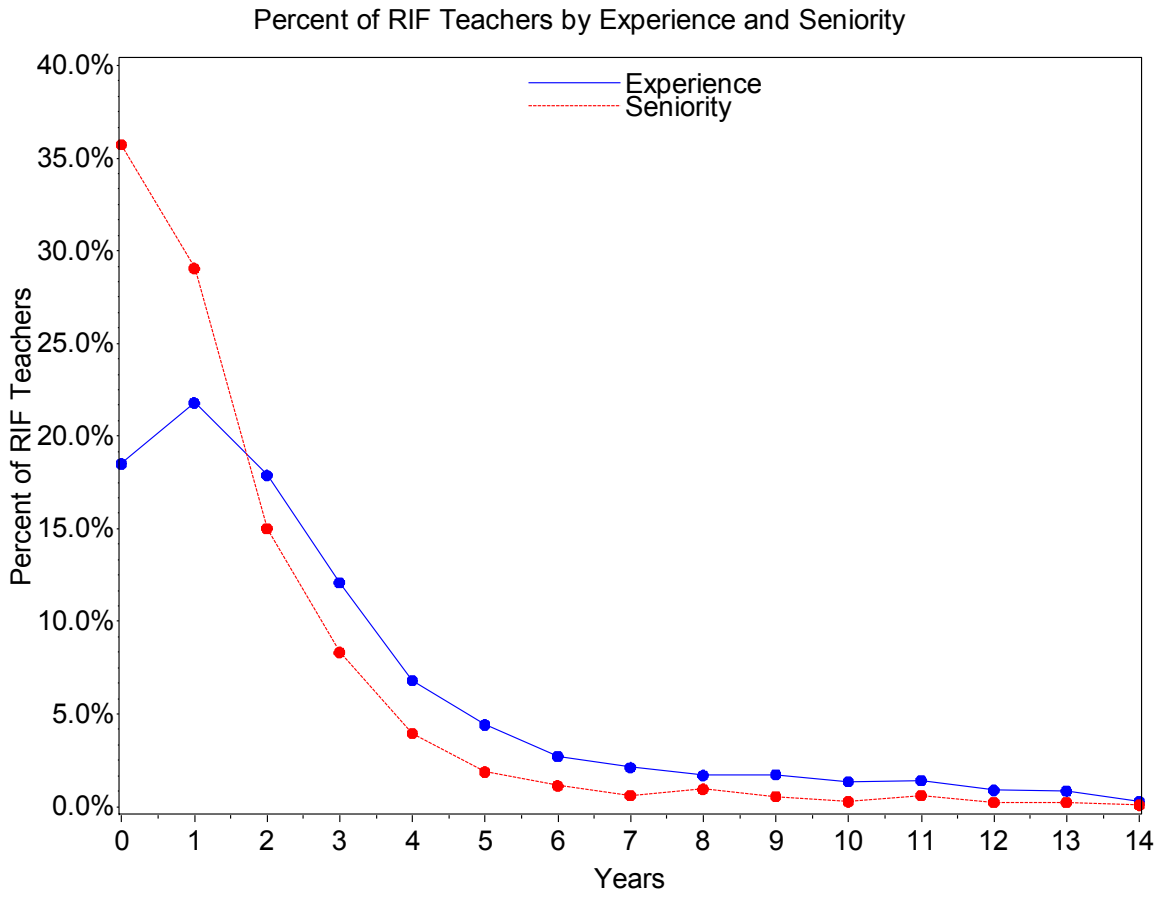
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Figures

Figure 1: Percent of RIF Teachers by Experience (state) and Seniority (district)



NOTE: Data include 2008-09 and 2009-10 RIF notices

Figure 2: Distribution of Teacher Effectiveness

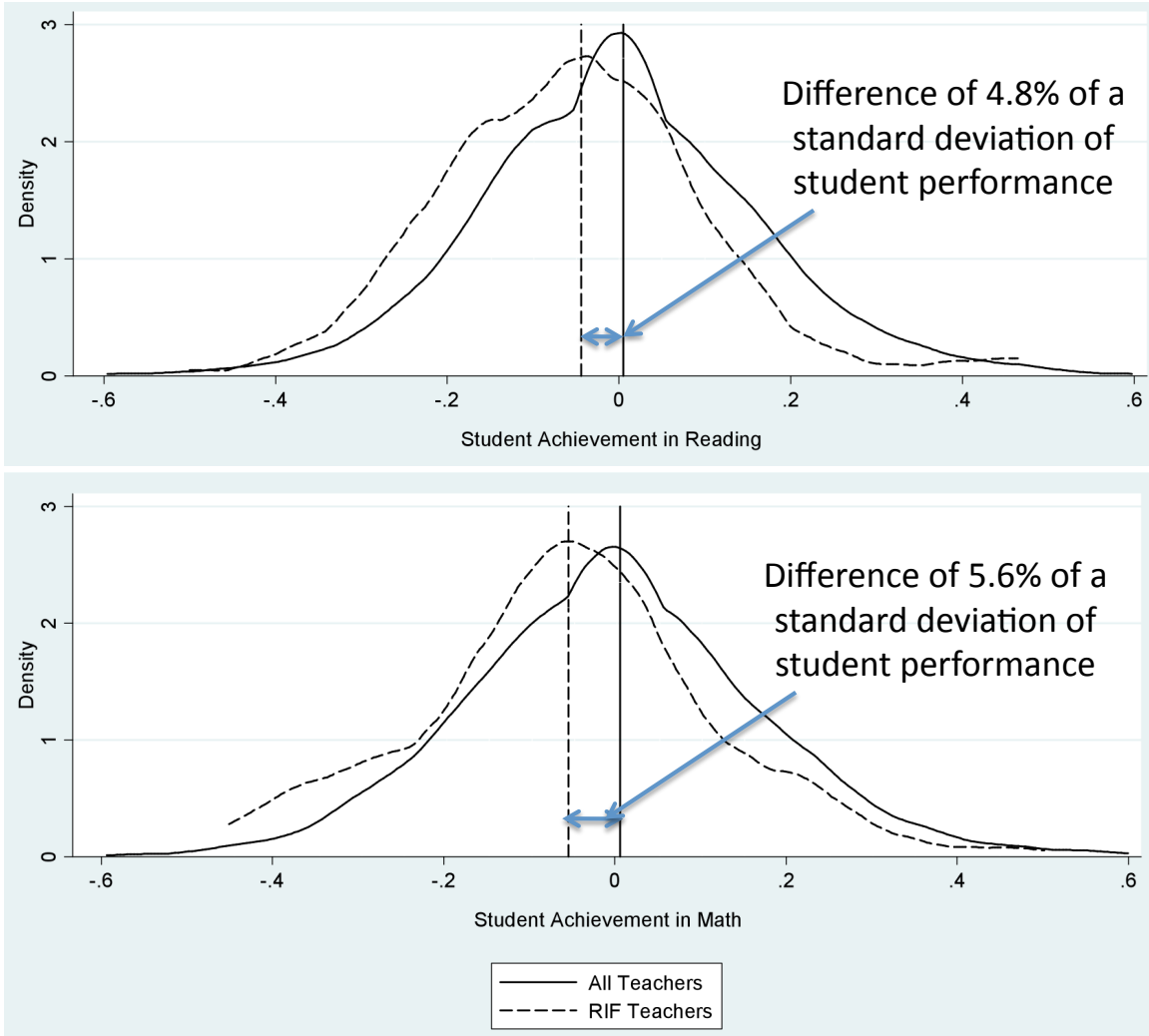
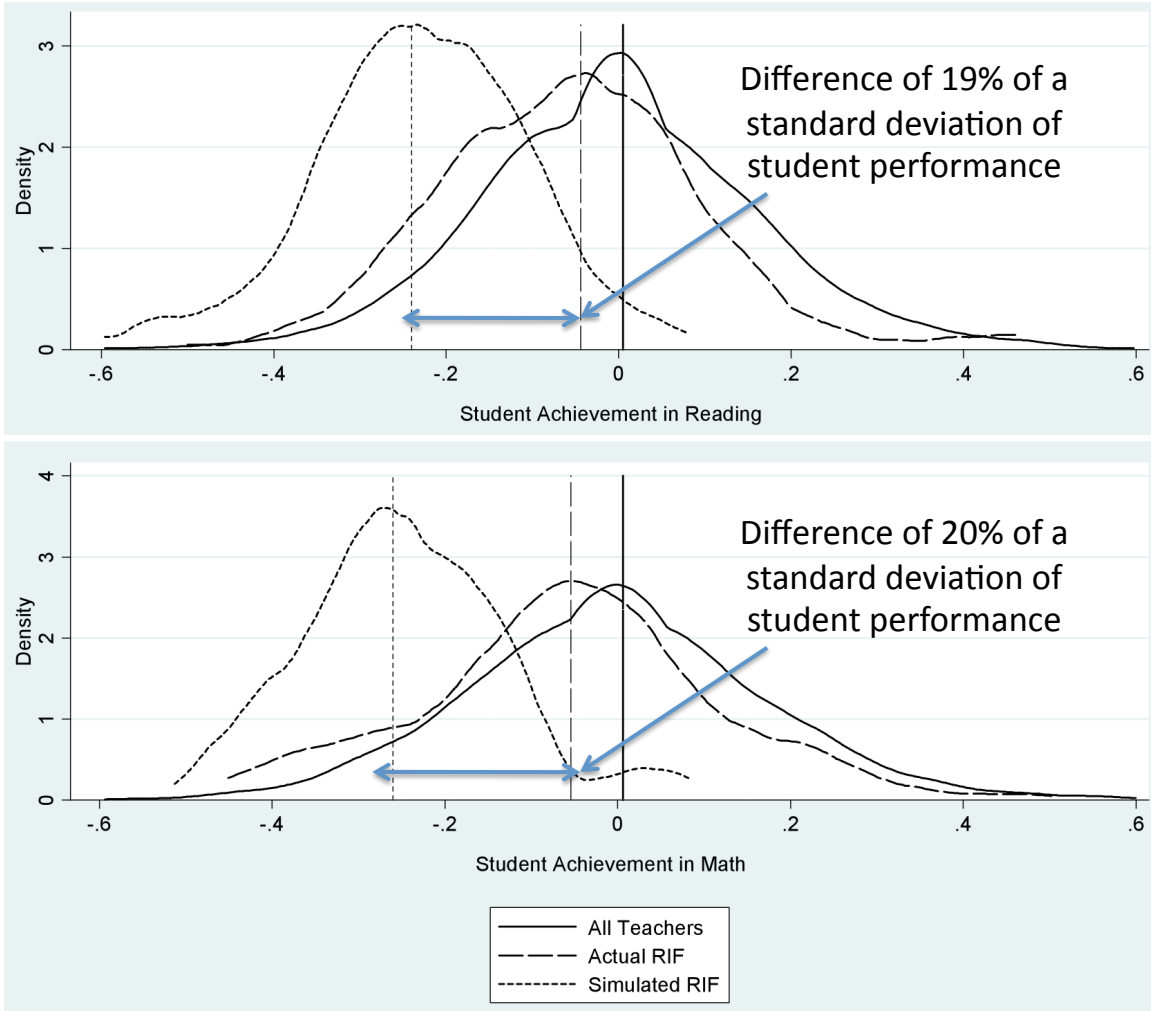


Figure 3: Actual vs. Simulated Effectiveness-Based RIFs



Tables

Table 1: Distribution of Seniority of Washington Teachers by Most Recent Credential: 2008-09

Most Recent Endorsement Area	Mean	10th percentile	25th percentile	Median
“High-Needs Area”	8.55	0.00	2.00	6.00
Math	7.05	0.00	1.00	4.00
Science	9.00	1.00	2.00	6.00
English/LA	9.56	1.00	3.00	8.00
Social Studies	12.60	1.00	4.00	10.00
Elementary Ed	7.86	1.00	2.00	6.00
Special Ed	8.89	0.00	2.00	6.00
Health/PE	12.56	1.00	5.00	11.00
Agriculture/Tech/Other	11.79	1.00	4.00	10.00
Arts	10.42	1.00	3.00	8.00
Foreign Languages	9.83	1.00	3.00	8.00

Table 2: Selected Summary statistics for RIF and non-RIF teachers in WA in 2008-09

	RIF	No RIF
Panel 1: All Teachers in Sample	N = 1717	N = 53,939
Teacher Characteristics	Mean (SD)	Mean (SD)
Final salary	\$42,826 (\$11,194)	\$57,898 (\$14,705)
Years of experience in state	3.43 (5.16)	13.66 (9.65)
Years of seniority in district	1.68 (3.26)	9.93 (8.44)
Master's degree or higher	44.32%	64.15%
Most Recent Endorsement Area⁷⁴		
“High-Needs Area”	13.33%	15.10%
Math	3.55%	3.09%
Science	4.95%	5.12%
English/LA	13.45%	12.40%
Social Studies	7.63%	10.70%
Elementary Ed	45.60%	37.46%
Special Ed	4.83%	6.89%
Health/PE	4.02%	4.42%
Agriculture/Tech/Other	6.23%	8.87%
Arts	6.99%	5.25%
Foreign Languages	1.69%	2.42%
School Characteristics		
% Urban	11.07%	14.96%
School size	707.00 (469.22)	747.30 (519.07)
Student/teacher ratio	17.01 (3.28)	17.11 (4.22)
% free/reduced lunch	39.64%	42.08%
% white students	68.30%	64.00%
% black students	5.81%	5.60%
% Hispanic students	10.45%	15.84%
% other races	15.44%	14.56%
% special education	12.53%	12.40%
% passed English WASL	72.59%	72.54%
% passed Math WASL	51.70%	51.75%
Panel 2: VAM sub-sample	N = 145	N = 6400
Classroom Characteristics⁷⁵		
% free/reduced lunch	45.91%	44.20%
% white students	64.81%	64.41%
% black students	8.00%	5.52%
% Hispanic students	12.48%	16.30%
% other races	14.71%	13.77%
% special education	11.57%	11.76%
% passed English WASL	68.41%	72.00%
% passed Math WASL	48.19%	54.88%
Average Teacher Value-Added⁷⁶		
Value-added in reading (in student SDs)	-0.048 (0.17)	0.0013 (0.18)
Value-added in math (in student SDs)	-0.054 (0.17)	0.00049 (0.19)

⁷⁴ For ease of comparison we only present statistics for a teacher's most recent endorsement area.

⁷⁵ Classroom statistics are from the most recent year we can calculate that teacher's value-added.

⁷⁶ The VAM estimates pooled across all years of data and shrunken by EB methods.

Table 3: Selected Summary Statistics for VAM* and non-VAM Teachers with an Elementary Endorsement

	Non-VAM	VAM	T-statistic
	N = 24,308	N = 5729	
Teacher Characteristics	Mean (SD)	Mean (SD)	
Final salary	\$54,865 (\$14,763)	\$56,858 (\$12,611)	10.40***
Years of experience in state	11.20 (7.98)	11.23 (7.72)	0.31
Years of seniority in district	8.17 (6.98)	8.74 (6.92)	5.58***
Master's degree or higher	63.64%	66.92%	4.73***
School Characteristics			
% Urban	14.95%	13.07%	-3.75***
School size	573.98 (336.39)	509.24 (170.15)	-20.65***
Student/teacher ratio	16.70 (4.48)	16.67 (2.69)	-0.56
% free/reduced lunch	45.24%	45.59%	1.04
% white students	61.90%	62.90%	2.96**
% black students	5.79%	5.25%	-4.67***
% Hispanic students	17.13%	16.72%	-1.39
% special education	13.17%	13.51%	5.10***
% passed English WASL	71.07%	72.36%	7.12***
% passed Math WASL	55.29%	58.52%	14.07***

* VAM teachers are teachers who appear in the sample for specification 3, defined in Table 6.

Table 4: Estimated Marginal Effects on Probability of Receiving RIF Notice

	1	2	3	4	5
Teacher Variables					
Seniority in district	-0.0065*** (t = -36.13)	-0.0063*** (t = -36.53)	-0.0061*** (t = -35.22)	-0.0060*** (t = -34.99)	-0.0079*** (t = -37.88)
Master's degree or higher	-0.0065*** (t = -7.67)	-0.0063*** (t = -7.73)	-0.0050*** (t = -6.05)	-0.0057*** (t = -6.99)	-0.0071*** (t = -7.64)
Endorsement Area	Reference category is Elementary Education				
	Most recent		All endorsements		
“High-Needs Area”	-0.0066*** (t = -5.52)				
Math		-0.0032 (t = -1.47)	-0.0046* (t = -1.92)	-0.0065** (t = -2.57)	-0.010*** (t = -3.70)
Science		-0.0033* (t = -1.69)	-0.0051** (t = -2.29)	-0.0076*** (t = -3.21)	-0.0094*** (t = -3.60)
English/LA		0.0011 (t = 0.85)	0.0017 (t = 1.04)	-0.000054 (t = -0.03)	0.00049 (t = 0.24)
Social Studies		0.0000 (t = 0.00)	0.0019 (t = 0.97)	0.00038 (t = 0.19)	0.0013 (t = 0.55)
Special Ed		-0.0088*** (t = -4.69)	-0.010*** (t = -4.55)	-0.012*** (t = -5.37)	-0.016*** (t = -6.12)
Health/PE		0.0069*** (t = 3.31)	0.0096*** (t = 4.26)	0.0078*** (t = 3.46)	0.0085*** (t = 3.27)
Agriculture/Tech/ Other		-0.00056 (t = 0.33)	-0.0011 (t = -0.50)	-0.0032 (t = -1.43)	-0.0050* (t = -1.89)
Arts		0.0066*** (t = 3.94)	0.0067*** (t = 3.79)	0.0049*** (t = 2.71)	0.0044** (t = 2.13)
Languages		-0.0033 (t = -1.12)	0.00066 (t = 0.19)	-0.0026 (t = -0.74)	-0.0036 (t = -0.92)
Math * add'l endorsements			-0.00020 (t = -0.09)	-0.00021 (t = -0.09)	0.0027 (t = 1.06)
Science * add'l endorsements			-0.00029 (t = -0.13)	-0.00011 (t = -0.05)	0.00038 (t = 0.22)
Engl./LA * add'l endorsements			-0.0026* (t = -1.76)	-0.0017 (t = -1.12)	-0.0027 (t = -1.55)
Social Stu. * add'l endorsements			-0.0047*** (t = -2.71)	-0.0049*** (t = -2.84)	-0.0058*** (t = -2.95)
Special Ed * add'l endorsements			--0.0026 (t = -1.31)	-0.0020 (t = -1.02)	-0.0024 (t = -1.06)
Health/PE * add'l endorsements			-0.013*** (t = -4.58)	-0.012*** (t = -4.35)	-0.012*** (t = 4.10)
Ag/Tech * add'l endorsements			0.00045 (t = 0.24)	0.0012 (t = 0.64)	0.000012 (t = 0.00)
Arts * add'l endorsements			-0.0056*** (t = -2.77)	-0.0055*** (t = -2.74)	-0.0070*** (t = -3.04)
Languages * add'l endorsements			-0.0041 (t = -1.43)	-0.0018 (t = -0.64)	-0.0021 (t = -0.66)
School Variables	None	None	None	Covariates	Covariates
District Variables	None	None	None	Covariates	Fixed-effect

Note: Models combine both years of RIFs with year fixed-effect (55,656 teachers in 08-09 with 1717 RIFs, 54,996 teachers in 09-10 with 407 RIFs). All specifications also include college selectivity, female dummy, and non-white dummy. Marginal effects of school covariates (size, level, student/teacher ratio, racial composition, percent passing state exams, and urbanicity) and district covariates (size, per pupil expenditures, and funding sources) not shown.

Table 5: Estimated Marginal Effects on Probability of Receiving RIF Notice: Non-Linear Effects

	1	2	3	4	5
Teacher Variables: Reference category is teachers with 12+ years seniority					
0–1 years seniority	0.074*** (t = 27.32)	0.074*** (t = 27.26)	0.092*** (t = 30.28)	0.074*** (t = 27.23)	0.092*** (t = 30.30)
1–2 years seniority	0.071*** (t = 25.97)	0.069*** (t = 25.54)	0.083*** (t = 27.21)	0.069*** (t = 25.47)	0.083*** (t = 27.24)
2–3 years seniority	0.060*** (t = 21.44)	0.058*** (t = 20.93)	0.068*** (t = 21.88)	0.059*** (t = 20.92)	0.069*** (t = 21.90)
3–4 years seniority	0.053*** (t = 18.10)	0.051*** (t = 17.59)	0.060*** (t = 18.35)	0.051*** (t = 17.60)	0.060*** (t = 18.37)
4–6 years seniority	0.037*** (t = 12.39)	0.036*** (t = 12.17)	0.040*** (t = 12.45)	0.036*** (t = 12.21)	0.040*** (t = 12.46)
7–11 years seniority	0.018*** (t = 5.34)	0.017*** (t = 5.19)	0.019*** (t = 5.29)	0.017*** (t = 5.30)	0.019*** (t = 5.32)
Master’s degree or higher	-0.0042*** (t = -5.13)	-0.0050*** (t = -6.15)	-0.0068*** (t = 7.21)	-0.0049*** (t = -5.92)	-0.0067*** (t = 7.09)
School Percent Minority Students (by quintile in state): 1st (lowest) Quintile is reference					
2 nd Quintile		0.0021 (t = 1.05)	-0.0067** (t = -2.18)		
3 rd Quintile		0.0012 (t = 0.60)	-0.0034 (t = -1.04)		
4 th Quintile		-0.0045** (t = -2.20)	-0.0025 (t = -0.71)		
5 th Quintile (highest)		-0.014*** (t = -6.47)	0.0030 (t = 0.74)		
School Percent Free/Reduced Meal Participation (by quintile in state): 1st Quintile is reference					
2 nd Quintile				0.0037** (t = 2.20)	0.0032 (t = 1.16)
3 rd Quintile				0.0042** (t = 2.23)	0.0024 (t = 0.77)
4 th Quintile				-0.0011 (t = -0.52)	-0.00086 (t = -0.25)
5 th Quintile				-0.0076*** (t = -3.04)	-0.0017 (t = -0.43)
School Variables	None	Covariates	Covariates	Covariates	Covariates
District Variables	None	Covariates	Fixed-effect	Covariates	Fixed-effect

Note: Models combine 2008-09 and 2009-10 RIF notices with year fixed-effect (55,656 teachers in 08-09 with 1717 RIFs, 54,996 teachers in 09-10 with 407 RIFs). All specifications also include college selectivity, female dummy, non-white dummy, and all teacher endorsement areas. Marginal effects of school covariates (size, level, student/teacher ratio, racial composition, percent passing state exams, and urbanicity) and district covariates (size, per pupil expenditures, and funding sources) not shown. Models are estimated separately for Percent Minority and Percent Free/Reduced Meal Participation due to high bivariate correlation (0.72).

Table 6: Estimated Marginal Effects on Probability of Receiving a RIF notice, including teacher effectiveness estimates

	1	2	3	4	5	6
Full Model						
Seniority	-0.015*** (t = -7.44)	-0.0057*** (t = -7.15)	-0.0085*** (t = -9.65)	-0.0084*** (t = -9.62)	-0.0085*** (t = -9.66)	-0.0086*** (t = -9.58)
Math value-added	-0.0024 (t = -1.19)	-0.0025 (t = -1.08)	-0.0026 (t = -1.25)	-0.015 (t = -1.36)	-0.0059 (t = -0.71)	0.00016 (t = 0.04)
Reading value-added	-0.0018 (t = -0.93)	-0.00042 (t = -0.18)	-0.0022 (t = -1.08)	-0.016 (t = -1.35)	-0.0076 (t = -0.93)	-0.010 (t = -1.40)
District F.E. Model						
Seniority	-0.028*** (t = -7.07)	-0.018*** (t = -7.21)	-0.019*** (t = -9.53)	-0.018*** (t = -9.50)	-0.018*** (t = -9.54)	-0.018*** (t = -9.39)
Math value-added	-0.0030 (t = -0.43)	-0.0029 (t = -0.64)	-0.0013 (t = -0.35)	-0.012 (t = -0.61)	0.0031 (t = 0.21)	-0.0066 (t = -0.93)
Reading value-added	0.012 (t = 1.56)	0.0056 (t = 1.39)	0.0018 (t = 0.51)	-0.0034 (t = -0.17)	-0.0090 (t = -0.67)	-0.0058 (t = -0.49)

*Full models also include teacher covariates (college selectivity, master's degree, gender, and race), school covariates (size, student/teacher ratio, racial composition, and urbanicity), and district covariates (size, per-pupil expenditure, and funding sources). District fixed-effect models include the teacher and school covariates above and a district fixed-effect. The regressions in each column use a different specification of the VAM model, described below:

- 1:** Single-year VAM estimate from year of RIF notices (08-09) (N = 2611, 88 RIF teachers)
- 2:** Single-year VAM estimate from year before RIF notices (07-08) (N = 4728, 86 RIF teachers)
- 3:** Pooled-year VAM estimate across all three years of data (06-09) (N = 6545, 145 RIF teachers)
- 4:** Pooled-year VAM estimate, controlling for experience (06-09) (N = 6545, 145 RIF teachers)
- 5:** Pooled-year VAM estimate, including school fixed-effect (06-09) (N = 6545, 145 RIF teachers)
- 6:** Pooled-year VAM estimate, including student fixed-effect (06-09) (N = 6545, 145 RIF teachers)

Table 7: Simulated probability of Receiving a RIF Notice

		Years of Seniority						
		0-1	1-2	2-3	3-4	4-6	6-12	12+
Endorsement Area	Math	9.3%	7.0%	3.7%	2.4%	0.95%	0.31%	0.11%
	Science	9.1%	6.9%	3.6%	2.4%	0.93%	0.31%	0.11%
	English/LA	13%	10%	5.4%	3.6%	1.4%	0.47%	0.17%
	Social Studies	13%	9.7%	5.2%	3.4%	1.4%	0.44%	0.16%
	Elementary Ed	10%	7.8%	4.2%	2.7%	1.1%	0.36%	0.13%
	Special Ed	6.2%	4.7%	2.4%	1.6%	0.62%	0.20%	0.074%
	Health/PE	17%	13%	7.4%	4.9%	2.0%	0.65%	0.24%
	Agriculture/Tech/Other	11%	8.1%	4.3%	2.8%	1.1%	0.37%	0.13%
	Arts	15%	12%	6.4%	4.3%	1.7%	0.56%	0.21%
	Foreign Languages	12%	9.2%	4.9%	3.2%	1.3%	0.42%	0.15%

*Overall probability of receiving a RIF notice was 1.9%

Table 8: Probability of a student’s teacher receiving a RIF notice

	1	2	3	4
	Probability of RIF (actual)	Probability of RIF (simulated)	Average VAM (actual RIF teachers)	Average VAM (simulated RIF teachers)
All students	2.41%	2.20%	-0.0487 (0.136)	-0.241 (0.0757)
White students	2.40%	2.31%	-0.0410 (0.130)	-0.238 (0.0769)
Non-white students	2.42%	2.00%	-0.0632 (0.145)	-0.248 (0.0727)
Black students	3.77%	2.81%	-0.0559 (0.141)	-0.244 (0.0654)
Hispanic students	1.86%	1.54%	-0.0800 (0.161)	-0.263 (0.0760)
Low-income students	2.59%	2.28%	-0.0526 (0.144)	-0.250 (0.0740)

*Standard deviations in parentheses. All VAM estimates are the mean pooled-year VAM estimate used for the VAM simulations. N = 143,005 students; 93,116 white, 7958 black, 22,462 Hispanic, 62,114 low income