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AIR

Are There Hidden Costs Associated with Conducting Layoffs?The Impact of RIFs and Layoffs on Teacher Effectiveness

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Abstract

Few studies examine employee responses to layoff-induced unemployment risk; none that we know of quantify the impact of job *insecurity* on individual employee productivity. Using data from the Los Angeles Unified School District and Washington State during the Great Recession, we provide the first evidence about the impact of the layoff process on teacher productivity. In both sites we find that teachers impacted by the layoff process are less productive than those who do not face layoff-induced job threat. LAUSD teachers who are laid off and then rehired to return to the district are less productive in the two years following the layoff. Washington teachers who are given a reduction-in-force (RIF) notice and are then not laid off have reduced effectiveness in the year of the RIF. We argue that these results are likely driven by impacts of the layoff process on teachers' job commitment and present evidence to rule out alternate explanations.

Keywords: job displacement, reduction-in-force, layoffs, employment threat, school finance, teacher labor market, worker productivity

JEL classification: I20, I28, J08, J21, J45, J63

1. Introduction

The Great Recession of 2008 led to layoffs in both the public and private sectors at a scale unseen in recent history (Farber, 2015). In the public sector in particular, estimates suggest job loss of nearly 600,000 employees (by July 2012), leading to the lowest level of public sector employment in 30 years (Greenstone & Looney, 2012). Extant empirical work shows the direct costs of such employment reductions, including earning losses of individual workers, increased unemployment benefits and lower savings rates (e.g. Chan & Stevens, 1999; Couch & Placzek, 2010; Farber, 1997; Kletzer, 1998; Topel, 1990). But there also are less obvious, and potentially quite important, consequences associated with layoffs and the process through which layoffs occur: the employment instability associated with layoffs could affect employee productivity, potentially having far-reaching implications for the economic welfare of the country.

To that end, literature in economics and psychology finds that employees who are displaced from their jobs experience a decline in productivity – as measured by wage rates or special task completion in the case of psychology-based studies – that often persists long after the layoff itself (Brockner, Davy & Carter, 1992; Hammermesh, 1989; Kletzer, 1998; Gibbon & Katz, 1989; Brockner, Grover, et al., 1985; Jacobson, LaLonde & Sullivan, 1993; Allen, Freeman, et al., 2001; Davis & von Wacter, 2011). However, the productivity costs associated with public sector layoffs in particular have not received much recent research attention, especially in the context of the most recent fiscal crisis. And, to our knowledge, there has been no assessment of whether the *threat* of job loss affects worker productivity.

We examine this issue as it pertains to public school teachers who faced layoffs and layoff threat during the Great Recession, when reduced school funding from state and local governments resulted in educator layoffs in quantities greater than any time in recent history.

Public school teachers are a particularly pertinent case for the study of potential productivity losses associated with employment displacement. National estimates of teacher layoffs range from 170,000 to 240,000 by the 2011-12 school year alone (Bureau of Labor Statistics, 2012; National Education Association, 2010), and while layoffs have dissipated as the economy has rebounded, they are still a routine event in districts across the country due to budget shortfalls and/or drops in student enrollment in individual school districts (see, for examples, Blume (2017) and Leal (2017)).

We focus not only on layoffs themselves, but on the potential that the *layoff process* affects teachers. The distinction is important. The layoff process begins early in the spring semester, when teachers first receive notice – usually by way of a Reduction-in-Force (RIF) notice – that they are *at risk* of being let go. Then, later in the spring semester, but almost always before state and district budgets are set, a portion (but as we show, not nearly all) of RIFed teachers receive official layoff notices. As budgets and enrollment numbers firm up over the summer and early fall, some subset of laid off teachers are offered their jobs back, and those who have not found alternate employment return to their districts. This process results in significantly more teachers receiving RIF notices than will eventually be laid off, and, in turn, more teachers being laid off than will eventually need to be removed from the district. The likely impact of the layoff process, then, as opposed to simply job loss associated with layoffs, is that a greater quantity of employees may suffer productivity impacts. In particular, the layoff process leads to two primary treatments that may impact teachers' productivity at different points in time. First, teachers' current-year productivity could be harmed by the receipt of a layoff notice, whether or not she eventually loses her job. Second, teachers who are let go and then are rehired and return to teaching in the following year could suffer productivity losses.

Using longitudinal administrative data from the Los Angeles Unified School District (LAUSD) and Washington State that track teachers impacted by the layoff process during the Great Recession (the 2008-09 through 2011-12 school years), this study provides the first evidence about the impact of the *layoff process* on employee productivity in both the current and future years. In particular, we ask: *Does teacher effectiveness change in the face of layoff-induced unemployment threat?* This is an important question to ask given that, in a related study (AUTHORS, 2016a) we show that teachers' receipt of RIF notices, not just layoffs themselves, dramatically increases the amount of teacher turnover across schools within districts, and there is evidence that this type of churn has negative consequences for student test achievement (Hanushek, Rivkin & Schiman, 2016; Ost, 2014; Ronfeldt et al., 2013).

We find that, in both LAUSD and Washington State, teachers impacted by the layoff process are less productive (based on value-added measures of teacher effectiveness, which isolate individual teachers' contributions to their students' achievement growth on standardized English Lanugage Arts (ELA) and mathematics tests) than those who do not face layoff-induced job threat. In particular, LAUSD teachers who are laid off and then rehired to return to the district are less productive in the two years following the layoff, and Washington State teachers who are given a RIF notice and are then not laid off have reduced effectiveness in the year of the RIF. We argue that these results are likely driven by impacts of the layoff process on job commitment, and present evidence to rule out alternate explanations such as selection bias or the deterioration of teachers' organization- or position-specific human capital, which may be affected given that the layoff process can result in teacher transitions to new schools, grade levels, or teaching positions.

2. The Potential for the Layoff Process to Impact Teacher Productivity

Layoffs and the layoff process can impact teacher productivity in several ways. To date, extant research has focused on the effect of layoffs on the quality of the teacher workforce as a whole. In particular, several studies find that seniority-based "Last in, first out" ("LIFO") layoff processes instituted to attain budget reduction targets result in the layoff of significant numbers of effective teachers. For instance, researchers find that in New York City (Boyd et al., 2011) and Washington State (Goldhaber & Theobald, 2013), the use of a LIFO process rather than a performance-based system requires districts to lay off substantially higher quality teachers (20-26% of a standard deviation in student achievement). In the Charlotte-Mecklenburg School District, where school administrators may take other factors beyond seniority (such as teacher quality) into account, Kraft (2015) finds that layoffs had negative effects on students' math achievement if the district removed an effective teacher, while there was little detectible effect on students' math achievement if the district removed a teacher based on seniority.

Although the work reviewed above is critical for understanding how layoffs impact the quality and size of the workforce, these papers do not assess the impacts of the *layoff process* beyond the consequences for students resulting from the specific teachers who are/are not employed because of layoffs. In particular, teachers' productivity may well be harmed as a result of receiving a RIF notice, whether or not they are actually laid off – a cost of the layoff process that is as yet unstudied in education. There are two main pathways through which teachers' productivity may be affected. First, teachers may become less attached to their current teaching position because they judge it to be at risk. They could, for instance, devote time to searching for other jobs, or suffer psychological or morale costs associated with the layoff process that affects their productivity. Second, the process may result in changes to teacher assignments causing reductions in their individual or grade-, school-, or district-specific human capital.

2.1 Job Commitment, Psychological or Morale Effects of the Layoff Process

After a layoff or a layoff threat, employees may experience decreased organizational commitment and/or motivation, which may in turn diminish their productivity.[1] It is natural, for instance, for employees at risk of job loss to engage in more intensive alternative job search behavior (Ashford, Lee & Bobko, 1989; Lim, 1996). Indeed, work from the psychology literature suggests that the employment threat introduced by the layoff process can impact individuals' organizational commitment, motivation and productivity, thus reducing their overall effectiveness (e.g., Allen, Freeman, et al., 2001; Brockner, Davy & Carter, 1985; Brockner, Grover, et al., 1992). For instance, Brockner, Davy and Carter (1985) conduct psychological studies of simulated layoffs in lab settings and find that exposure to layoff threat decreases motivation and self-esteem. Research participants reported high levels of "worry" when they had already been exposed to past layoffs and when they perceived that layoff processes were conducted "unfairly." This has direct implications for the impacts of the entire layoff process (not just layoffs) on teachers, as many more teachers than necessary are threatened by job loss even in the absence of actual layoff (see AUTHORS (2016a)), and because the majority of school districts let go of teachers using a "last-in-first-out" process, which may be viewed by some teachers as arbitrary or unfair due to its reliance on seniority rather than merit.

It is also possible that layoffs and the layoff process harm teachers' professional environments, thus further impacting teachers' morale and commitment and accentuating the negative impact of layoffs on teachers' collective productivity. A number of studies have begun

[1] Other studies focus on employees in industries with high unemployment risk or who are exposed to coworker layoffs. Across industries (outside education), negative working conditions associated with high risk of unemployment increase employee quit intentions and actual departures and require wage premiums for labor markets to clear (Abowd & Ashenfelter, 1981; Böckerman & Ilmakunnas, 2009; Delfgaauw, 2007).

to document how a poor workplace environment can negatively impact teacher effectiveness (e.g., Bryk et al., 2010; Sass et al., 2012; Johnson, Kraft & Papay, 2012; Kraft, Marinell & Yee, 2016). For example, Kraft and Papay (2014) find that teachers exhibit lower returns to experience in schools they perceive to have poor working conditions. Other studies show that teachers prefer working in schools where they perceive there to be a supportive working environment and strong administrative support (Boyd et al., 2011; Johnson et al., 2012; Ladd, 2011).

2.2 Human Capital Effects of the Layoff Process

The layoff process may also affect teachers' specific human capital – human capital connected to their schools or grades, for instance – if the process causes teachers to switch schools and/or positions within the district at otherwise greater rates. Indeed, a recent paper on teacher layoffs shows that the layoff process itself creates teacher churn; teachers receiving RIF notices are more likely to switch schools (AUTHORS, 2016a).[2] This can occur either because teachers feel insecure in their current role or because of the structural churn that is set into motion once districts are forced to re-staff schools to fill vacancies caused by laid off teachers. Either way, a teacher in a new role may need to rebuild role-specific expertise.

Work on job displacement or "unemployment scarring" from the economics literature finds that being laid off immediately and permanently reduces employees' firm-specific human capital and contributes to the deterioration of general human capital during a spell of unemployment (Couch & Placzek, 2010; David & von Wacter, 2011). Job displacements are

[2] Recent studies show that this type of teacher churn negatively impacts school climate and student achievement (e.g., Guin, 2004; Ronfeldt, Loeb, & Wyckoff, 2013; Hanushek & Rivkin, 2013; Atteberry, Loeb & Wyckoff, 2016; Hanushek, Rivkin & Schmian, 2016). Thus, RIF-induced teacher churn may also contribute to potential morale effects. Turnover may be even more harmful in the context of layoffs: Sepe and Roza (2010) argue that the teacher churn brought on by layoffs destroys established relationships between administrators, families, teachers and students, destabilizing schools and negatively impacting learning environments.

particularly harmful for more experienced workers and during periods of economic decline, when employees have fewer labor market opportunities to identify high-quality matches (Davis & von Wacter, 2011; Jacobson, LaLonde & Sullivan, 1993). Not surprisingly given the above literature, layoffs lead to a decline in employee productivity and lifetime earnings (Couch & Placzek, 2010; Hamermesh, 1987; Kletzer, 1998).

The risk to teachers of losing their jobs may also affect the acquisition of human capital. For instance, laid off teachers often did not receive indication that they would be offered a job the following school year until just before the beginning of or several weeks into the year. Consider that teachers typically spend at least some of their summer months preparing for the next school year, attending district professional development, and engaging in other useful activities intended to improve their instruction in the following year. Teachers who believe that they do not have a job in the coming year may spend less time in preparation and improvement activities, which may result in a failure to maintain and build new job-specific human capital. These teachers may therefore be less productive in the next school year than had their jobs not been at risk.

3. The Teacher Layoff Process in LAUSD and Washington State

In this study, we are concerned with changes in teachers' productivity that may occur as a result of the *layoff process*, rather than simply job loss. While the layoff process varies to some extent across states and districts, the basic structure is similar: there is a period after which teachers are notified that their jobs are at risk and before they find out whether they will be laid off. However, given differences in state and district regulations, the timing of the layoff process can vary substantially, which may lead to differences in the impacts of various stages of the layoff process (e.g., RIFs versus actual layoffs). Moreover, as we discuss below, the timing of the process also affects when we might expect to detect an impact on teacher productivity (i.e., the year in which teachers first receive a RIF notice versus the year after experiencing a RIF or a layoff).

Figure 1 depicts the timing of layoffs in both LAUSD and Washington. In California, districts are required to issue RIF notices by March 15 and to notify teachers if their RIF has or has not been rescinded by May 15. At this point, teachers whose RIFs were not rescinded are let go for the following school year. But districts learn more about budgets, enrollments and voluntary attrition over the course of the summer and into the early fall and, based on updated budget projections, offer re-employment to many teachers who have been laid off. In Washington, the RIF process is not as heavily regulated by the state, but most district collective bargaining agreements (CBAs) contain provisions that require district administrators to give early notification to teachers who may face employment threat. Lists are often posted in March and in many districts as early as January or February (see Appendix Examples of CBA Early Notification Provisions – Washington State for examples).

This process gives rise to four main categories of teachers, shown in Table 1: (a) teachers who do not receive a RIF notice, and thus face no threat of layoff; (b) teachers who receive a RIF notice but then later receive notice that their RIF has been rescinded, and thus face a threat but no actual layoff; (c) teachers who receive a RIF notice that is not rescinded, but who are rehired either by their district or by another district in the following year as a full time teacher[3]; and (d) teachers who are laid off and do not return to their districts (LAUSD) or to teaching (WA) in the following year. In LAUSD category (c) includes teachers who are RIFed, then laid off, and then

[3] In LAUSD, principals often fill empty teaching positions by hiring short-term substitutes who become long-term substitutes if their teaching positions are not filled approximately a month into the school year. We exclude long-term substitutes in our analysis, but results are consistent if they are included (available upon request).

rehired by LAUSD. In Washington we are able to observe teachers across districts, thus this category includes teachers who receive layoffs and return to their district or to a different district within the state.

The staged structure of the layoff process has implications for the likely mechanisms through which RIFs and layoffs impact teacher productivity. The receipt of a RIF that is then rescinded during the same year most likely affects teachers' productivity through decreases in morale and working conditions experienced by impacted teachers and by changes in job search behavior during the year. A same-year RIF-rescission likely does not affect teachers' acquisition of organization-specific human capital. By contrast, the receipt of a layoff that causes actual job loss, even if teachers return to teaching, likely impacts both teachers' morale and working conditions *and* their human capital accumulation. In particular, teachers who return to teaching may do so in a new grade, school or district (AUTHORS, 2016a), causing potential losses in firm- or position-specific human capital. Moreover, teachers who are let go and forced to search for a new position at the end of the school year or over the summer may not only experience decreases in their individual productivity because of psychic effects resulting from job loss, but also because they likely shift their efforts to job search activities over the summer in place of individual human capital accumulation or maintenance.

The differences in the timing of the layoff processes across contexts (shown in Figure 1), suggest that the discrete treatments encapsulated in the layoff process (RIFs and layoffs), may vary in their impacts across the two sites in this study. In LAUSD, any productivity losses attributable to the receipt of a RIF notice are unlikely to have concurrent year detectible impacts on student test scores. This is because LAUSD teachers receive their RIF notices in the midst of the state's window for testing student achievement, when the instruction reflected by the year's test scores is already for the most part complete. Thus, even if the RIF and recission has same-year psychic or morale effects on teachers in LAUSD, these likely will not be captured in the same-year test scores. By contrast, in Washington, teachers often receive notice of a potential job loss well before testing occurs, so we might expect to see impacts of RIFs on teachers' current year productivity. Similarly, the variation in the layoff process also suggests potentially different results in terms of the impact of the layoff itself on teachers' productivity. As shown in Table 1, in LAUSD a relatively large proportion of teachers are laid off and then return to work in the district in the following year. This suggests a high degree of threat and tumult over the summer months, which could lead to lesser performance in the next school year. However, in Washington, relatively few teachers are impacted in this way, suggesting that we might see relatively small or null impacts overall on teacher productivity in the year following layoffs.

Table 1 shows the number and proportions of teachers in LAUSD and Washington who were directly impacted by the layoff process in any way across the four years of layoffs, from 2008-09 through 2011-12. Over this time, 14,142 LAUSD teachers received RIF notices (the sum of the bottom three rows in the top panel of Table 1), and 4,445 teachers were laid off. In Washington, 3,538 teachers received RIF notices and 561 were laid off. The layoff process cut deeper in LAUSD than in Washington: on average, 13.3% of LAUSD teachers received a RIF notice each year, compared to only 1.6% of Washington teachers. Of those teachers who were RIFed, almost a third of LAUSD teachers were laid off, compared to less than 20% in Washington. The contexts also vary when we consider the proportion of laid off teachers who were ultimately let go (did not return to teaching in either the district or state): in LAUSD, only one-half of laid off teachers did not return to teach in the district in the following year.[4] In

[4] These rates of rescission are similar to those of districts across California (Estrada, 2012). We cannot assess teachers who were laid off and return to teaching in other public school districts in California.

Washington, the definition of laid off and return varies slightly as the data permit teachers to be observed across districts. In our Washington models, we are concerned with teachers who are RIFed or laid off and return to teaching in the state in the following year. Approximately two-thirds of laid off Washington teachers did not return to a public teaching position in the state (63.1%).[5]

In addition to the layoff process timeline described above, state (California) and school district (Washington) provisions that require layoffs to be made almost entirely based on seniority also impact the distribution of RIFs and layoffs and their magnitude. California state law requires that teacher layoffs are administered in order of reverse seniority within teaching area. District administrators may take into account specific programmatic needs beyond basic teaching credentials but they cannot consider other factors such as teachers' effectiveness, evaluations, or rates of absenteeism (California Education Code Sections 44930-44988). In Washington, districts must lay off within credential area but are allowed flexibility when designating the order (see WAC Chapter 181-82). Despite this autonomy, locally-negotiated CBAs require administrators to lay off by seniority in over 95 percent of districts.

These requirements are reflected in the distribution of RIFs and layoffs shown in Table 2**,** which shows the characteristics of teachers in our analytic sample (4th through 7th grade teachers for whom we can calculate VAMs) in each layoff threat category, for the years in which layoffs took place (2008-09 to 2011-12). As expected, in both LAUSD and Washington, much greater proportions of novice teachers (in their first through third years of teaching experience in the district) than mid-career or veteran teachers were laid off, whereas much greater proportions of veteran teachers were unaffected by RIFs than were mid-career or novice teachers. Table 2 also

[5] Although not shown in Table 1, over 90 percent of laid off Washington teachers did not return in the next year to their original districts.

shows that RIF and layoff rates differ by endorsement area, with teachers in traditionally hard-to-staff subjects such as math and science facing less employment threat as a result of the layoff process.[6]

4. Data and Analytic Approach

The LAUSD and Washington State data we use for this study cover six school years, 2007-08 to 2012-13. In both sites the datasets link teachers to their students, schools, and districts across years.[7] Both datasets contain information about which teachers received RIF and layoff notices. There are three primary reasons these data are well-suited to address our research focus. First, the longitudinal data in both sites permit a measure of teacher productivity: value added measures of teachers' contributions to student test scores on state assessments (California Standardized Tests (CSTs) in Math and English Language Arts (ELA) in LAUSD and Washington Assessment of Student Learning (WASL) in Math and ELA in Washington State). Second, we are able to identify which teachers are impacted by RIFs and layoffs, as described above, including which teachers return to teaching following a layoff. Third, in both sites teachers received layoff notices and layoffs in four separate school years, providing substantial variation in layoff threat across teachers.

4.1 Longitudinal Data in LAUSD and Washington State

The LAUSD data were provided by LAUSD's Offices of Human Resources and Data and Accountability and include all certificated personnel employed by the district. The primary data

[6] These results are the same for the full sample of LAUSD teachers (available from the authors upon request). The only difference is that in our analytic sample shown in Table 2 we drop all teachers who teach special education classes and only retain teachers who have a special education credential but are teaching in mainstream 4th- 7th grade classes. As a result, even though special education teachers are protected from RIFs in LAUSD (which is reflected in our broader sample of teachers), in our analytic sample it appears that teachers with special education credentials were actually more at risk for unemployment threat.

[7] In Washington, CEDARS data includes fields designed to link students to their individual teachers, based on reported schedules. However, limitations of reporting standards and practices across the state may result in ambiguities or inaccuracies around these links.

source for Washington is the Office of the Superintendent of Public Instruction (OSPI)'s S-275 administrative database, which provides a record of certificated and classified personnel employed within Washington State's school districts. In both sites the administrative data include employee demographic information (e.g., race/ethnicity, gender, years of experience), teachers' educational backgrounds (e.g., highest-degree earned and endorsements/credentials held by each employee[8]), job title, contract status (permanent, probationary, etc.) and teachers' school and classroom placement. We restrict the sample to "classroom teachers"[9] who teach in grades 4-7 and for whom we can generate value-added measures of teachers' contributions to student performance on standardized exams.[10,11] We further restrict the sample to teachers who teach at least eight students with current and prior year test scores available. Our final sample consists of 31,160 teacher-year observations in LAUSD and 45,436 teacher-year observations in Washington State for school years 2007-08 to 2012-13. For school year 2011-12, the final year of layoffs, these data include 4,934 unique teachers in LAUSD and 9,205 in Washington. As is shown in the bottom panel of Table 1, over all four years of RIFs/layoffs, 3,625 and 279 4th – 7th grade teachers in LAUSD and Washington, respectively, receive a RIF and have it rescinded. Another 1,333 and 33 teachers are laid off, and 634 and 17 of those teachers return to teaching

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[8] In Washington, we use the PESB credentials database to obtain measures of teacher endorsement areas. In LAUSD, we obtain these data from the HR dataset. In our regression models, we use the following four mutually exclusive categories to control for teacher endorsement area: (a) special education (SPED) credential; (b) science or math credential (STEM), no special education credential; (c) other non-elementary credential besides SPED or STEM; and (d) elementary credential only.

[9] In LAUSD we define teachers as non-administrator personnel with teaching job titles who can be linked to a school site. We limit our analytic sample to teachers in K-12 district schools and dependent charters that operate within the district's CBA thus are subject to LAUSD's RIF and layoff processes. We exclude non-traditional schools (alternative, special education, and community day). In Washington, we restrict the analytic sample to employees appearing in the S-275 (they were hired by October 1 of the year they received a layoff notice) and whose assignment ID indicates they were in a teaching position that year.

[10] In each context, we can calculate VAM estimates for teachers in additional grades; however, we can only estimate identical models across each context in grades 4-7.

[11] In Washington, 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.

the following year in LAUSD and Washington.

These teacher data are merged with student-level data that contain students' performance on state math and ELA standardized achievement tests (standardized by grade/subject and year), race/ethnicity, gender, grade level, school and classroom placement, free lunch status, disability (if any), English language proficiency, home language, course enrollment, and teacher assignment. The data are then combined with publicly-available school-level data in both California (from the California Department of Education) and Washington (from the Washington State Report Card and the Common Core of Data), which include each school's total enrollment and average student demographic information.

4.2 Layoff and Layoff Threat

LAUSD data include annual lists of all teachers who received a RIF notice and all teachers who were laid off. In Washington, information on RIF notices was originally collected by the State's Professional Educator Standards Board in 2008-09 and 2009-10. For subsequent years (2010-11 and 2011-12), the authors surveyed and received responses from all of Washington's 297 school districts about which teachers were issued RIF notices.[12] We merge these sources of information with our longitudinal datasets, enabling us to generate precise indicators of each type of layoff threat described in Table 1.

We note that it is not possible in our data to differentiate between teachers who were laid off and offered a job back but declined the position and those who were laid off and not offered a job. If teachers appear in the data as a classroom teacher in the year following a layoff, we assume they were offered and accepted a teaching job. If teachers do not return to the dataset in

[12] We surveyed Washington school districts in the summer of 2012. We were also able to obtain data from the Lind School District prior to its merge with the Ritzville School District in 2012 as well as the Palouse and Garfield districts, which consolidated in 2008-09 due to the recession. As of 2014, Washington had 295 school districts.

the following year, we assume they were not offered a position. It is possible, however, that some teachers were offered reemployment and declined. LAUSD officials assure us that very few teachers fall into this category (personal communication, 2015), and in Washington we identify very few teachers as returning to employment in the state post-layoff. Moreover, this limitation has little bearing on our results as we are interested in what happens to teachers who return to teaching after a RIF or a layoff.

4.3 Value Added Measures

Our primary outcome of interest is teacher's job performance. There are many ways to characterize teaching performance, such as formal observations of teacher practice, teachers' abilities to engage students (e.g. as often measured by student perception surveys), or teachers' ability to help students' socio-emotional growth. We assess job performance based on teachers' contributions to students' achievement on standardized tests ("value added"). While there are advantages to considering each outcome, we focus on teachers' value-added measures both for practical reasons – many of the aforementioned measures are not available for teachers in our settings – and because value added measures have been shown to be predictive of the test score growth and later life outcomes of the students taught by teachers in the future (Chetty, Friedman & Rockoff, 2014; Goldhaber & Hansen, 2010).

To obtain estimates of teachers' contribution to students' ELA and math achievement scores ("value added"), we estimate the following model separately for each school year from 2006-07 to 2012-13:

$$A_{ijkst} = \alpha A_{i(t-1)} + X_{it}\beta + \theta_{jt} + \varepsilon_{ijkst} \tag{1}$$

In equation (1), we index for students, (i), teachers (j), schools (k), subject area (s, math or reading) and school year (t). A_{ijkst} represents student achievement normed within grade and year, which is regressed against students' prior year achievement in both math and reading, $A_{i(t-1)}$, and a vector of student characteristics, X_{it}, which includes free or reduced price lunch eligibility, race/ethnicity, and special education and gifted status. The teacher fixed effect, θ_{jt}, is the VAM estimate for teacher *j* in school year *t*, and the error term, ε_{ijkst}, is assumed independently identically distributed with respect to the other variables in the model. For teachers that have value-added scores in both subjects in the same year, we take the average of the two scores.

We estimate teacher-year models rather than pooling data over time because we are interested in teachers' measures of effectiveness in each year they teach, and the possibility that their yearly performance is affected by layoff threats. In order to test the robustness of our value-added estimates to alternative specifications commonly employed in the literature, we estimate several variations of this basic model and assess the correlation between our preferred model and alternate specifications (see Koedel and Betts, 2007; McCaffrey, Sass, Lockwood, and Mihaly, 2009; Rothstein, 2010 and Koedel, Mihaly, and Rockoff, 2015). Consistent with other studies (Chetty, Friedman & Rockoff, 2014; Ehlert et al., 2014; Goldhaber, Walch & Gabele, 2014), the value-added performance estimates generated by the various described models are highly correlated (0.90 or above). Thus, it is not surprising that the findings we describe below are not sensitive to the value-added specification (results provided in Appendix Tables A1 and A2).

Our measure of teacher effectiveness is a linear term, which identifies an individual teacher's relative position on the effectiveness distribution. All value-added measures are reported in student-level standard deviations. Consistent with VAM estimates from other contexts (see Hanushek and Rivkin (2012) for a summary, Kane and Staiger (2008) for specific figures based on LAUSD, and Goldhaber and Theobald (2013) for Washington), the standard deviation of our one-year teacher effectiveness measures in LAUSD and Washington is 0.274 and 0.258, respectively. These estimates are not shrunken by empirical Bayes methods and are based on models that do not include school fixed effects, so they include both within and between school differences in teacher effectiveness.[13]

4.4 Analytic Approach

We ask whether teachers' job performance changes in the current year in which a teacher experiences a RIF or a layoff or in the years following a RIF or layoff. As we noted in Section 3, the timing of the layoff process differs across the two sites, thus it is important to model both the receipt and rescission of a RIF and a layoff on teacher effectiveness in time *t* (the year that a RIF is received), the following year, and potentially later years. To do this, we predict the value-added effectiveness estimates – derived from equation (1) above – for teacher *i* in school *s*, in year *t* (denoted VA_{ist}), based on teacher *i*'s current and prior year RIF and layoff experience. First, following Jackson's (2013) event study approach, we examine teacher effectiveness before, during and after the layoff or RIF event by estimating equation (2) by OLS:

$$VA_{jst} = X_{jst}\alpha + S_{jst}\gamma + \sum_{\tau=-4}^{3}\left[I_{t=\tau} \cdot RIF\text{-}re_{\tau} + I_{t=\tau} \cdot layoff_{\tau}\right] + \theta_j + \delta_{\tau} + \eta_{jst}, \qquad (2)$$

where θ_j is a teacher fixed effect, X_{jst} and S_{jst} are vectors of time-varying teacher characteristics (educational attainment, experience, and endorsements) and school characteristics (total enrollment, the percent of students at the school that identify as an underrepresented minority race/ethnicity, and the school level), respectively. We include the teacher fixed effect so that each teacher's effectiveness in a given year is compared to their own effectiveness in other years. We include educational attainment because it is considered by some to be a predictor of teacher quality, although little evidence exists to support this assertion. Importantly, the other time-

[13] Of course, VAMs are a noisy measure of individual teacher performance (see, for examples, Goldhaber & Hansen (2013) and McCaffrey et al. (2009)) and there is concern about bias as well (Rothstein, 2009; 2010). However, concerns about noise in VAMs should be lessened given that our analyses aggregate across a large number of teachers. This is not fundamentally different than looking at the returns to any teacher credential when student tests, which themselves are noisy measures of student learning, are used as a dependent variable.

varying characteristics included in X_{jst} are the main determinants of whether or not a teacher receives a RIF, has it rescinded, is laid off, and/or is rehired. The inclusion of these observable characteristics directly controls for the selection process into treatment given the strict rules around layoffs in both California (California Education Code §44955) and Washington (Goldhaber & Theobald, 2013). We include the vector of school characteristics because to some extent they describe teachers' working conditions which can affect teachers' effectiveness.

$RIF\text{-}re_{\tau}$ and $layoff_{\tau}$ are the covariates of interest in this event study. In short, the coefficients for $RIF\text{-}re_{\tau}$ and $layoff_{\tau}$ provide the effects of receiving a rescinded RIF notice or receiving a layoff notice in τ years from year t, the year the layoff process event affected teacher *j*, (i.e., $layoff_{t=-3}$ is the effect for a teacher who will be laid off in three years and $layoff_{t=2}$ is the effect for a teacher who was laid off two years ago). Any coefficient capturing the "effect" of the receipt of a rescinded RIF or of a layoff that resulted in a rehire before the teacher was impacted by the layoff process ($t < 0$) should be zero, since teachers should not be impacted by a RIF or layoff before they have received one. Given that RIF and layoff notices are distributed late in the school year in LAUSD (see Figure 1), we also expect the estimates for impact of treatment on the year of the receipt of a rescinded RIF or layoff (i.e., $RIF\text{-}re_{t=0}$ and $layoff_{t=0}$) to be zero for LAUSD, while post-treatment effects ($t > 0$) would be negative if RIFs or layoffs negatively impact teachers' effectiveness. Therefore, the coefficients for $RIF\text{-}re_{t=1,2,3}$ and $layoff_{t=1,2,3}$ answer our primary research question of how teacher effectiveness changes in the years following teachers' experience exposure to layoff threat (*RIF-re*) or are actually layoff and rehire (layoff).

As in a typical event study, we include indicators for all potential treatments in each year pre-treatment (t<0), the year of treatment (t=0), and all years post-treatment (t>0). Our LAUSD data enable us to examine as many as four years (t=-4) before and three years after (t=3) a teacher might experience his or her first RIF-rescission or layoff and rehire. For each time period of the event study, the reference category for the RIF and layoff variables is teachers who were present but did not receive a RIF or layoff notice in each particular year relative to the event. Following the event study methods used in Jackson (2013), teacher-observations representing the receipt of a second, third, or fourth RIF or layoff notice are excluded from the analysis, but these teachers enter back into the event study after their last treatment. Teacher fixed effects are included in θ_j, year fixed effects are included in δ_τ, and η_{jst} represents the residuals. This event study analysis enables us to compare changes in an individual teacher's effectiveness over time, for those who are impacted by the layoff process to changes over time in effectiveness for teachers who do not receive a RIF or layoff.

While this is our preferred specification, given the small sample of teachers in Washington State with value-added estimates who return after receiving a RIF or layoff notice, the event study is only possible in LAUSD. As such, we employ a second analytic approach in which we estimate identical teacher fixed effects models in LAUSD and Washington that predict VA_{jst} (again derived from equation 1):

$$VA_{jst} = \beta_0 + \beta_1 RIFre_{jst} + \beta_2 Layoff_{jst} + \beta_3 RIFre_{jst\text{-}1} + \beta_4 Layoff_{jst\text{-}1}$$
$$+ X_{jst}\beta_5 + S_{jst}\beta_6 + \theta_j + \delta_t + \mu_{jst} \tag{3}$$

where $RIFre_{jst}$ and $Layoff_{jst}$ indicate whether a teacher received a RIF notice in year t that was rescinded or was laid off in year t, respectively, and $RIFre_{jst\text{-}1}$ and $Layoff_{jst\text{-}1}$ indicate whether a teacher was RIF-rescinded or laid off in the prior year, $t\text{-}1$. X_{jst} and S_{jst} are again vectors of time-varying teacher and school characteristics. We include year fixed effects (δ_t) to account for changes in teacher effectiveness that are idiosyncratic to a particular year. Again, the inclusion of teacher fixed effects, θ_j, in equation (3) allows us to examine changes in teacher effectiveness within teachers. Thus estimates of a teacher's job performance are relative to that same teacher's performance in a typical year. This alleviates many concerns about selection bias, as we are comparing within teacher changes in value added for those who are or are not affected by layoff or layoff threat. In both equations (2) and (3), standard errors are clustered at the teacher level. We weight observations by the inverse of the standard error of the value-added estimate so that teachers with more precise estimates of their teaching effectiveness contribute more towards the estimation of our parameters of interest. In alternative models testing the robustness of our findings, we also estimate equation (2) and (3) with school fixed effects and with teacher-by-school fixed effects.

The coefficients β_1 to β_4 in equation (3) address our primary research question of how exposure to threat of layoff or actual layoff, in the current or prior year of teaching, is associated with teaching performance. Following from our discussion in Sections 2 and 3, significant estimates of β_1 and β_3 (the coefficients on the RIF-rescinded indicators) may reflect different mechanisms by which the layoff process impacts teachers' productivity than would significant estimates of β_2 and β_4 (the coefficients on the layoff-rehire indicators). Any significant impacts of receiving a RIF and having it rescinded on teacher productivity in either year t or t+1 may be more likely to reflect the psychic costs of layoff threat, whereas actually being let go and then rehired sometime over the summer or fall is more likely to reflect some combination of psychic and human capital costs. Similarly, we may expect to see differences across contexts in the impacts of layoff or RIF in the current year, t, (β_1 and β_2), as opposed to being affected by a layoff or RIF in the previous year, t-1, (β_3 and β_4). Given the testing window and timing of layoff notification across contexts, estimates of the effect of receiving a rescinded RIF notice or a layoff notice in the current year are of less interest in LAUSD. Similarly, as Table 1 shows, estimates of the coefficient $Layoff_{ist-1}$ are of less interest in Washington, since so few teachers are laid off and then rehired for the following school year.

Equation (3) does not separate the effect of "treatment" (being subjected to the layoff process) from other factors that may diminish productivity, in particular the placement of a teacher in a new grade or school apart from the layoff specifically. Although productivity losses associated with within-school or within-district mobility may contribute to the overall effect of the layoff process on teachers' effectiveness, it is important to distinguish the extent to which mobility drives results above and beyond mobility both to assess whether or not there is an impact of RIFs or layoffs above and beyond mobility and to begin to determine if the effect on teacher productivity stems from human capital or psychic effects. To isolate the impact of the layoff process itself, net of teachers' within-school or within-district mobility, we also estimate equation (3) including indicators for whether or not a teacher was new to her school or to her grade and interactions to examine differential impacts of RIFs and layoffs for teachers who did and did not move.

We of course want to be cautious about our ability to infer causality in the relationship between layoff or layoff threat and teacher effectiveness. First, our results may be biased by sample selection; equation (3) only provides unbiased estimates of the impact of RIFs and layoffs if the selection of teachers into these conditions is uncorrelated with teacher effectiveness conditional on the observable teacher and school characteristics in the model. In addition, our results could be biased by non-random attrition if more or less effective teachers are more likely to be re-hired and return after layoffs or threat of layoff. In particular, there is a possibility that teacher assignment is non-random and could bias our results either downward (if laid off or

RIFed teachers return to classrooms with students that have unobserved traits associated with lower-achievement) or upward (if these teachers are granted easier classrooms upon return). These concerns are lessened substantially by our inclusion of teacher fixed effects in the model, which enable us to compare teachers to their own performance in untreated years. Moreover, as we will discuss in our results section below, equation (2) returns null estimates of any layoff or RIF-rescission "effects" in the years before a teacher is treated, confirming the lack of selection bias. However, we cannot entirely rule out the possibility that teachers return to more difficult classes after the receipt of a layoff and rehire. In addition, our results might be biased because of unintentionally omitted variables that should be present in our models, or because our preferred specification for our measure of teachers' value-added contributions to student achievement affect our results. Nonetheless, after we present our main results below we also test these potential sources of bias and present evidence suggesting that our findings are not subject to any of the potential biases described above.[14]

5. Results

5.1 Main Results

Our main results can be found in Tables 3 and 4. All models include the covariates discussed above, but in the interest of space we only report the variables of interest (results showing all covariates are available upon request).[15] Table 3 presents our results for the event studies for LAUSD teachers who receive a rescinded RIF notice or were let go and rehired.

[14] We also experimented with regression-discontinuity (RD) based estimates and our results were qualitatively similar to our preferred models. However, given data constraints in the accuracy and completeness of the running variable (hire date) in both contexts, RD specifications are less appropriate than our preferred models.

[15] The coefficients on the control variables are consistent with the literature, (e.g., Feng & Sass, 2011; Goldhaber, Gross, & Player, 2011; Hanushek, Kain & Rivkin, 2004; Harris & Sass, 2011; Ost, 2014). Experience is positively related to measures of effectiveness, especially in the early years of teaching. Teachers who acquire graduate degrees are not significantly more effective than those with bachelor's degree. Teachers are generally less effective in the years in which they switch schools or grade levels, skip a year, or are new to the district, relative to the years in which the teacher remains in the same placement.

Model 1 includes teacher and year fixed effects, Model 2 adds school fixed effects, and Model 3 includes teacher-by-school fixed effects. (Model 4 is a specification check which we will discuss in greater detail below.) Each column provides estimates for two "treatments": the receipt of a RIF notice that is then rescinded and the receipt of a layoff-rehire. Coefficients in the first row provide estimates of the effect of the receipt of treatment (RIF or layoff) on teacher VAMs for teachers who will first be treated (i.e., receive their first rescinded RIF notice or be laid off and then rehired) in four years. Because we control for teachers who are not present in four years, the reference group for these coefficients is teachers who will be present but will not be treated in four years. The next row provides estimates for the "impact" of being treated in three years on teachers' effectiveness (VAMs), and so on down the rows. The fifth row shows estimates of the impact of being RIFed or laid off in the current year (year *t*), and this is the first time we might expect to see a significant effect. The last three rows provide estimates of the impact of being treated in year t on effectiveness in years *t*+1, *t*+2 and *t*+3. Given that we normalize the value-added estimates of teacher effectiveness, the coefficients are interpreted as the change in teacher effectiveness, measured in student-level standard deviation units, associated with a teacher's RIF/layoff status.

Models 1 through 3 show that, as expected given the timing of RIF notices in LAUSD, rescinded RIF notices do not have a significant effect on teachers' value-added in LAUSD. However, across all three models, receiving a layoff notice lowers teachers' value-added in the year following the layoff. In particular, teachers who receive a layoff notice and then come back to LAUSD, on average, have value-added that is lower by about 0.06 standard deviation (SD) units of student achievement in the year following the layoff. Two years after a layoff, teachers' value-added is between 0.04 and 0.03 SD lower, depending on the model (and not significant when including teacher-by-school fixed effects).[16] These results are displayed graphically in Figure 2.

Table 4 presents the results from models described in equation (3) for both LAUSD and Washington. The first set of models predicts the effect of current and prior year RIF/layoff variables with teacher fixed effects, with identical models run in each context. In LAUSD, as expected based on the results of the event study, current year RIF and layoff notices have no effect on value-added, but receiving a layoff notice in the prior year, and returning to the district is associated with a 0.06 SD decrease in value-added. Thus, the achievement of a student in year *t* who has a teacher who was laid off in the prior year and returned to the district in year *t* is expected to be approximately six percent of a standard deviation lower than if that student had a teacher who was unaffected by layoff threat. This is approximately equivalent to having a first year teacher as opposed to a teacher with three to four years of teaching experience.

The results for Washington tell a somewhat different story. In Washington we find that receiving a RIF notice and having it rescinded is significantly and negatively associated with lower teacher effectiveness in the same year by about 0.05 student-level standard deviations. The magnitude of the Washington RIF findings are similar to those reported above for LAUSD, approximately equivalent to the difference in achievement associated with a student having a first year versus a third year teacher. Given the timing of RIF notices (before assessments) and the small sample of teachers who are laid off and return, these findings are not surprising. All models in Table 4 are based on data that are pooled across six years. In both LAUSD and Washington this pooling of data is supported by Chow tests that fail to reject the null hypothesis that the coefficients are significantly different in any year (available upon request).

[16] We also estimated the event study using shrunken VAM estimates. Our results are similar to the main results and available form the authors upon request.

To assess whether or to what extent the findings are driven by teachers being placed in a new grade level, school or job category, we estimate equation (3) including indicators for being new to the school (column 2) or to the grade (column 3), and including school fixed effects (column 4).[17] Although not shown, we also run a series of variants of equation (3) this time interacting the mobility indicator variables with the RIF and layoff variables that were found to be significant in our main models (*lagged* RIF and layoff indicators in LAUSD and *current year* RIF and layoff indicators in Washington). Our main results are robust to these specifications and the interactions are almost all insignificant, implying that our main results are not significantly different for teachers who switch grades or schools (results from interaction models available upon request). The models included in columns 2 and 3 are particularly important for two separate reasons. First, they show that our results are not driven simply by the impact of mobility on teachers' productivity. Second, because mobility does not drive our results, the models in columns 2 and 3 suggest that the impact of the layoff process on teacher effectiveness does not stem from than depreciation in teachers' job-specific human capital but rather may be attributable to psychic or job search costs stemming from job insecurity.

5.2 Robustness and Validity Checks

The results presented above provide strong evidence that the layoff process adversely impacts the productivity of teachers who receive a RIF notice that is then rescinded (in Washington) and are let go but then rehired (Los Angeles). Our strongest evidence stems from the event study analysis in LAUSD, which shows that there is no "effect" of layoff-rehire on

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[17] We also estimate all models without teacher covariates, without lagged layoff threat variables, and without year *t* threat variables (only examining lagged threat). In addition, we test for interactions between current and prior year RIFs and layoffs to determine the extent to which the threat of layoff in multiple years affects our results. Results of our main models are consistent across each of these specifications. In LAUSD, we also specify models that include covariates and interactions for RIF and layoff variables in year t-2. Results confirm our event study analysis presented in Table 3. We also estimate the models presented in Table 4 including teacher-by-school fixed effects. Results remain consistent with our main specification. All results are available upon request.

teachers' effectiveness in the years before the layoff occurred. Given data constraints in Washington, we cannot perform equivalent analyses there. So, in order to assess the validity of our main results and support a causal interpretation of our findings, we conduct a number of additional analyses designed to test the model's assumptions and assess the robustness to different samples. We describe each of these in turn below.

5.2.1 Tests of Model Assumptions

One threat to the accurate identification of the impact of the layoff process on teachers' productivity is that our estimates could be biased by the failure to include some unobserved omitted variables. One way to assess the sensitivity of our estimates to omitted variable bias is to determine the proportion of the estimates that would need to be due to bias to invalidate our claims. Following Frank (2000) and Frank, Maroulis, Duong and Kelcey (2013), we examine how large the correlations must be between (a) the omitted (confounding) variable and the outcome variable, $r_{cv \bullet y}$; and (b) the omitted variable and the variable of interest, $r_{x \bullet y}$, such that the treatment effect is not statistically significant. In our main model in LAUSD, 61% of the estimated effect would have to be due to bias to invalidate the inference, which is a more robust finding than over two-thirds of the observational studies reported in Frank et al. (2013). Even when we include school or school-by-teacher fixed effects to the preferred model, 60% and 48% of the estimated effect would have to be due to bias to invalidate the inference, respectively. In Washington, 33% of the estimated effect would have to be due to bias to invalidate the inference, based on our preferred model. The number is also 33% with school fixed effects, but increases to 38% with teacher-by-school fixed effects.[18]

[18] In robustness checks described below that control for classroom student composition, we also use a method proposed by Oster (2016) that compares changes in the coefficient of interest to changes in the r-squared between the null model (with no covariates) to the full model (with all covariates). Specifically, the bias-adjusted treatment effect is $\beta_{full} - \delta * (\beta_{null} - \beta_{full}) * [(R_{max} - R_{full}) / (R_{full} - R_{null})]$, where R_{max} is the expected r-squared if all observable

One particular form of omitted variable bias stems from the possibility that teachers who are laid off or RIFed are assigned to more challenging students upon return. Prior research suggests, for example, that less senior teachers are assigned to lower achieving classrooms within schools (Dieterle et al., 2015; Grissom et al., 2015; Kalogrides et al., 2013). Classroom composition could therefore bias our estimates of the effects of receiving a rescinded RIF or layoff notice if (a) previously laid off teachers return to lower achieving classrooms and (b) classroom composition lowers teachers' measure of effectiveness. To provide some assurance that our estimates are not biased due to classroom effects, we run our preferred models with controls for the average student achievement and the average percent of students who identify as an underrepresented minority. As shown in Appendix Table A3, our main findings are robust to these additional covariates.[19]

Finally, it is conceivable that the way we model our VAMs could impact our estimates of the impact of RIF-recission or layoff-rehire on teacher effectiveness. To check for this, we re-estimate our main results from equation (3) using alternate VAM specifications that (a) control for students' lagged achievement, but exclude other student covariates; and (b) include controls for both lagged achievement and twice-lagged achievement. As noted earlier, these results

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and unobservable covariates were included (assumed to be 1), δ is the proportion of selection bias due to observable versus unobservable factors, and the subscripts full and null refer to the β and r-squared for the full model, with all covariates and the null model, with no covariates (Oster, 2016). In LAUSD, we find that the bias-adjusted treatment effect is larger than the treatment effect estimated in our preferred model (-0.075 relative to -0.061). In Washington, the bias-adjusted treatment effect is slightly smaller in magnitude (0.044) compared to the estimated effect in our preferred model (0.047), but still statistically and educationally significant.

[19] We also estimate models predicting classroom assignments based on prior year treatment, as in Dieterle, Guarino, Reckase & Wooldridge (2015), Grissom, Kalogrides & Loeb (2015) and Kalogrides, Loeb & Beteille (2013). We find that teachers who received a rescinded RIF notice, a final layoff notice, or who were not present in the prior year were assigned to classrooms with students who had lower average achievement in the prior year compared to teachers who did not receive a RIF notice in the prior year. If the observable variables in the student achievement models properly account for student background then our estimates of the impacts of the layoff process on teacher productivity remain unbiased, but if they do not fully account for the sorting of students to teachers (e.g. Rothstein, 2009, 2010), then value-added estimates may be biased. However, this is no different than any bias found in estimates of the productivity returns to experience (see, for examples, Papay & Kraft, 2015; Boyd et al., 2008).

appear in the Appendix Table A1 and show that our findings are robust to the use of alternate VAM specifications. In Appendix Table A2, we show that results for the event study analysis in LAUSD (equation 2) are also consistent across these same two VAM specifications. The small magnitude of changes in the layoff coefficient across VAM specifciations provides additional evidence that, conditional on the covariates included, changes in student sorting to classroom based on unobservable characteristics is not correlated with the timing of layoffs.

5.2.2 Tests to Assess the Robustness of our Results to the Selected Sample

An additional concern is that our findings could be biased by sample selection into RIF or layoff conditions. In particular, if teachers are RIFed or laid off based on their effectiveness (as captured by VAMs), our results might be biased. Given the stringent legal requirements in LAUSD and in most Washington districts, we believe that there is little risk of bias associated with selection into RIF or layoff status.[20] Nonetheless, we estimate separate models that predict RIFs and layoffs, including teachers' prior year VAMs and trends in VAMs (shown in Appendix Table A4). We find that, as expected, the likelihood of treatment is related only to experience and credential area, both of which we control for in all models.[21]

There is also the possibility that our results are driven by non-random attrition from the study sample, which could bias the estimates in two ways. On the one hand, if administrators deviated from state-mandated re-hiring policies by, for example, offering jobs back only to teachers who were expected to have better than average performance in the following year, such discrepancies would most likely positively bias our estimates. On the other hand, selection bias

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[20] And in the case of Washington, little evidence that layoff status is associated with teacher effectiveness (Goldhaber & Theobald, 2013).

[21] In addition to the layoff procedures described earlier, LAUSD principals had no way of ascertaining their teachers' VAMs. LAUSD provided teachers with their VAMs (estimated by the Value-Added Research Center at the University of Wisconsin) for a subset of the years in which RIFs and layoffs were implemented, but explicit regulations prevented the district from providing principals with their teachers' VAMs.

could result from teachers' own selection back into the LAUSD workforce once they have been laid off. Our estimates of the impact of layoff on effectiveness could be negatively biased if the likelihood a laid off teacher returns is greater for those who are expecting a decline in their VAM the following year. We are not particularly concerned with either source of bias in LAUSD (where about half of the teachers who were laid off return to the district, whereas only 7% of teachers in Washington who were laid off return), as district personnel in the human resources department made clear to us that they hire back only in reverse order of seniority within credential/need area, and that the far majority of laid off teachers who are offered their jobs back return to the district (personal communication, 2015). For confirmation, we explicitly tested whether laid off teachers' likelihood of returning to the district in the proximate year is related to the growth in a teachers' VAM from the prior to the current year, or trends in value added over time (prior year VAM minus twice-lagged VAM). These models, presented in Appendix Table A5, show that, as in other contexts, teachers with greater VAM growth (trends over time) are less likely to exit LAUSD and no more or less likely to exit in Washington (e.g., Henry, Bastian, and Fortner (2011); Goldhaber et al, 2011). Important for our analysis, however, we find that laid off or RIF-rescinded teachers are no more or less likely to return to their district in either LAUSD or Washington, even if they have greater VAM growth or growth trends. To further assess whether teachers who are laid off and then rehired were more or less effective in the year prior to layoff, we estimate model (2) predicting VAMs constructed by using students' *lagged achievement* as the outcome. This analysis is only possible in LAUSD because so few teachers in Washington were laid off and then re-hired. This analysis is shown in the final two columns of Table 3. We find that the effect of receiving a layoff notice on teachers' contributions to their students' test scores in previous years is not significantly different from zero, suggesting that teachers' layoff and rehire status is not associated with their previous VAMs.

We also examine what happens when we narrow our analysis sample to better isolate the impact of RIF rescission and layoff-rehire on teacher productivity. We do this to focus on teachers who are more likely to be directly impacted by the layoff process (results are shown in Appendix Table A6). In column 1 we show the results when we limit our sample to only the subset of teachers who ever receive a RIF or a layoff notice.[22] Because RIFs and layoffs are based almost entirely on teachers' years of experience and their endorsement area, in column 2 we show the results when we limit the sample to only those teachers with experience at or below that of the most experienced RIFed (Washington) or laid off (LAUSD) teacher. Finally, in column 3, we show the results for a sample limited to years in which layoffs took place. We find that our main results are largely unchanged when we narrow the sample in these different ways.

6. Discussion and Policy Implications

This paper is the first that we know of to assess the impact of the layoff *process* on employee productivity. In the case of public school teachers, our findings show that the layoff process does more to harm student achievement than simply removing effective teachers from schools and increasing class sizes. The job instability brought about by the layoff process appears to negatively impact teacher productivity: in LAUSD this is the case for teachers who are let go and return to the district in the following year; and in Washington, teachers who receive a RIF notice – even if it is rescinded – perform worse in terms of their contributions to student achievement.

The difference between the LAUSD and Washington findings can help to shed some light

[22] Because far fewer teachers were ever treated in Washington, the non-significant findings are likely the result of substantially reduced power (the sample reduced from 45,436 to 1,929 teachers in Washington, whereas the sample in LAUSD is reduced from 31,160 to 10,391 teachers).

on the mechanisms by which job loss and threat of job loss impact teacher productivity. In particular, the finding that the RIF-rescission has a significant and negative impact on teacher effectiveness in Washington suggests that concurrent year job search or psychic or morale effects of the layoff process drive the negative outcomes of the layoff process. As discussed above, the receipt of a RIF that does not then manifest in an actual layoff should have little impact on a teacher's individual- position or school-specific human capital. However, the emotional effects of such threat can cause substantial upheaval, especially given that so much of the instructional year is spent in a state of uncertainty in Washington. Although this psychic cost likely also exists in LAUSD, there is little time for it to manifest as decreased student achievement on year *t* standardized tests.

Similarly, the LAUSD findings – that the receipt of a layoff in year *t* impacts teacher effectiveness in year *t*+1 – also may suggest that job search, morale or psychic effects of the layoff process affect teacher productivity. It is plausible that teachers do lose some school-specific human capital when they are forced to shuffle around the district as a result of the layoff process (AUTHORS, 2016a). However, various specifications in our analyses control for teachers being new to the school, district, grade, and job category in which we assess their productivity. Thus, the negative effects we report for receipt of a layoff notice are in addition to the impact of school or grade changes, suggesting that the reduced effectiveness is not attributable to a loss in organization-specific human capital. We conclude therefore that the negative effects of the layoff process induce substantial stress and upheaval, and/or a loss of job commitment, possibly because of alternative job search that manifests itself in reductions in job performance.

There are several reasons that we might expect to see the differential patterns of impacts across contexts in our study. First, as discussed earlier in the paper, it should not be surprising that current year RIFs impact teacher effectiveness in Washington more than in LAUSD. This is because teachers in Washington tend to receive notification of the likelihood of being RIFed far earlier than they do in LAUSD. This leaves Washington teachers longer to live with the stress of the possibility of losing their jobs, and, importantly, longer before the student testing window, thus providing substantial opportunity for current-year employment risk to affect teachers' productivity. In addition, it is not surprising that we do not see similar impacts of being laid off and then rehired on teacher effectiveness in Washington as we do in LAUSD. The estimate on the prior year layoff coefficient is imprecise in Washington because far fewer teachers are impacted by the layoff process in Washington overall, and few Washington teachers are actually let go and then return in the following year. However, in addition to the issue of imprecision, it is also possible that the effect of receiving a layoff notice and being rehired is more harmful in LAUSD than in Washington because the threat of job loss is greater. There are far more teachers who are laid off and far more who receive multiple layoff notices, possibly leading to a reduction in job attachment across years. For instance, those who receive layoff notices in t-1 may be engaging in job-search activities in year t.[23] Together, these findings suggest that the *threat of job loss* may impact teacher motivation and organizational commitment.

There are multiple ways that policy might be amended to mitigate the harmful effects of the layoff process on teacher effectiveness. Given that many more teachers receive a RIF notice than is necessary for budgetary reductions in the size of the workforce, the simplest way would

[23] We also ran models examining the productivity of teachers who were not themselves impacted by the layoff process, but who were in schools with high proportions of RIFs and/or layoffs, to assess the degree to which peer employment threat impacts teachers' productivity. We find no significant relationship between peer threat in year t or year t-1 (defined as either the proportion of peers RIFed, the proportion of peers laid off or the proportion of RIFed peers who were laid off) and teacher productivity.

be to maintain a source of additional revenue that can be used in times of emergency – a risk pool of sorts that enables districts to draw down funds to avoid making unnecessary cuts to personnel. Alternatively, as the California Legislative Analyst's Office has recommended (Estrada, 2012) the state could tie the layoff notification deadline (currently May 15) to the state's budget release (as is done in several other states) rather than months before the final state budget is released in June or July (at the earliest). States might also be required to develop their budget projections by a specified time, enabling districts to have better information before they make staffing decisions. Of course, states *are* supposed to release final budgets early in the year, but in most states missing this deadline results in few or no consequences (Estrada, 2012). By enabling districts to develop more accurate budget projections, and as a result more accurate staffing requirements, fewer teachers would be impacted by the layoff process.

Although we focus mostly on the average effects of layoff threat on teacher effectiveness, it is important to note that there are likely distributional consequences of the layoff process. Specifically, research shows that teachers employed in the most disadvantaged schools—schools with higher proportions of low-income, minority, and English language learner students (Sepe & Roza, 2010; UCLA/IDEA, 2009)—are most likely to receive a RIF notice or be laid off. This is because these schools tend to have the most junior teachers, who are let go first under traditional LIFO policies. As a result, reductions in teacher effectiveness that go along with the layoff process will adversely impact traditionally disadvantaged students (AUTHORS, 2016b). States and districts might mitigate this negative distributional impact by diminishing the reliance on seniority in layoff processes or by protecting highly impacted schools.

Our findings have serious implications for school districts that may be forced to issue layoff notices in the future. More generally, however, we believe it is important to assess whether employee productivity in other sectors of the economy might also have been affected by the Great Recession in hidden ways, e.g. for psychological or job search reasons, and what lessons might be learned about how to lessen the potential negative impacts on productivity.

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FIGURE 1

Timeline of reduction-in-force and layoff notices and testing window in LAUSD and Washington State

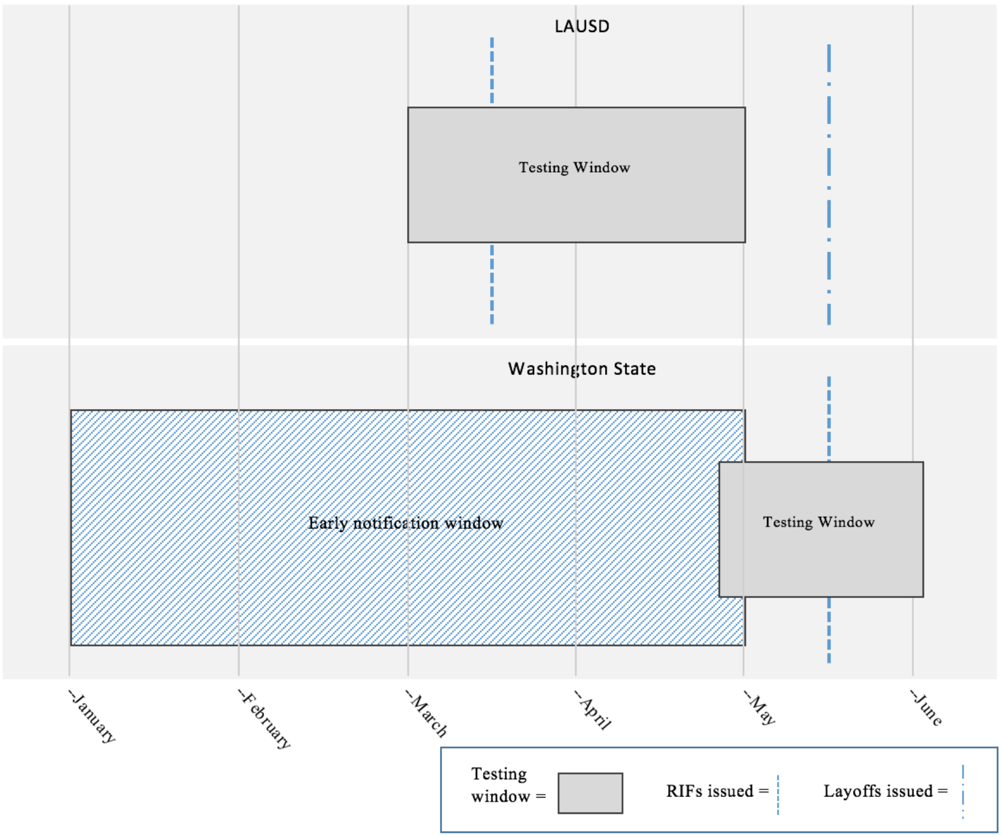
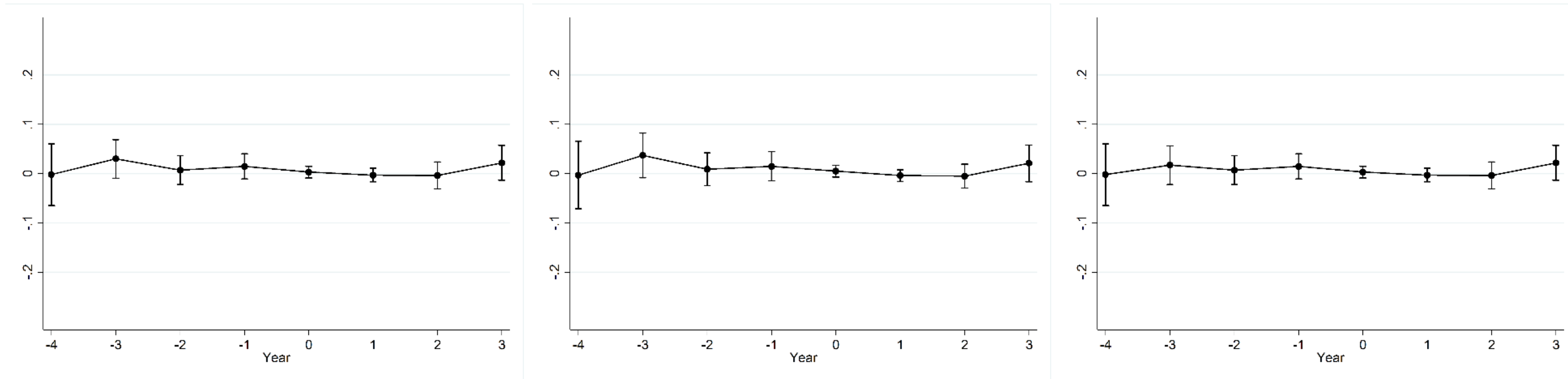


FIGURE 2

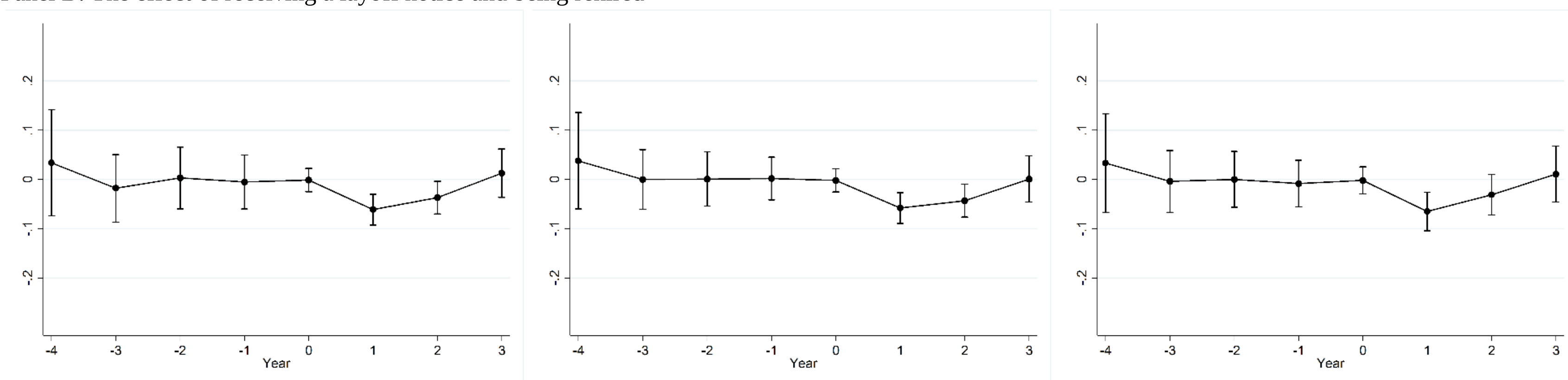
Change in teacher value added in LAUSD before and after receiving a reduction-in-force notice (Panel A) and a layoff notice (Panel B), with 95% confidence intervals

1. Teacher fixed effects — 2. Teacher and school fixed effects — 3. Teacher-by-school fixed effects

Panel A: The effect of receiving a rescinded RIF notice



Panel B: The effect of receiving a layoff notice and being rehired



Note. these figures depict the models reported in Table 3.

TABLE 1

Number of teachers in each layoff category, by year and location

	2008-09		2009-10		2010-11		2011-12		Total	
	All LAUSD teachers									
No RIF	24,212	83.2%	24,577	91.8%	22,070	85.4%	21,259	86.5%	92,118	86.7%
RIF-rescinded	3,064	10.5%	1,826	6.8%	2,492	9.6%	2,315	9.4%	9,697	9.1%
Laid off, but return	456	1.6%	212	0.8%	770	3.0%	699	2.8%	2,137	2.0%
Laid off and do not return	1,356	4.7%	143	0.5%	500	1.9%	309	1.3%	2,308	2.2%
Total	29,088		26,758		25,832		24,582		106,260	
	4-7th Grade LAUSD Teachers with VAMs									
No RIF	3,768	69.5%	4,368	82.8%	3,894	74.8%	3,852	78.1%	15,884	76.2%
RIF-rescinded	993	18.3%	852	16.1%	958	18.4%	822	16.7%	3,625	17.4%
Laid off, but return	117	2.2%	35	0.7%	265	5.1%	217	4.4%	634	3.0%
Laid off and do not return	546	10.1%	22	0.4%	88	1.7%	43	0.9%	699	3.4%
Total	5,424		5,277		5,205		4,934		20,840	
	All Washington teachers									
No RIF	55,333	96.7%	55,633	99.2%	55,386	98.4%	54,904	99.4%	221,256	98.4%
RIF-rescinded	1,666	2.9%	346	0.6%	752	1.3%	213	0.4%	2,977	1.3%
Laid off, but return	52	0.1%	39	0.1%	59	0.1%	57	0.1%	207	0.1%
Laid off and do not return	196	0.3%	39	0.1%	84	0.1%	35	0.1%	354	0.2%
Total	57,247		56,057		56,281		55,209		224,794	
	4-7th Grade Washington Teachers with VAMs									
No RIF	2,632	96.6%	9,374	99.5%	9,375	98.5%	9,177	99.7%	30,558	99.0%
RIF-rescinded	87	3.2%	46	0.5%	126	1.3%	20	0.2%	279	0.9%
Laid off, but return	0	0.0%	4	0.0%	7	0.1%	6	0.1%	17	0.1%
Laid off and do not return	6	0.2%	1	0.0%	7	0.1%	2	0.0%	16	0.1%
Total	2,725		9,425		9,515		9,205		30,870	

TABLE 2

Summary statistics by layoff threat level (teacher-year observations), 2008-09 to 2011-12

	LAUSD					Washington				
			RIF					RIF		
	Overall	No RIF	RIF-resc.	Laid off-return	Laid off-not return	Overall	No RIF	RIF-resc.	Laid off-return	Laid off-not return
All Teachers	20,840	15,882	3,625	634	699	30,870	30,558	279	17	16
		76.21%	17.39%	3.04%	3.35%		98.99%	0.90%	0.01%	0.01%
Value-added measures										
1-year FE estimates	-0.02	-0.02	0.01	-0.01	-0.08	-0.02	-0.02	-0.07	-0.11	-0.12
	(0.274)	(0.276)	(0.274)	(0.286)	(0.228)	(0.258)	(0.258)	(0.253)	(0.240)	(0.230)
Experience / education										
1st - 3rd yr.	4.83%	23.04%	27.21%	8.64%	41.11%	9.49%	94.23%	5.16%	0.31%	0.31%
4th - 8th yr.	25.10%	46.97%	41.66%	7.63%	3.75%	24.77%	98.56%	1.35%	0.04%	0.05%
9th year or above	70.07%	90.35%	8.03%	1.01%	0.61%	65.74%	99.84%	0.12%	0.02%	0.01%
Mean yrs. of exp.	9.6	10.9	6.3	5.3	3.1	13.5	13.6	3.3	5.5	6.1
MA deg. or higher	36.12%	76.70%	17.84%	3.11%	2.35%	69.25%	99.38%	0.54%	0.06%	0.02%
Endorsement area										
Special Education	2.22%	66.95%	17.28%	7.13%	8.64%	12.22%	99.58%	0.40%	0.03%	0.00%
Math or Science	9.91%	83.39%	13.27%	1.60%	1.74%	11.61%	98.94%	0.95%	0.08%	0.03%
Other non-elem.	26.15%	74.28%	18.04%	2.90%	4.79%	43.27%	99.40%	0.52%	0.04%	0.04%
Elementary	61.72%	76.21%	17.79%	3.19%	2.81%	32.90%	98.25%	1.59%	0.08%	0.09%
RIF / layoff in year t-1										
No RIF	83.66%	86.37%	10.03%	0.79%	2.81%	93.46%	99.44%	0.52%	0.01%	0.03%
RIF-resc.	13.04%	21.94%	66.21%	9.35%	2.50%	1.55%	91.46%	6.25%	1.88%	0.42%
Layoff	1.60%	21.26%	8.38%	57.49%	12.87%	0.05%	100.00%	0.00%	0.00%	0.00%
Not present	1.70%	44.51%	13.80%	14.08%	27.61%	4.93%	92.78%	6.50%	0.32%	0.40%

Note: the overall column in the first panel (value-added measures) shows the overall mean values for all teachers (and standard deviations), and the following three columns show the mean value for each RIF/layoff category. In the second, third, and forth panel, the overall column shows the percent of teachers with that characteristic, while the next three columns show the percent of teachers that fall into each of the three RIF/layoff categories. Within RIF/layoff categories, rows sum to 100%. Our final analytic sample also includes one school year before and after the period of layoffs (2007-08 and 2012-13). In LAUSD, these two years add 10,320 teacher-year observations, bringing the total analytic sample to 31,160 and in Washington we add 14,566 teacher-observations for a total of 45,436.

TABLE 3

Regression coefficients predicting teachers' value-added measure of effectiveness based on the number of years until / since treatment in Los Angeles Unified School District (LAUSD)

	(1)		(2)		(3)		(4)	
	Treatment = RIF notice	Treatment = layoff notice	Treatment = RIF notice	Treatment = layoff notice	Treatment = RIF notice	Treatment = layoff notice	Treatment = RIF notice	Treatment = layoff notice
4 years before treatment	-0.002	0.038	-0.003	0.034	-0.002	0.033	0.014	0.022
	(0.027)	(0.042)	(0.029)	(0.046)	(0.027)	(0.042)	(0.019)	(0.034)
3 years before treatment	0.030+	0.000	0.037+	-0.018	0.017	-0.004	0.002	0.010
	(0.017)	(0.026)	(0.019)	(0.029)	(0.017)	(0.027)	(0.012)	(0.020)
2 years before treatment	0.012	0.001	0.009	0.003	0.007	0.000	-0.001	0.010
	(0.012)	(0.023)	(0.014)	(0.027)	(0.012)	(0.024)	(0.009)	(0.018)
1 year before treatment	0.009	0.002	0.015	-0.005	0.015	-0.008	0.001	0.011
	(0.010)	(0.018)	(0.012)	(0.023)	(0.011)	(0.020)	(0.007)	(0.016)
Year of treatment	0.003	-0.002	0.005	-0.001	0.003	-0.002	0.000	0.001
	(0.005)	(0.010)	(0.005)	(0.010)	(0.005)	(0.012)	(0.007)	(0.013)
1 year after treatment	-0.006	-0.058***	-0.004	-0.061***	-0.003	-0.065***	-0.009	-0.009
	(0.005)	(0.013)	(0.005)	(0.013)	(0.006)	(0.017)	(0.007)	(0.018)
2 years after treatment	-0.007	-0.043**	-0.005	-0.037**	-0.004	-0.031+	-0.009	0.004
	(0.010)	(0.014)	(0.010)	(0.014)	(0.012)	(0.017)	(0.016)	(0.020)
3 years after treatment	0.021	0.001	0.021	0.013	0.022	0.011	-0.017	-0.038
	(0.017)	(0.020)	(0.016)	(0.021)	(0.015)	(0.024)	(0.011)	(0.030)
Constant	0.409***		0.527*		0.562***		0.176+	
	(0.728)		(0.252)		(0.136)		(0.100)	
N	31,160		31,160		31,160		21,799	
R-squared	0.731		0.743		0.761		0.619	
Teacher FE	Yes		Yes		No		Yes	
School FE	No		Yes		No		No	
Tcher-by-sch. FE	No		No		Yes		No	

Note: This table shows three event study regression models. In the first column for each model, we report coefficients for the effect of receiving a RIF notice. In the second column for each model, we report coefficients for the effect of receiving a layoff notice. Model 4 is a placebo test, in which we predict teacher effectiveness based on models predicting students' lagged achievement. We only report the variables of interest, while controlling for year fixed effects, time-varying teacher characteristics as well as school characteristics (dropping time-invariant school characteristics in models with school fixed effects or teacher-by-school fixed effects). For the RIF-rescinded treatment effects, the cell sizes for each treatment effect, beginning with four years before treatment are 80, 172, 190, 493, 513, 535, 404, 285, and 241, respectively. For the layoff treatment effects, the cell sizes for the same treatment periods are 43, 98, 134, 295, 343, 141, 88, 61, and 78, respectively.

TABLE 4

Regression coefficients predicting teachers' value-added measure of effectiveness, 2007-08 to 2012-13

	(1)		(2)		(3)		(4)	
	LAUSD	WA	LAUSD	WA	LAUSD	WA	LAUSD	WA
Year t layoff threat								
RIF-re. in t	0.003	-0.047**	0.002	-0.046**	0.003	-0.046**	0.003	-0.050**
	(0.005)	(0.016)	(0.005)	(0.016)	(0.005)	(0.016)	(0.005)	(0.017)
Laid off in t	0.000	-0.082	-0.001	-0.083	-0.001	-0.089	-0.001	-0.261***
	(0.008)	(0.067)	(0.008)	(0.067)	(0.008)	(0.068)	(0.009)	(0.071)
Year t-1 layoff threat								
RIF-re. in t-1	-0.009+	-0.011	-0.008	-0.009	-0.009+	-0.008	-0.007	-0.009
	(0.005)	(0.012)	(0.005)	(0.012)	(0.005)	(0.012)	(0.005)	(0.012)
Laid off in t-1	-0.061***	0.158	-0.049***	0.162	-0.059***	0.161	-0.059***	0.161
	(0.012)	(0.130)	(0.012)	(0.128)	(0.012)	(0.128)	(0.012)	(0.127)
Not pres. yr. t-1	-0.038**	-0.034***	-0.042***	-0.032***	-0.042***	-0.029***	-0.037**	-0.040***
	(0.012)	(0.008)	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)	(0.007)
New to school			-0.035***	-0.012*				
			(0.005)	(0.005)				
New to grade					-0.016***	-0.048***		
					(0.003)	(0.004)		
R-squ.	0.704	0.716	0.705	0.716	0.704	0.718	0.718	0.730
Tch. FE	X	X	X	X	X	X	X	X
Sch. FE							X	X

Note: Model 1 is our baseline model with teacher fixed effects. All models include the following control variables: year fixed effects, indicator variables for teacher experience (0,1, 2, 3, 4, 5-6, 7-9, 8-10, and 10-12, with the reference category teachers who are in their thirteenth or greater year), whether the teacher holds a master's degree or higher, and dummy variables for endorsement areas. We also include the following school-level variables: the log of total enrollment, the percent of students at the school that identify as an underrepresented race/ethnicity, and the school type (elementary, middle, high school, or span school). "Not pres. yr t-1" (Not present in year t-1) captures teachers who were not in the district in t-1 in LAUSD and who were not teaching in the state for Washington. Models 2 and 3 add controls for whether the teacher is in a new school within the district from the prior year, and whether the teacher is in a new grade from the prior year. The reference category for year t layoff variables is not RIFed in year t and the reference category for year t-1 layoff variables is not RIFed in year t-1. For LAUSD, the cell sizes for treatment effects are as follows: 3,625 and 1,333 for RIF-rescinded and laid off, respectively, and 3,494, 551, and 1,022 for RIF-rescinded in the prior year, laid off in the prior year, and not present in the prior year, respectively. For Washington, the cell sizes for treatment effects are as follows: 279 and 33 for RIF-rescinded and laid off, respectively, and 498, 21, and 7,872 for RIF-rescinded in the prior year, laid off in the prior year, and not present in the prior year, respectively.
* p<0.05, ** p<0.01, *** p<0.001.

APPENDIX

Examples of CBA Early Notification Provisions – Washington State

Granite Falls - The Board shall provide to the Association a second seniority list by March 1 of each school year which shall include any correction, deletions and additions of personnel for the school year occurring since November 1, ranking each employee from greatest to least seniority.

Kennewick - The district will compile and publish a state seniority list by March 1. The state seniority list will be posted in each building and five copies will be given to the association. Challenges to seniority placement will be made in writing to the Human Resources office by March 31. A corrected seniority list will be published and posted in each building; five copies will be given to the association by April 15.

Lake Stevens - "Seniority" within the meaning of this paragraph shall mean the total years of certificated teaching experience in the state of Washington. The determination of a year of teaching experience in the state of Washington shall be consistent with OSPI guidelines for determining a year of teaching experience. A seniority list shall be provided to the Association no later than February 1.

In the event the Board determines that probable cause for reduction in force exists, each certificated employee in the District shall be listed based on the employee's seniority and certification, including required primary and supporting endorsements. The list will be posted electronically for all employees to view by April 30. Employees and the Association will be informed when the list is posted and the Association President will be given a hard copy.

Marysville - By March 15 of any year when it is anticipated that a layoff may be necessary, the District shall publish and distribute to each employee and to the Association a complete seniority list ranking all employees in accordance with the seniority definition.

North Franklin - A seniority list shall be developed and distributed each January. Each employee shall be given ten (10) working days to examine the list and make corrections. Once the list is certified as correct, no changes shall be allowed until the next posting of the list for such corrections in January of the following year. New hires shall be added to the list as they commence employment.

Rosalia – By January 15th of each year, the District will provide each certificated employee with a statement of his/her seniority. If the statement is incorrect, the employee has 10 working days to provide proof verifying seniority.

Spokane - Each January the District will compile and place on the District website the certificated employee seniority list, by individual employee ID number, listing each employee from greatest to least senior. The District will also place on the District website the employee certification and endorsement list by individual employee ID number.

Shelton - Seniority shall be based on total longevity in Washington State. In order to determine that number of years, the District and the Association agree that a year's credit as properly reported on the current S-275 form shall control. The District will provide a copy of the February S-275 report to the Association.

APPENDIX TABLE A1

Regression coefficients from main models predicting teachers' value-added measure of effectiveness, using alternate VAM specifications as outcome measures.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: LAUSD			
year t layoff threat						
RIF-rescinded in t	0.003	0.000	0.003	0.000	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Laid off in t	0.000	-0.005	-0.001	-0.005	0.003	0.002
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
year t-1 layoff threat						
RIF-rescinded in t-1	-0.009+	-0.005	-0.007	-0.004	-0.014**	-0.012*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Laid off in t-1	-0.061***	-0.054***	-0.059***	-0.052***	-0.060***	-0.057***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Not present in year t-1	-0.038**	-0.036**	-0.037**	-0.035**	-0.033**	-0.032**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
			Panel B: Washington			
year t layoff threat						
RIF-rescinded in t	-0.047**	-0.044**	-0.048**	-0.050**	-0.047**	-0.057**
	(0.016)	(0.016)	(0.019)	(0.017)	(0.018)	(0.020)
Laid off in t	-0.082	-0.090	-0.081	-0.261***	-0.252***	-0.326***
	(0.067)	(0.064)	(0.079)	(0.071)	(0.068)	(0.087)
year t-1 layoff threat						
RIF-rescinded in t-1	-0.011	-0.008	-0.015	-0.008	-0.006	-0.018
	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)
Laid off in t-1	0.158	0.136	0.187	0.134	0.117	0.123
	(0.130)	(0.125)	(0.155)	(0.110)	(0.127)	(0.174)
Not present in year t-1	-0.034***	-0.035***	-0.033**	-0.029**	-0.029**	-0.025*
	(0.008)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)
Baseline value-added model	X			X		
VAM with no stu. cov.		X			X	
VAM with twice lag scores			X			X
Teacher fixed effects	X	X	X	X	X	X
School fixed effects				X	X	X

Note. As with all other models in this study, models shown here include teacher and school covariates including: year fixed effects, indicator variables for teacher experience (1, 2, 3, 4, 5, 6-7, 8-10, 11-13, and 14 or more years), whether the teacher holds a master's degree or higher, dummy variables for teachers' endorsement areas, the log of total school enrollment, the percent of students at the school that identify as an underrepresented race/ethnicity, and the school type (elementary, middle, high school, or span school). "Not pres. yr t-1" (Not present in year t-1) captures teachers who were not in the district in t-1 in LAUSD and who were not teaching in the state for Washington. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

APPENDIX TABLE A2

Regression coefficients for event study for Los Angeles Unified School District (LAUSD) predicting the effect of receiving a layoff notice and being rehired on teachers' value-added measure of effectiveness, using alternate value-added model specifications

	Baseline		VAM with no student covariates		VAM with twice-lagged test score	
	(1)	(2)	(3)	(4)	(5)	(6)
4 years before layoff	0.038	0.034	0.010	0.004	0.011	0.008
	(0.042)	(0.046)	(0.019)	(0.022)	(0.025)	(0.027)
3 years before layoff	0.000	-0.018	0.013	0.000	0.011	-0.005
	(0.026)	(0.029)	(0.011)	(0.013)	(0.015)	(0.017)
2 years before layoff	0.001	0.003	0.013	-0.004	0.018	0.005
	(0.023)	(0.027)	(0.009)	(0.012)	(0.012)	(0.016)
1 year before layoff	0.002	-0.005	0.003	-0.001	0.002	0.005
	(0.018)	(0.023)	(0.007)	(0.010)	(0.010)	(0.014)
Year of layoff	-0.002	-0.001	-0.004	-0.003	-0.006	-0.007
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
1 year after layoff	-0.058***	-0.061***	-0.055***	-0.056***	-0.055***	-0.055***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
2 years after layoff	-0.043**	-0.037**	-0.035*	-0.029+	-0.041**	-0.035*
	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
3 years after layoff	0.001	0.013	0.004	0.017	-0.001	0.007
	(0.020)	(0.021)	(0.020)	(0.021)	(0.019)	(0.019)
Teacher FE	X	X	X	X	X	X
School FE		X		X		X

Note. The table shows coefficeint for the effect of receiving a layoff notice in eight separate models. The first two models are the baseline specification, first with teacher fixed effects, than adding school fixed effects. The subsequent models are based on value-added measures that include not student covariates (models 3 and 4), a control for a twice- lagged test score (models 5 and 6), and a model that predicts a students' prior year test score, conditioning on that student's twice- lagged test score and other student covariates. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

APPENDIX TABLE A3

Regression coefficients predicting teachers' value-added measure of effectiveness, including control variables for classroom composition

	Baseline model (1)		Control for classroom composition (2)	
	LAUSD	WA	LAUSD	WA
Year t layoff threat				
RIF-re. in t	0.003	-0.047**	0.003	-0.047**
	(0.005)	(0.016)	(0.005)	(0.016)
Laid off in t	0.000	-0.082	0.001	-0.035
	(0.008)	(0.067)	(0.008)	(0.068)
Year t-1 layoff threat				
RIF-re. in t-1	-0.009+	-0.011	-0.009+	-0.010
	(0.005)	(0.012)	(0.005)	(0.015)
Laid off in t-1	-0.061***	0.158	-0.057***	0.149
	(0.012)	(0.130)	(0.012)	(0.160)
Not pres. yr. t-1	-0.038*	-0.034***	-0.037*	-0.034***
	(0.012)	(0.008)	(0.012)	(0.009)
Average pre-score in Math and ELA			0.040***	-0.001
			(0.004)	(0.009)
Percent White / Asian students assigned to teacher			0.154***	0.045**
			(0.017)	(0.015)
N	31,160	45,436	31,160	45,436
R-squared	0.727	0.716	0.730	0.716

Note. As with all other models in this study, models shown here include teacher and school covariates including: year fixed effects, indicator variables for teacher experience (1, 2, 3, 4, 5, 6-7, 8-10, 11-13, and 14 or more years), whether the teacher holds a master's degree or higher, dummy variables for teachers' endorsement areas, the log of total school enrollment, the percent of students at the school that identify as an underrepresented race/ethnicity, and the school type (elementary, middle, high school, or span school). "Not pres. yr t-1" (Not present in year t-1) captures teachers who were not in the district in t-1 in LAUSD and who were not teaching in the state for Washington. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

APPENDIX TABLE A4

Regression coefficients from linear probability models predictingwhether a teacher receives a reduction-in-force (RIF) notice or a final layoff notice, for Los Angeles Unified School District (LAUSD) and Washington State (WA)

	Likelihood of RIF notice		Likelihood of layoff notice	
	LAUSD	WA	LAUSD	WA
School context factors				
Log enrollment	0.014	0.000	0.004	0.839
	(0.012)	(0.003)	(0.004)	(1.100)
Delta enrollment	0.116**	-0.013	0.010	-5.726*
	(0.041)	(0.010)	(0.020)	(2.591)
Percent non-White / non-Asian students	0.015	-0.000**	-0.014	-0.016*
	(0.026)	(0.000)	(0.011)	(0.007)
High school	-0.040	-0.002	0.016	0.000
	(0.060)	(0.002)	(0.028)	(0.000)
Middle school	-0.066*	0.001	0.000	0.360
	(0.029)	(0.002)	(0.012)	(0.949)
K-12 school (reference category is Elementary)	-0.095+	0.001	0.003	0.000
	(0.053)	(0.002)	(0.026)	(0.000)
Teacher characteristics				
VAM_{t-1}	0.029+	-0.001	-0.003	-0.030
	(0.017)	(0.002)	(0.007)	(0.990)
	-0.009	0.002	-0.005	0.927
VAM trend (VAM_{t-1} minus VAM_{t-2})	0.014	0.003	0.007	0.990
	(0.016)	(0.091)	(0.006)	(1.573)
3rd year teacher (reference is >13th year)	0.773***	0.035**	0.218***	3.467***
	(0.033)	(0.012)	(0.027)	(0.905)
4th year teacher	0.798***	0.029***	0.057***	3.559***
	(0.025)	(0.008)	(0.010)	(0.866)
5th year teacher	0.562***	0.011*	0.178***	2.545**
	(0.021)	(0.005)	(0.017)	(0.925)
6th or 7th year teacher	0.541***	0.004*	0.102***	1.583+
	(0.015)	(0.002)	(0.009)	(0.942)
8th - 10th year teacher	0.185***	0.001	0.019***	0.257
	(0.009)	(0.001)	(0.003)	(1.038)
11th - 13th year teacher	0.045***	0.002+	0.005+	0.000
	(0.008)	(0.001)	(0.003)	(0.000)

STEM endorsement (reference is elementary)	-0.115***	0.000	-0.037***	0.694
	(0.026)	(0.002)	(0.010)	(1.029)
Other non-elementary endorsement	0.047+	0.000	-0.003	0.555
	(0.025)	(0.002)	(0.011)	(0.426)
MA or higher degree (reference is BA)	0.044***	0.000	0.008*	-0.308
	(0.009)	(0.001)	(0.004)	(0.373)
Year fixed effects				
2012 (reference is 2009)	0.163***	-0.009***	0.050***	-3.146***
	(0.009)	(0.003)	(0.005)	(0.821)
2011	0.145***	-0.003	0.053***	-0.526
	(0.009)	(0.004)	(0.005)	(0.417)
2010	0.020**	-0.008**	-0.001	-1.611**
	(0.007)	(0.003)	(0.003)	(0.589)
Constant	-0.180*	0.007	-0.042	-10.786
	(0.072)	(0.016)	(0.027)	(7.200)
N	12,748	9,749	12,748	5,234
R^2	0.283	0.241	0.120	0.226

Note: RIF-rescission refers to receiving a reduction-in-force notice that is later rescinded. The reference group for experience variables is teachers with 13 or more years of experience. Because we control for both prior year VAM and the trend in prior VAM, teachers with only one or two years of experience drop out of the model. This effectively limits the sample to teachers with two or more years of experience. Although a greater proportion of teachers in LAUSD received RIF notices in 2009 compared to other years, among the sample of teachers with lagged VAMs and twice lagged VAMs (e.g., teachers in their third or greater year), a *lower* proportion received RIF notices in 2009 compared to other school years. These models also show that teachers with master's or doctorate degrees are more likely to receive RIF and layoff notices for similar reasons. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

APPENDIX TABLE A5

Logistic regression coefficients predicting the likelihood a teacher exits the Los Angeles Unified School District (LAUSD) and Washington

	LAUSD				Washington			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
RIF/layoff variables								
RIF-rescinded	0.203+	0.293*	0.305*	0.310*	0.231	0.45	0.056	0.709
	(0.112)	(0.124)	(0.130)	(0.147)	(0.360)	(0.426)	(0.747)	(1.004)
Laid off	2.805***	2.806***	2.431***	2.511***				
	(0.120)	(0.133)	(0.168)	(0.187)				
VAM growth and trend								
VAM growth (VAM_t - VAM_{t-1})	-0.045	-0.059	-0.329	-0.320	0.185	0.169	0.286	0.286
	(0.181)	(0.239)	(0.256)	(0.256)	(0.157)	(0.157)	(0.275)	(0.276)
VAM growth squ	0.205	0.485	0.170	0.157	0.286	0.291	-0.024	-0.038
	(0.371)	(0.486)	(0.447)	(0.447)	(0.268)	(0.268)	(0.496)	(0.496)
VAM trend (VAM_{t-1} - VAM_{t-2})			-0.518*	-0.677*			0.172	0.170
			(0.251)	(0.306)			(0.241)	(0.241)
VAM trend squ			-0.268	0.003			-0.067	-0.046
			(0.546)	(0.639)			(0.489)	(0.487)
RIF/layoff interactions								
VAM growth x RIF-rescinded		-0.426				2.410		
		(0.435)				(2.485)		
VAM growth squ x RIF-rescinded		-1.501				-7.991		
		(1.004)				(7.871)		
VAM growth x layoff		0.319						
		(0.347)						
VAM growth squ x layoff		-0.146						
		(0.780)						
VAM trend x RIF-rescinded				0.331				9.688
				(0.485)				(15.503)
VAM trend squ x RIF-rescinded				-0.141				-61.623
				(1.235)				(84.006)
VAM trend x layoff				0.408				
				(0.576)				
VAM trend squ x layoff				-1.445				
				(1.486)				

Teacher/school characteristics								
2nd year (ref. is >13th year)	3.310***	3.310***			0.718***	0.702***		
	(0.248)	(0.249)			(0.176)	(0.176)		
3rd year teacher	2.653***	2.645***	3.086***	3.077***	0.202	0.205	0.200	0.197
	(0.232)	(0.232)	(0.285)	(0.284)	(0.180)	(0.180)	(0.282)	(0.282)
4th year teacher	1.914***	1.916***	2.136***	2.136***	0.036	0.040	0.011	0.013
	(0.242)	(0.242)	(0.301)	(0.301)	(0.163)	(0.163)	(0.237)	(0.237)
5th year teacher	1.310***	1.314***	1.651***	1.636***	0.011	0.007	0.121	0.120
	(0.238)	(0.238)	(0.285)	(0.286)	(0.154)	(0.154)	(0.214)	(0.214)
6th or 7th year teacher	1.362***	1.355***	1.515***	1.521***	0.033	0.032	0.057	0.055
	(0.209)	(0.209)	(0.252)	(0.253)	(0.116)	(0.116)	(0.158)	(0.158)
8th - 10th year teacher	1.490***	1.488***	1.603***	1.603***	-0.269*	-0.269*	-0.429**	-0.429**
	(0.183)	(0.183)	(0.218)	(0.219)	(0.112)	(0.112)	(0.160)	(0.160)
11th - 13th year teacher	0.255	0.256	0.414	0.411	-0.568***	-0.567***	-0.565***	-0.563***
	(0.245)	(0.245)	(0.288)	(0.288)	(0.105)	(0.105)	(0.141)	(0.141)
SPED	-0.046	-0.050	0.481	0.472	0.070	0.059	0.049	0.048
	(0.290)	(0.291)	(0.331)	(0.331)	(0.130)	(0.130)	(0.181)	(0.181)
STEM	-0.009	0.006	0.639+	0.633+	0.394**	0.391**	0.453**	0.449**
	(0.320)	(0.318)	(0.361)	(0.360)	(0.120)	(0.121)	(0.174)	(0.174)
Other (reference is elementary)	0.226	0.225	0.627+	0.621+	0.257**	0.253**	0.277*	0.277*
	(0.297)	(0.296)	(0.346)	(0.345)	(0.088)	(0.088)	(0.123)	(0.123)
Master's or higher degree	0.494***	0.495***	0.519***	0.517***	-0.222**	-0.222**	-0.168+	-0.171+
	(0.083)	(0.083)	(0.098)	(0.098)	(0.070)	(0.070)	(0.097)	(0.097)
Nonwhite	-0.058	-0.058	-0.108	-0.103	-0.108	-0.106	-0.111	-0.113
	(0.082)	(0.083)	(0.101)	(0.101)	(0.125)	(0.125)	(0.173)	(0.173)
Male	0.065	0.065	0.030	0.028	-0.127+	-0.131+	-0.175	-0.174
	(0.083)	(0.083)	(0.102)	(0.102)	(0.077)	(0.077)	(0.107)	(0.107)
School context factors								
Log enrollment	-0.286**	-0.284**	-0.395**	-0.398**	0.073	0.073	0.046	0.044
	(0.101)	(0.101)	(0.122)	(0.122)	(0.094)	(0.094)	(0.138)	(0.138)
Percent non-White / non-Asian students	0.161	0.156	0.011	0.008	0.006**	0.006**	0.009**	0.009**
	(0.363)	(0.362)	(0.448)	(0.449)	(0.002)	(0.002)	(0.003)	(0.003)
Highest quintile of API	-0.210	-0.219	-0.234	-0.237	0.147	0.144	0.190	0.190
	(0.155)	(0.156)	(0.192)	(0.193)	(0.118)	(0.118)	(0.161)	(0.161)
Lowest quintile of API	0.204+	0.208*	0.311*	0.311*	-0.050	-0.050	-0.012	-0.012
	(0.106)	(0.106)	(0.128)	(0.128)	(0.102)	(0.102)	(0.142)	(0.142)
High school	-0.215	-0.227	-0.249	-0.233	0.455+	0.452+	0.163	0.161

	(0.614)	(0.610)	(0.675)	(0.678)	(0.250)	(0.250)	(0.462)	(0.462)
Middle school	0.187	0.188	-0.059	-0.050	-0.168+	-0.169+	-0.126	-0.124
	(0.312)	(0.310)	(0.366)	(0.366)	(0.087)	(0.087)	(0.132)	(0.132)
K-12 school (ref. is Elementary)	0.079	0.074	-0.042	-0.027	0.902**	0.901**	0.278	0.276
	(0.459)	(0.461)	(0.570)	(0.571)	(0.341)	(0.341)	(0.756)	(0.756)
Year fixed effects								
2009	-3.066***	-3.085***	-2.718**	-2.713**	-3.147***	-3.162***	-3.236***	-3.225***
	(0.712)	(0.712)	(0.864)	(0.865)	(0.581)	(0.582)	(0.857)	(0.857)
2010	-3.048***	-3.069***	-2.500**	-2.491**	-3.357***	-3.373***	-3.237***	-3.220***
	(0.715)	(0.714)	(0.867)	(0.868)	(0.581)	(0.582)	(0.863)	(0.863)
2011	-3.521***	-3.540***	-2.953***	-2.950***	-3.497***	-3.503***	-3.470***	-3.458***
	(0.707)	(0.706)	(0.857)	(0.857)	(0.591)	(0.592)	(0.866)	(0.866)
2012	-3.329***	-3.348***	-2.700**	-2.691**	-3.699***	-3.705***	-3.644***	-3.637***
	(0.704)	(0.703)	(0.857)	(0.858)	(0.595)	(0.596)	(0.871)	(0.871)
N	16,325	16,325	13,203	13,203	17,815	17,815	9,777	9,777
Chi2	5339.701***	5346.290***	4148.669***	4139.263***	7184.502	7174.888	3888.569	3883.305

Note. Because Models 1 and 2 include prior year value-added measures, all first-year teachers drop out. Second year teachers drop out of Models 3 and 4 because of the inclusion of the VAM trend variable.

APPENDIX TABLE A6

Regression coefficients predicting teachers' value-added measure of effectiveness, based on various sample specifications

	(1)		(2)		(3)	
	LAUSD	WA	LAUSD	WA	LAUSD	WA
Year t layoff threat						
RIF-re. in t	-0.003	-0.036	0.003	-0.044*	-0.004	-0.059**
	(0.006)	(0.022)	(0.005)	(0.019)	(0.007)	(0.021)
Laid off in t	-0.007	-0.018	0.001	0.025	-0.009	-0.019
	(0.010)	(0.071)	(0.009)	(0.074)	(0.014)	(0.084)
Year t-1 layoff threat						
RIF-re. in t-1	-0.011+	0.004	-0.010*	-0.011	-0.005	-0.018
	(0.006)	(0.016)	(0.005)	(0.013)	(0.007)	(0.013)
Laid off in t-1	-0.063***	0.147	-0.061***	0.194	-0.048*	0.181
	(0.013)	(0.123)	(0.012)	(0.213)	(0.017)	(0.130)
Not pres. yr. t-1	-0.048**	-0.057*	-0.040*	-0.044***	-0.022	-0.023*
	(0.015)	(0.028)	(0.013)	(0.009)	(0.026)	(0.010)
N	10,391	1,929	27,433	23,528	20,840	37,576
R-squ.	0.708	0.749	0.733	0.772	0.771	0.741

Note. Model 1 includes only the subset of teachers who ever receive a RIF or layoff notice. Model 2 limits the sample to only those teachers with experience at or below that of the most experienced RIFed (Washington) or laid off (LAUSD) teacher. For LAUSD, the most experienced teacher receiving a layoff notice in each of the four years of layoffs had 9, 13, 13, and 14 years of experience, respectively. Two laid off teachers in LAUSD had experience above these thresholds (out of 1,333 laid off teachers). Given these two teachers' high experience levels, they were likely laid off for not having the appropriate credential for their teaching position. For Washington, where our significant results are derived from the impact of rescinded RIF on teacher effectiveness, we use a slightly different method; we narrow the sample to only those teachers with experience at or below the 95th percentile of experience for all RIFed teachers in a given year (experience less than or equal to 15 years). We do this because this allows us maintain a larger sample of RIFed teacher-year observations whereas the year-by-year restriction effectively eliminates pre- and post-treatment observations for teachers with higher levels of experience in a given year. Model 3 includes only the years in which layoffs took place (2008-09 to 2012-13). All models include the following control variables: year fixed effects, indicator variables for teacher experience (1, 2, 3, 4, 5, 6-7, 8-10, 11-13, and 14 or more years), whether the teacher holds a master's degree or higher, dummy variables for teachers' endorsement areas, the log of total school enrollment, the percent of students at the school that identify as an underrepresented race/ethnicity, and the school type (elementary, middle, high school, or span school). "Not pres. yr. t-1" (Not present in year t-1) captures teachers who were not in the district in t-1 in LAUSD and who were not teaching in the state for Washington. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.