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Are 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, and none that we know of attempt to quantify the impact of the layoff process on individual employee productivity. In this study we use data from the Los Angeles Unified School District (LAUSD) and Washington State during the Great Recession to 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. We argue that these results are driven by teachers' job insecurity and uncertainty associated with the layoff process, since various tests rule out alternate explanations, including selection bias or temporary drops in productivity associated with transitions to a new school, grade level, or teaching position.

The Great Recession of 2008 led to layoffs in public and private sectors across the country. There are theoretical reasons to believe that the employment instability associated with the threat of layoffs could affect employee productivity, though this issue has not received much attention in economic research. We examine this issue in the context of 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 at any other time in recent history. National estimates of teacher layoffs range from 170,000 to 240,000 in the 2011–12 school year alone (Bureau of Labor Statistics, 2012; National Education Association, 2010), and although layoffs have dissipated as the economy has rebounded, they are still a routine event in districts across the country because of budget shortfalls and drops in student enrollment.

Recent studies that examine the effects of layoffs on the distribution of teacher quality in school districts find that layoffs, especially those governed by seniority-based "Last-In-First-Out" (LIFO) processes, cause the overall quality of teachers in a district to decrease as higher-quality junior teachers are let go and less productive senior teachers are retained. This finding has clear implications for students: more students are taught by lower-quality teachers, negatively impacting student achievement.

In this paper, we focus not only on layoffs themselves, but also on the layoff process. 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 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 the district. 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.

Using longitudinal administrative data from the Los Angeles Unified School District (LAUSD) and Washington State that track teachers affected by the layoff process during the Great Recession (the 2008–09 through 2011–12 school years), this study provides the first evidence describing the impact of the layoff process on employee productivity. 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 (Goldhaber, Strunk, Brown, & Knight, 2015), 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 (Ost, 2014; Ronfeldt, Loeb, & Wyckoff, 2013).

We find that in both LAUSD and Washington State, teachers affected by the layoff process are less productive (based on value-added measures of teacher effectiveness) than those who do not face layoff-induced job threat. We argue that these results are driven by teachers' job insecurity and uncertainty associated with the layoff process, and we present evidence to rule out alternate explanations, such as selection bias or transitions to a new school, grade level, or teaching position. These results have serious implications for students, especially given that teachers who serve the most traditionally disadvantaged students are generally those who are most impacted by the layoff process.

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

Extant research shows that layoffs directly affect the quality of the teacher workforce. In particular, several studies find that seniority-based LIFO layoff processes instituted to attain budget-reduction targets result in the layoff of significant numbers of highly 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 layoffs are not solely dictated by seniority—administrators may take other factors, such as teacher quality, into account—Kraft (In Press) finds that layoffs increased student achievement over what it would have been had seniority been the determining factor. Moreover, Kraft finds that layoffs decrease grade-level achievement generally, and the loss of an effective teacher as opposed to an ineffective teacher (judged by either value-added or principal ratings) has even more detrimental effects on students' mathematics achievement.[1]

The work reviewed above is critical for understanding how layoffs impact the quality and size of the workforce, but none of these papers assesses the impacts of the *layoff process* beyond what occurs as a direct result of actual layoffs. In particular, little attention has been paid to the impact of "surviving" a layoff. One way in which the layoff *process* can impact the teacher workforce is by causing teachers to switch schools within the district at greater rates than they otherwise would have. A recent paper by Goldhaber and colleagues (2015) assesses the extent to which layoff threat—as operationalized by the receipt of a RIF notice or by colleagues' receipt of RIF notices—impacts teachers' propensities to exit their schools. They find that in LAUSD and Washington, teachers who receive a RIF notice are significantly more likely to exit their schools, and LAUSD teachers with greater peer-induced layoff threat are also more likely to exit their schools. This may itself be detrimental to students and schools,

[1] Seniority-driven layoffs in particular result in a need to lay off a greater proportion of teachers (Boyd et al., 2011; Goldhaber & Theobald, 2013; Kraft, In Press) because junior teachers earn lower salaries than veteran teachers. This implies that class sizes are larger than what they would be were a different layoff method used, and this may also have negative effects on student performance (Angrist & Lavy, 1999; Jepsen & Rivkin, 2009; Krueger, 1999; Rivkin, Hanushek, & Kain, 2005).

given that recent studies show that teacher churn negatively impacts school climate and student achievement (see Guin, 2004; Ronfeldt et al., 2013; Hanushek & Rivkin, 2013).[2]

It is also likely that layoffs and the layoff process harm teachers' professional environments, thus accentuating the negative impact of layoffs on teachers' collective productivity. To that end, a number of studies have begun to document how poor working conditions may negatively impact teacher productivity (see Hannaway, Sass, Figlio & Feng, 2009; Johnson, Kraft & Papay, 2012). For example, Johnson et al. (2012) 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 a supportive working environment and strong administrative support (Boyd et al., 2011; Ladd, 2011). This research suggests that, by causing churn and poor working environments, the layoff process is likely detrimental to teacher productivity and student outcomes.

Only a small body of economic research focuses on the effects of job commitment and performance as it relates to job security. Sousa-Poza and Henneberger (2004) review economics research on turnover intentions and while they cite several studies that focus on job commitment, none examines the role of job security in predicting job commitment or performance. The authors explicitly note that the majority of work on this topic comes from the field of psychology.

Work from psychology literature suggests that the employment threat introduced by the layoff process may impact individual teachers' organizational commitment and productivity, thus reducing their instructional effectiveness (see Allen, Freeman, Russell, Reizenstein, & Rentz, 2001; Brockner, Davy, & Carter, 1985; Brockner, Grover, Reed, & Dewitt, 1992). Studies find that workers are less

[2] Ronfeldt et al. (2013) study grade- and school-level teacher churn in New York City schools and find that a 100% increase in turnover lowers student achievement by between .066 and .081 standard deviations, with greater effects for low-income and minority students. Hanushek and Rivkin (2013) find that a 1% increase in teacher turnover in a large Texas district lowered achievement by 0.028 standard deviations. 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 among administrators, families, teachers, and students, destabilizing schools and negatively impacting learning environments.

motivated and less productive when their jobs are threatened (see Allen et al., 2001; Brockner et al., 1992). For instance, Brockner et al. (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 been exposed to past layoffs and when they perceived that layoff processes were conducted “unfairly.”

Beyond the potential psychological impacts of receiving a layoff notice, teacher productivity could be affected for pragmatic reasons. For instance, in many cases laid-off teachers did not receive an indication that they would be offered a job the following school year until just before the beginning of the year, or, in some cases, 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 and more time searching for new employment opportunities—activities that likely do not contribute to improvements in teaching performance in the following year.[3]

II. The 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. Although the process varies to some extent from state to state and district to district, 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. In California, districts are required to

[3] Although no research that we know of discusses the impact of job search activities on teacher productivity, a 2006 survey of Texas teachers who “moonlight” (i.e., work a second job to increase their overall compensation) finds that 67% of teachers believe that moonlighting had a negative effect on their performance. Teachers reported that moonlighting reduced their preparation time, caused increased stress, diminished collaboration with peers, and in some cases harmed their ability to interact with students (Parham & Gordon, 2011).

issue RIF notices by March 15 and to notify teachers whether 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 because the district learns more about budgets and enrollments over the course of the summer and into the early fall, they offer many teachers who have been laid off reemployment when they know that they have the budget to fill positions. In Washington, the RIF process is not as heavily mandated 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 A 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 receive notice that their RIF has been rescinded, thus facing a threat but no actual layoff; (c) teachers who receive a RIF notice that the district *does not* rescind but are rehired and return to their districts in the following year as a full-time teacher[4]; and (d) teachers who are laid off and do not return to their districts in the following year.[5]

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 and 4,445 teachers were laid off.

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[4] 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 from the authors upon request).

[5] It is not possible in our data to differentiate between teachers who were laid off and offered a job back, but declined to accept the position, and those who were laid off and not offered a job back. If teachers appear in the data as a classroom teacher in the year following a layoff, we assume they were offered a teaching job and that it was accepted. If teachers do not return to the dataset in the year following a layoff, we assume they were not offered a position. It is possible, however, that some teachers who were laid off and do not show up in the data in the following year were offered reemployment and declined. However, LAUSD district officials assure us that very few teachers do not accept offers of reemployment (personal communication, 2015) and this category is almost nonexistent in Washington. Moreover, this limitation has little bearing on our results as we are interested in what happens to teachers who return to the district after a RIF or a layoff.

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 dramatically when we consider the proportion of laid-off teachers who were ultimately let go (did not return to the district): in LAUSD, only one-half of laid-off teachers did not return to teach in the district in the following year[6], whereas nearly all laid-off Washington teachers did not return (92.4%).

In addition to the layoff process timeline described above, state (California) and district (Washington) layoff provisions that require layoffs to be made almost entirely based on seniority also impact the distribution of RIFs and layoffs, and who is impacted. In particular, California state law requires districts facing budget constraints to lay off teachers 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 more than 95% 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. As expected, in both LAUSD and Washington State, much greater proportions of novice teachers (in their first through third years of teaching experience in the district) than midcareer or veteran teachers were laid off, whereas much greater

[6] These rates of rescission are similar to those of districts across California (Estrada, 2012).

proportions of veteran teachers were unaffected by RIFs than were midcareer or novice teachers. Table 2 also shows that RIF and layoff rates differ by credential area, with teachers in traditionally hard-to-staff subjects such as mathematics and science facing less employment threat as a result of the layoff process.[7]

III. Data and Analytic Approach

The data used in this study are derived from two educational settings—LAUSD and Washington State—over 6 school years, 2007–08 to 2012–13.[8] In both sites the datasets link teachers to their students, schools, and districts across years. 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 based on student test scores on state assessments (California Standardized Tests [CSTs] in mathematics and English language arts [ELA] in LAUSD and Washington Assessment of Student Learning [WASL] in mathematics and ELA in Washington State). Second, we are able to identify which teachers face the various forms of layoff threat described above, including which teachers return to their districts following a layoff. Third, in both sites teachers received layoff notices and layoffs in all 4 years under study, providing substantial variation in layoff threat across teachers.

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 source

[7] 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 (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.
[8] Our main models use six years of data. However, in our placebo tests (described below), we also include data from 2006–07.

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 (see race/ethnicity, gender, years of experience), teachers' educational backgrounds (see highest degree earned and endorsements/credentials held by each employee[9]), job title, contract status (permanent, probationary, etc.), and teachers' school and classroom placement. We restrict the sample to "classroom teachers"[10] who teach in grades 4–7 and for whom we can generate value-added measures of teachers' contributions to student performance on standardized exams.[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.[12] For school year 2012–13, the most recent year of data used in the analyses, these data include 4,722 unique teachers in LAUSD and 9,441 in Washington State. As is shown in the bottom panel of Table 1, 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 2 of those teachers return the following year, respectively, in LAUSD and Washington.

[9] In Washington, we use the PESB credentials database to obtain measures of teacher endorsement areas. In LAUSD, we obtain these data from the human resources 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 nonelementary credential besides SPED or STEM; and (d) elementary credential only.

[10] In LAUSD we define teachers as nonadministrative 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 and are thus are subject to LAUSD RIF and layoff processes). We exclude nontraditional 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.

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

[12] LAUSD's teacher demographic data are available beginning in 2007–08. We impute experience, education, and credential information for 2006–07 for the majority of teachers. However, in both contexts we exclude 2006–7 from our main analysis and use only that year in specification checks.

These teacher data are merged with student-level data that contain students' performance on state mathematics 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.

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.[13] We merged these sources of information with our longitudinal datasets, enabling us to generate precise indicators of each type of layoff threat described in Table 1.

Value-Added Measures

Our primary outcome of interest is teacher's job performance. To obtain estimates of teachers' contribution to students' ELA and mathematics achievement scores (value added), we estimate the following model separately for each school year from 2006–07 to 2012–13, indexing for student *i*, teacher *j*, and school*s*:

[13] 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 has 295 school districts.

$$A_{ijs}^{Math} = a_1 A_{ijs(t-1)}^{Math} + a_2 A_{ijs(t-1)}^{ELA} + a_3 X_{ijs} + \tau_{js} + \varepsilon_{ijs} \quad (1)$$

A_{ijs}^{Math} is a measure of student *i*'s achievement on the mathematics CST or WASL, standardized within year and test. We control for lagged test scores in both mathematics ($A_{ijs(t-1)}^{Math}$) and ELA ($A_{ijs(t-1)}^{ELA}$) and a vector of student characteristics (X_{ijs}) that includes family income (as measured by eligibility for free and reduced-price lunch), English language proficiency, whether English is spoken in the home, whether the student is enrolled in any additional courses in mathematics or English (depending on which test score is being predicted), whether the student is in her or his first year in the district, and indicators for students' grade level. Our main focus is the estimate of teacher effects (value added), τ_{js}, a vector of teacher fixed effects. The error term, ε_{ijs}, is assumed independently identically distributed with respect to the other variables in the model. We run an identical model for ELA (again using both mathematics and ELA lagged test scores as controls). For teachers who 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' measure 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 commonly employed specifications (see Koedel & Betts, 2007; McCaffrey, Sass, Lockwood, & Mihaly, 2009; Rothstein, 2010; Koedel, Mihaly, & Rockoff, 2015; Lubienski & Lubienski, 2013). Consistent with other studies (Chetty, Friedman, & Rockoff, 2014; Ehlert, Koedel, Parsons, & Podgursky, 2014; Goldhaber, Walch, & Gabele, 2014), the value-added performance estimates generated by the various described models are highly correlated (0.90 or above). This assures that the findings we describe below are unlikely to be sensitive to the chosen value-added specification.

Our measure of teacher effectiveness is a linear term, which identifies an individual teacher's relative position on the effectiveness distribution. We use the average estimate between mathematics and ELA for teachers with VAM measures in both subjects. All value-added measures are reported in student-level standard deviations. Consistent with VAM estimates from other contexts (see Hanushek & Rivkin, 2010, for a summary; Kane & Staiger, 2008, for specific figures based on LAUSD; and Goldhaber & Theobald, 2013, for Washington), the standard deviation of our 1-year teacher effectiveness measures in LAUSD and Washington is 0.274 and 0.258, respectively.[14]

Analytic Approach

We ask whether teachers' job performance changes after experiencing a layoff or the threat of layoff. To address this question, 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:

$$VA_{ist} = \beta_0 + \beta_1 RIFre_{ist} + \beta_2 Layoff_{ist} + \beta_3 RIFre_{ist-1} + \beta_4 Layoff_{ist-1}$$

$$+\beta_5 X_{ist} + \beta_6 S_{ist} + Year_{is} + \tau_{is} + \mu_{is} + \varepsilon_{ist} \qquad (2)$$

In equation (2), $RIFre_{ist}$ and $Layoff_{ist}$ indicate whether a teacher received a RIF notice in year *t* that was rescinded or was laid off in year *t*, respectively, and $RIFre_{ist-1}$ and $Layoff_{ist-1}$ indicate whether a teacher was RIF-rescinded or laid off in the prior year. The variables X_{ist} and S_{ist} are vectors of time-varying teacher characteristics and school characteristics, respectively. Teacher-level covariates include educational attainment, experience (including whether a teacher was not in the dataset in the prior year, meaning that he or she is a novice to either LAUSD or Washington State), and endorsements. At the school level, we control for the log of total enrollment, the percent of students at the school that

[14] These estimates are not shrunken by empirical Bayes methods and are based on models that do not include school-fixed effects so include within and between school differences in teacher effectiveness.

identify as an underrepresented minority race/ethnicity, and the school type (elementary, middle, high school, or span school).[15] We include year-fixed effects (denoted *$Year_{is}$*) to account for changes in teacher effectiveness that are idiosyncratic to a particular year. The inclusion of teacher fixed effects, τ_{is}, in equation (2) allows us to examine changes in teacher effectiveness within teachers over time. Thus estimates of a teacher's job performance are relative to that same teacher's performance in a typical year. Standard errors are clustered at the teacher level (i.e., divided into a teacher-specific component, μ_{is}, and a teacher-observation component, ε_{ist}). In all models, we weight observations by the inverse of the standard error of the value-added estimate, which allows teachers with more precise estimates of their teaching effectiveness to contribute more towards the estimation of our parameters of interest.[16] In alternative models, we also estimate equation (2) without the teacher fixed effects to better understand the naïve estimates of the relationship between layoff threat and teacher effectiveness.

The coefficients β_1 - β_4 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. As Table 1 shows, estimates of the coefficient on the latter variable, $Layoff_{ist-1}$, is of less interest in Washington, since so few teachers are laid off and then rehired for the following school year.

IV. Results

Our main results can be found in **Table 3**. All models include the covariates discussed above, but in consideration of space we only report the variables of interest (results showing all covariates are available upon request).[17,18] Before estimating the model shown in equation (2), as a baseline estimate

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[15] Although most teachers remain at the same school type over their window of observation, some switch school types and these dummies remove any bias associated with these school-level switches.

[16] We estimate fixed-effects models using the areg command in Stata in order to be able to weigh for the precision of the estimates. However, for short panels, the degrees of freedom adjustment in areg produces standard errors that are too large (Cameron & Miller, 2015); thus the statistical inferences we describe below should be interpreted as being conservative.

[17] The coefficients on the control variables are consistent with the literature, (see Feng & Sass, 2011; Goldhaber,

we first present results from an OLS regression that does not include teacher fixed effects. This specification (shown in the first column of Table 3) is identified both by between teacher differences in the effectiveness and within teacher, over time, differences in effectiveness. Importantly, the teachers that inform estimates of our coefficients of interest are different in the models with and without teacher fixed effects: only teachers who have a change in RIF or layoff status inform our main models with teacher fixed effects, whereas all teachers in the sample inform models that do not include the fixed effects.[19] In addition, in the teacher fixed effects model, we compare teachers' VAMs to their average level of effectiveness over the course of our panel, whereas in the model without fixed effects we compare the effectiveness of teachers who face layoff threat to teachers who do not. While the specification without teacher fixed effects does include controls for teacher experience—which is correlated with value added—we still consider these to be naïve estimates if teachers might be targeted for layoffs in part based on their effectiveness—especially, for instance, in Washington districts in which collective bargaining agreements do not determine the order of layoffs.[20]

In LAUSD, the naïve estimates show that teachers in LAUSD who were laid off in *t*-1 have measures of effectiveness 0.040 standard deviations lower than those that were not RIFed in the prior year. There are no significant relationships between productivity and being RIFed and having the notice rescinded in *t*-1 or being laid off in year *t.* In contrast, we find a positive and statistically significant coefficient on RIF-rescinded in year *t*. The latter relationship is surprising, but it reflects the descriptive

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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, and continue at least until the 10th year of teaching. Teachers who acquire graduate degrees are not significantly more effective than those with a 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 same teacher is in the same placement as the prior year.

[18] We run all models without teacher covariates as well. Results of our main models are consistent with and without teacher-level controls and are available upon request.

[19] The findings for these models are largely unchanged when we estimate them with only the subset of teachers that experience a change in layoff threat status.

[20] Were less effective teachers targeted for layoffs, we would expect the specification omitting teacher fixed effects to overstate the casual effect of receiving a layoff on productivity.

statistics in Table 2 showing that RIF-rescinded teachers are marginally more effective, on average, then teachers who were not RIFed. As we describe below, this appears to be a by-product of the cross-sectional comparison of teachers as the RIF-rescinded coefficient is not statistically significant in the models that identify the coefficient based on within teacher variation in RIF status. In Washington, we find that teachers who were RIF-rescinded had 0.043 standard deviations lower VAM scores, compared to teachers who were not RIFed in the current year, and teachers who were laid off in year *t* were 0.083 standard deviations less effective than non-RIFed teachers. Being RIFed or laid off in *t*-1 is not significantly associated with year *t* effectiveness.

The second set of columns in Table 3 shows estimates from equation (2) that include teacher fixed effects. In LAUSD, teachers' receipt of a layoff in year *t*-1 remains negatively associated with their VAM score in year *t*, and the magnitude on this coefficient remains statistically significant. Given that we normalize our value-added estimates of teacher effectiveness, we can interpret our coefficients as the change in effectiveness in student-level standard deviation units. As a result, the coefficient of -0.061 shown column 2 implies that teachers laid off and rehired experienced a decline in effectiveness of more than 6% of a student-level standard deviation. In other words, the achievement of a student in year *t* who has a teacher who was laid off in year *t*-1 and returned to the district in year *t* is expected to be approximately 6% of a standard deviation lower than if she or he 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 or four years of teaching experience.[21] In LAUSD, there are no significant effects of receiving a RIF notice and having it rescinded in year *t*-1 or receiving a RIF or a layoff notice in year *t*.

[21] This comparison is based on coefficients for experience for our baseline model with teacher fixed effects using indicators for experience and teachers with 13 or more years of experience as the reference category. The coefficient for teachers in their first, second, third, fourth, and fifth year of teaching are: -0.139, -0.098, -0.095, -0.053, and -0.047, respectively. Therefore, the estimated effect of having a third-year teacher as opposed to a first-year teacher is 0.044 standard deviations (the difference between the coefficient for teachers in their first year and those in their third year). Similarly, the model suggests the effect of having a fourth-year teacher as opposed to a first-year teacher

The findings for Washington are somewhat different. Specifically, 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 -0.047 student-level standard deviations. This is approximately equivalent to a student having a first-year versus a third-year teacher. This finding, as well as that reported above for LAUSD, is robust to the inclusion of controls for being new to the school (column 3) or the grade (column 4). All models are based on data that are pooled across 6 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).

The difference between the LAUSD and Washington findings may be related to the difference in layoff process timelines or the numbers of teachers affected between the two contexts. First, it is not surprising that current-year RIFs impact teacher effectiveness in Washington more than in LAUSD. This is because teachers receive notification of the likelihood of being RIFed in many if not most Washington districts 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 testing window. Specifically, in many districts teachers are informally notified that their jobs are at risk as early as January and testing in Washington occurs in May. In LAUSD, by contrast, teachers are notified that their jobs are at risk in mid-March and most testing occurs in LAUSD just after that—in March and April. This means that most of the instruction that feeds into LAUSD students' test scores occurs before teachers receive word of their RIF.

Second, there is a clear reason that we do not see similar impacts in Washington of being laid off and then rehired on teacher effectiveness as we do in LAUSD. As Table 1 shows, the estimate on the prior-year layoff coefficient is imprecise in Washington because far fewer teachers are impacted by the layoff process in the state overall, and almost no Washington teachers are actually let go and then

is 0.086 standard deviations.

return in the following year. 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, teachers who receive layoff notices in *t*-1 may be engaging in job-search activities in year *t*.

Robustness and Validity Analyses

In order to assess the validity of our main results, we conduct a number of specification tests and a placebo test to support a causal interpretation of our findings. Our main results remain robust through all specifications described below.

Robustness Tests. Our main robustness tests assesses whether our results are driven by teachers being placed in a new grade level, school, or job category, which we examine because previous work shows they are associated with lower teacher productivity (see Ost, 2014). We first fit the baseline model with a control for whether the teacher switched grades from the prior year and then interact the new grade-level variable with the RIF and layoff variables. We specifically test the coefficients that were found to be significant in our main models: for LAUSD, we interact teacher mobility variables with *lagged* RIF and layoff indicators, whereas in Washington State we interact teacher mobility indicators with *current year* RIF and layoff indicators. We repeat these two models using a new school indicator (if teacher is new to his or her school).[22] Models that control for teacher mobility are also shown in Table 3, and models that interact these variables with the RIF and layoff indictors are shown in columns 3 and 4 of Appendix Table A1. None of the interactions is significant and our main layoff threat results are largely unchanged in either magnitude or significance.

[22] We also test models with controls for and interactions with whether the teacher becomes a substitute. This is feasible only in LAUSD given data constraints in Washington. In LAUSD, becoming a substitute does not significantly change teachers' value-added scores (results available upon request).

We also 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 (shown in Appendix Table A1, column 4). Results are again robust to this addition.[23] Although not shown, we also run models that interact experience with the relevant RIF and layoff variables; however, in both contexts the experience interaction terms are not significantly different from zero (available from the authors upon request).

Placebo Test. We also conduct a placebo test in which we estimate the effect of a pseudo RIF or layoff in the prior year for teachers who were likely to be assigned to these conditions *before the district began implementing layoffs*. To do this, we use the following procedure: first, we predict the likelihood that a teacher receives an initial RIF notice during the years in which layoffs actually took place (2008–09 to 2011–12). For teachers who did receive an initial RIF notice, we also predict their likelihood of receiving a layoff notice. We then make an out-of-sample prediction of each teacher's likelihood of receiving an initial RIF and final layoff notice, based on their observable characteristics in the years before layoffs (2006–07 and 2007–08). These results show each teacher's likelihood of receiving a RIF or layoff notice both before layoffs took place and during the period of layoffs. Next, we generate a random number and assign teachers to either the No RIF or the RIF notice condition, based on whether their random number is above their predicted likelihood of receiving a RIF notice. We assign teachers who are predicted to have received a RIF notice to the layoff condition if their likelihood of receiving a layoff is greater than their random number. Following these steps allows us to identify, based on observable characteristics, which teachers would have been RIF-rescinded and laid off in the years prior to layoffs. The final step in this procedure is to estimate the effect of receiving a pseudo RIF or layoff

[23] In LAUSD we also include covariates and interactions for RIF and layoff variables in year t-2. We find that being laid off in year t-2 lowers value-added scores by about half as much as being laid off in t-1; however, we find no evidence of compounding effects of being laid off (i.e., interactions between year t-1 and t-2 layoff variables are insignificant). It is not feasible to run these tests in Washington State because so few teachers who are laid off return the following year.

notice in year t and t-1, *for the two years prior to layoffs actually taking place*.[24] We check that the placebo RIF and layoff conditions adequately replicate the actual likelihood that teachers would have been RIF-rescinded or laid off and find that these patterns are consistent with actual RIFs and layoffs in the years before (and of) layoffs.[25] This placebo test, then, supports a causal interpretation of the findings if the coefficients for the pseudo RIF and layoff variables show no relationship with teachers' predicted measure of effectiveness.

For ease of comparison, the first and third columns in **Table 4** again show the findings from Table 3 column 2 (our main results from equation [2]) for LAUSD and Washington, and the second and fourth columns provide the results from the placebo tests in each context. In LAUSD the lagged layoff coefficient is not significantly different from zero in the placebo model, and in Washington the placebo RIF in year *t* coefficient is not significantly different from zero. These results provide support for a causal interpretation of our baseline estimates.

Sample Selection. A final concern is that our findings could be biased by sample selection into RIF or layoff conditions or by nonrandom attrition from the study sample. The models we use in this study only provide unbiased estimates of the impact of RIFs and layoffs if the selection of teachers into these conditions is unrelated to teachers' measures of effectiveness, after controlling for observable teacher and school characteristics. Given the stringent legal requirements in LAUSD and in most

[24] Because not enough teachers were laid off and then rehired in the following school year in Washington, we estimate the placebo models only for teachers facing layoff threat in year *t* for Washington State.

[25] We first compare the proportion of teachers assigned to pseudo RIF and layoff conditions in the prelayoff years to the proportion of teachers who actually fell into these conditions during the layoff years. We find that during the two years preceding layoffs, the proportion of LAUSD and Washington teachers who would have received a RIF and had it rescinded and who would have been laid off is in line with the actual percent of teachers RIF-rescinded and laid off. We next compare the proportion of teachers who were actually RIF-rescinded and laid off during the layoff years to the proportions who were assigned to those pseudo conditions *during the same years*. This analysis shows, in both LAUSD and Washington, that about the same proportion of teachers are assigned to the placebo RIF and layoff conditions each year as were actually RIF-rescinded and laid off. Finally, we examine the overlap between the pseudo RIF-rescinded and layoff conditions and the actual RIF and layoff conditions during the years in which layoffs actually took place. In both contexts, there is substantial overlap between the real and placebo RIF and layoff conditions.

Washington districts, we believe that there is little risk of bias associated with selection into RIF or layoff status. Nonetheless, we estimate separate models that predict RIFs and layoffs (available from the authors upon request in LAUSD, and shown in Goldhaber and Theobald [2013], for Washington State). We find that the likelihood of treatment is related only to experience and credential area, both of which we control for in all models.[26]

The issue of nonrandom attrition from the study sample really only arises 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 to their districts. This could bias estimates in two ways. First, if administrators deviated from state-mandated rehiring policies—for example, by 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. This would occur because returning teachers would be more effective than nonreturning teachers, thus making the relationship between layoff in *t*-1 and year *t* effectiveness more positive. Thus, the negative relationship found in our results would be an underestimate. On the other hand, selection bias 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 less effective teachers who are offered reemployment with the district opt to return (perhaps more effective teachers received an external offer of employment). We are not particularly concerned with either source of bias in LAUSD, 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).

[26] 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.

V. Discussion and Policy Implications

This paper is the first that we know of that assesses the impact of the layoff *process* on employee productivity. In the case of teachers, our findings show that the layoff process does more than simply remove effective teachers from schools and increase class sizes. Rather, the general lack of job security brought on by the 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. In Washington, by contrast, teachers who receive a RIF notice—even if it is rescinded—perform worse in terms of their contributions to student achievement. The differences in findings for LAUSD and Washington make sense when we consider the different layoff processes and timelines in the two contexts. First, not enough teachers in Washington are laid off and then return the following year to enable precise estimation of the *t*-1 effect. Second, the period between when teachers receive a RIF notice and eventually have it rescinded is far greater in most Washington districts than in LAUSD and substantially impacts instructional time before achievement tests. This may lead to greater potential for detrimental layoff threat-induced uncertainty and decreased motivation in Washington than in LAUSD.

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 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 (Knight & Strunk, 2015). States and districts might mitigate this negative distributional impact by diminishing the reliance on seniority in layoff processes.

Our findings have serious implications for school districts that may be forced to issue layoff notices in the future, for budgetary or other reasons. 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—for example, 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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Tables

TABLE 1

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

	All LAUSD Teachers					All Washington Teachers				
	2008–09	2009–10	2010–11	2011–12	Total	2008–09	2009–10	2010–11	2011–12	Total
No RIF	24,212	24,577	22,070	21,259	92,118	55,333	55,633	55,386	54,904	221,256
RIF-rescinded	3,064	1,826	2,492	2,315	9,697	1,666	346	752	213	2,977
Laid off	1,812	355	1,270	1,008	4,445	248	78	143	92	561
Total	29,088	26,758	25,832	24,582	106,260	57,247	56,057	56,281	55,209	224,794
% of teachers RIFed	16.76%	8.15%	14.56%	13.52%	13.31%	3.34%	0.76%	1.59%	0.55%	1.57%
% laid off of those RIFed	37.16%	16.28%	33.76%	30.33%	31.43%	12.96%	18.40%	15.98%	30.16%	15.86%
% who do not return of those RIFed	27.81%	6.56%	13.29%	9.30%	16.32%	12.33%	16.27%	14.86%	27.87%	14.78%
% who do not return of those laid off	74.83%	40.28%	39.37%	30.65%	51.92%	95.16%	88.46%	93.01%	92.39%	93.23%

	4–7th Grade LAUSD Teachers with VAMs					4–7th Grade Washington Teachers with VAMs				
	2008–09	2009–10	2010–11	2011–12	Total	2008–09	2009–10	2010–11	2011–12	Total
No RIF	3,768	4,368	3,894	3,852	15,882	2,632	9,374	9,375	9,177	30,558
RIF-rescinded	993	852	958	822	3,625	87	46	126	20	279
Laid off	663	57	353	260	1,333	6	5	14	8	33
Total	5,424	5,277	5,205	4,934	20,840	2,725	9,425	9,515	9,205	30,870
% of teachers RIFed	30.53%	17.23%	25.19%	21.93%	23.79%	3.41%	0.54%	1.47%	0.30%	1.01%
% laid off of those RIFed	40.04%	6.27%	26.93%	24.03%	26.89%	6.45%	9.80%	10.00%	28.57%	10.58%
% who do not return of those RIFed	53.53%	63.82%	45.56%	43.61%	52.09%	11.83%	15.69%	15.71%	35.71%	16.35%
% who do not return of those laid off	82.35%	38.60%	24.93%	16.54%	52.44%	100.00%	80.00%	92.86%	100.00%	93.94%

TABLE 2

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

	LAUSD				Washington			
			RIF				**RIF**	
	% Overall	**No RIF**	**RIF-rescinded**	**Laid off**	**% Overall**	**No RIF**	**RIF-rescinded**	**Laid off**
All Teachers	20,840	15,882	3,625	1,333	30,870	30,558	279	33
		76.21%	17.39%	6.40%		98.99%	0.90%	0.11%
Value-added measures								
1-year fixed effects estimates	-0.02	-0.02	0.01	-0.05	-0.02	-0.02	-0.07	-0.12
	(0.274)	(0.276)	(0.274)	(0.259)	(0.258)	(0.258)	(0.253)	(0.232)
Pooled estimates with EB shrinkage	0.01	0.01	0.02	-0.03	0.00	0.00	-0.04	-0.04
	(0.205)	(0.207)	(0.201)	(0.186)	(0.191)	(0.191)	(0.190)	(0.184)
Exp-adj pooled estimates with EB shrinkage	0.00	-0.01	0.04	0.02	-0.01	-0.01	0.01	-0.01
	(0.205)	(0.207)	(0.201)	(0.188)	(0.164)	(0.164)	(0.165)	(0.153)
Experience / Education								
Novice teachers (1st–3rd year)	4.83%	23.04%	27.21%	49.75%	9.49%	94.23%	5.16%	0.61%
Mid - career teachers (4th–8th year)	25.10%	46.97%	41.66%	11.37%	24.77%	98.56%	1.35%	0.09%
Veteran teachers (9th year or above)	70.07%	90.35%	8.03%	1.62%	65.74%	99.84%	0.12%	0.04%
Mean years of experience	9.6	10.9	6.3	4.1	13.5	13.6	3.3	5.8
Master's degree or higher	36.12%	76.70%	17.84%	5.46%	69.25%	99.38%	0.54%	0.08%
Endorsement Area								
Special Education	2.22%	66.95%	17.28%	15.77%	12.22%	99.58%	0.40%	0.03%
Mathematics or Science	9.91%	83.39%	13.27%	3.34%	11.61%	98.94%	0.95%	0.11%
Other nonelementary	26.15%	74.28%	18.04%	7.69%	43.27%	99.40%	0.52%	0.08%
Elementary	61.72%	76.21%	17.79%	6.00%	32.90%	98.25%	1.59%	0.17%
Lagged RIF/layoff								
No RIF in t-1	83.66%	86.37%	10.03%	3.60%	93.46%	99.44%	0.52%	0.04%
RIF-rescinded in t-1	13.04%	21.94%	66.21%	11.85%	1.55%	91.46%	6.25%	2.29%
Layoff in t-1	1.60%	21.26%	8.38%	70.36%	0.05%	100.00%	0.00%	0.00%
Not present in year t-1	1.70%	44.51%	13.80%	41.69%	4.93%	92.78%	6.50%	0.72%

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 panels, the % overall column shows the percent of teachers with those characteristics, 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%.

TABLE 3

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-rescinded in t	0.012*	-0.043*	0.003	-0.047*	0.002	-0.046*	0.003	-0.046*
	(0.005)	(0.020)	(0.006)	(0.020)	(0.006)	(0.020)	(0.006)	(0.020)
Laid off in t	-0.012	-0.084*	0.000	-0.082	-0.001	-0.083	-0.001	-0.089
	(0.008)	(0.039)	(0.010)	(0.085)	(0.010)	(0.084)	(0.010)	(0.085)
Year t-1 layoff threat								
RIF-rescinded in t-1	0.008	-0.010	-0.009	-0.011	-0.008	-0.009	-0.009	-0.008
	(0.005)	(0.014)	(0.006)	(0.015)	(0.006)	(0.015)	(0.006)	(0.015)
Laid off in t-1	-0.040***	0.087	-0.061***	0.158	-0.049**	0.162	-0.059***	0.161
	(0.012)	(0.113)	(0.015)	(0.163)	(0.015)	(0.161)	(0.015)	(0.160)
Not present in year t-1	-0.082***	-0.048***	-0.038*	-0.034**	-0.042**	-0.032**	-0.042**	-0.029**
	(0.010)	(0.007)	(0.015)	(0.011)	(0.015)	(0.011)	(0.015)	(0.011)
New to school (but not district)					-0.035***	-0.012+		
					(0.006)	(0.006)		
New to grade							-0.016***	-0.048***
							(0.004)	(0.004)
Teacher FE			X	X	X	X	X	X
N	31,160	45,436	31,160	45,436	31,160	45,436	31,160	45,436
R-squared	0.128	0.112	0.727	0.716	0.728	0.718	0.728	0.710

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Note: Model 1 is our baseline model with no teacher fixed effects and Model 2 is our baseline model with teacher fixed effects. All models include the following control variables: 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, and dummy variables for endorsement areas. Model 1 also includes time-invariant controls for teacher race/ethnicity and gender. 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 minority race/ethnicity, and the school type (elementary, middle, high school, or span school). "Not present in year t-1" captures teachers who were not in the district's dataset in t-1 in LAUSD and who were not in the state dataset in 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.

TABLE 4

Regression coefficients predicting teachers' value-added measure of effectiveness, using actual RIF/layoff threat (2007–08 to 2012–13) and placebo tests (2006–07 to 2007–08)

	LAUSD		Washington	
	Real threat	Placebo threat	Real threat	Placebo threat
year t layoff threat				
RIF-rescinded in t	0.003	-0.005	-0.047*	0.014
	(0.006)	(0.016)	(0.020)	(0.063)
Laid off in t	0.000	0.002	-0.082	0.039
	(0.010)	(0.023)	(0.085)	(0.144)
year t-1 layoff threat				
RIF-rescinded in t-1	-0.009	-0.01		
	(0.006)	(0.021)		
Laid off in t-1	-0.061***	0.015		
	(0.015)	(0.029)		
N	31,160	10,782	45,436	10,463
R-squared	0.727	0.898	0.716	0.837

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Note: The placebo test for Washington that includes lagged layoff threat effects would not run due to small sample size, so we show for Washington the actual model and placebo test for the model that includes only year t threat. All real threat models are run school years 2007–08 to 2012–13, while the placebo tests are run on the two years preceding layoffs (2006–07 and 2007–08).

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 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 certified 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 predicting teachers' value-added measure of effectiveness based on current and prior year RIF/layoff variables and interaction terms, for Los Angeles Unified School District (LAUSD) and Washington State (WA)

	Baseline model (1)		New school (2)		New grade (3)		Year t & t-1 threat (4)	
	LAUSD	WA	LAUSD	WA	LAUSD	WA	LAUSD	WA
Year t layoff threat								
RIF-rescinded in t	0.003	-0.047*	0.002	-0.037+	0.003	-0.045*	0.001	-0.03
	(0.006)	(0.020)	(0.006)	(0.019)	(0.006)	(0.02)	(0.007)	(0.024)
Laid off in t	0.000	-0.082	-0.001	-0.094	-0.002	-0.087	0.013	-0.192
	(0.010)	(0.085)	(0.010)	(0.092)	(0.010)	(0.086)	(0.015)	(0.135)
Year t-1 layoff threat								
RIF-rescinded in t-1	-0.009	-0.011	-0.008	-0.006	-0.005	-0.006	-0.007	-0.007
	(0.006)	(0.014)	(0.006)	(0.014)	(0.007)	(0.014)	(0.008)	(0.015)
Laid off in t-1	-0.061***	0.158	-0.053**	0.155	-0.040*	0.154	-0.078***	0.189
	(0.015)	(0.163)	(0.018)	(0.161)	(0.019)	(0.16)	(0.018)	(0.162)
Not present in year t-1	-0.038*	-0.034**	-0.041**	-0.031**	-0.051***	-0.029**	-0.031*	-0.033**
	(0.015)	(0.011)	(0.015)	(0.014)	(0.015)	(0.01)	(0.016)	(0.01)
Interactions with year t-1 RIF/layoff (LAUSD) and year t RIF/layoff (WA)								
New to school (but not district)			-0.036***	-0.012+				
			(0.007)	(0.006)				
New to school ×RIF-rescinded			0.003	-0.019				
			(0.016)	(0.038)				
New to school ×Laid off			0.008	0.053				
			(0.026)	(0.201)				
New to school × Not present (in t-1)			-0.175					
			(0.127)					
New to grade					-0.014***	-0.047***		
					(0.004)	(0.003)		
New to grade × RIF-rescinded					-0.009	0.021		
					(0.010)	(0.056)		
New to grade × Laid off					-0.040	0.034		
					(0.025)	(0.126)		
New to grade × Not present in t-1					0.100*			
					(0.050)			
RIF-rescinded in t × RIF-rescinded in t-1							0.000	-0.052
							(0.011)	(0.071)
RIF-rescinded in t × Laid off in t-1							0.041	-0.002
							(0.054)	(0.03)
RIF-rescinded in t x Not present in t-1							0.024	-0.033
							(0.043)	(0.04)
Laid off in t x RIF-rescinded in t-1							-0.036	0.072
							(0.024)	(0.17)
Laid off in t x Laid off in t-1							0.010	0.001
							(0.028)	(0.01)
Laid off in t x Not present in t-1							-0.070	0.371
							(0.050)	(0.271)

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Note: For LAUSD models, we interact *year t-1* RIF and layoff variables with each of the covariates listed (new to school, new to grade, class size, and current year RIF/layoff). For Washington State (WA), we interact *current year* RIF and layoff variables with each of the covariates listed (new to school, new to grade, class size and prior year RIF/layoff). As we explain in the text, we do this because the year t-1 layoff variable is significant in LAUSD, whereas year t RIF variable is significant in Washington.