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Lessons Learned from the Great Recession: Layoffs and the RIF-Induced Teacher Shuffle

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Abstract

One consequence of the Great Recession is that teacher layoffs occurred at a scale previously unseen. In this paper we assess the effects of receiving a layoff notice on teacher mobility using data from Los Angeles and Washington State. We find strong evidence that the receipt of a layoff notice increases the likelihood that teachers leave their schools, even in the absence of actually losing their position due to a layoff. Placebo tests suggest that it is the layoff process that induces "structural churn" rather than differential mobility of the teachers who are targeted by this process.

Significant budget shortfalls in the years following the Great Recession pressured many states to enact widespread cuts to programs and services. Federal stimulus programs partially shielded primary and secondary education from spending cuts in certain years, but reductions in the resources allocated to public K–12 education associated with the economic downturn forced school districts nationwide to lay off teachers at a scale previously unseen.[1]

Given the scope of recessionary-induced layoffs and the growing evidence that individual teachers are the most important school-based factor in predicting student achievement on standardized tests (e.g., Aaronson, Barrow, and Sander 2007; Goldhaber and Hansen 2013; Rivkin, Hanushek, and Kain 2005) as well as longer term outcomes (Chetty, Friedman, and Rockoff 2014), it is not surprising that the teacher layoff process and any outcomes of this process have become issues of considerable policy concern. Although some states now require school districts to consider performance when deciding which teachers to lay off, the great majority of districts historically relied heavily on seniority—a "last in, first out" (or "LIFO")—system to determine the order by which teachers are targeted for layoffs.[2]

Recent research indicates that concern about the LIFO process is warranted. LIFO-based layoffs have a *direct* adverse impact on schools and students: They alter the quality composition of the teacher workforce by removing more effective teachers from schools than would be the case under alternative layoff processes, such as those based on measures of effectiveness or that allow administrators discretion in selecting personnel for removal (Boyd et al. 2011; Goldhaber and Theobald 2013; Kraft Forthcoming).

Although the direct effect of teacher layoffs has received empirical attention, the potential *indirect* effects of teacher layoffs have remained unexplored. The layoff process itself may cause teachers who are *not* ultimately laid off but do feel indirectly affected by the process—either by

[1] Despite federal stimulus programs, such as the American Recovery and Reinvestment Act of 2009 and the Education Jobs Fund 2010, it is estimated that by 2010 the Great Recession had resulted in 170,000 teacher layoffs nationwide (National Education Association, 2010).

[2] This situation has changed since the Great Recession with an increasing number of states (12 in 2015–16) requiring that teacher performance be considered, and 10 other states explicitly prohibiting the use of tenure or seniority as a primary factor in layoff decisions, a doubling of the number of states with that requirement in 2012 (Thomsen 2014).

feeling that their jobs are threatened by the likelihood of layoff or by being forced to move between schools to keep their jobs. Specifically, the existing layoff process in place in most states requires school districts to send Reduction-in-Force (RIF) notices to *any* teacher who might conceivably be laid off for the next school year. These RIF notices must be provided in the early spring of the school year, well in advance of when legislatures adopt their budgets for the upcoming fiscal year. Once budgets are adopted, districts determine who in fact must be laid off —usually only a small fraction of the positions identified for RIFs. Thus, there is a period during which many teachers face an acute *threat* of losing their jobs, but do not know if they will *actually* lose their jobs. This RIF-induced layoff threat may affect their choices to remain in their school, district, or in the profession.

Moreover, and perhaps more importantly, this layoff process on its own may create *churn* (teacher mobility) beyond any impacts on teachers who receive a RIF notice. This occurs because LIFO-based systems do not consider the staffing needs of schools, consequently the most junior teachers face layoffs regardless of the schools where they teach. This results in some rebalancing of staffing across schools to minimally and at least somewhat equitably staff schools. In these instances, teachers may be forced to move to another school if they wish to keep their jobs. In other words, the layoff process can create a "ripple effect" given the schools in which teachers targeted for layoffs are employed.[3]

The potential for a RIF-induced teacher shuffle has not yet been investigated. However, given recent evidence that teacher churn is detrimental both to the teachers who remain in the schools and to student outcomes (e.g., Guin 2004; Ronfeldt, Loeb, and Wyckoff 2013; Hanushek and Rivkin 2013; Ost 2014), layoff-induced teacher mobility is worthy of attention.

In this paper, we use longitudinal data from two educational environments, the Los Angeles Unified School District (LAUSD) and Washington State, to assess the indirect impact of the layoff

[3] In this scenario teacher mobility is "structural" in the sense that it is driven by the needs of the school system for balanced staffing. Whether due to structural moves or the desire to avoid the threat of a layoff (as in the first scenario), in a sense, any indirect effects of the layoff process occur as a result of teachers' choices, albeit choices that may be constrained in the event that they are required to move to maintain employment in a district. Thus in describing our findings, we use terms like "teachers' reactions," which imply that an observed move reflects teachers' preferences; our line of reasoning suggests this is true, but readers should keep in mind that these are in some cases likely to be preferences under the threat of job loss.

process on the probability that teachers leave their schools. We use logistic regression models to focus on the propensity for teachers who are faced with the threat of a layoff—those who receive a RIF notice (are "RIFed") but who are not actually laid off from their school district—to leave their schools. We find that far more teachers leave their schools because of their own or their colleagues' receipt of a RIF notice than is necessary to reach budget savings targets; the mere receipt of a RIF notice—even when it is rescinded—induces a good deal of teacher churn. Little evidence exists that this RIF-induced churn varies significantly for teachers of different levels of effectiveness, but we do see differences in the response to the receipt of a RIF notice across teacher experience in a direction that is consistent with expected reactions under LIFO-layoff processes. Finally, we find that district and state policies can affect the degree to which teachers exit their schools and districts. Specifically, we find that more junior teachers are less likely to exit their districts under collectively bargained district policies that allow for layoffs to take into account factors other than seniority, and that layoff protections given to subsets of high-risk schools significantly decrease teacher churn.

We cannot separate the mobility impact of layoff threat on teacher behavior from mobility arising as a consequence of districts rebalancing staffing due to layoffs. However, regardless of the cause, the finding that RIFs induce extensive teacher shuffling is important given the adverse impacts of teacher mobility on students and schools (e.g., Guin 2004; Ronfeldt, Loeb, and Wyckoff 2013; Hanushek and Rivkin 2013). Moreover, from a policy perspective, it is particularly important that much of the churn that exists is unnecessary given the number of actual layoffs that are required to reach budgetary targets.

The remainder of the paper proceeds as follows. Section I provides background on the impact of layoffs and the potential responses to layoff threat. Section II outlines the relevant policies governing the teacher layoff process in both LAUSD and Washington State. Section III describes our data and the analytic methods used to assess these data. Section IV provides our findings, and Sections V and VI discuss these results, offer policy implications, and conclude.

I. Background on Layoffs and Layoff Threat

As discussed above, we would expect the layoff process, and RIFs in particular, to have both *direct* and *indirect effects* on teachers. But the existing empirical literature on layoffs focuses solely on the *direct effects of layoffs* on teachers (those teachers who receive RIF notices) and the student achievement implications of teacher layoffs. In this section, we review this literature and then discuss the ways we might expect teachers to respond to the indirect, RIF-induced threat of layoffs.

Direct Effects of Layoffs

As noted above, the direct effects of RIFs on mobility are movements that occur because teachers are, in fact, laid off. Countless newspaper articles and reports have documented this direct impact of layoffs on the teacher labor force (e.g., Gordon 2011; Winter 2014). Although LIFO protections were put into place in an attempt to ensure "objective" layoffs, so that administrators did not try to protect favorite teachers or those with lower salaries (Barkan 2011), ample evidence now shows that the credentials (e.g., seniority and degree level) that help protect teachers from being laid off (Goldhaber and Theobald 2013) are, at best, only weakly associated with teacher effectiveness (Glazerman et al. 2010; Goldhaber et al. 1999; Rivkin, Hanushek, and Kain 2005). In essence, LIFO-type layoffs ignore teacher effectiveness in favor of objectivity.

Research suggests this method of determining layoffs has consequential implications for student achievement. Researchers find that in New York City (Boyd et al. 2011) and Washington State (Goldhaber and Theobald 2013), the use of a LIFO-layoff process rather than a performance-based system (relying on value-added measures of teacher effectiveness) requires districts to lay off substantially more and higher quality teachers (20% to 26% of a standard deviation in student achievement) to reach equivalent budget savings targets. In the Charlotte-Mecklenburg School District, where layoffs are not dictated solely by seniority but instead administrators may take other factors, such as teacher quality, into account, Kraft (Forthcoming) finds that layoffs increased student achievement over what it would have been had seniority been the sole determining factor, and

simultaneously decreased the number of teachers that the district had to lay off. Together, these three studies indicate that not only are more teachers laid off under LIFO policies, but more high-quality teachers are laid off than is necessary.

Indirect Effects of Layoffs

The above research shows that the layoff system has significant implications for both student achievement and the number of layoffs that occur. But this research does not speak to the potential indirect effects of layoffs, and in particular layoff threat induced by the receipt of a RIF notice, on teachers and school systems. We might expect teachers who have received a RIF notice but do not yet know if they will be laid off, or who have received a RIF notice that is then rescinded, to exit their schools, districts, and/or the profession to find a more stable placement. But, to our knowledge, no research has focused on whether this threat of layoff affects teachers' labor market behavior. In what follows, we look to the literature to help us untangle how we might expect teachers—both teachers in general and specific kinds of teachers—to react to the *threat* of layoff.

Potential Responsiveness to Layoff Threat

A large body of work related to employees outside the teaching profession focuses on how the risks of unemployment affect labor market decisions generally and job choices in particular. These studies suggest that workers consider job risk when making job choices and favor jobs with lower risk of unemployment (Abowd and Ashenfelter 1981; Adams 1985; Moretti 2000; Topel 1984).[4] Thus, we might think that teachers would choose to exit schools and districts—and even the teaching profession—if their employment risk increases. However, research shows that labor market mobility varies inversely with unemployment rates (Akerlof et al. 1988). Based on these findings, we might expect increased job-risk-associated teacher mobility to be tempered because layoffs occur when unemployment levels, especially in the teaching profession, are high.

[4] In the private sector, the risk of unemployment is often reflected in a risk premium of about 2% to 6% per year for jobs that have a higher risk of unemployment, all else equal (Abowd and Ashenfelter 1981). Teachers' wages are not competitively determined, and generally dependent solely on degree and experience levels.

The impact of layoff threat on teachers' mobility decisions may also vary based on observed or unobserved teacher characteristics, such as teachers' experience, effectiveness, and certification area. A large volume of research, for instance, has shown that novice teachers are less attached to the teacher labor market than their more experienced counterparts, as evidenced by the significantly higher rates at which they exit schools and the profession (e.g., Goldhaber, Gross and Player 2011; Johnson, Kraft, and Papay 2012; Loeb, Darling-Hammond, and Luczak 2005; Smith and Ingersoll 2004). Given that the majority of districts consider seniority in determining which teachers receive RIF notices, layoff threat should affect primarily teachers with lower levels of in-district experience. If layoff threat increases junior teachers' propensities to exit their schools, districts, or the profession, this will likely amplify the preexisting trend of junior teachers' increased propensities to leave.

Layoff threat may also have different impacts on teachers according to their effectiveness. In particular, high-quality teachers may be more likely to exit their schools or districts when faced with the threat of layoff because they do not receive protections in their current placement based on their merit and because they are particularly attractive to other administrators in the market place (Boyd et al. 2011). If effectiveness translates to success in other fields, and employers outside education are similarly able to assess quality and make job offers to higher quality teachers (which evidence suggests they do—see Goldhaber (2010) and Chingos and West (2011; 2012)), then the most productive teachers are more likely to exit the profession when faced with the threat of job loss. Thus, effective teachers who are less likely to choose to exit teaching on average (Goldhaber, Gross, and Player 2011; Boyd et al. 2011), may be more likely to exit in response to layoff threat.

Similarly, teachers who have credentials in high-need areas such as math, science, and special education may react differently to the threat of layoff. As with more effective teachers, teachers with credentials in hard-to-staff subjects may face increased employment opportunities both within and outside their districts. Moreover, research finds that math and science teachers, in particular, experience sizable salary differentials compared to similarly trained counterparts employed outside teaching (Goldhaber et al. 2008; Hampden-Thompson, Herring, and Kienzl 2008;

Murnane and Olsen 1990; Rumberger 1987; West 2013). As a result, these teachers may be more likely to exit their schools, districts and the profession, when faced with the threat of layoff.

Variations in types of layoff threat

The majority of our discussion thus far has focused on teachers' potential reactions to the *direct* threat of layoffs as observed by the receipt of a RIF notice, but teachers may well respond to *indirect* layoff threats that occur even in the absence of, or in addition to, their own receipt of a RIF notice. In particular, it is likely that teachers perceive that they are under threat of job loss if their peers receive RIF notices. There are a few studies from the psychology literature that suggest how teachers may react to "peer-induced layoff threat." This research shows that, although layoff survivors report greater motivation and effort (Brockner, Davy, and Carter 1985; Brockner, Grover, Reed, and Dewitt 1992; Brockner, Grover, O'Malley, Reed, and Glynn 1993), they also report lower organizational commitment and greater intention to quit, especially when they held close relationships with their laid off colleagues (Brockner, Grover, Reed, De Witt, and O'Malley 1987; Moore, Grunberg, and Greenberg 2006).

The precise policies that dictate how layoffs are instituted and executed vary across school districts, and in some rare instances, within district across schools. Given this, we might expect teachers' reactions to layoff threat to vary according to the policy context in which they teach. The most commonly found policy variation occurs because district-level policies dictate the procedures by which teachers are laid off. In the majority of states, locally negotiated collective bargaining agreements (CBAs) determine the layoff system, placing varying degrees of weight on seniority as opposed to other teacher characteristics (described more extensively in the next section).[5] Teachers working in districts with different levels of reliance on LIFO will face varying levels of layoff threat. Presumably, for instance, a more effective junior teacher is at a lower risk if she is teaching in a district in which job performance can be used as a factor in determining who is laid off. In addition,

[5] LAUSD and slightly more than 96% of districts in Washington State use seniority as the primary factor in the layoff process, while slightly less than 4% consider additional factors or the process is not specified.

states and districts can implement or change policies that regulate layoff procedures in ways that may indirectly affect the degree of layoff threat faced by teachers.[6]

There is also another potential indirect effect of layoffs associated with RIFs that has less to do with layoff threat, but rather results from the LIFO process that guides layoffs in LAUSD and in most districts in Washington State. In particular, sending and rescinding RIF notices based on seniority may cause unnecessary shuffling of teachers between schools within the district as junior teachers are RIFed and eventually laid off from schools that still need teacher coverage, necessitating relatively more senior teachers to be slotted into these positions.

II. Layoff Threat in LAUSD and Washington State

As in other districts and states, teachers in LAUSD and Washington face multiple types of layoff threats. In this section, we lay out the specific threats that teachers in our study sample face.

Direct Layoff Threat

The most obvious type of layoff threat is a direct threat—a teacher's receipt of a RIF notice that indicates that she may receive a layoff notice that will cause her to lose her job for the proximate school year. The timeline for when RIF notices are dispersed differs slightly between LAUSD and Washington State, but in both contexts teachers are made aware that they are RIFed or will likely face a RIF in the early spring, and final layoffs are determined months later, in the late spring.[7] This process gives rise to three main categories of direct layoff threat: (1) teachers who do not receive a RIF notice, and thus face no direct threat of layoff (No RIF); (2) teachers who receive a RIF notice but then receive notice that their RIF has been rescinded, thus facing a direct threat of

[6] Although most states allow districts to determine layoff procedures, California state code dictates that teacher layoffs in all districts, with a few exceptions, must be determined by LIFO (California Ed. Code § 44930-44988).

[7] In LAUSD RIF notices are issued in March and official layoff notices are sent in May to teachers whose RIFs are not rescinded. In Washington, in the event layoffs are deemed likely, districts provide seniority lists to the local teachers' union and then post finalized lists at the school site anywhere between January and April. Districts typically convey general estimates regarding staffing reductions during this time. Final RIF notices are issued to individuals in May. Teachers are then let go at the completion of the school year if they have not had their RIF rescinded.

layoff but no actual layoff (RIF-rescinded); and (3) teachers who receive a RIF notice that the district *does not* rescind (laid off).

Table 1 shows the number of teachers who fall into the categories discussed above.[8] RIFs occurred in the 2008–09 through 2011–12 school years in both LAUSD and Washington, and the threat of layoffs varied across years and sites, but, in both settings far more teachers received RIF notices than were actually laid off. In LAUSD, 13.3% of teachers received RIF notices each year, on average, and 4.2% were eventually laid off, highlighting a process that sent layoff notices to approximately 3.2 times more teachers than were actually laid off. In Washington, an average of only 1.6% of teachers were RIFed each year across the state, and only 0.25% of teachers were actually laid off, such that roughly 6.3 times as many RIF notices as layoffs occurred. These statistics suggest that a substantial number of teachers were affected by a direct layoff threat in each context, and that the number of teachers affected by the layoff process far exceeded the number of teachers who would eventually be removed for budgetary reasons.[9]

Table 2 shows descriptive statistics for teachers who fall into these three direct threat categories. As expected, given districts' reliance on seniority in layoffs, we find that teachers who do not receive a RIF notice have far greater average experience than those who receive a RIF notice but it is rescinded or who are laid off. Also not surprisingly, the proportion of novice (1st–3rd year) teachers who receive RIF notices or are laid off is far higher than the proportion of novice teachers in the workforce. **Table 2** also shows that teachers with a master's degree or higher are less likely to receive a RIF notice and be laid off across both sites, which is likely a function of experience. The next set of descriptive statistics helps to paint a picture of how districts enacted layoffs. In LAUSD, as in Washington State, the district can prioritize layoffs for specific kinds of teachers (with different endorsement areas) depending on district need (California Ed. Code §44955). We find that

[8] The data we use for the construction of **Tables 1–3,** discussed in this subsection, are described in Section IV.

[9] The LAUSD numbers are similar to trends found across California (Estrada 2012). Table 1 also shows that only 52% of teachers who were laid off in LAUSD actually lost their jobs, far different from the case in Washington, where 93% of teachers who were laid off actually lost their jobs. The potential that teachers are laid off but rehired represents a fourth threat category, but this category is difficult to measure given that the only way to assess rehire is to see if teachers turn up in the data the next year. Thus, we do not consider this category in our analysis of layoff threat.

elementary and arts teachers are the most likely to receive notices and be laid off in both contexts, with English language arts (ELA) and math teachers the next most likely.

Finally, this table provides cursory evidence that the receipt of a RIF notice has implications for teacher mobility. As expected, we see that teachers who do not receive a RIF notice are the most likely to stay in their schools. However, in both sites the proportion of teachers who leave their schools when they receive a RIF notice that is rescinded—20.9% in LAUSD and 30.6% in Washington—is significantly higher than the proportion of teachers who leave their schools—15.2% in LAUSD and 14.2% in Washington. Of course this may be related simply to the fact that more junior teachers are both more likely to leave their schools and more likely to be RIFed, an issue we explore using the models described in Section IV.[10]

Indirect Peer-Induced Layoff Threat

As discussed above, teachers can also face *indirect* threats of layoff. The first way this may present itself is in a *peer-induced indirect* layoff threat, in which a teacher's colleagues receive RIF notices. Panel A of **Table 3** depicts the level of indirect threat faced by teachers in LAUSD and Washington in terms of the proportion of teachers (other than the teacher himself or herself) who receive RIF notices in a teacher's school at various points along the distribution of schoolwide RIF saturation. This indirect peer-induced layoff threat may be a more accurate measure of the threat internalized by teachers, as peer RIFs do not affect the teacher himself or herself, but rather indicate the severity of the potential current and future cuts. In our models (described below), we use a somewhat different measure of peer threat: the proportion of a teacher's peers who were laid off in the previous year, of those who received RIF notices. This measure of peer threat is shown in the bottom of Panel A and may reflect better the level of indirect threat faced by teachers, as it signals the credibility of the RIF-induced layoff threat.

[10] Table 2 also provides breakdowns by RIF status of teacher mobility within the district (switch schools) and out of the district (leave district). We run all of our models in a multinomial framework as specification checks, the results of which are shown in Appendix Tables A3 and A4.

Virtually all teachers in LAUSD were in schools in which at least one other teacher received a RIF notice, a situation very different from Washington, where less than 20% of teachers were in a school in which at least one peer received a RIF notice. Not surprisingly then, we see that the proportion of teachers who receive a RIF notice at different points in the schoolwide RIF profile are quite different in the two sites, and teachers in LAUSD face more peer-induced layoff threat than do teachers in Washington. Specifically, when examining the sample of teachers who see any form of RIF-induced threat (at least one teacher RIFed), a teacher in an LAUSD school in which relatively few teachers receive RIF notices (at the 10th percentile) has between 1.5% and 6.6% of the teachers in her school RIFed in a given year, whereas a teacher in a school at the 90th percentile of RIF impact sees between 18.2% and 31.1% of her colleagues receive RIF notices. In Washington, by contrast, a teacher in a school at the 10th percentile of teacher RIF saturation experiences between 1.4% and 2.6% of her colleagues receiving RIF notices, and at the 90th percentile, only 12.7% to 17.4% of teachers receive RIF notices. When we consider peer threat as measured by the proportion of a teacher's colleagues who were laid off the prior year, of those who had been RIFed, the differences become even more starkly defined. The differences across these contexts suggest that the indirect threat of RIFs is likely to be less of a concern for Washington teachers than those employed in LAUSD.

Indirect Policy-Induced Layoff Threat

The layoff policy variation in LAUSD is related to the 2009 class action lawsuit *Reed vs. State of California et al.* ("Reed"). The court order in the Reed decision required that LAUSD protect teachers in 45 Reed schools from budget-based teacher layoffs in the 2010–11 and 2011–12 school years.[11] In all, 13 schools were protected by the Reed decision in 2010–11 only; 32 schools were protected in both 2010–11 and 2011–12; and 13 schools were protected in 2011–12 only. As a result, in the affected years, teachers in Reed-protected schools experienced a drastically reduced layoff

[11] In the Reed case, plaintiffs argued that recessionary budget cuts (teacher layoffs) disproportionately affected low-performing schools. In 2010, the state judge ruled on the side of the plaintiffs, directing LAUSD to adopt protective factors to ensure particular schools would not bear an incommensurate level of burden in the event of layoffs.

threat. Teachers received RIF notices, but were not subject to budget-based layoffs (i.e., teachers could be laid off only for structural reasons such as diminishing enrollment). Because the Reed decision was entirely externally determined (LAUSD, the teachers' union, and the teachers did not know how the judge would rule, or what actions LAUSD would or could take in response), we believe the Reed protections can be seen as an exogenous treatment that drastically changed the degree of layoff threat faced by teachers in Reed schools. Panel B of **Table 3** shows the number of teachers in Reed schools treated in each year of the intervention, and in a set of comparison schools selected based on similarities in rates of teacher turnover, potential impact of RIFs, and student performance.[12,13]

In Washington the variation in policy threat arises at the district level. As in many states, districts in Washington collectively bargain over the process by which teachers are laid off, and there is some variation in the layoff provisions included in the CBAs in Washington's school districts. Specifically, Washington CBA layoff provisions can be categorized as those in which: (1) seniority is the *only* factor that can be considered in layoffs; (2) seniority is one of several factors that can be considered in layoffs; and (3) the CBA is silent on the topic of layoff procedures or simply no CBA exists. Each category *potentially* brings with it different levels of layoff threat to different types of teachers.[14] We say potentially because the fact that a CBA does not explicitly mandate the extent to which seniority in a layoff process does not mean that seniority is not being used in a particular way (Hess and Loup 2008). However, we combine categories 2 and 3 in our analyses because of the small

[12]In the Reed Settlement Agreement, approved by LAUSD and the teachers' union on December 14, 2010, protected Reed schools are selected for one of two reasons: (1) schools with the highest teacher turnover rates that were also in the bottom 30%of API, but demonstrating positive API growth, and with at least 15 teachers; and (2) new schools that were established by September 1st of the current year that would be adversely affected by layoffs. Using an identical selection mechanism, we generated a set of comparison schools consisting of those that would have been picked if a greater number of Reed schools were designated for the policy. The settlement decision also required that no non-Reed district school could be affected by the decision in such a way that would cause more than district-average proportion of layoffs to occur in that school. Our comparison schools did not see substantial increases in RIFs and layoffs due to protections for teachers in Reed schools. Summary statistics can be found in Appendix Table A1.

[13] Because part of the Reed selection criteria targeted schools that opened within the prior 2 school years, the number of Reed schools in school years 2008–09 and 2009–10 reported in Table 3 is lower than the number ultimately present in the district during the school years the Reed decision was in place.

[14] For instance, a strictly seniority-based LIFO policy may cause highly effective junior teachers to feel the greatest threat, whereas senior teachers may face the least threat from such a policy.

number of districts that implement such layoff policies. As a result, we compare teachers and schools working under CBAs that either require that seniority is the only factor to be considered in layoffs, or do not restrict layoff decision to be based solely on seniority. As Panel B of **Table 3** shows, the great majority of schools (95%) and teachers (97%) in Washington are in districts in which the CBAs require seniority to be the sole determining factor in layoff order (LIFO).[15]

III. Data and Analytic Approach

The data used in this study are derived from two educational settings—the Los Angeles Unified School District (LAUSD) and Washington State—over 6 school years, 2007–08 to 2012–13.[16] In both sites the datasets link teachers to their students, schools, and districts across years. In addition, both datasets contain information about which teachers received RIF notices. These data are well-suited for our study for many reasons. First, we are able to track teachers' career trajectories (mobility) over time. Second, we can assess which teachers face the various forms of layoff threat that we describe above. Third, the detailed teacher-level data enable us to assess whether responses to layoff threat vary across teachers with different characteristics (experience, credentials, and, for a subset of teachers, effectiveness as measured by value-added models (VAMs)). Last, each setting offers distinctive policy mechanisms—within-district (LAUSD) and across-district-within-state (Washington State)—to investigate. In what follows, we describe the longitudinal data we use along with the analytic approach we employ to answer the following research questions: (1) *To what extent do the above types of layoff threat affect the mobility of teachers?*; and (2) *Is there evidence that layoff threat differentially influences the mobility of teachers according to their effectiveness, training, or experience?*

[15] In 2012, after the recession, the Washington legislature passed ESSB 5895, which requires districts to incorporate the state's new evaluation system as one of "multiple factors in making human resource and personnel decisions."

[16] Our main models rely on data that extend back to 2008–09, although results do not change substantially when we include the 2007–08 school year in our main models.

Longitudinal Data in LAUSD and Washington State

For each site we use panel administrative data that track all teachers within each system over time. These data include employee demographic information (e.g., race/ethnicity, gender, years of experience[17]); teachers' educational backgrounds (e.g., highest degree earned and endorsements/credentials held by each employee[18]); job title, contract status (e.g., permanent, probationary); and teachers' school and classroom placement.[19] 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. In both datasets, we limit our analytic samples to capture certificated personnel teaching K–12 schools in the given school year. The primary data 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.

These administrative 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), including each school's aggregate performance (in LAUSD, the Academic Performance Index score (API), a composite score that combines various

[17] In LAUSD, available datasets track experience differently: One caps experience at "10 or more years" (in line with the salary schedule) and another (which we use in our main models) includes teachers' years of experience beyond the 10th year. As a specification check, we ran all of our models using both definitions of experience and specified each as either a continuous or categorical variable. Our results are consistent across all variables and specifications.

[18] In Washington, we use the PESB credentials database to obtain measures of teacher endorsement areas. Teachers are designated into 10 areas for which special credentialing is typically required: math, science, English/reading, social studies, elementary education, special education, health/PE, arts, languages, and other (including agriculture/technology, office staff, administration, etc.). In LAUSD, we obtain these data from the HR dataset, which provides all endorsement areas for each teacher in the district. Because many teachers have more than one endorsement area, these categories on not mutually exclusive. 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.

[19] In LAUSD, we were provided teachers' schools placements from three sources taken at different times in the school year. Our preferred location identifier comes from the teacher demographic file, which records teachers' school locations in October of each year. However, we use alternate location sources as specification checks and results are consistent across data sources. As an additional specification check, we coded only those teachers who left the district or switched schools as exiting their schools, and coded teachers who returned to their school the following year in a nonteaching position as remaining in their school. Again our results were consistent across this alternate school exit coding.

student performance measures into a single weighted measure, and in Washington the Washington Assessment of Student Learning [WASL]), total student enrollment, number of students tested, and the percentage of students who are classified in the following categories: special education; enrolled in free or reduced-price lunch programs; reclassified English proficient; African American; Asian; Filipino; Hawaiian/Pacific Islander; Latino; and White. These teacher data can be 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. For a particular subset of teachers—those teachers in tested grades and subjects (ELA and math teachers in third through eighth and tenth grades)—we can estimate value-added measures of teachers' effectiveness.[20] We restrict our data in each site to "classroom teachers."[21] Our final analytic dataset includes 106,260 teacher–year observations in LAUSD and 224,794 teacher–year observations in Washington in the years 2008–09 through 2011–12. In 2011–12, these data include 24,582 unique LAUSD teachers in 658 schools and 55,209 unique teachers in 2,238 schools in 295 Washington districts.[22]

Layoff Threat and Mobility Outcomes

The LAUSD data included 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 the 2008–09 and 2009–10 school years. For

[20] There is no universally accepted method for estimating teacher VAMs (see, for example McCaffrey et al. (2009), Ishii and Rivkin (2009), Kane and Staiger (2008), Rothstein (2009), and Todd and Wolpin (2003)); the specific model we employ is described in detail in Appendix B.

[21] In LAUSD we limit our analytic sample to teachers in K–12 district schools and dependent charters. We exclude nontraditional schools (e.g., community day schools, alternative schools, early education and special education centers). We include all teachers with teaching job titles listed in the nonadministrator demographic file that can be linked to a school site. Our results are consistent when we limited the dataset to only those with teaching job titles and that are linked to students in the student-level data. 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.

[22] Additionally, we use data from 2007–08, the period before there were any budget-based RIFs or layoffs, for our placebo tests. This year of data includes 29,373 and 56,856 unique teachers in LAUSD and Washington, respectively.

subsequent years (2010–11 and 2011–12), the authors surveyed and received responses from each of Washington's 297 school districts about which teachers were issued RIF notices.[23]

The policy-induced layoff threat data in LAUSD were provided by the district and were publicly available on the district website. These data consist of lists of "Reed schools" (i.e., affected by the *Reed vs. California* ruling) in 2010–11, 2011–12, and in both 2010–11 and in 2011–12. As described above, we also use our administrative data to construct a set of comparison schools that are similar to Reed schools but not in fact treated by the policy. Reed, comparison, and the remaining LAUSD schools are described in in Appendix Table A1. For Washington we obtain the district-level layoff threat through analysis of CBAs, which were collected beginning in the summer of 2012. The CBA data provide information on 273 of 297 districts in the state. There are 24 districts for which CBA RIF-related provision information is not specified or is missing. We merge these sources of information with our longitudinal datasets, described above, enabling us to generate precise indicators of each type of layoff threat described above in **Tables 1–3**.

We use the teacher-level administrative data to ascertain teachers' mobility outcomes. In both sets of data, we measure two main mobility outcomes: (1) return to the same school; and (2) exit the school, which includes both exiting the school and the district (and, in the case of Washington, exiting the profession in Washington public schools). These categories are mutually exclusive. The bottom panel of **Table 2** shows the proportion of teachers who fall into each outcome category, separated by RIF treatment. In robustness checks (shown in Appendix Tables A3 and A4), we also examine multinomial outcomes, incorporating two alternative outcomes (return as a teacher to another school in the same district and exit the district).

Analytic Approach

To assess how different types of layoff threat affect the subsequent mobility patterns of

[23] We surveyed districts in the summer of 2012. We also were able to obtain data from the Lind School District before its merge with the Ritzville School District in 2012 as well as the Palouse and Garfield districts, which consolidated in
2008–09 as a direct result of the economic recession. As of 2014, 295 school districts were in Washington.

teachers, we employ logistic regression models that account for a range of student, teacher, school, and, in Washington, district characteristics. Although these models describe teacher mobility, we cannot determine the extent to which the mobility patterns we observe are related to teacher versus administrator preferences; we only observe teachers employed in specific jobs when there are matches between their preferences and those of hiring officials.[24] However, in some sense any employment outcome of a teacher—whether she stays in or exits her school—must reflect that teacher's choice. For instance, a district may give a teacher a RIF notice and then not lay her off, informing her that there is no longer a position in her school but she could work in a different school in the district. This teacher must make the choice to move to another school or exit the district. As such, we discuss teachers' mobility outcomes in the context of RIFs as teachers' choices, recognizing that they may be made under additional employment constraints exerted by the district. It is also worthy of note that these employment constraints also may not be administrators' preferences—administrators' choices are similarly shaped by constraints placed upon them by the layoff policies dictated in their CBAs (Washington) or by the state (LAUSD).

In our logit model, we define $P_{ijkt}(m)$ as the probability that a teacher leaves his or her school. We estimate the log odds of the probability,

$\log\left(\frac{P_{ijkt}(m))}{P_{ijkt}(0)}\right)$, of these outcomes as a function of individual teacher, $\boldsymbol{X_{ijkt}}$,

and school, $\boldsymbol{S_{jkt}}$ characteristics, and a vector of variables identifying different types of layoff threats, $\boldsymbol{THREAT_{ijkt}}$; indexing for individuals (i), schools (j), districts (when examining Washington data) (k), and time (t):

$$\log\left(\frac{P_{ijkt}(m))}{P_{ijkt}(0)}\right) = \beta_{0m} + \beta_{1m}\mathbf{X}_{ijkt} + \beta_{2m}S_{it} + \beta_{3m}THREAT_{ijkt} + \gamma_t + \varepsilon_m$$

The individual teacher variables in **X** include teachers' experience, race/ethnicity, gender, credentials, educational backgrounds, and national board certification. We include these measures

[24] For a more comprehensive discussion of this matching issue, see Boyd et al. (2013).

because these teacher characteristics are plausibly associated with their mobility decisions. For instance, teachers with less experience are more likely to exit schools and districts and leave the profession than are more senior teachers (Boyd et al. 2011; Boyd et al. 2005; Ingersoll 2001). Similarly, female and male teachers may exhibit different trajectories throughout their careers (Hanushek, Kain, and Rivkin 2004). In addition, as discussed above, teachers with varying levels of effectiveness, different market opportunities (e.g., with particular training or educational backgrounds) and/or who teach in high demand fields (i.e., endorsement shortage areas) may be differentially affected by layoff threat.

The school-specific variables in the models include schools' size (natural log of enrollment); the proportion of minority students; school level (K–12, middle, and high, with elementary as the reference category); and indicators for school performance level (for LAUSD we control for whether or not a school is in the highest quintile or lowest quintile of API performance, and for Washington we use student achievement measures from the state's annual assessment standardized by year and grade level).[25,26] We include these controls because they, too, are likely to affect teachers' mobility decisions (e.g., Hanushek, Kain, and Rivkin 2004; McCaffrey and Lockwood 2004).

Our main focus is on the estimated effects of the threat variables. As shown in **Table 1,** we assess the direct threat of layoff as a teacher: (1) not receiving a RIF notice; (2) receiving a RIF notice but having it rescinded; or (3) receiving a RIF notice and being laid off.[27] We focus our discussion below on those teachers who receive a RIF notice but do not get laid off, as they are the teachers who are directly affected by the *threat* of a layoff, but who are given the opportunity to remain in the

[25] We do not include the proportion of students who are in poverty in our models due to collinearity with race/ethnicity and academic achievement measures.

[26] Washington discontinued use of the Washington Assessment of Student Learning (WASL) in summer 2009. For 2010–12 the state Measurements of Student Progress (MSP) is given to students Grades 3–8, while the High School Proficiency Exam (reading) and End of Course exam (math) is given to high school students.

[27] Some teachers in both contexts were laid off but rehired with a reduced workload. According to our data, only 14 LAUSD teachers had their hours formally reduced yet remained in a teaching position following a layoff. In Washington, 254 teachers had their hours reduced following a receipt of a layoff or roughly 8% of the total RIFed population. These teachers switch schools/district/state at comparable rates as to those RIF-rescinded without a reduction in hours.

school system.[28] In some specifications, we interact these threat categories with teacher characteristics that might influence labor market mobility and opportunities in and outside teaching, including experience, endorsement/credential area and effectiveness.[29]

Measuring peer-induced layoff threat is more complex than the relatively straightforward measurement of direct layoff threat. We choose to measure indirect peer-induced layoff threat as the proportion of a teacher's peers in t-1 who received RIF notices and were laid off (i.e., the school-level proportion of RIFs not rescinded in the prior year), controlling for whether or not at least one teacher in the school received a RIF notice. We believe that this definition best captures how teachers see a credible employment threat stemming from the layoff process. We consider three different measures based on differing ways of defining a teacher's peers: a teacher's *current* peers' experience with layoffs in year t-1, a teacher's *prior* year peers' experience with layoffs in year t-1, and the proportion of RIFs not rescinded at the school building, in year t-1 (regardless of whether the teacher was present in the building or not). In **Table 6,** we define each of these as Definitions A, B, and C, respectively. In addition, because the 2008–09 school year was the first in our panel in which teachers were RIFed and/or laid off, we exclude the 2008–09 year from our peer-induced layoff threat analyses.

Finally, when examining policy-induced layoff threat, we switch our analyses to reflect the outcomes that pertain to the specific LAUSD and Washington State policy contexts. Specifically, because the policy-threat (or lack thereof) of interest in LAUSD is the Reed Settlement, which provides protections to teachers in a set of schools, we continue to restrict our outcomes to stay versus exit the school. In Washington, the policy change occurs at the district level, with negotiated

[28] Teachers who were reported to have retired at the completion of a year in which they were RIFed were eliminated for that year given that they likely would have left their schools even in the absence of a RIF notice. However, our results are consistent with or without retired teachers (available from the authors upon request). For Washington, a total of 0.4% of teachers (n = 89) were removed from the sample because they retired. For LAUSD, a total of 2.5% of teachers were removed from the sample because they retired at the end of the year (n = 2,769).

[29] For more on the relationship between teaching specialization and effectiveness and mobility, see Chingos and West, (2012), Goldhaber, Gross and Player (2011), and Hanushek, Kain and Rivkin (2004).

layoff provisions that rely to a greater or lesser extent on seniority. In these models, we examine dichotomous outcomes of stay in versus leave the district.

IV. Results

Our main results can be found in **Tables 4–8: Table 4** and the top panel of **Table 6** provide the log-odds coefficients for the direct and indirect peer-induced layoff threat categories, respectively, and **Table 5** and the bottom panels of **Table 6** provide the marginal probabilities for key variables.[30] All these models are based on data that are pooled across all 4 years. In Washington this pooling of data is supported by Chow tests that fail to reject the null hypothesis that the coefficients are different in any year. In LAUSD the Chow test does reject the null for the 2008–09 and 2009–10 school years, which is not surprising given that in these years there were substantial policy differences from the norm. Year 2008–09 saw a greater proportion of teachers affected than in other years, and was the first year of layoffs for LAUSD. In 2009–10 LAUSD received substantial stimulus funding that limited layoffs. However, given that our coefficients of interest are qualitatively similar whether we pool across all years in LAUSD or estimate the findings separately by year, we report only the pooled results.[31]

Before we turn to a discussion of how layoff threat influences teacher mobility, it is worth highlighting a few ancillary findings. Although we do not report these results in our tables (they are available upon request), they are consistent with the extant literature on teacher mobility. We find that teachers with credentials in science, technology, engineering and math (STEM) fields and special education (SPED) are more likely to leave their schools (Hanushek, Kain, and Rivkin 2004; Ingersoll 2001), and that the likelihood of exit decreases as teachers become more experienced (Clotfelter et al. 2008; Imazeki 2005; Ingersoll 2001; Loeb, Darling-Hammond, and Luczak 2005). In addition,

[30] We calculated adjusted marginal probabilities based on the model described above (in equation 1). Marginal probabilities are estimated based on the population of teachers who received an initial RIF notice. To confirm the accuracy of these marginal probabilities, we also estimate marginal probabilities based on the population of teachers who did not receive an initial RIF notice. In both LAUSD and Washington, our results were similar for each population. In **Table 5,** we report marginal probabilities of mobility outcomes across layoff variables and interactions.

[31] The separate year results are available from the authors upon request.

teachers are more likely exit if they teach in schools with higher proportions of minority students, although this relationship is not significant in Washington State. We also find that teachers in high-performing (top quintile) schools are less likely to exit their schools, whereas teachers in low-performing (bottom quintile) schools are more likely to exit. These results echo those from other contexts (Boyd et al. 2007; Hanushek, Kain, and Rivkin 2004; Lankford, Loeb, and Wyckoff 2002). In line with the literature on teacher mobility, we find that more effective teachers are significantly less likely to leave their schools (Goldhaber, Gross, and Player 2011; Hanushek et al. 2005). Finally, and not surprisingly, teachers who are laid off are significantly more likely to exit their schools. However, as noted earlier, we do not to focus on teachers who are laid off and return to their districts.[32]

In what follows, we first discuss the effects of direct layoff threat on teachers' propensities to exit their schools and how these relationships differ for teachers with varying experience, credentials, and effectiveness. Then we describe the relationship between indirect layoff threats and mobility.

Direct Layoff Threat and Teacher Mobility

In **Table 4** we report the log-odds coefficient estimates for the direct threat variable (RIF-rescinded) and in **Table 5** the marginal probabilities. We find consistent evidence across all models that teachers who face the threat of a layoff are more likely to exit their schools. Moreover, the magnitude of these findings are is large: The top row of **Table 5** shows that the increase in school exit attributable to the receipt and recall of a RIF notice is estimated to be 5.9 and 9.9 percentage points in LAUSD and Washington, respectively. Teachers in LAUSD who are not RIFed have a 16.3% probability of exiting their schools, while those whose RIF has been rescinded have a 22.2% likelihood of school exit. In Washington, these figures are 14.3% and 24.2%, respectively. Considering that the sample mean proportions of teachers who exit their schools are 15.2% in LAUSD and 14.2% in Washington, these findings suggest that there is a substantial impact of RIFs and their recall on teacher churn within districts.

[32] The mobility results for teachers who are laid off in all of our specifications are available from the authors upon request.

There is also evidence that the impact of layoff threat on mobility outcomes varies for different kinds of teachers. First, the relationship between direct layoff threat and mobility outcomes varies by teacher experience level. Panel 2 of **Table 4** and the experience panel in **Table 5** show that, in both LAUSD and Washington, more experienced teachers who face the threat of a layoff are significantly more likely to exit their schools. Although RIFed and rescinded teachers with 1 year or 3 years of LAUSD teaching experience are not significantly more likely to exit their schools than are inexperienced teachers who do not receive RIF notices, 5th-year teachers who are RIFed and rescinded are 4.2 percentage points more likely to exit their schools, and 10th-year teachers who receive RIFs that are then rescinded are 7.6 percentage points more likely to exit their schools then similarly experienced teachers who are not RIFed at all. In Washington, 1st- and 3rd-year teachers who receive RIFs that are then rescinded are 11.0 and 12.4 percentage points more likely to leave their schools than similarly experienced teachers who are not RIFed, and more experienced teachers are even more likely to exit if they receive a RIF notice that is then rescinded.

Next, we examine whether the relationship between layoff threat and mobility outcomes varies for teachers with STEM and special education credentials, relative to teachers with an elementary education credential. **Table 4** confirms what we know from other studies of mobility—that teachers who hold hard-to-staff credentials (STEM and special education) are more likely than elementary teachers to exit their schools. However, **Table 4** suggests that teachers with hard-to-staff credentials whose RIFs are rescinded may be somewhat *less* likely than their elementary counterparts to exit their schools. The credential panels of **Table 5** show these relationships using the marginal probabilities of RIFed versus non-RIFed teachers to exit schools. The significance tests shown in the right-most columns of each panel show the differences between non-RIFed and RIF-rescinded teachers within each credential group. We see that, across all credential types, teachers who are RIF-rescinded are significantly more likely to exit their schools than are teachers who do not face a RIF. This difference is greatest in LAUSD for special education teachers (who are 7.3 percentage points more likely to exit their schools if they receive a RIF notice that is then rescinded

than if they do not receive a RIF notice at all) and for elementary teachers in Washington (the difference being 9.2 percentage points). However, in Washington, special education teachers are *less likely* to respond to a direct layoff threat by increasing their propensities to exit than are elementary teachers. **Table 5** shows that the increased propensity to exit schools for RIF-rescinded versus non-RIFed special education teachers is 5 percentage points lower than the similar difference for elementary teachers. Similarly, in LAUSD, STEM teachers are *less likely* to exit their schools in response to layoff threat than are elementary teachers: The increased likelihood of RIF-rescinded STEM teachers in LAUSD to exit their schools relative to non-RIFed STEM teachers is 3.6 percentage points less than the equivalent difference for elementary teachers (significant at $p < .01$).[33]

Last, **Table 4** shows how the relationship between layoff threat and teachers' likelihood of school exit changes across the distribution of teacher effectiveness. Upon first glance, these results appear to be inconsistent across the two contexts. For LAUSD, the effect of a rescinded RIF appears to be greater for teachers with higher measures of effectiveness. However, the squared term is negative, of greater magnitude and significant at the .10 level. As a result, no clear pattern emerges in nonlinear specifications that use VAM quintiles and deciles (available from the authors upon request). [34] In Washington, our results suggest that more effective teachers whose RIF was rescinded are *less* likely to exit (although only significant at $p < .10$). Because there is not a smooth or consistent increase in the marginal effect of a rescinded RIF along the VAM distribution in either context, we conclude that there is generally little evidence that teachers of differing effectiveness respond differently to the receipt of a RIF notice.

[33] The marginal effect of a rescinded RIF on switching schools is the difference in the adjusted marginal probability of switching schools between teachers who have not been RIFed and those whose RIF has been rescinded. We run separate marginal probabilities and marginal effects commands in STATA to estimate standard errors for each.

[34] Specifically, the positive coefficient we find in our continuous VAM specification for LAUSD appears to be driven by teachers in the 4th value-added quintile (or the 7th and 8th decile, in specifications that use VAM deciles) and these results do not hold for teachers in the 5th quintile (or 9th and 10th decile—those with the highest value-added). When we test alternate VAM specifications such as those adjusted for teacher experience we find virtually no relationship between VAM and the effect of being RIF-rescinded. Results are available from the authors upon request.

Indirect Threats and Teacher Mobility

Peer Threat.

Table 6 provides both the log-odds coefficient estimates for the peer threat models (Panel A) and the accompanying marginal probabilities for key variables of interest (Panel B). Again, we define peer threat as the proportion of a teacher's peers in the previous year who were laid off, of those who received RIF notices. If this proportion is high, it signals to teachers that the receipt of a RIF notice is likely to lead to the loss of employment. If this proportion is low, teachers may feel safe even if they receive a RIF notice. We use the three definitions of peer threat discussed earlier (A, B, and C), and note that our findings are little affected by the definition of a teacher's peers. We report the coefficients on the direct threat variable (RIF receipt and rescission) and note that the relationship between direct layoff threat and mobility outcomes is consistent even when controlling for indirect peer threat. We run our models both on the full sample of teachers, with a control for being affected at all by peer threat (i.e., at least one teacher receives a RIF notice), and on a conditional sample of teachers who were at all affected by peer threat. The results are substantively the same, so we show only the results from the conditional sample. We condition in this way to adjust for the drastically different peer threat contexts in LAUSD and Washington.

Panel A of **Table 6** shows that, across all definitions of peers in LAUSD, peer-induced layoff threat is positively associated with teachers' propensities to exit their schools, and significantly so for definitions A and B. In other words, teachers are *more* likely to switch schools if a greater proportion of their previous year's peers who received RIF notices were eventually laid off. In Washington, we see no significant relationship between peer-induced layoff threat and teachers' propensities to exit their schools. These results are reflected in Panel B of **Table 6,** which can be interpreted as the marginal probabilities of a teacher leaving a school with varying degrees of RIF impact. We consider "low" affected schools to be those in the 10th percentile and "high" affected schools to be those in the 90th percentile. We find that, regardless of which definition of peer threat we use, LAUSD

teachers facing the most peer-induced layoff threat have about 2 percentage points greater probability of exiting their schools, as compared to those facing the least peer-induced layoff threat (also shown in Panel C). These differences are significant at the 90% confidence level across all three definitions. It is no surprise that we do not see substantial differences in the probabilities of exit in Washington based on teachers' peer-induced layoff threat. As discussed above, the Washington and LAUSD contexts are very different. Only 1.6% of teachers in Washington received RIF notices across all 4 years of RIFs, whereas over 13% of teachers received RIFs in LAUSD in the same period. And far fewer teachers in Washington were actually laid off than in LAUSD, (561 vs. 4,445). Given these drastically different contexts, it is unsurprising that peer-induced layoff threat was more poignant in LAUSD.

LAUSD: Policy Threat Associated With Reed Decision.

The results from LAUSD suggest that the Reed protections significantly affected teacher mobility in Reed schools. Panel A of **Table 7** provides results from our difference-in-difference logistic regressions that assess the impact of Reed protections on three sets of Reed-treated schools: schools treated in both years of the intervention (2011/12 Reed schools); schools treated in just the first year of the intervention (2011); and schools treated in just the 2nd year (2012). As described earlier, we compare Reed schools to a set of similar schools that were "near-selected" for Reed treatment. We also estimate difference-in-difference analyses using all non-Reed schools as the comparison group, shown in the right-most column of **Table 7.** We examine the impact of Reed by comparing the average school exit rates in the years pre-Reed to the years in which the schools were treated by Reed, relative to the relevant comparison group. As in earlier models, we measure the impact of Reed protections on teachers' propensities to exit the school relative to staying in the same school. This outcome is particularly pertinent in this policy context because Reed is a school-level treatment, and is intended to reduce teacher turnover in particular schools that have been historically highly affected by both turnover and layoff-induced churn. All values shown in **Table 7** Panel A are marginal

probabilities depicting the impact of the Reed intervention on the attrition of all teachers in Reed schools. We also provide the full logistic regression output in **Appendix Table A2.**

Table 7 Panel A shows that, regardless of comparison group (near-selected or all schools), teachers in Reed schools treated in the 1st year of the intervention (2010–11) and both years of the intervention (2010–11 and 2011–12) are significantly less likely to exit their schools in treated years. The top panel of the table shows that teachers in schools treated by both years of Reed protections are 3.71 percentage points less likely to switch schools, than they would have been in a set of near-selected comparison schools. The second panel of the table shows the difference-in-difference estimate for teachers in Reed schools just treated in the 2010–11 school year. The top row of this panel shows that, relative to the 2 years pre-Reed, teachers in 2011 Reed schools are 2.99 percentage points less likely to exit their schools, relative to teachers in the near-selected comparison schools. However, when the protections are removed from these schools in the 2011–12 school year, teachers become 9.1 percentage points more likely to exit their schools relative to the change between 2010–11 and 2011–12 in similar schools. The bottom of Panel A in **Table 7** provides results for teachers protected by Reed in just 2011–12. Although these teachers are approximately 2.4 percentage points less likely to exit their protected schools in 2011–12, relative to similar teachers in the near-selected schools, this relationship is only significant at $p < .10$. Results remain consistent when we use all non-Reed schools as the comparison group.[35]

Washington: Policy Threat Associated with CBA Provisions.

In the context of assessing the policy threat associated with CBA layoff provisions we focus on whether more junior teachers are differentially likely to stay or leave their districts based on the way that the CBA requires the district to handle layoffs. As shown in **Table 3,** there are relatively few districts in Washington that rely on factors other than seniority for making layoff decisions or that do

[35] As is shown in **Appendix Table A2,** we do not find significant interactions with Reed treatment and experience, suggesting that the impact of Reed does not vary greatly for teachers with different levels of experience.

not have CBA provisions that speak to the way layoff decisions are made. Given this, the sample of teachers observed with different mobility outcomes is quite small, especially for subgroups of teachers such as those with STEM or SPED credentials or varying levels of value-added effectiveness. **Table 7** reports the logit coefficients (Panel B1) and marginal probabilities (Panel B2) for the likelihood that teachers of varying experience leave Washington districts whose CBAs either: (1) require that seniority be used as the sole criterion for layoff decisions ("seniority only districts"), or (2) permit other factors to be considered (both districts that have a CBA that explicitly allows for other factors to be considered and that do not have a CBA so, in principle, have discretion over how layoffs are handled).[36] The omitted category in these models is teachers with 10 or more years of experience in districts that require seniority be used as the sole criterion, so the coefficients should be interpreted as the likelihood of teachers with a specified level of experience leaving a district relative to those with 10 or more years of experience in the seniority-only districts. In essence, we are testing whether a junior teacher in a school district in which there is less policy threat (because seniority may play a reduced role in layoff decisions) is less likely to leave.

Consistent with the notion that teachers respond to policy threat, we observe differences in school attrition between teachers of varying experience levels across district CBA types. Specifically, junior teachers (fewer than 3 years of experience) in districts in which the CBAs allow administrators to consider factors other than seniority in layoff decisions are less likely to leave the district relative to junior teachers in seniority only districts, by about 2.6 percentage points.[37] There are no other experience categories for which the attrition is different across districts' CBA types. These findings are in line with the hypothesis that junior teachers are less likely to leave districts where they face less layoff threat, but we cannot draw strong conclusions given that there may be other unobserved factors in districts with different CBA provisions that also influence teacher attrition.

[36] Factors other than seniority are considered in the case of seniority ties in the seniority-only districts.

[37] Multinomial logit models show that these differences are driven largely by a reduced likelihood that junior teachers leave districts that have CBAs permitting less reliance on seniority. Results are available from authors upon request.

Placebo Test

The results discussed above indicate that there is a significant amount of teacher mobility or "churn" in the workforce associated with teachers who receive RIF notices, but this does not necessarily mean that the RIFs themselves create this churn. Rather it is possible that the teachers who are targeted for RIFs tend to be teachers with differential mobility patterns. To test this possibility, we perform the following placebo test. First, for each site, we estimate a logit of the likelihood of receiving a RIF notice for all the teachers in our (2008–09 to 2011–12) sample. The coefficient estimates are very similar to those reported in Goldhaber and Theobald (2013): Teachers with master's degrees are somewhat less likely to receive a RIF notice and there are some differences in the likelihood of being RIFed across teacher endorsement areas (e.g., math teachers are less likely to receive a RIF notice), but the single strongest predictor of being RIFed is a teacher's experience. For teachers who do receive a RIF notice, we estimate the likelihood of their RIF being rescinded.[38] To our knowledge this outcome has not been assessed before, but the findings are not surprising: Consistent with the language in state statute (in California) and many CBAs (in Washington), the more experienced of the RIFed teachers are likely to have their RIF notice rescinded.

Second, we use the regression coefficients from the above models to predict whether each teacher in the sample would have received a RIF notice in the 2007–08 school year, *the year before there were any budget-based RIFs*. Each teacher in the sample is assigned a probability of receiving a RIF notice based on their characteristics and the schools in which they teach, and assigned to receive a pseudo-RIF if the probability exceeds a randomly generated number between 0 and 100 (generated assuming a uniform distribution). Those teachers who are assigned a pseudo-RIF are then assigned to have that RIF rescinded (or not) using an analogous process with the RIF-rescinded model coefficients.

[38] Again, we use the Goldhaber and Theobald (2013) specification in estimating both the probability of receiving a RIF notice and the probability of having a RIF rescinded.

The categorization of teachers into RIF and RIF-rescinded categories results in samples that look quite similar to the samples of teachers in LAUSD and Washington State in the 2008–09 to 2011–12 period who actually received RIFs and/or had these rescinded. For instance, our pseudo-RIF procedure creates a 2007–08 sample in which 16% of teachers in LAUSD would receive a RIF notice and 70% of these would have that notice rescinded as compared to actual RIF percentages of 13% and 69%, respectively. Similarly in Washington, the pseudo-RIF and pseudo-rescinded percentages are 2% and 83% as compared to actuals of 2% and 84%.

In the final stage of the placebo test, we estimate logit models for the 2007–08 school year using the pseudo-RIF categories, the creation of which we describe above. We include nine experience categories (years 1, 2, 3, 4, 5, 6–7, 8–9, 10–12, 13+) and interact these with the placebo-RIFs to see if it appears that teachers we estimate to receive RIF notices are systematically more or less likely to leave their schools than those who do not *in a year in which RIFs did not actually occur*.[39]

The results of this exercise are reported in **Figure 1.** We show the predictive margins for each experience category for teachers who did and did not receive RIFs in each site in the years in which RIFs occurred (Panel A), and the analogous figures in the 2007–08 years for those teachers who were or were not assigned pseudo-RIFs (Panel B). Panel A of the figure reflects our findings described above—teachers who receive a RIF notice are significantly more likely to leave their school across all experience categories. In Panel B, by contrast, we see that teachers who received a placebo-RIF (i.e., those we estimate would have been targeted for a RIF) are not significantly more likely to leave their schools than those who were not assigned a pseudo-RIF. These findings lend support to the idea that the mobility patterns we report in the main results sections are causally related to the RIFs that teachers receive, not just differential mobility of those teachers who receive RIFs.

[39] Note that we group first and second-year teachers together in the first experience category, because for school years 2008–09 to 2011–12 in LAUSD, only 108 first-year teachers and only 12 received RIF notices. Of those, only two were rescinded and both of those teachers remained in their school the following year. When we perform the placebo test in Washington with separate categories for first- and second-year teachers, there are not significant differences in attrition for teachers in either category when they receive a placebo RIF.

V. Discussion and Policy Implications

Our results make clear that the receipt of unnecessary RIF notices (i.e., they end up being rescinded) results in substantial teacher turnover in schools. Although our findings strongly suggest that RIFs affect teacher mobility, it is difficult to disentangle what causes the RIF-induced churn. Some of our findings likely reflect the structural reasons for which RIFs are rescinded. For example, many teachers who receive RIF notices but who are not subsequently laid off from a district are transferred to a different school site within the district. This is a function of the LIFO layoff policies, which require the most junior teachers in the district to be laid off first, regardless of school-specific needs, leading districts to shuffle teachers between sites. As teachers receive RIF notices and then are laid off, those teachers who received RIF notices that were then rescinded will be relocated to other schools in the district to fill layoff-generated vacancies. As a result, teachers will move around the district in response to RIFs, but this is due to the structure of predominantly LIFO-based RIF policies.[40]

The indirect threat findings, however, are more likely to reflect teacher responses to the layoffs they are seeing or the policy environment in which they find themselves. Peer-induced layoff threat should not structurally affect teachers' mobility: A teacher should not be any more likely to exit her school for structural reasons if more of her peers were substantially affected by RIFs. As a result, any movement we see in response to our measure of peer impact likely is due to peer-induced layoff *threat*. As is shown in **Table 6** and discussed above, we find consistent evidence in LAUSD that teachers in schools with higher proportions of teachers who were RIFed but whose notices were *not* rescinded are *more* likely to exit their schools.[41] These results suggest that peer-induced layoff threat alone may cause teachers to leave a seemingly risky situation. That we do not find these results in

[40] This hypothesis is also supported by our multinomial logistic regression outcomes provided in **Appendix Tables A4 and A5:** The coefficients on the RIF-rescinded variable are positive and significant for switching schools relative to staying, but not significant (or in some cases negative and significant, in Washington) for the leave district estimates.

[41] Multinomial logistic regression results (available from the authors upon request) confirm that LAUSD teachers with greater indirect peer threat are more likely to leave the district, but no more or less likely to switch schools within the district. This is consistent with the hypothesis that our findings result from layoff *threat* and not structural churn.

the Washington context makes intuitive sense: There is little peer-induced layoff threat in Washington schools, especially relative to LAUSD. As a result, we should not expect to see strong reactions to minimal peer-induced layoff threat.

Similarly, in the case of policy-induced layoff threat (or in the case of LAUSD, a reduction in threat), the predominant mechanism by which teacher mobility should be affected is through threat rather than RIF-induced structural mobility. In LAUSD, teachers in Reed-protected schools are less likely to exit their schools, controlling for their own RIF status. This appears to be a clear result of the reduced level of threat they face by being in a protected school relative to an unprotected school within the district, or even an unprotected school in another (unprotected) district. In Washington, we would expect the variation in layoff policies to primarily affect inexperienced teachers, who should feel less threat in a district with a CBA that does not require sole reliance on seniority in layoffs. This is indeed what we see in our results, suggesting that policy-induced layoff threat, or more precisely the policy-induced removal of threat, results in lower attrition for targeted teachers.

Regardless of whether the mobility patterns we see reflect structural moves associated with layoffs or moves associated with teachers' preferences, there are potentially important implications of the churn created by the need to layoff teachers, particularly in reverse order of seniority, and the fact that many more layoff notices are distributed than are required to meet budgetary targets. In particular, as we discussed above, the RIF-induced churn of teachers may affect school culture and student achievement outcomes (Guin 2004; Hanushek and Rivkin 2013; Ronfeldt, Loeb, and Wyckoff 2013). It would stand to reason that RIF-induced mobility—whatever the cause of it—would similarly harm student achievement and school culture, not to mention the damage it might do to the pool of potential teachers seeking stable employment.

To understand the magnitude of our results, we generate a measure of RIF-induced attrition, or churn. To do this, we estimate the predicted probabilities of school exit, based on our baseline model shown in **Table 4.** We then recode the RIF-rescinded variable to zero for all RIF-rescinded teachers and reestimate the predicted probabilities of school exit. This second attrition rate is the

estimated rate of churn if only those teachers who *needed* to be RIFed (i.e., those who were eventually laid off) actually received RIF notices. The difference between these two averages represents the RIF-induced increment to the attrition rate. We find that the average RIF-induced attrition rate is approximately 0.5 percentage points in LAUSD and 0.2 percentage points in Washington. These small figures are to be expected, given that the effects of RIFs are averaged across a great many teachers who do not receive them. In schools that experience more RIF-induced attrition, the impact is estimated to be far greater, and when we focus on the RIF-induced increment to the attrition rate in schools that were at the 90th percentile or above, the figures are 1.1 percentage points for LAUSD (calculated without the schools affected by the Reed decision) and 1.3 percentage points in Washington.[42] Although a 1.1 or 1.3 percentage point increase still seems relatively small, this translates into a 9.9% increase in school-level attrition over the 2008 prelayoff year in LAUSD, and an 8.5% increase in Washington. Clearly, the RIF-induced attrition rates are substantial in both contexts, and, importantly, this mobility is unnecessary from a budgetary standpoint in the sense that it is related solely to the mobility induced by RIFs that end up being rescinded. The reason that the number of RIFs exceeds what is necessary to achieve budget targets is that state laws require that districts notify teachers of potential layoffs far in advance of the actual budgets and student enrollment projections being finalized.[43]

Interestingly, the impact of these laws appears to be far greater in Washington than in LAUSD. A possible explanation for the high RIF-to-layoff ratio in Washington relative to LAUSD may stem from the relatively small size of districts in Washington. For perspective, the average district in Washington has about 3,400 students. (The entire state public school system educates a total of 1 million students across 295 school districts.) By contrast, LAUSD is the second-largest district in the country and educates 640,000 students across 720 square miles. With such size may come greater

[42] This impact would be even greater in Washington if we considered the RIF-induced attrition rate in schools that were at all affected by at least one RIF (as shown in **Table 3).**

[43] Note also that LIFO-based RIFs cause a cascade of churn in that there are more teachers who need to be RIFed under a LIFO-layoff process than one that considers teacher effectiveness (Boyd et al. 2011; Goldhaber and Theobald 2013).

capacity to make more accurate projections of how many layoffs are required to address budgetary needs. Moreover, LAUSD has extensive experience with implementing layoffs (LAUSD has seen consistent enrollment decline for nearly a decade, on the order of 2.5% per year) (Edwards and Prichard 2006; Llanos 2010), necessitating ongoing management of teachers across schools), and a larger and more sophisticated central office staff.

Regardless of the differences between educational contexts, our results make clear that RIF-induced teacher churn is a harmful, and unnecessary, tax on districts. Although the Great Recession is over and most districts have ended or significantly reduced the amount of layoffs required to balance budgets, layoffs, and with them RIFs that are eventually recalled, are not a thing of the past. Teacher RIFs and eventual layoffs exist today, often a result of fluctuating enrollments (e.g., Rich, 2012). And although state and local finances have recovered somewhat from the Great Recession, the next recession threatens to bring with it another round of budget-based layoffs.

All of this points to the need for states and districts to implement policies that protect against future unnecessary RIFs. A simple policy fix would be to remove legislation that requires districts to notify teachers of the potential for loss of employment before budgets are finalized, or that ties notification to a date a specific number of weeks or months after states have provided districts with final budget allocations. Another possible policy would be to incentivize states to determine their final budget earlier by requiring the state to somehow cover all or part of the costs associated with keeping additional employees on the books due to uncertain state budget projections. States could also consider the development of budget risk pools that could hedge against unexpected fluctuations in revenue from enrollment and from state and local tax bases that are at the mercy of the overall economy. Such risk pools might enable districts or states to dampen the effects of revenue fluctuations in ways that can minimize the need for layoffs entirely, but also the need for RIFs that are then recalled. These policies would not entirely solve the problem of RIF-induced churn, but would help to minimize it.

VI. Conclusion

In this paper we provide some of the first evidence demonstrating the *indirect* effects of teacher layoffs on teacher mobility by measuring changes in teacher responses to layoff-induced job insecurities for teachers with varying characteristics and who are embedded within schools and districts with contrasting policy contexts. Specifically, we assess the relationships between direct and indirect teacher layoff threat and teacher mobility within and outside school districts. Overall, we find that layoff threat—or the provision of RIF notices that are often then rescinded—causes substantial teacher churn both between schools within and out of districts. Moreover, we show that policies implemented at the state and district level can reduce the churn associated with layoff threat.

These findings are particularly important to consider as the Great Recession winds down and public school systems begin to restaff schools. Layoffs likely will not get the attention that they did during the Great Recession, but they are a fact of life that arises due to difficulties with matching school needs for teacher labor with revenue changes associated with declining enrollments from population shifts and/or the rise of alternative education solutions (e.g., the rise in charter school enrollments). Given this, it is important that we learn from the recent recession and understand how to enact policies that minimize the damage to existing programs and services; in particular education and the stability of the teacher workforce.

This study sheds light on the policies that dictate how layoffs are instituted and executed and offers lessons for how states and districts might amend current policy to dampen the effects of RIF-induced churn. For instance, state and district policies that dictate the timing of layoffs might be revised to allow for more accurate predictions of layoff requirements. Similarly, district-level policies that require RIFs and layoffs to be executed based on teacher seniority might be reconsidered to enable districts to reduce the amount of layoff-induced churn between schools. In addition, states and districts can implement or change policies that exist to protect certain high-need schools from being adversely affected by layoff policies, as the Reed Settlement did in LAUSD. There is also a

potential role for budget risk pools that would help diminish the impacts of RIF-induced churn. All of these policies would help schools and students during times—recessions or other fiscal hardships—when students and teachers need the most stability. Without revisions to current state and local policies, we can expect to see the next recession or time of budget uncertainty lead to another round of the RIF-induced teacher shuffle.

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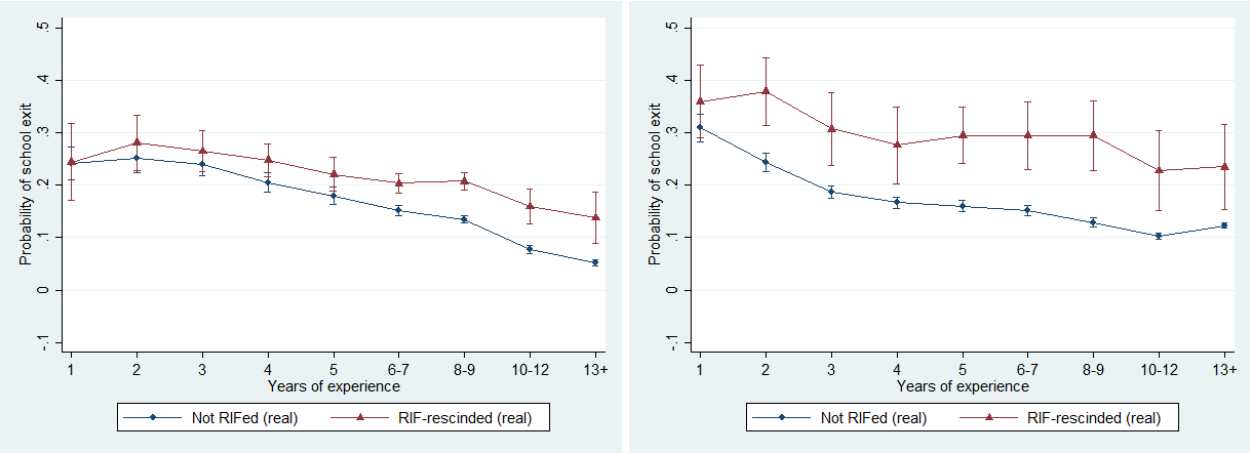
Figures

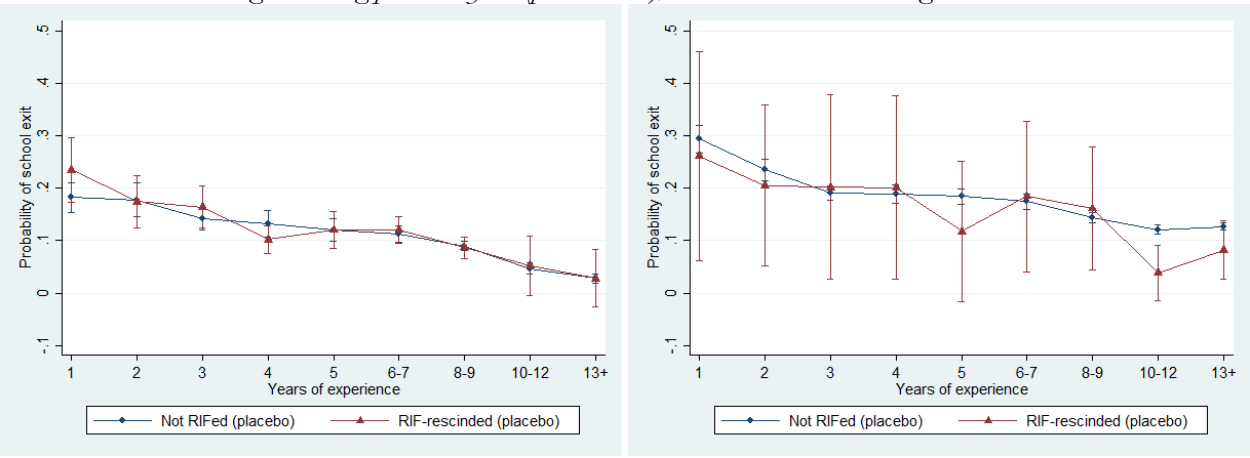
Figure 1. Predictive margins by experience category for teachers who did and did not receive RIFs, during RIF years (Panel A) and during the pre-RIF year (placebo test, Panel B).

Figure 1. Predictive margins by experience category for teachers who did and did not receive RIFs, during RIF years (Panel A) and during the pre-RIF year (placebo test, Panel B)

Panel A. Predictive margins during RIF years, LAUSD and Washington



Panel B: Predictive margins during pre-RIF year (placebo test), LAUSD and Washington



Tables

Table 1. Teachers Layoff Threat Status, by Year and Location

	LAUSD					Washington				
	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
Percent of teachers RIFed	16.76	8.15	14.56	13.52	13.31	3.34	0.76	1.59	0.55	1.57
Percent 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
Percent let go of those RIFed	27.81	6.56	13.29	9.30	16.32	12.33	16.27	14.86	27.87	14.78
Percent let go of those laid off	74.83	40.28	39.37	30.65	51.92	95.16	88.46	93.01	92.39	93.23

Note: RIF stands for Reduction-in-Force. RIF-rescinded refers to teachers who received an initial RIF notice, but later had the notice rescinded.

Table 2. Summary statistics by layoff threat level (teacher–year observations)

	LAUSD				Washington			
	Percent overall	No RIF	RIF		Percent overall	No RIF	RIF	
			RIF-rescinded	Laid off			RIF-rescinded	Laid off
All teachers	106,260	92,118	9,697	4,445	224,794	221,256	2,977	561
		86.69	**9.13**	**4.18**		**98.43**	**1.32**	**0.25**
Experience/Education								
Novice teachers (1st–3rd year)	7.03	60.96	15.95	23.09	10.79	91.66	7.21	1.13
Midcareer teachers (4th–8th year)	22.10	68.30	23.60	8.10	22.42	98.13	1.61	0.26
Veteran teachers (9th year or above)	70.87	94.98	3.94	1.08	66.79	99.62	0.28	0.10
Mean years of experience	10.1	10.9	6.0	4.1	13.9	14.0	4.0	6.3
Master's degree or higher	36.52	87.18	9.26	3.56	65.72	98.89	0.93	0.17
Endorsement Area								
Special Education	14.68	96.93	1.65	1.42	16.93	99.01	0.84	0.16
Health/PE	5.46	92.31	2.90	4.79	9.18	98.91	0.86	0.23
Science	5.86	92.26	6.52	1.22	9.14	98.82	0.98	0.19
Foreign Languages	3.07	91.53	3.99	4.48	5.08	98.83	0.92	0.25
Math	7.34	89.75	9.22	1.03	8.03	98.55	1.24	0.22
Agriculture/Tech/ Other elective	4.44	88.75	5.87	5.38	15.26	98.95	0.77	0.28
Social Studies	9.12	87.63	7.44	4.93	20.72	99.01	0.77	0.21
English/LA	11.38	85.44	9.31	5.25	22.98	98.61	1.18	0.21
Elementary Ed	42.69	82.77	12.68	4.55	53.56	98.44	1.37	0.19
Arts	6.85	81.77	10.34	7.89	8.83	98.35	1.37	0.28
Binary outcomes								
Stay at school	84.81	88.22	79.13	26.61	85.76	86.19	69.40	4.46
Leave school	15.19	11.78	20.87	73.39	14.24	13.81	30.60	95.54
Multinomial logit outcomes								
Switch schools in district	7.21	5.97	12.48	21.46	5.77	5.56	22.14	2.32
Leave district	7.98	5.81	8.39	51.92	8.47	8.25	8.46	93.23

Note: The "Percent overall" columns show the overall percentage of teachers with that characteristic, endorsement area, or mobility outcome. With the exception of the first row in the "All teachers" row and the "Mean years of experience" row, results are reported in percent values. For teacher characteristics and endorsement areas, rows sum to 100% within threat types ("No RIF," "RIF-rescinded," and "Laid off"), whereas in the binary outcomes panel, columns sum to 100%. In the "Multinomial logit outcomes" panel, columns sum to the percentage that exited their school.

Table 3. Indirect threat by year and location (restricted to schools with at least one peer RIF in building)

Panel A: Peer Threat

	LAUSD					Washington State				
	2008–09	2009–10	2010–11	2011–12	Mean	2008–09	2009–10	2010–11	2011–12	Mean
At least one peer RIFed	96.79	88.32	97.80	97.30	94.91	38.30	12.61	19.18	6.89	19.39
Percent of peers RIFed in building										
10th percentile	5.75	1.50	6.56	6.49	3.45	2.56	1.38	2.43	1.35	2.53
50th percentile	14.81	7.00	13.64	12.73	11.76	6.38	3.85	5.41	4.00	4.78
90th percentile	31.13	18.18	27.27	26.19	24.24	17.37	12.72	15.61	16.47	15.81
Percent laid off in t-1 that were RIFed in t-1										
10th percentile	–	0.00	0.00	0.00	0.00	–	0.00	0.00	0.00	0.00
50th percentile	–	9.52	0.00	20.00	10.71	–	0.00	0.00	0.00	0.00
90th percentile	–	33.33	81.82	55.56	50.00	–	0.00	33.33	25.00	25.00

Panel B: Policy Threat

	LAUSD							
	2008–09		2009–10		2010–11		2011–12	
Policy	Teachers	Schools	Teachers	Schools	Teachers	Schools	Teachers	Schools
School selected for Reed in both 2010–11 and 2011–12	2,223	27	1,992	27	1,819	32	1,655	32
School selected for Reed in 2012 only	1,054	10	951	10	868	10	734	13
School selected for Reed in 2011 only	250	7	255	9	336	13	342	13
Comparison schools	7,729	140	7,122	143	6,902	155	6,484	164

	Washington							
	2008–09		2009–10		2010–11		2011–12	
Policy	Teachers	Schools	Teachers	Schools	Teachers	Schools	Teachers	Schools
Seniority is sole factor	55,283	2,093	54,263	2,093	54,442	2,131	53,409	2,128
Seniority one of several factors ("includes not specified")	1,964	113	1,794	105	1,839	109	1,800	110

Note: A set of 45 schools was selected for the Reed layoff protection in the 2010–11 school year. A second set of 45 schools was selected for Reed for the 2011–12 school year, of which 13 had not been selected the prior year. Therefore, a total of 58 schools were selected for Reed in either 2010–11 only (n = 13), 2011–12 only (n = 13), or in both years (n = 32). Because the Reed was targeted, in part, to new schools, the total number of Reed schools present in the district during the 2008–09 and 2009–10 schools years is lower than 58. The number of schools in Washington State changes markedly; however, these numbers comport with changes in total schools according to NCES (Common Core Data 2009–2011).

Table 4. Log odds coefficients showing the relationship between direct layoff threat and mobility, with experience, credential area, and VAM interactions, LAUSD and Washington State, 2008–09 to 2011–12

	(1) Baseline model		(2) Experience interactions		(3) Endorsement interactions		(4) VAM interactions	
	LAUSD	WA	LAUSD	WA	LAUSD	WA	LAUSD	WA
RIF-rescinded	0.394***	0.682***	-0.066	0.534***	0.501***	0.775***	0.421***	1.134***
	(0.041)	(0.104)	(0.110)	(0.151)	(0.060)	(0.135)	(0.079)	(0.295)
Experience	-0.117***	-0.128***	-0.130***	-0.129***	-0.115***	-0.128***	-0.126***	-0.121***
	(0.008)	(0.006)	(0.009)	(0.006)	(0.008)	(0.006)	(0.017)	(0.008)
Experience squared	0.001***	0.003***	0.001***	0.003***	0.001***	0.004***	0.001+	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Experience x RIF-rescinded			0.089**	0.062*				
			(0.028)	(0.030)				
Experience squ x RIF-rescinded			-0.002	-0.002*				
			(0.002)	(0.001)				
SPED	0.338***	0.332***	0.328***	0.332***	0.398***	0.245***	0.07	0.190**
	(0.045)	(0.032)	(0.045)	(0.032)	(0.050)	(0.030)	(0.181)	(0.073)
STEM	0.411***	0.212***	0.420***	0.211***	0.492***	0.112***	-0.086	0.241***
	(0.065)	(0.030)	(0.066)	(0.030)	(0.072)	(0.029)	(0.194)	(0.057)
SPED x RIF-rescinded					-0.040	-0.419*		
					(0.172)	(0.165)		
STEM x RIF-rescinded					-0.327**	-0.182		
					(0.118)	(0.175)		
VAM average							-0.830***	-0.561***
							(0.144)	(0.099)
VAM average squared							1.151**	0.056
							(0.371)	(0.285)
VAM average x RIF-rescinded							0.532*	-1.714+
							(0.271)	(0.962)
VAM average squ x RIF-rescinded							-1.429+	-11.754***
							(0.840)	(2.534)

Note: Models shown in this table include covariates for teacher and school characteristics. Because we control for layoff, the reference category for RIF-rescinded and its interactions are teachers who were not RIFed. The reference category for credential variables is an elementary endorsement. When we run our baseline model on just the VAM sample, our results are generally consistent. Full results are available from the corresponding author upon request. + p < .10, * p < .05, ** p < .01, *** p < .001.

Table 5. Marginal probabilities of exiting a school for different kinds of teachers facing direct layoff threat

	LAUSD			Washington State		
	No RIF	RIF-re	Marginal Effect of RIF-re	No RIF	RIF-re	Marginal Effect of RIF-re
Overall	16.34	22.21	5.86***	14.28	24.16	9.88***
	(0.004)	(0.006)	(0.006)	(0.003)	(0.018)	(0.018)
Experience						
1st year	26.71	25.49	-1.22	25.28	36.23	10.95***
	(0.011)	(0.019)	(0.020)	(0.008)	(0.033)	(0.033)
3rd year	22.19	24.00	1.81	21.03	33.40	12.37***
	(0.007)	(0.011)	(0.012)	(0.006)	(0.024)	(0.024)
5th year	18.38	22.55	4.17***	17.73	30.91	13.19***
	(0.005)	(0.007)	(0.008)	(0.005)	(0.019)	(0.020)
10th year	11.53	19.12	7.59***	12.49	26.08	13.59***
	(0.003)	(0.007)	(0.007)	(0.003)	(0.024)	(0.024)
Credential						
Elementary	12.14	18.42	6.28***	12.91	22.13	9.22***
	(0.005)	(0.008)	(0.008)	(0.003)	(0.023)	(0.023)
SPED	16.96	24.25	7.29*	15.01	19.27	4.26+
	(0.004)	(0.029)	(0.030)	(0.004)	(0.022)	(0.022)
STEM	18.29	20.95	2.67+	13.46	20.84	7.38***
	(0.008)	(0.014)	(0.016)	(0.003)	(0.022)	(0.022)

Note: Marginal probabilities are adjusted for all covariates in the logistic regressions described above and based on teachers similar to those who received a RIF notice. The column labeled "No RIF" reports the probability that a teacher exits her school given that she was not RIFed. The column labeled "RIF-re" reports the probability that an otherwise similar teacher whose RIF was rescinded exits her school. The adjusted marginal probabilities shown in the row labeled "Overall" correspond to our baseline model with no interactions. The panel labeled "Experience" corresponds to Model 2 of Table 4, which interacts experience with layoff threat, while the panel labeled "Credential" corresponds to Model 3 of Table 4, which interacts credentials with layoff threat. The column labeled "Marg. Effect of RIF-re" represents the difference between marginal probabilities; significance tests measure whether these values are significantly different than zero. As shown in Table 4, the marginal effect of RIF-rescinded increases with additional years of experience in both contexts, as demonstrated by the RIF-re X experience interaction. Table 4 also shows that the effect of RIF-rescinded is significantly lower for STEM teachers in LAUSD ($p < .10$) and SPED teachers in Washington ($p < .05$), as compared to elementary teachers. Adjusted marginal probabilities and marginal effects based on teachers similar to those who were not RIFed are generally similar to (although consistently lower than) those reported here and are available from the authors upon request. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6. Log odds coefficients and marginal probabilities showing the relationship between mobility and indirect peer threat, LAUSD and Washington (restricted to schools with at least one peer RIFed)

	LAUSD			Washington		
	Panel A: Log odds coefficients					
Definition:	A	B	C	A	B	C
Peer threat						
Percent laid off in t-1 RIFed in t-1	0.293*	0.264*	0.281	-0.043	-0.094	-0.128
	(0.140)	(0.124)	(0.183)	(0.101)	(0.085)	(0.082)
Threat level						
RIF-rescinded	0.378***	0.494***	0.404***	0.462**	0.461**	0.418**
	(0.047)	(0.049)	(0.057)	(0.177)	(0.170)	(0.151)
	Panel B: Marginal probabilities					
	10th Percentile	50th Percentile	90th Percentile	10th Percentile	50th Percentile	90th Percentile
Current peers (definition A)	14.52	14.86	16.19	14.65	14.65	14.50
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
Year t-1 peers (definition B)	13.05	13.86	15.16	13.73	13.73	13.46
	(0.006)	(0.004)	(0.007)	(0.005)	(0.005)	(0.004)
School-level (definition C)	14.89	15.57	17.17	14.98	14.98	14.59
	(0.008)	(0.006)	(0.011)	(0.005)	(0.005)	(0.004)
	Panel C: Difference in marginal probabilities					
	10th–50th	50th–90th	10th–90th	10th–50th	50th–90th	10th–90th
Current peers (definition A)	0.35	1.33+	1.68*	0.00	0.00	-0.15
Year t-1 peers (definition B)	0.81	1.30+	2.11*	0.00	0.00	-0.27
School-level (definition C)	0.68	1.60	2.28+	0.00	0.00	-0.38

Note: The log odds coefficients shown in the first row are from models that include all covariates in our baseline models. We restrict the sample to just those schools with at least one peer RIFed in year t-1 so that the two contexts are more comparable. We also ran these models on the whole sample, both with and without dummies indicating that at least one peer received a RIF notice in year t-1. Our results are not substantially different across these models. All specification checks are available from the authors upon request. We define definition A as: percent of year t peers' RIFs in t-1 that were not rescinded (never missing because everyone has year t peers); definition B as percent of year t-1 peers' RIFs in t-1 that were not rescinded (coded to 0 for new teachers, who do not have year t-1 peers); and definition C as: percent of RIFs that were not rescinded at the building level, regardless of whether or not the individual teachers was in the building last year (coded to 0 for new schools). + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 7. Impacts of indirect policy threat on the likelihood of exit

Panel A: Difference-in-Difference (DID) estimates on the impact of Reed on the likelihood of exiting the school (LAUSD)

	DID Comparison	Comparison schools	All schools
2011/2012 Reed schools			
Mean of 2009–10 to mean of 2011–12	Mean of two pretreatment years to mean of both years of treatment	-3.71*	-3.90*
2011 only Reed schools			
Comparing mean of 2009–10 to 2011	Mean of two pretreatment years and treatment year	-2.99*	-3.84*
Comparing 2011 to 2012	Treatment year and first posttreatment year	9.10***	10.02***
2012 only Reed schools			
Comparing mean of 2009–11 to 2012	Mean of three pretreatment years and treatment year	-2.40+	-1.93

Panel B: District CBA policy interactions with experience predicting the likelihood of exiting the district/public schools (Washington)

Panel B1: Log odds		Panel B2: Marginal probabilities		
	Other factors permitted		Other factors permitted	Seniority primary factor
Experience (< 3)	-0.385**	Experience (< 3)	12.56	15.23
	(0.127)		(0.010)	(0.005)
Experience (3–4)	0.011	Experience (3–4)	11.07	9.57
	(0.115)		(0.010)	(0.003)
Experience (5–9)	0.083	Experience (5–9)	9.71	7.86
	(0.099)		(0.009)	(0.003)
		Experience (10+)	8.42	7.32
			(0.004)	(0.002)

Note: The models reported in this table control for all teacher and school (and district) characteristics in our main models. In panel A (LAUSD), our set of comparable schools represents the schools that were next in line for selection, had the Reed intervention targeted more than just 45 schools each year. These include all schools in the bottom 40% of API showing growth over the previous 3 years with teacher turnover above average for the district and all schools that opened in the previous 2 years that received at least one RIF notice. We perform multiple specification checks with narrower comparison groups, and our results remain substantially the same (available upon request). Panel A shows results from the difference-in-difference analysis when we consider the wide set of comparison schools and all schools in the district. The models reported in Panel B (WA) also control for whether the teacher was laid off and an interaction between the layoff variable and policy (CBA) variables; therefore, the reference group for all layoff threat variables is teachers who were not RIFed. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.