The Effects of Teacher Tenure on Productivity and Selection

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Abstract

I examine productivity and selection effects of K-12 teacher tenure by leveraging variation from New Jersey's TEACHNJ Act, which extended the pretenure period. Using a difference-in-differences design, I evaluate the productivity effects of tenure by comparing fourth-year tenured and pretenured teachers. I find math value-added declines but English language arts value-added and ratings remain unchanged. Focusing on labor market effects, I compare teachers hired before and after TEACHNJ within the same district and experience level. TEACHNJ disproportionately increased male and Black teacher turnover, as the policy was tied to subjective evaluation criteria. TEACHNJ did not impact the quality of the teacher labor market as measured by value-added, though higher rated teachers often filled new vacancies. This matches principal-agent models where schools only use ratings to guide personnel decisions. Overall, tenure generates small declines in math value-added, while reforms tied to subjective evaluations disproportionately increase male and Black teacher turnover.

Keywords: K-12 Teacher Tenure, Evaluation, Value-Added, Turnover, Productivity

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1 Introduction

Teacher tenure is a hallmark of the United States public education system; 55.6% of teacher jobs are secured by tenure (National Center for Education Statistics, 2012). Tenure remains contentious because teachers are a core input into the education production function.[1] Prior to tenure receipt, pretenured teachers may be fired without cause or a hearing. In comparison, tenured teachers may only be dismissed for inefficiency, incapacity, or unbecoming conduct after receiving a hearing. Thus, proponents argue that tenure attracts high-quality teachers through compensating differentials associated with increased job security. Opponents assert that tenure has become a cost-prohibitive barrier to justified dismissals, permitting teachers to shirk responsibilities while protecting low-quality educators. In addition, these reforms are often tied to subjective evaluation criteria, which may disproportionately increase male and Black teacher turnover. Much of this debate hinges on how teachers respond to tenure and how it impacts students. I provide novel evidence to address these questions.

In this paper, I use the Teacher Effectiveness and Accountability for the Children of New Jersey (TEACHNJ) Act and teacher-student linked administrative data to isolate the productivity and selection effects of tenure. The New Jersey Department of Education (NJDOE) provides two measures of teacher performance: value-added and summative ratings. Summative ratings combine student tests scores and classroom observations based on an NJDOE approved evaluation rubric. These rubrics capture competencies, such as lesson planning, classroom management, and professionalism. Ratings[2] measure components of performance that are distinct from value-added, though the rubrics offer scope for evaluator discretion.

To estimate productivity effects of tenure, I leverage the TEACHNJ provision that extended the time to tenure from three to four years. Using a difference-in-differences framework, I compare fourth-year tenured teachers hired before TEACHNJ to fourth-year pretenured teachers hired after TEACHNJ. I find math value-added declines by 0.033 standard

[1] In fact, Figure A1 shows that tenure reforms remain at the forefront of legislative action with 222 tenure laws passed between 1994 and 2020.

[2] I use the terms "summative rating" and "rating" interchangeably throughout the paper.

deviations with no change in English language arts (ELA) value-added or ratings. Estimates from Chetty et al. (2014) equate this math value-added decline to a $237 present value loss per student. However, these estimates remain smaller than the returns to the first four years of experience. Replacing teachers due to these productivity declines would remain counter-productive on average, unless schools account for this lost accrued experience and find novice teachers whose initial math value-added is at least 0.046 standard deviations higher.

Next, I estimate the selection effects of tenure reforms on turnover rates and average performance by comparing teachers hired before and after TEACHNJ. This strategy identifies the labor market effects of weakening tenure protections, though the policy variation does not estimate the effects of eliminating tenure. TEACHNJ disproportionately increased male and Black teacher turnover, as they received lower average summative ratings and the reforms were tied to subjective evaluation criteria.[3] However, these teachers produced similar value-added to female and White teachers. Although value-added and ratings capture distinct, potentially valuable components of teacher effectiveness, male and Black teachers only performed less effectively along the one dimension of performance with scope for subjectivity: summative ratings. In fact, biases may influence these ratings because male and Black teachers receive lower ratings when paired with principals of other genders and races. Thus, tenure reforms tied to subjective evaluation criteria may have unintended consequences on teachers who are underrepresented in the profession. Although removing low-rated male and Black teachers improves average teacher quality, the disparate effects on turnover may harm male and Black students because their academic achievement improves when paired with teachers of the same gender (Dee, 2007) or race (Gershenson et al., 2018; Dee, 2004; Egalite et al., 2015).

Finally, TEACHNJ attracted new teachers whose ratings were 0.021 points (0.065 standard deviations) higher but had no effect on value-added. Since TEACHNJ included tenure reforms tied to ratings, average performance improved along the dimension that dictated

[3] Although overall male and Black teacher turnover increased, the effects vary based on each administrator's implementation of TEACHNJ at the district level, as described in Appendix Section A.1.

personnel decisions (ratings) but remained unchanged along other dimensions (value-added). This result aligns with a multitask principal-agent model where only one of several measures of performance is used to evaluate the employee (Holmstrom & Milgrom, 1991; Baker, 2002).

Overall, tenure generates small declines in math value-added, while reforms tied to subjective evaluation criteria disproportionately increased male and Black teacher turnover. Thus, the efficacy of tenure reforms to improve teacher performance is limited.

2 TEACHNJ Act

This study relies on variation from the TEACHNJ Act, which passed on August 6, 2012 as a means to improve student achievement. The law lengthened the pretenure period from three years to four years, introduced a teacher mentor program, reformed teacher evaluation criteria, and modified the tenure appeals process. The TEACHNJ Act was New Jersey's largest teacher tenure reform since it passed comprehensive tenure laws in 1909. The teacher union immediately notified its members about the law, which included 97.6% of New Jersey public school teachers (National Center for Education Statistics, 2012).

The TEACHNJ Act extended the pretenure period from three to four years for those hired on or after August 6, 2012.[4] Since pretenured teachers work on annual contracts, this extension did not guarantee an additional year of employment for pretenured teachers. To receive tenure, teachers hired after TEACHNJ must receive at least two "effective" ratings in their second to fourth years. In comparison, each district designed its own requirements for tenure receipt among those hired before TEACHNJ. Teachers are notified about these tenure decisions by May 15 of their final pretenure year.

During their first year of teaching, novice teachers hired after TEACHNJ receive a mentor to provide feedback, support, and opportunities for modeling. The mentor must be an experienced, "effective" teacher who completed a mentor training program.

[4] Appendix Section A.2 shows that three-year tenure clocks are common throughout the United States.

As described in Appendix Section A.1, teacher evaluation criteria evolved from a two-tier (satisfactory or unsatisfactory) to a four-tier system (highly effective, effective, partially effective, or ineffective). While evaluation criteria previously varied by school, they now rely on Teacher Practice, Student Growth Objectives (SGO), and median Student Growth Percentiles (mSGP).[5] Teachers rated as ineffective or partially effective must create a Corrective Action Plan (CAP) with their supervisors. Each CAP includes specific demonstrable goals, timelines for improvement, and responsibilities of the teacher and school.

Tenured teachers rated ineffective or partially effective for consecutive years may receive a charge of inefficiency. Teachers may receive a third opportunity if the second rating is partially effective. However, three consecutive partially effective or ineffective ratings guarantee a charge of inefficiency. The teacher's employment is then subject to an arbitration process of no more than 48 days. Previously, there was no time limit for the process.

Tenure reforms like the TEACHNJ Act often introduce subjective evaluations, because the original tenure laws rarely provided criteria for evaluation. In fact, only 2 states incorporated performance evaluations in their tenure decisions by 2008 (National Council on Teacher Quality, 2008). More recently, every state began to rely on subjective classroom observations to assess their teachers (Ross & Walsh, 2019). Therefore, when new tenure laws are introduced, they apply the subjective criteria to standardize tenure receipt.

3 Data

I use the NJDOE's teacher-student linked administrative test score data from 2012 to 2018.[6] These math and ELA tests include the New Jersey Assessment of Skills and Knowledge (NJASK) for Grades 3 to 8 from 2012 to 2014, the High School Proficiency Assessment (HSPA) for grades 11 to 12 from 2012 to 2014, and the Partnership for Assessment of Readiness for College and Careers (PARCC) exam for grades 3 to 11 from 2015 to 2018.

[5] Summative ratings for grades 4 to 8 ELA and grades 4 to 7 math teachers rely on Teacher Practice, SGO, and mSGP, while ratings for other teachers only depend on Teacher Practice and SGO.

[6] I define academic years by their spring semesters. For example, I define the 2011-2012 year as 2012.

These data include student gender, race, Free or Reduced-Price Lunch (FRPL) eligibility, English Language Learner (ELL) status, and special education status. In addition, the dataset contains teacher gender, race, and experience.[7] The data lack tenure status information, though districts dismiss teachers who are not offered tenure after the pretenure period. Using administrative records, I mark tenure receipt as an indicator for remaining in the same district for four years if hired before TEACHNJ or five years if hired after TEACHNJ.

I calculate annual value-added using the following regression:

$$A_{ijgst} = \alpha A_{it-1} + \beta X_{it} + \eta C_{it} + \lambda S_{it} + \Theta_{jt} + \varepsilon_{ijgst} \tag{1}$$

where A_{ijgst} is the test score of student i in teacher j's grade g class in school s and year t.[8] I control for the student's previous year test score (A_{it-1}), as well as student, classroom, and school characteristics. The student variables (X_{it}) include gender, race, FRPL eligibility, ELL status, and special education status. The classroom controls (C_{it}) are class size and aggregated student controls. School covariates (S_{it}) include urbanicity[9], enrollment, racial composition, and percentage of FRPL eligible. Value-added is measured annually by Θ_{jt}.

Summative ratings from 2014 to 2018 capture components of performance that are distinct from value-added. Figure 1 shows the correlation coefficient between math and ELA value-added in Panel A (0.522) is over four times larger than those between value-added and ratings (0.118–0.128) in Panels B and C.

These ratings measure performance using a weighted average of Teacher Practice, SGO, and mSGP. In Teacher Practice, supervisors observe classes using an NJDOE approved rubric. These rubrics evaluate various teaching competencies, such as lesson planning, classroom management, and professionalism. Administrators and teachers in each district collaborate to design their own SGO based on state standards. The SGO measure student growth

[7] Table 1 provides summary statistics for students (first column) and teachers (second column). These statistics match expectations given New Jersey's demographic composition and national proficiency rates.

[8] Each grade-year exam is standardized to have mean 0 and standard deviation 1.

[9] I merge urbanicity data from the National Center for Education Statistics (2018) using the crosswalk from the New Jersey Department of Education (2017).

based on the percentage of students improving their scores. Grades 4 to 8 ELA and grades 4 to 7 math teachers rely on mSGP, which measure student growth on state assessments. The mSGP differ from value-added because they only account for previous test scores rather than a variety of student, classroom, and school characteristics.[10]

Table A1 shows the weighting schemes for 2014 and 2017–2018 (first two columns), as well as 2015–2016 (last two columns).[11] Ratings primarily rely on Teacher Practice with some weight placed on student achievement. The odd columns record the weights for subjects that partially rely on state tests. The even columns show the weights for other subjects. Based on these weights, teachers receive a summative rating between 1.00 and 4.00. These ratings place teachers into one of four categories with minimum thresholds included in parentheses: ineffective (1.00), partially effective (1.85), effective (2.65), and highly effective (3.50).

4 Productivity Effects

To estimate the productivity effects of tenure, I use the following difference-in-differences model:

$$y_{jtc} = \gamma ten_{jt} + \sum_{\tau=1}^{T} \delta_\tau \mathbf{1}(exp_{jt} = \tau) + \psi_j + \nu_c + \mu_t + \varepsilon_{jtc}. \tag{2}$$

In equation (2), y_{jtc} is teacher j's performance in year t at school c as measured by value-added or summative ratings.[12] I include an indicator for tenure status (ten_{jt}), as well as experience ($\mathbf{1}(exp_{jt} = \tau)$) and teacher ($\psi_j$) fixed effects. Thus, the model accounts for non-linear returns to experience (first difference) and level differences across teachers (second difference). Treatment is separately identified from experience because year 4 tenure status varies by date of hire. In year 4, those hired before TEACHNJ receive tenure (treated

[10] Betebenner (2011) provides a detailed description of the Student Growth Percentile methodology.

[11] For 2015–2016, the NJDOE reduced mSGP weights to give educators time to acclimate to the PARCC tests (Shulman, 2016). The rating effects are robust to limiting the sample to 2015–2016 (not shown).

[12] I simplify the value-added model to one step as described in Appendix Section A.3.

group), while those hired after TEACHNJ do not receive tenure (control group).[13] I only include school (ν_c) and year (μ_t) fixed effects in the rating regressions because test scores are demeaned each year and the value-added equation controls for school characteristics.[14] The coefficient of interest (γ) would be negative if tenure eliminates some effort incentives.

In Table A2, I describe the sample restrictions and record the number of remaining observations. I restrict the analysis to math and ELA teachers with non-missing value-added in years 2 and 3 to guarantee multiple observations of pretenure performance. For the rating regressions, I also limit the samples to teachers with non-missing ratings in years 2 and 3. I cluster standard errors at the school level to account for autocorrelation in the residuals generated by each principal's implementation of TEACHNJ.[15]

4.1 Productivity Effects Assumptions

In equation (2), I separately identify the productivity effects of tenure (γ) from experience fixed effects by leveraging variation in fourth-year tenure receipt based on date of hire. Therefore, equation (2) relies on the assumption that the effects of experience on performance are not changing for those hired before and after TEACHNJ. This assumption has two components: no confounding factors at tenure receipt and identical relative returns to experience, which are analogous to parallel trends. Since the difference-in-differences model compares teachers hired before and after TEACHNJ, the other components of the policy could confound the estimated effect. As a result, γ in equation (2) would capture the productivity effects of tenure in addition to differences in tenure receipt standards and the mentor program. Section 4.2 addresses the core of these confounding factors. These components also may generate differences in the relative returns to experience across cohorts that would bias

[13] The TEACHNJ Act allows me to isolate the productivity effects of tenure from returns to experience because tenure status does not change in years 3 and 4 for those hired after TEACHNJ. The model estimates the returns to experience year 4 using those hired after TEACHNJ and applies the estimates to those hired before TEACHNJ. With this projection, the equation can isolate the impact of tenure on performance.

[14] However, value-added results are robust to the inclusion of school and year fixed effects (not shown).

[15] Results are robust to clustering by cohort and adjusting for few clusters (Cameron et al., 2008) (not shown).

the estimated γ. Section 4.3 addresses this concern.

This policy variation and these assumptions allow me to overcome two obstacles. First, experience and tenure receipt are typically collinear, making it impossible to isolate the productivity effects of tenure when using fixed effects to flexibly control for non-linear returns to experience (Kraft & Papay, 2015; Wiswall, 2013). Second, cross-sectional variation using cross-state comparisons are confounded with teacher unions[16] and human resources policies, such as performance pay (Jones, 2015; Roberts, 2018). Leveraging the TEACHNJ Act, I overcome the fundamental challenge to identifying the productivity effects of tenure: the inability to disentangle it from experience, teacher unions, human resources policies, and voluntary turnover.

4.2 No Confounding Factors at Tenure Receipt

To test for confounding factors, I must address the other components of TEACHNJ. First, I consider the tenure dismissal and appeals reform. Since all observations occur after 2012, every teacher in the sample encountered these changes. Thus, equation (2) estimates the effects of the new, weaker tenure protections rather than the old, stronger protections. The standardized tenure removal procedure and the streamlined appeals process can only bias my estimates if teachers reacted differently to the law over time. This is unlikely because the union immediately informed teachers about the law.

The other potentially confounding aspects of the reform are the first-year mentor program and standardized tenure receipt. Considering the mentor program, prior research has shown mentors generate null effects (Rockoff, 2008) or positive, persistent improvements (Papay et al., 2020). In either case, teacher fixed effects (ψ_j) would capture these level shifts in performance. It could only bias the estimates if the first-year mentor program impacted the

[16] According to National Center for Education Statistics (2012), tenure and union membership are correlated, as 63.5% of teacher union members have tenure. However, they remain distinct, as 33.3% of non-union members also have tenure. Cowen and Strunk (2015) find much of the teacher union literature suggests null to slightly negative effects on student achievement (Hoxby, 1996; Marianno & Strunk, 2018). Similarly, Lovenheim and Willén (2019) find teacher unions have negative effects on student labor market outcomes.

relative returns to experience near tenure receipt in years three and four. In other words, the program would only generate bias if it differentially impacted the returns to experience two years after the program ended. While this is possible, I provide evidence of identical relative returns to experience in the first three years, which supports my empirical design.

Next, I consider standardized tenure receipt. For those hired after TEACHNJ, teachers are incentivized to maximize their summative ratings by increasing student test scores (mSGP and SGO) and earning higher classroom observation scores (teacher practice). For those hired before TEACHNJ, each district relied on its own, potentially opaque evaluation criteria. As a result, TEACHNJ incentivized summative rating performance. This would likely generate a level-shift in performance, as teachers hired after TEACHNJ can focus on the exact relevant dimension of performance. Teacher fixed effects would account for this variation.

In addition, minimum performance standards increased for those hired after TEACHNJ. In Appendix Section A.4, I describe and simulate a model of teacher tenure to address these changes in performance standards. In the model, districts dismiss teachers who fail to meet minimum performance requirements. The minimum performance threshold is higher for pre-tenured teachers than tenured teachers. Since TEACHNJ extended the pre-tenure period and standardized tenure receipt, the law increased the minimum performance thresholds for those hired after TEACHNJ. These stricter standards may increase effort in the first three years relative to the fourth year causing teacher fixed effects to overestimate teacher quality for those hired after TEACHNJ. Specifically, it may attribute some of the fourth-year pre-tenure effort to innate ability. In the difference-in-differences design, this will underestimate the pretenured group's effort relative to that of the tenured group and bias the estimated productivity effects upward. However, when simulating the model to match observed changes in teacher retention, I find the bias is negligible.

4.3 Identical Relative Returns to Experience

As discussed in Section 4.2, the other components of TEACHNJ have little impact on the estimated productivity effects of tenure. However, performance standards became stricter due to the standardized tenure receipt. These differences in performance standards may manifest in differential returns to experiences that would threaten identification. Evidence of identical relative returns to experience before and after TEACHNJ would alleviate concerns regarding these confounding factors. To evaluate this assumption, I estimate the returns to experience using the following equation:

$$y_{jtc} = \sum_{\tau=2}^{6} \beta_\tau \mathbf{1}(exp_{jt} = \tau) * (1 - post_{jt}) + \sum_{\tau=1}^{6} \delta_\tau \mathbf{1}(exp_{jt} = \tau) * post_{jt} + \psi_j + \nu_c + \mu_t + \varepsilon_{jtc}. \quad (3)$$

In this model, y_{jtc} is the annual performance measure (value-added or summative rating), while $post_{jt}$ is an indicator for being hired after TEACHNJ.[17] I include teacher fixed effects (ψ_j) in all specifications. I only include school (ν_c) and calendar year (μ_t) fixed effects in the rating regressions. I limit the sample to teachers in their first six years of teaching to focus on the period near tenure receipt. If $\delta_1 = \delta_2 = \delta_3$, then I have evidence of identical relative returns to experience for those hired before and after TEACHNJ. In Section 4.4, I graph β_τ and δ_τ from equation (3) and connect them to my main results.

4.4 Productivity Effects Results

Following equation (3), Figure 2 shows the event study graphs for math value-added (Panel A), ELA value-added (Panel B), and summative ratings (Panel C). The solid black dots measure the returns to experience before TEACHNJ (β_τ), while the hollow red dots show the returns after TEACHNJ (δ_τ). The relative returns to the first three experience years remain

[17] Teachers may be hired before and after TEACHNJ if they switch districts, so $post_{jt}$ may vary within teachers. However, all results are robust to making $post_{jt}$ time invariant by restricting the sample to teachers in their first district (not shown).

nearly identical, which provide further evidence that the standardized tenure receipt and mentor program do not threaten identification. Given identical relative returns to the first three years, I would expect identical returns to experience year 4 in the absence of differential tenure receipt. Thus, any differences in fourth-year performance would be attributable to tenure. In Panel A, I show that math value-added declines in year 4 when those hired before TEACHNJ receive tenure and appear to experience a productivity decline, while Panels B and C show no such decline for ELA value-added and summative ratings. In year 5, math VA declines slightly for those hired after TEACHNJ who receive tenure, though the difference is not statistically significant.[18] As a result, the year 5 and 6 performance of those hired before TEACHNJ is quite similar to that of those hired after TEACHNJ.

Figure 2 suggests a decline in math value-added for tenured teachers hired before TEACHNJ in year 4 but no change in the other performance measures. I corroborate these findings in Table 2 where I estimate equation (2) using math value-added (Panel A), ELA value-added (Panel B), and summative ratings (Panel C). In Column (1), I estimate the productivity effects among all teachers. Math value-added declines by 0.033 standard deviations, while ELA value-added and ratings remain unchanged. In fact, the 95% confidence intervals rule out productivity declines larger than 0.015 ELA standard deviations and 0.046 rating points. As seen in brackets, the point estimates are −0.106, 0.025, and −0.057 teacher standard deviations of math value-added, ELA value-added, and summative rating points, respectively.[19] The productivity effects are smaller than the returns to the first four years of experience, which are 0.079 standard deviations, 0.043 standard deviations, and 0.19 points for math

[18] In Figure 2, there is a much smaller decline in performance at tenure receipt for those hired after TEACHNJ in year 5 than for those hired before TEACHNJ in year 4. At the same time, there appears to be relatively large returns to experience between years 4 and 5 for tenured teachers hired before TEACHNJ. Since tenure status does not change for those teachers, the improvements are likely attributable to experience. If there are identical relative returns to experience, the year 5 tenure productivity decline for those hired after TEACHNJ would be offset by large returns to the fifth year of experience causing minimal declines in math VA for these teachers.

[19] In all tables relying on performance as the dependent variable, the main effects are measured in student test score standard deviations. I also include a standardized estimate of the effect in brackets by dividing the coefficient by the standard deviation of teacher performance in the sample.

value-added, ELA value-added, and ratings, respectively.[20]

The smaller effects on ELA relative to math in Table 2 match common patterns in the literature (Taylor & Tyler, 2012; Hanushek & Rivkin, 2010; Aucejo et al., 2019; Biasi, 2021; Roth, 2017; Ost, 2014; Nagler et al., 2015; Wiswall, 2013). Previous research has offered multiple explanations for this trend. First, math is primarily learned in the classroom, whereas out of school exposure to ELA is quite common. As a result, teachers have more influence over math performance than ELA performance (Jackson et al., 2014). Second, reading tests are not as sensitive to teacher effort (Kane & Staiger, 2012). Since teachers have more control over math scores than ELA scores, the negative productivity effects of tenure manifest in math value-added declines.

I also consider additional threats to identification due to selection into tenure, occupation sorting, and value-added bias. Since turnover rates varied before and after TEACHNJ, the regression may confound the effects of tenure with selection. In Figure 2, identical relative returns to experience suggest limited scope for selection to bias the estimates, though I can further account for this problem in three ways.

First, I bound the results in Appendix Section A.5 following Lee (2009). The math value-added, ELA value-added, and summative rating effects are bound by $[-0.059, 0.001]$, $[-0.037, 0.059]$, and $[-0.043, -0.003]$, respectively. Even the worst-case scenarios show the productivity effects of tenure on math value-added remain smaller than early career returns to experience, while tenure has little to no effect on ELA value-added or summative ratings.

Second, I use predetermined characteristics to limit the sample to teachers who are unlikely to turnover. Using teachers hired after TEACHNJ, I regress persistence into year 4 on initial rating, race, gender, cohort, and district. I predict persistence among those hired before and after the law. I remove the bottom 27% of predicted values among both groups to match turnover rates after TEACHNJ and generate a counterfactual group that accounts

[20] These values were calculated by regressing the performance of teachers hired after TEACHNJ on experience and teacher fixed effects. These teachers received tenure in year 5, so the returns to experience are not confounded with tenure receipt in the first four years.

for potential changes in selection into teaching. Column (2) of Table 2 shows the estimated productivity effects for these teachers are similar to those found in Column (1).

Third, I estimate equation (2) with a sample that only includes "high-quality" teachers who are likely to receive tenure. Since TEACHNJ relies on ratings to make personnel decisions,[21] I define "high-quality" teachers as those whose third-year performance exceeds the twenty-fifth percentile of third-year ratings for eventually tenured teachers. Column (3) of Table 2 shows the estimated productivity effects for "high-quality" teachers are quite similar to those found in Column (1). These three tests provide evidence that equation (2) accounts for this selection bias. These results also show that teachers who are likely to receive tenure still experience negative productivity effects.

Another threat to identification is occupation sorting in response to TEACHNJ. Occupation sorting could bias the estimates in either direction if they altered the returns to experience. However, Figure A3 shows similar trends in education bachelor's (Panel A) and master's (Panel B) degrees awarded in New Jersey colleges (dashed red and dashed and dotted blue) relative to other United States colleges (solid black). The supply of new teachers appears to be unaffected by the passage of TEACHNJ.[22] To further reduce the likelihood of sorting by teachers-in-training, I limit the sample to teachers hired before 2013. As college seniors or certified teachers when TEACHNJ passed in 2012, these prospective teachers had little time to change occupations.[23] Column (4) of Table 2 shows the results are robust to samples with limited scope for sorting.[24]

In addition, value-added biases may arise if teachers have systematically different class compositions before and after receiving tenure (Rothstein, 2017). Tenured teachers may

[21] Figure A2 plots tenure receipt rates by pretenure performance. Ratings are strong predictors of tenure receipt (Panel C), while math (Panel A) and ELA (Panel B) value-added are weak predictors.

[22] In Section 5.2, I find TEACHNJ did not impact new hire quality besides a slight increase in ratings.

[23] Although introduced to the senate on February 6, 2012, the bill had little media coverage prior to June 2012. Since teacher certification programs require several semesters of coursework, it is unlikely that teachers-in-training anticipated the policy and changed majors that late in their college careers.

[24] Sorting into other states and charter schools also threatens identification. However, cross-state sorting is limited by licensure requirements and pension structures (Goldhaber et al., 2015). Also, tenure concerns would not cause public school teachers to switch to charter schools, which have weaker tenure protections.

receive preferential treatment if districts allow them to select students who are most likely to improve. To evaluate this hypothesis, I estimate the following regression:

$$C_{jt} = \gamma ten_{jt} + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}(exp_{jt} = \tau) + \varepsilon_{jt}. \tag{4}$$

In this model, C_{jt} includes class size, class demographics (gender, race, FRPL, ELL, and special education composition), and an indicator for switching grade levels. The coefficient of interest (γ) identifies the effect of receiving tenure on the outcome. If $\gamma \neq 0$, tenured teachers may be manipulating their class rosters.

Using equation (4), Table A3 shows tenured teachers switch grades less frequently, have fewer Black students, and more FRPL eligible students. The value-added models control for student race and FRPL eligibility but do not account for grade switching.[25] Previous research finds that switching grades leads to short-term value-added declines (Ost, 2014). This would bias tenured teachers' performance and the estimated effects of tenure upward.

To test for bias due to grade switching, I reestimate equation (2) with an indicator for whether a teacher switches grades in a given year. This allows level shifts in performance due to grade switching. Column (5) of Table 2 shows the math value-added estimate declines to -0.040 standard deviations but remains statistically indistinguishable from the main results in Column (1). I find no evidence that differences in class composition bias the estimates.[26]

Value-added also may be biased by the transition from the NJASK and HSPA to the PARCC in 2015. Ex-ante, the direction of the bias is unclear. The transition to the new test may lower scores and reduce the value-added of those hired after TEACHNJ reducing the estimated productivity effects. Alternatively, the new test may be easier leading to higher scores and increased estimated productivity effects. To test for bias, I limit the value-added analysis to only years in which the PARCC test was administered.[27] Column (6) of Table 2

[25] The rating results are robust to controlling for Black and FRPL eligible class compositions (not shown).
[26] The results also are robust to excluding teachers who switched grades (not shown).
[27] I cannot estimate the effects of tenure with a sample of only NJASK and HSPA tests because no teacher hired after TEACHNJ had four years of experience prior to 2014. As a result, I do not have any fourth-year pretenured teachers to serve as a comparison group.

shows the difference-in-differences results are robust to limiting the sample to PARCC years.

The estimated effects are robust to a variety of specifications that account for selection into tenure, occupation sorting, and value-added bias. When considering policy implications, the 0.033 standard deviation decline in math value-added from Table 2 is economically meaningful, though practically small. Using partial equilibrium estimates from Chetty et al. (2014), this fourth-year decline equates to a present value loss of about $237 per student.[28]

As discussed in Rothstein (2015), there are multiple ways to overcome this productivity decline. First, districts could increase dismissal rates to remove additional lower-performing teachers. To fill the vacancies, districts would replace these teachers with new hires. However, test scores will only rise if districts replace these tenured teachers with novices of higher initial quality. Specifically, math value-added increases by 0.079 standard deviations between years 1 and 4, while tenure induces a productivity decline of 0.033 standard deviations. As a result, districts would have to hire a novice whose initial performance is at least 0.046 standard deviations (0.15 teacher standard deviations) higher than the teacher they replace. This type of reform would be challenging to implement because it is very difficult to identify teacher quality based on observable characteristics at the point of hire (Hanushek, 1997; Buddin & Zamarro, 2009). Second, districts could eliminate tenure protections. While this policy would eliminate these negative productivity effects, the effectiveness of this reform also depends on selection.[29]

[28] Chetty et al. (2014) estimates a one standard deviation increase in value-added for one grade generates a present value gain of $7,000 per student. I scale this estimate by the 4% of the teacher workforce that has four years of experience, the 0.106 teacher standard deviation decline in math value-added, and the eight grades for which I can calculate value-added.

[29] Either policy could improve teacher quality if the productivity effects demonstrate significant heterogeneity. In Appendix Section A.6, I find the negative effects are concentrated in wealthier, higher-achieving schools with few minority students. However, nearly all the effects remain smaller than the returns to experience in the first four years, so the efficacy of targeted reforms remains limited.

5 Effects on Teacher Retention and Average Quality

While the previous sections found a decline in math value-added, this section evaluates the effects of the tenure reform on the teacher labor market. TEACHNJ may create vacancies, as more stringent requirements increase teacher turnover and alter sorting patterns. These sorting patterns may contribute to inequalities if the teacher workforce becomes less diverse. In addition, weaker tenure protections may remove low-quality teachers, although reduced compensating differentials also may induce high-quality teachers to leave the profession for more lucrative opportunities. As a result, TEACHNJ has a theoretically ambiguous effect on average teacher quality.

When evaluating the labor market impacts of TEACHNJ, I focus on the increased pre-tenure time and standardized tenure requirements because the teacher-student linked data start in 2012. Every observation occurs after TEACHNJ passed, when the standardized evaluation criteria and streamlined tenure removal process had already been universally implemented. However, those hired before TEACHNJ only needed to wait three years to receive tenure, which depended on district-specific evaluation standards. In comparison, those hired after TEACHNJ needed to wait four years and earn at least two effective ratings to receive tenure. In this analysis, I compare teachers hired before and after TEACHNJ.[30]

5.1 Retention Effects of TEACHNJ

TEACHNJ made tenure receipt more difficult. This would increase both the number of pretenure dismissals and the voluntary attrition rate for those hired after TEACHNJ. Fewer teachers will meet the tenure receipt standards, while more teachers will voluntarily quit due to reduced compensating differentials associated with the more arduous process. To evaluate this hypothesis, I estimate the following regression:

[30] The strategy also captures effects from the mentor program, though it likely had far less impact on teacher sorting than tenure reforms that directly impacted job security.

$$y_{jdt} = \gamma post_{jt} + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}(exp_{jt} = \tau) + \nu_d + \varepsilon_{jdt}. \tag{5}$$

In this model, y_{jdt} is an indicator for teacher j leaving district d after year t.[31] I estimate the effects of being hired after TEACHNJ using $post_{jt}$. I include experience ($\mathbf{1}(exp_{jt} = \tau)$) and district ($\nu_d$) fixed effects to account for differences by experience level and district. I use district fixed effects because I define turnover as leaving the district rather than moving between schools within a district.[32] Thus, I cluster standard errors at the district level.

In this regression, I cannot simultaneously control for experience, year, and cohort because they are nearly collinear. I must include controls for cohort because the coefficient of interest compares teachers hired before and after TEACHNJ. Thus, I can control for either experience or year fixed effects. If I control for experience and exclude year fixed effects, I must assume that turnover rates are invariant across calendar years in my sample. If I control for calendar years and exclude experience fixed effects, I must assume that turnover rates are invariant across years of experience. To test which assumption is more reasonable, I plot turnover rates by experience (Panel A) and calendar year (Panel B) in Figure A4. I find large variation in turnover rates across experience years and little variation across calendar years, so I use experience fixed effects.[33] Without controls for experience, the model would overestimate the effect of TEACHNJ on turnover, as less-experienced post-TEACHNJ hires would have much higher turnover rates than more experienced pre-TEACHNJ hires.

Table 3 reports estimates of equation (5). In Column (1), the extended pretenure time and standardized tenure requirements increased overall teacher turnover by 6.3 percentage points. As seen in the row labeled "Mean", 12.6% of pretenured teachers leave their district each year. Thus, the reforms dramatically increased overall turnover rates among these

[31] The results are similar when using an indicator for teachers leaving the profession altogether (not shown).

[32] In fact, the district, rather than the school, employs the teacher. Teachers retain tenure protections when moving between schools within a district but lose these protections when switching districts.

[33] Ideally, I would provide an event study graph depicting turnover rates prior to the passage of TEACHNJ. However, I cannot generate this graph because I do not have retention data prior to 2013.

inexperienced teachers.[34]

While TEACHNJ increased overall teacher turnover, it is important to identify which teachers are leaving. Teachers may voluntarily leave the district following TEACHNJ due to reduced compensating differentials or involuntarily leave the district as they fail to meet the higher standards. Although I cannot precisely measure the source of turnover, Table 4 provides a proxy for it by dividing the sample of teachers into those receiving high ratings (Panel A) and low ratings (Panel B). Since teachers who receive high ratings do not face performance-related dismissals, Panel A provides a proxy for voluntary attrition among effective teachers.[35] In comparison, Panel B measures both involuntary and voluntary turnover among teachers receiving low ratings. Column (1) shows TEACHNJ increased the proxy for voluntary attrition by 3.8 percentage points and turnover among low-performing teachers by 21.4 percentage points.[36] Therefore, TEACHNJ primarily increased low-performing teacher turnover, though there also was a meaningful rise in effective teacher turnover.

Changes in turnover rates also may vary by teacher characteristics. Some teachers may be disproportionately impacted by TEACHNJ leading to increased turnover. In Columns (2)–(8) of Table 3, I evaluate differential turnover rates by interacting the independent variables in equation (5) with teacher gender and race. Columns (2)–(4) show the effects are larger for men (7.6 percentage points) than women (6 percentage points), while Columns (5)–(8) show higher increases in turnover among Black teachers (8.6 percentage points) than other teachers (about 6 percentage points). Columns (4) and (8) show these differences are statistically significant.[37] The increased turnover among male and Black teachers could be a result of

[34] The increase in turnover is not attributable to a corresponding change in salaries. Using data from an NJDOE Open Public Records Act request, I find no evidence that districts increased starting salaries in response to the TEACHNJ Act (not shown).

[35] In fact, it is very difficult to identify voluntary and involuntary turnover in any dataset. For example, some low-performing teachers may appear to voluntarily leave the district if they knew that they would be dismissed shortly afterwards. As a result, comparing turnover among low- and high-performing teachers provides a reasonable proxy for these measures.

[36] During the sample period, pretenure turnover rates among effective and ineffective teachers hovered near 10% and 33%–42%, respectively.

[37] Table 3 differs from Figure 3 because Table 3 does not control for summative ratings, while Figure 3 is limited to teachers in their first districts. However, the overall pattern of results in Table 3 is robust to this sample variation (not shown).

voluntary attrition or involuntary dismissals. In Panel A of Table 4, the proxy for voluntary attrition for male and Black teachers increased by 4.5 and 4.3 percentage points, respectively. However, other teachers only experienced 3.5–3.7 percentage point increases in the proxy for voluntary attrition. Similarly, Panel B shows turnover among low-performing male and Black teachers increased by 22.7 and 26.6 percentage points, respectively, while other teachers experienced 19.9–20.5 percentage point increases. The differences among low-performing teachers are not statistically significant; however, the point estimates suggest male and Black teachers encountered disproportionately higher turnover rates for poor performance.

Male and Black teachers also were disproportionately affected by TEACHNJ because they consistently received lower summative ratings and the reforms were tied to subjective evaluation criteria. Figure 4 shows the cumulative distribution functions of the ratings by teacher gender (Panel E) and race (Panel F). The distribution of ratings for female (dashed red) and White (dashed red) teachers first order stochastically dominates the distribution for male (dashed and dotted blue) and Black (solid black) teachers, respectively. This finding matches previous research that has documented similar racial and gender gaps in teacher evaluation scores (Bailey et al., 2016; Drake et al., 2019; Sartain & Steinberg, 2020; Chi, 2021; Grissom & Bartanen, 2022). Since TEACHNJ includes provisions to dismiss teachers earning low ratings, the lower scoring male and Black teachers faced greater turnover rates. These teachers' lower ratings may be due to a variety of factors including sorting patterns, differences in performance, and evaluation bias.

Male and Black teachers may sort into different schools than other teachers. To evaluate whether this mechanism could generate the differential turnover rates by race and gender, Table 5 presents estimates of equation (5) by school size, poverty level (Panel A), racial composition (Panel B), and proficiency rates (Panel C). TEACHNJ increased turnover similarly across school types with differences in point estimates that are no larger than 0.6 percentage points. None of the differences are statistically significant at the 10% level.[38] Given similar

[38] In addition, the mean turnover rates are similar across school types.

changes in turnover rates across school characteristics, the increase in turnover among male and Black teachers is unlikely to be attributable to differences in school attributes.[39]

Next, I test for differences in performance along other dimensions of teacher quality. I plot the cumulative distribution functions of value-added by gender and race in Figure 4 (Panels A–D). While male and Black teachers consistently receive lower summative ratings, I find similar distributions of value-added by gender and race. In fact, relative to White teachers, Black teachers have slightly higher average value-added. Although value-added and ratings capture distinct, potentially valuable components of teacher performance, it is surprising that male and Black teachers perform so much worse along the only potentially subjective dimension.

Given similar value-added by gender and race, rating biases may contribute to the discrepancies. For example, supervisors may offer more lenient ratings to teachers of the same gender or race (Chi, 2021; Grissom & Bartanen, 2022; Campbell, 2020). Thus, teachers from other groups may receive lower ratings and encounter increased risk of dismissals. To evaluate this hypothesis, I estimate the following model:

$$rate_{jtp} = \gamma group_j + \delta rate_{j(t-1)} + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}(exp_{jt} = \tau) + \xi_p + \varepsilon_{jtp}. \tag{6}$$

In equation (6), $rate_{jtp}$ is the summative rating of teacher j in year t who is assigned to principal p, while $group_j$ is an indicator for teacher gender or race. In the gender and race regressions, the omitted groups are female and White teachers, respectively. I include experience ($\mathbf{1}(exp_{jt} = \tau)$) and principal ($\xi_p$) fixed effects to account for returns to experience and differential evaluation standards by principal. I control for prior year summative rating ($rate_{j(t-1)}$) and interact each variable with the principal's gender or race to test for differences in rating standards by group membership.[40] Table 6 presents estimates of γ where column headers define principal characteristics. This table shows that male (Panel A) and Black

[39] In fact, controlling for school characteristics in equation (5) does not impact the estimates (not shown).

[40] The results are robust to controlling for previous year value-added, as well as omitting controls for past performance (not shown).

(Panel B) teachers consistently receive lower ratings but the differences are even larger when paired with an out-of-group principal.[41] For example, male teachers earn ratings that are 0.028 points lower than female teachers when paired with a male principal. However, the disparity increases by an additional 0.007 points to −0.035 when paired with a female principal. Similarly, Black teachers earn ratings that are 0.024 points lower when paired with Black principals. This disparity increases to 0.033 points when paired with White principals. These differences across principal characteristics are statistically significant at the 5% level for both groups. The increased out-of-group rating disparities suggest evaluation biases contribute to the lower ratings for male and Black teachers.

Although greater turnover among male and Black teachers with low ratings improves average retained teacher quality, the increased turnover for male and Black teachers is problematic for male and Black students. Gershenson et al. (2018) find Black students' graduation and college enrollment rates increased when paired with Black teachers. Other papers show test score improvements when male and Black students were assigned to teachers of their own gender (Dee, 2007) or race (Dee, 2004; Egalite et al., 2015). Similarly, Dee (2005, 2007), Ehrenberg et al. (1995), and Gershenson et al. (2016) find teachers had worse perceptions of out-of-group students. Many of these papers also suggest that simply increasing the number of male and Black teachers could have symmetric negative impacts on female and White students. However, Table 1 shows that male and Black teachers are underrepresented relative to the size of the corresponding student populations. About 52% of students are male, while only 20% of teachers are male. Similarly, about 20% of students are Black, whereas only 8% of teachers are Black.[42] With already limited access to in-group teachers, male and Black students may be disproportionately harmed by increased in-group turnover when implementing reforms relying on subjective evaluations.

[41] Hispanic teachers also receive lower ratings than White teachers but the differences are smaller.

[42] These gender and racial disparities are prevalent throughout the United States (National Center for Education Statistics, 2020a, 2020b).

5.2 Labor Market Effects: Teacher Quality

The TEACHNJ Act also may impact average teacher performance. Previous research finds short-term improvements in teacher quality by weakening tenure protections (Carruthers et al., 2018; Loeb et al., 2015; Anderson et al., 2019; Rodriguez, 2018; Kraft, 2015; Goldhaber et al., 2016; Staiger & Rockoff, 2010) and reforming evaluation systems (Cullen et al., 2021), as schools dismiss low-performing teachers (Adnot et al., 2017). However, these policies may eventually cause high-quality teachers to sort into other professions (Strunk et al., 2017), as well as generate disruptions to the teaching staff, such as lost teaching experience (Ronfeldt et al., 2013; Hanushek et al., 2016; Sorensen & Ladd, 2020).

The TEACHNJ Act standardized tenure receipt and removal, such that they only rely on summative ratings rather than value-added. As a result, schools may alter hiring practices to focus on the rating dimension, while the law incentivizes potentially highly rated teachers to sort into the profession.

To estimate these labor market effects, I reestimate equation (5) and replace y_{jdt} with value-added and ratings. As discussed earlier, I cannot estimate the effects of being hired after TEACHNJ while simultaneously controlling for both experience and year fixed effects. To prevent this collinearity, I omit year fixed effects because average value-added does not drift over time[43] and the rating returns to the first five years of experience are over twice as large as their drift across calendar years. Without controls for experience, the model would underestimate the effect of TEACHNJ on performance, as less-experienced post-TEACHNJ hires would have worse performance than more experienced pre-TEACHNJ hires.

Table 7 presents the results. There is no change in value-added and a 0.021 point increase in summative ratings following TEACHNJ's passage. The 95% confidence intervals rule out

[43] This is a mechanical effect of the annual test score standardization.

declines larger than 0.009 math and 0.011 ELA standard deviations.[44]

These results show that teaching candidates who perform well on ratings disproportionately filled vacancies following the TEACHNJ Act. However, these candidates were not necessarily more effective as measured by value-added. As a result, teacher labor market quality improved along the dimension that dictated personnel decisions (ratings), while quality remained unchanged along other dimensions of performance (value-added). This result aligns with a multitask principal-agent model where only one of several measures of performance is used to evaluate the employee (Holmstrom & Milgrom, 1991; Baker, 2002).

6 Conclusion

I find negative productivity effects of tenure on math value-added with no impact on ELA value-added or ratings. Since these effects are smaller than early career returns to experience, replacing teachers due to productivity concerns will likely cause declines in performance.

Focusing on retention effects, male and Black teachers are disproportionately affected by the evaluation reforms of TEACHNJ. These teachers tend to earn lower summative ratings leading to greater turnover when switching to more stringent accountability standards. Despite lower ratings, male and Black teachers have similar value-added as their female and White counterparts. While these reforms tied to subjective evaluation criteria remove the lowest rated teachers, they may unintentionally increase male and Black teacher turnover. Worse yet, summative ratings with subjective components may vary by gender and race leading to disproportionate effects. Since tenure laws are often linked to subjective evaluations, policymakers need to consider these unintended consequences when enacting future reforms.

[44] As a robustness test, I use a second, indirect calculation. In Table A4, I reestimate equation (2) without teacher fixed effects to calculate the combined productivity and selection effects of TEACHNJ. Differencing the productivity effects (Table 2) from the combined effects (Table A4) isolates the selection effects of TEACHNJ. While none of the estimates are statistically significant, the point estimates show TEACHNJ raised math value-added by about 0.019 standard deviations, while it had virtually no effect on ELA value-added. TEACHNJ also raised ratings by about 0.015 points. Overall, the results remain similar.

TEACHNJ created vacancies that were filled by teachers who received higher summative ratings. However, these new hires produced similar value-added to previous cohorts. The discrepancies between the value-added and summative rating results demonstrate the importance of carefully analyzing these performance metrics. If research can link summative ratings to future student outcomes, similar to Chetty et al. (2014) for value-added, these rating gains may prove to be useful. Without this clear relationship, schools may be manipulating their hiring practices to improve along a less meaningful metric.

Given these effects, the efficacy of tenure reforms to improve teacher performance is limited.[45] Other policies may be more effective instruments to increase teacher productivity. For example, the 0.033 standard deviation decline in math value-added is less than one-third of the magnitude of the 0.11 standard deviation improvement associated with increased teaching feedback (Taylor & Tyler, 2012). Increased feedback also generated improvements that persisted over several years without any evidence of negative labor market effects.

Overall, both sides of the tenure debate make valid points. Tenure induces a small math value-added productivity decline; however, tenure reforms also impact selection into teaching and retention. These reforms tied to subjective evaluation criteria have unintended consequences on male and Black teacher turnover, which may harm male and Black students.

[45] In Appendix Section A.2, I argue the study maintains external validity as New Jersey's laws match those of many other states.

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Tables

Table 1: Summary Statistics

	Students	Teachers
Female	0.484	0.798
	(0.500)	(0.402)
Black	0.197	0.080
	(0.398)	(0.272)
Hispanic	0.271	0.075
	(0.445)	(0.263)
Urban	0.911	0.913
	(0.285)	(0.281)
FRPL	0.377	
	(0.485)	
ELL	0.045	
	(0.207)	
Special Ed.	0.194	
	(0.395)	
Math Proficient	0.528	
	(0.499)	
ELA Proficient	0.582	
	(0.493)	
Experience		13.276
		(8.904)
Years in District		11.644
		(8.264)
Summative Rating		3.386
		(0.322)
Obs	12,405,063	905,574
Unique Obs	2,164,750	231,815

Notes: This table provides summary statistics at the student-year and teacher-year levels. The row headers define the variable. The first column provides the student-year summary statistics, while the second column provides the teacher-year summary statistics. The standard deviations of each value are listed in parentheses below the means. The final two rows count the number of observations and the number of unique individuals in the sample.

Table 2: Productivity Effects

Panel A: Math Value-Added

	(1) All	(2) Retention	(3) High Quality	(4) No Sort	(5) Grade Switch	(6) PARCC
Tenure	-0.033***	-0.035***	-0.037***	-0.041***	-0.040***	-0.038***
	(0.011)	(0.012)	(0.013)	(0.013)	(0.010)	(0.011)
	[-0.106]	[-0.115]	[-0.119]	[-0.134]	[-0.130]	[-0.124]
Num Schools	1,867	1,815	1,618	1,569	1,832	1,827
Num Teachers	3,199	2,853	2,013	1,850	3,199	3,120
Obs	514,487	453,848	334,481	339,216	397,131	388,186

Panel B: ELA Value-Added

	(1) All	(2) Retention	(3) High Quality	(4) No Sort	(5) Grade Switch	(6) PARCC
Tenure	0.007	0.003	0.005	0.005	0.001	-0.009
	(0.011)	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)
	[0.025]	[0.010]	[0.018]	[0.017]	[0.004]	[-0.031]
Num Schools	1,895	1,833	1,662	1,617	1,865	1,850
Num Teachers	3,562	3,136	2,290	2,074	3,562	3,467
Obs	645,807	562,415	430,883	426,977	491,214	478,726

Panel C: Summative Ratings

	(1) All	(2) Retention	(3) High Quality	(4) No Sort	(5) Grade Switch	(6) PARCC
Tenure	-0.018	-0.017	-0.015	-0.006	-0.024	NA
	(0.014)	(0.017)	(0.015)	(0.019)	(0.014)	NA
	[-0.057]	[-0.051]	[-0.047]	[-0.018]	[-0.073]	NA
Num Schools	1,568	1,525	1,345	1,141	1,534	NA
Num Teachers	3,871	3,569	2,812	1,936	3,871	NA
Obs	13,960	12,843	10,383	7,648	11,998	NA

Notes: This table shows γ from equation (2) for the performance measure listed in the panel title. Only Panel C includes school and year fixed effects. Column (1) shows the effect on all teachers. Column (2) shows the effect for teachers predicted to be retained into year 4. Column (3) shows the effect on teachers whose year 3 summative rating exceeds the 25^{th} percentile of eventually tenured teachers. Column (4) shows the effect on teachers hired by 2013. Column (5) shows the effect when including an indicator for switching grades. Column (6) shows the effect when restricting the sample to PARCC tests.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of TEACHNJ on Turnover Rates by Teacher Characteristics

	(1) All	(2) Male	(3) Female	(4) P-Value	(5) White	(6) Black	(7) Hispanic	(8) P-Value
Post	0.063***	0.076***	0.060***	0.000	0.061***	0.086***	0.060***	0.022
	(0.003)	(0.005)	(0.003)		(0.003)	(0.011)	(0.007)	
Mean	0.126	0.129	0.125		0.124	0.144	0.135	
Obs	673,601	140,347	533,220		578,442	48,754	47,058	

Notes: This table shows γ from equation (5). Column (1) shows the effect on all teachers. Columns (2) and (3) show the effect by interacting each independent variable in equation (5) with teacher gender. Column (4) provides the p-value from an F-test of equality for the coefficients. Columns (5)–(8) are defined similarly for teacher race. For race, the F-test evaluates whether the coefficients for Black and Hispanic teachers are jointly different from the coefficient for White teachers. The row titled "Mean" provides average turnover rates among pretenured teachers.

Standard errors in parentheses and clustered at the district level.

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Effect of TEACHNJ on Turnover Rates by Summative Rating

Panel A: Effective and Highly Effective Teachers

	(1) All	(2) Male	(3) Female	(4) P-Value	(5) White	(6) Black	(7) Hispanic	(8) P-Value
Post	0.038***	0.045***	0.035***	0.038	0.037***	0.043***	0.037***	0.818
	(0.003)	(0.005)	(0.003)		(0.003)	(0.011)	(0.008)	
Mean	0.100	0.098	0.101		0.100	0.092	0.109	
Obs	424,522	93,883	330,603		370,325	25,468	28,966	

Panel B: Ineffective and Partially Effective Teachers

	(1) All	(2) Male	(3) Female	(4) P-Value	(5) White	(6) Black	(7) Hispanic	(8) P-Value
Post	0.214***	0.227***	0.205***	0.661	0.199***	0.266***	0.204**	0.340
	(0.050)	(0.073)	(0.047)		(0.048)	(0.069)	(0.097)	
Mean	0.396	0.423	0.381		0.420	0.353	0.332	
Obs	6,702	2,265	4,311		4,192	1,701	704	

Notes: This table shows γ from equation (5) by teacher summative rating. Panel A shows the effect for effective and highly effective teachers, while Panel B shows the effect for ineffective and partially effective teachers. Column (1) shows the effect on all teachers. Columns (2) and (3) show the effect by interacting each independent variable in equation (5) with teacher gender. Column (4) provides the p-value from an F-test of equality for the coefficients. Columns (5)–(8) are defined similarly for teacher race. For race, the F-test evaluates whether the coefficients for Black and Hispanic teachers are jointly different from the coefficient for White teachers. The row titled "Mean" provides average turnover rates among pretenured teachers.

Standard errors in parentheses and clustered at the district level.

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Effects of TEACHNJ on Turnover by School Characteristics

Panel A: School Size and Poverty

	(1) 300+ Students	(2) <300 Students	(3) P-Value	(4) 20%+ FRPL	(5) <20% FRPL	(6) P-Value
Post	0.063***	0.061***	0.761	0.065***	0.060***	0.323
	(0.003)	(0.005)		(0.004)	(0.003)	
Mean	0.123	0.143		0.124	0.128	
Obs	562,793	87,250		389,256	260,679	

Panel B: School Racial Composition

	(1) 20%+ Black	(2) <20% Black	(3) P-Value	(4) 20%+ Hisp	(5) <20% Hisp	(6) P-Value
Post	0.064***	0.062***	0.795	0.064***	0.062***	0.749
	(0.006)	(0.003)		(0.005)	(0.003)	
Mean	0.134	0.122		0.124	0.127	
Obs	196,497	453,543		260,371	389,670	

Panel C: School Proficiency Rates

	(1) 50%+ Math Prof	(2) <50% Math Prof	(3) P-Value	(4) 50%+ ELA Prof	(5) <50% ELA Prof	(6) P-Value
Post	0.064***	0.061***	0.520	0.065***	0.059***	0.330
	(0.003)	(0.004)		(0.003)	(0.005)	
Mean	0.126	0.123		0.127	0.120	
Obs	326,364	273,896		405,127	195,012	

Notes: This table shows γ from equation (5). Panel A shows effects by school size and poverty levels. Panel B shows effects by school racial composition. Panel C shows effects by school proficiency rates. The column headers define the school characteristics. Columns (3) and (6) provide the p-value from an F-test of equality for the coefficients. The row titled "Mean" provides average turnover rates among pretenured teachers.

Standard errors in parentheses and clustered at the district level.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Teacher Demographics and Summative Ratings

Panel A: Gender

	(1) All Principals	(2) Male Principals	(3) Female Principals	(4) P-Value
Male Teacher	-0.031***	-0.028***	-0.035***	0.011
	(0.001)	(0.001)	(0.002)	
	[-0.096]	[-0.088]	[-0.110]	
Obs	319,693	183,926	135,766	

Panel B: Race

	(1) All Principals	(2) White Principals	(3) Black Principals	(4) Hispanic Principals	(5) P-Value
Black Teacher	-0.029***	-0.033***	-0.024***	-0.042***	0.017
	(0.002)	(0.003)	(0.003)	(0.007)	
	[-0.091]	[-0.102]	[-0.073]	[-0.129]	
Hispanic Teacher	-0.009**	-0.010**	0.005	-0.021*	0.111
	(0.004)	(0.004)	(0.010)	(0.011)	
	[-0.028]	[-0.030]	[0.015]	[-0.064]	
Obs	302,716	246,867	39,584	16,333	

Notes: This table shows γ from equation (6). In these regressions, $group_j$ defines teacher gender (Panel A) or race (Panel B). The omitted groups are female teachers (Panel A) and White teachers (Panel B). Column (1) shows the effect on all teachers. The remaining column headers define the effect when paired with a principal of a given gender or race. The final column provides the p-value from an F-test of equality for the coefficients.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* p<0.10, ** p<0.05, *** p<0.01

Table 7: Tenure Extensive Margin Effects

	(1) Math VA	(2) ELA VA	(3) Ratings
Post	0.001	-0.003	0.021***
	(0.005)	(0.004)	(0.003)
	[0.002]	[-0.010]	[0.065]
Obs	29,463	33,078	129,457

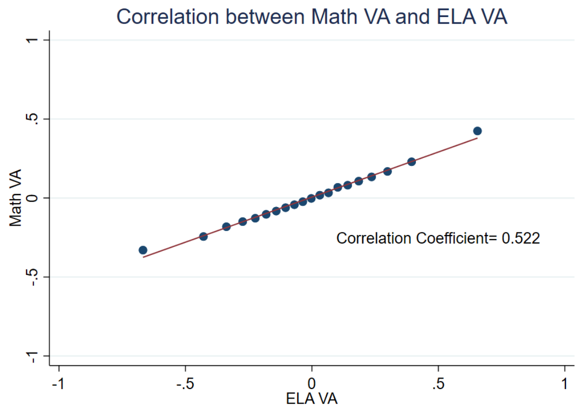
Notes: This table shows γ from equation (5). I limit the sample to teachers in their first five years in a particular district. The column headers define the performance measure.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

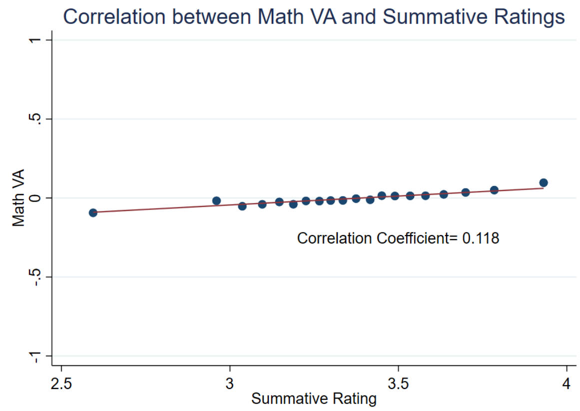
* p<0.10, ** p<0.05, *** p<0.01

Figures

Panel A: Math VA and ELA VA



Panel B: Math VA and Summative Ratings



Panel C: ELA VA and Summative Ratings

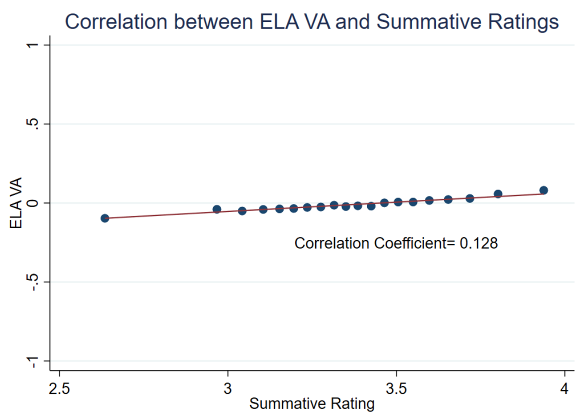
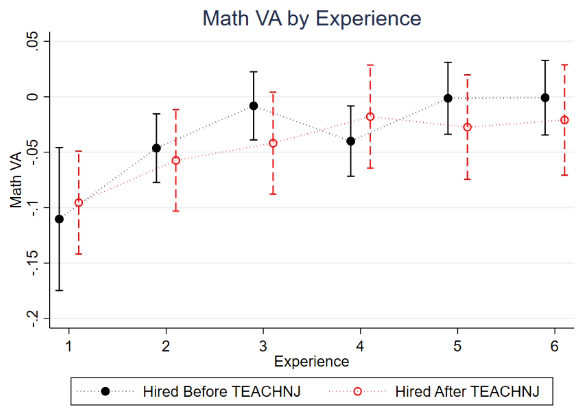


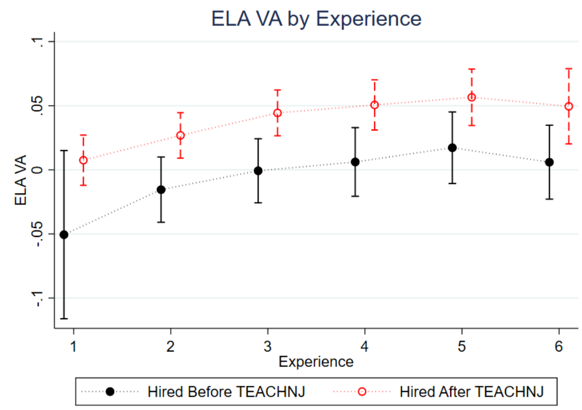
Figure 1: Correlation Between Performance Measures

Notes: This figure shows the relationship between performance measures. The x-axis and y-axis variables are labeled in each graph. The x-axis records the average value in 20 equal-sized bins, while the y-axis records the average value within that bin of the x-axis variable. The graphs include lines of best fit and correlation coefficients.

Panel A: Math Value-Added



Panel B: ELA Value-Added



Panel C: Summative Ratings

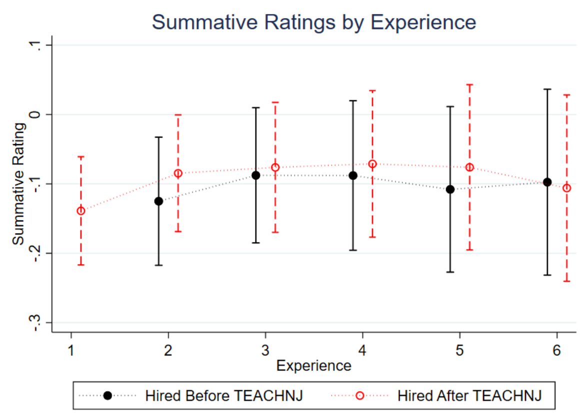


Figure 2: Performance by Experience and Tenure Regime

Notes: This figure shows the returns to experience separately for those hired before and after TEACHNJ. The panel title defines the performance measure. I plot the coefficients and 95% confidence intervals using equation (3). The x-axis records years of experience, while the y-axis records the performance level relative to the omitted group. In these graphs, the omitted group contains teachers with at least 7 years of experience. These values are 0.01 standard deviations, 0.03 standard deviations, and 3.41 points for math value-added, ELA value-added, and summative ratings, respectively. The solid black dots show the estimates for those hired before TEACHNJ, while the hollow red dots show the estimates for those hired after TEACHNJ.

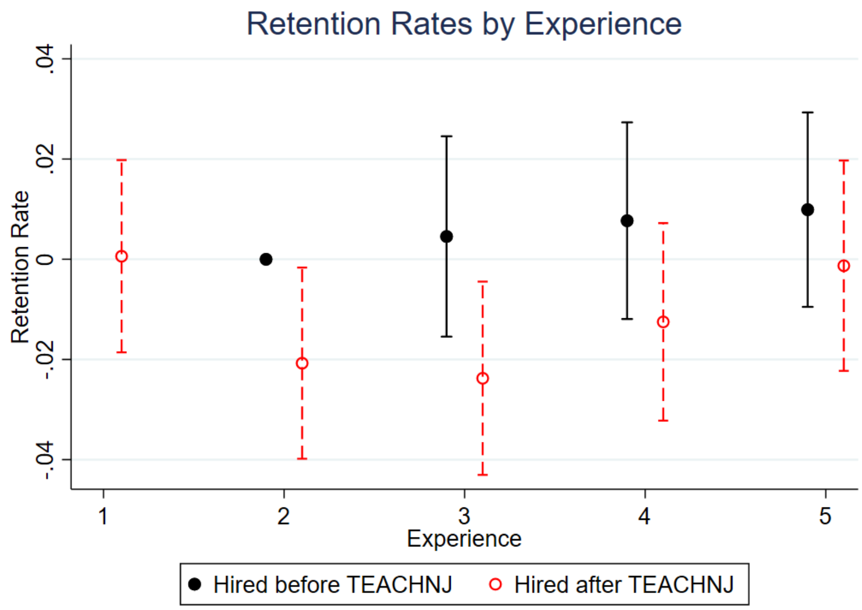
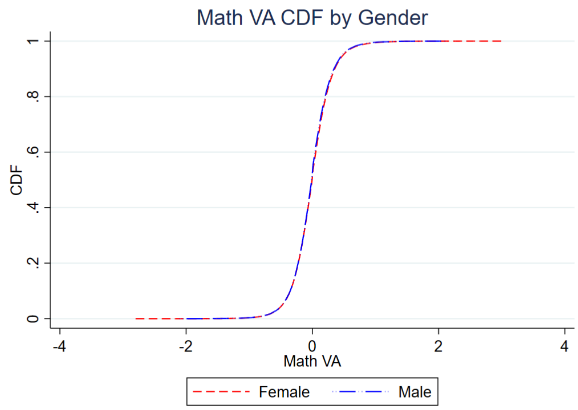


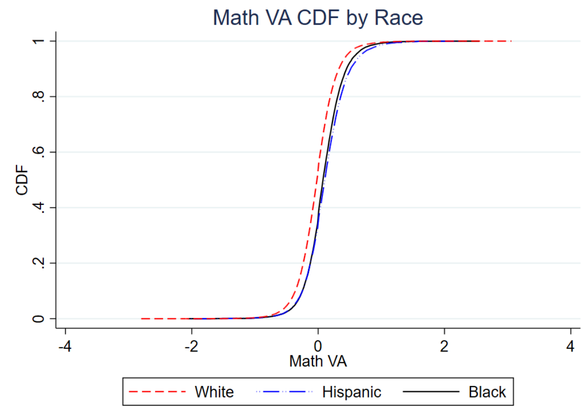
Figure 3: Retention Rates by Tenure Regime

Notes: This figure shows retention rates for those hired before and after TEACHNJ in their first district. I regress retention on experience fixed effects interacted with being hired before or after the law. I control for summative ratings to account for differences in teacher quality. I plot the estimated retention rates and 95% confidence intervals. The x-axis records experience, while the y-axis records the retention rates relative to second-year teachers hired before TEACHNJ. This value is 0.916 when using the average summative rating in this sample. Year 1 retention for those hired before TEACHNJ is omitted because I do not have year 1 summative ratings for them. The solid black dots show the estimates for those hired before TEACHNJ. The hollow red dots show the estimates for those hired after TEACHNJ.

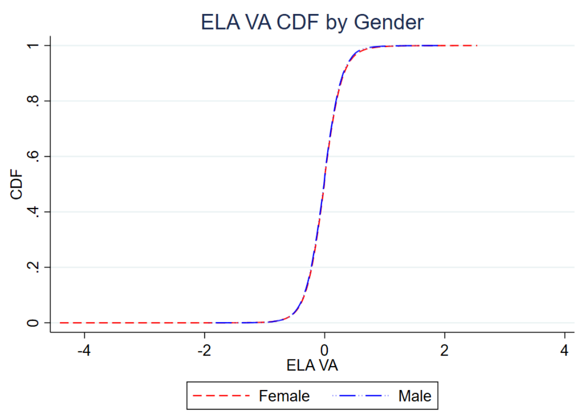
Panel A: Math Value-Added by Gender



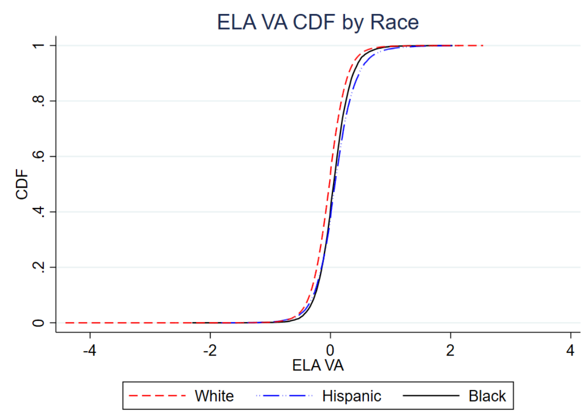
Panel B: Math Value-Added by Race



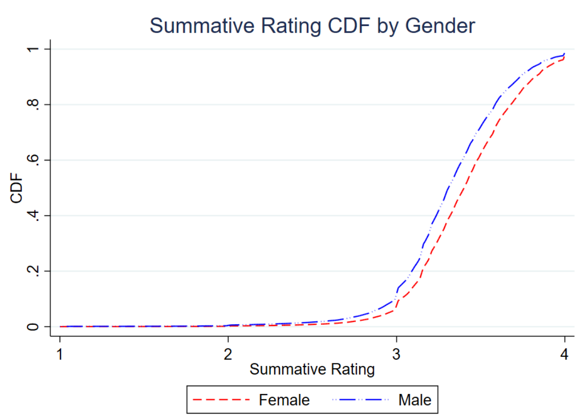
Panel C: ELA Value-Added by Gender



Panel D: ELA Value-Added by Race



Panel E: Ratings by Gender



Panel F: Ratings by Race

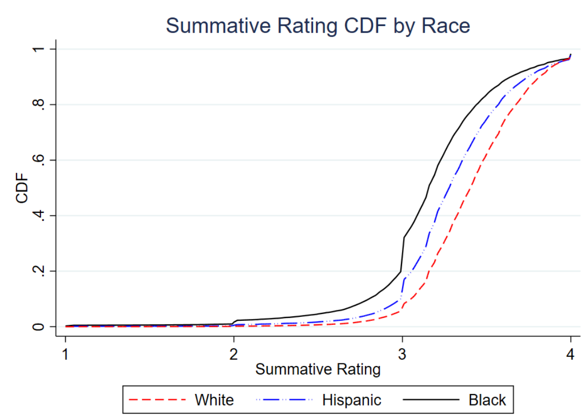


Figure 4: Performance CDF by Gender and Race

Notes: This figure shows the cumulative density of performance by gender (Panels A, C, and E) and race (Panels B, D, and F). The x-axis records performance, while the y-axis records the density. For gender (race), dashed red lines show female (White) teachers, while dashed and dotted blue lines depict male (Hispanic) teachers. Solid black lines show Black teachers.

A Appendix

A.1 New Jersey Summative Rating Implementation

Teacher summative ratings were carefully implemented in New Jersey following the passage of the TEACHNJ Act (State of New Jersey Department of Education, 2017). These ratings provided greater score differentiation than the previous two-tier rating system. In addition, teacher summative ratings have improved over time, which may be attributable to clearer expectations for good teaching, additional opportunities for feedback, and the use of data to improve teacher practice.

The NJDOE also provided districts with the autonomy to implement these systems. While this provided local control, it also allowed the distributions of teacher effectiveness to vary by district. In some districts, nearly every teacher received a highly effective rating. In other districts of similar sizes and student populations, teacher summative ratings are centered around effective ratings and distributed more normally. My specifications account for this variation by including either school, district, or principal fixed effects.

A.2 Relevance to Other States

While each state has a unique set of tenure policies, many components of New Jersey's tenure laws are common throughout the country (Thomsen, 2020). Specifically, the three- to four-year tenure length reform remains quite relevant because 32 states have three-year tenure clocks, while 4 states have four-year tenure clocks. In addition, the justifications for tenure dismissal in New Jersey include inefficiency, incapacity, or unbecoming conduct, which are common across states. Like most states, teachers facing dismissal are entitled to a hearing. Although there is slight variation in tenure policies across states, New Jersey's provisions are quite similar to those of many other states. Thus, this study maintains external validity.

A.3 Difference-in-Differences One-Step VA Model

For value-added, I embed the value-added equation into a modified version of the difference-in-differences model (without school and year fixed effects). Specifically, I use the following one-step model:

$$A_{ijgst} = \gamma ten_{jt} + \sum_{\tau=1}^{T} \delta_{\tau} \mathbf{1}(exp_{jt} = \tau) + \alpha A_{it-1} + \beta X_{it} + \eta C_{it} + \lambda S_{it} + \psi_j + \varepsilon_{ijgst}. \qquad (7)$$

In this regression, A_{ijgst} is the test score of student i in teacher j's grade g class in school s and year t. I control for the student's previous year test score (A_{it-1}), as well as student, classroom, and school characteristics. The student controls (X_{it}) include gender, race, FRPL eligibility, ELL status, and special education status. The classroom variables (C_{it}) are class size and aggregated student controls. School covariates (S_{it}) include urbanicity, enrollment, school racial composition, and percentage of FRPL eligible. The model also controls for teacher fixed effects (ψ_j); ε_{ijgst} is a mean-zero error term.

A.4 Model of Teacher Tenure

Let a_t be the teacher's ability in experience year t. Suppose a_t is an exogenously given, increasing, and concave function of t that may vary by initial ability. Assume student test scores in year t are given by $p_t = a_t + e_t$, where e_t is teacher effort. Define teacher utility as a strictly concave function ($u(a_t, e_t) \equiv u_t(e_t)$). Define e_t^* is its unique global maximum.[46]

I add an employment contract where retention depends on previous performance. Suppose teachers may be dismissed for poor annual performance that falls below annual performance standards n and y. Teachers without tenure are dismissed if $p_t < n$, while teachers with tenure are dismissed if $p_t < y$. Since tenured teachers have greater job security, let $n > y$. Also, assume teachers are offered tenure in year T if $\sum_{\tau=1}^{T} \frac{p_\tau}{T} \geq r$ and dismissed

[46] I model performance and utility as additively separable, though the results are similar when I allow initial ability (a_1) and effort (e_t) to interact multiplicatively (not shown).

otherwise. In words, teachers must perform above an average tenure receipt standard (r) during their pretenure years to receive tenure in year T. For the tenure receipt requirements to impact performance, $r > n$. Otherwise, any teacher dismissed at tenure receipt would have already been dismissed in an earlier year.[47]

In year t, teachers are offered continued employment if:[48]

$$m_t = \prod_{\tau=1}^{T} \mathbf{1}(p_\tau \geq n) \mathbf{1}\left(\sum_{\tau=1}^{T} \frac{p_\tau}{T} \geq r \right) \prod_{\tau=T+1}^{t-1} \mathbf{1}(p_\tau \geq y).$$

Suppose teachers have an outside option that produces utility level $f(a_t, t)$ for each of the remaining periods. Teachers who are dismissed or quit after year t receive utility $\sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau)$, where $\overline{T}$ is the retirement experience level. I define a value function ($V_t(e_t)$) recursively for teachers retained in experience year t as:

$$V_t(e_t) = u_t(e_t) + emp_{t+1} V_{t+1} + (1 - emp_{t+1}) \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).$$

In this equation, $u_t(e_t)$ is the utility from effort level e_t, while emp_{t+1} is an indicator for continued employment. The function $f(a_\tau, \tau)$ calculates the annual value of the outside option given ability a_t. Since teachers have perfect foresight, they may decide to quit prior to year t if:

$$V_t < \sum_{\tau=t}^{\overline{T}} f(a_\tau, \tau).$$

Thus, $emp_{t+1} = 1$ if the teacher meets the performance requirements ($m_{t+1} = 1$) and the remaining value from teaching exceeds the value from the outside option ($V_{t+1} \geq \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau)$).

[47] For computational simplicity, this setup varies slightly from the TEACHNJ Act. The law required teachers to receive two effective ratings prior to tenure receipt. In practice, 40% of ineffective and partially effective pretenured teachers immediately lost their jobs even if it was several years prior to tenure receipt. Thus, the combination of n and r are a close proxy for both the law and its actual implementation.

[48] Pretenure teacher job security ($t \leq T$) only relies on the first product, while teacher job security in experience year $T + 1$ only relies on the first two products.

First, I solve for tenured teachers where $t \geq T$. Since these teachers still have their jobs, I know that $\prod_{\tau=1}^{T} \mathbf{1}(p_\tau \geq n)\left(\sum_{\tau=1}^{T} \frac{p_\tau}{T} \geq r\right) \prod_{\tau=T}^{t-1} \mathbf{1}(p_\tau \geq y) = 1$. In this equation, p_t is the teacher's performance, while n, y, and r are the annual pretenure, annual tenure, and tenure receipt requirements, respectively. In this section, I assume the utility from teaching exceeds that from the outside option.[49] Then, the value function simplifies to:

$$V_t(e_t) = u_t(e_t) + \mathbf{1}(p_t \geq y)V_{t+1} + \mathbf{1}(p_t < y) \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).$$

Since job security only depends on the current year performance, e_t only impacts V_t through $u_t(e_t)$ and $\mathbf{1}(p_t \geq y)$. I take the first order condition with respect to effort and evaluate several cases. Without considering future employment, I find $e_t = e_t^*$ (which I call the single period optimal level of effort) and $p_t = a_t + e_t^*$. If I assume $p_t \geq y$, then the solution remains $e_t = e_t^*$ because the optimal single period utility level ensures an offer of continued employment. Even if teachers decide to quit after year t, e_t^* must maximize utility for period t or perfect foresight would have caused them to quit in a previous year.

Otherwise, $p_t < y$. In this case, the optimal solution is either $e_t = e_t^*$ or $e_t = y - a_t$. Any values between e_t^* and $y - a_t$ would not be optimal because the teacher would still not receive an offer of continued employment. However, they would move further away from the single period optimal solution. Since $u_t(e_t)$ is strictly concave and e_t^* is its unique global maximum, moving further away from e_t^* would result in less utility. Similarly, any values above $y - a_t$ would not gain any additional benefit of future employment but would reduce utility as they move further away from the single period optimal solution.

The optimal solution would be $e_t = e_t^*$ if:

[49] When simulating the model in Appendix Section A.4.1, I relax this assumption and incorporate quitting behavior.

$$
\begin{aligned}
V_t(e_t^*) &\geq V_t(y - a_t) \\
u_t(e_t^*) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) &\geq u_t(y - a_t) + V_{t+1} \\
V_{t+1} &\leq u_t(e_t^*) - u_t(y - a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).
\end{aligned}
$$

Otherwise, the solution would be $e_t = y - a_t$. Thus, for tenured teachers:

$$
e_t = \begin{cases} e_t^*, & e_t^* \geq y - a_t \text{ or } V_{t+1} \leq u_t(e_t^*) - u_t(y - a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) \\ y - a_t, & \text{otherwise.} \end{cases}
$$

Tenured teachers continue to exert the single period optimal level of effort if it meets the annual performance standards or if the future value of employment is sufficiently low relative to additional effort. Otherwise, teachers increase their effort to maintain job security by meeting the annual performance standards.

For pretenured teachers, I can write the problem for $t < T$ as:

$$
\begin{aligned}
V_t(e_t) = & u_t(e_t) + \mathbf{1}(p_t \geq n)\Bigg(u_t(e_{t+1}) + \cdots \Bigg(u_t(e_T) + \mathbf{1}(p_T \geq n)\mathbf{1}\Big(\sum_{\tau=1}^{T} \frac{p_\tau}{T} \geq r\Big) V_{T+1} \\
& + \mathbf{1}\Big(\sum_{\tau=1}^{T} \frac{p_\tau}{T} < r\Big) \sum_{\tau=T+1}^{\overline{T}} f(a_\tau, \tau)\Bigg) \cdots + \mathbf{1}(p_{t+1} < n) \sum_{\tau=t+2}^{\overline{T}} f(a_\tau, \tau)\Bigg) + \mathbf{1}(p_t < n) \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).
\end{aligned}
$$

I solve the model in the following cases:

1. The single period optimal level of effort (e_t^*) produces a sufficiently high rating to receive tenure. This occurs when $e_t^* + \overline{a} \geq r$.

   (a) The initial performance given effort level e_t^* is sufficient to maintain employment. This occurs when $a_1 + e_t^* \geq n$.[50]

[50] Since a_t is increasing in t, $a_1 + e_t^* > n$ implies $a_t + e_t^* > n$ for all t.

(b) The performance given effort level e_t^* is insufficient to maintain employment in the first $\bar{t}$ years. This occurs when $a_t + e_t^* < n$ for $t \in \{1, \ldots, \bar{t}\}$.[51]

2. The single period optimal level of effort (e_t^*) does not produce a sufficiently high rating to receive tenure. This occurs when $e_t^* + \bar{a} < r$.

   (a) The initial performance given effort level e_t^* is sufficient to maintain employment into year 2. This occurs when $a_1 + e_t^* \geq n$.

   (b) The performance given effort level e_t^* is insufficient to maintain employment in the first $\bar{t}$ years. This occurs when $a_t + e_t^* < n$ for $t \in \{1, \ldots, \bar{t}\}$.

      i. The minimum level of effort needed to earn tenure is sufficient to maintain employment. This occurs when $r - \bar{a} \geq n - a_t$ for all $t \in \{1, \ldots, T\}$, which is equivalent to $r - \bar{a} \geq n - a_1$, since a_t is strictly increasing in t.

      ii. The minimum level of effort needed to earn tenure is insufficient to maintain employment in the first $\widehat{t}$ periods. This occurs when $r - \bar{a} < n - a_t$ for $t \in \{1, \ldots, \widehat{t}\}$.

In the first case, suppose $e_t^* + \bar{a} \geq r$ and $a_1 + e_t^* \geq n$. The solution to the problem is e_t^* because the optimal single period effort level is sufficient to maintain employment.

In the next case, suppose $e_t^* + \bar{a} \geq r$ and $a_t + e_t^* < n$ for $t \in \{1, \ldots, \bar{t}\}$. If the cost of increased effort is sufficiently low, the teacher will exert effort level $e_t = n - a_t$ for $t \in \{1, \ldots, \bar{t}\}$. However, after period $\bar{t}$, the effort level returns to e_t^* because it is the single period optimal level and sufficient to receive tenure. Specifically, I assumed $e_t^* + \bar{a} \geq r$. Since $n - a_t > e_t^*$ for $t \in \{1, \ldots, \bar{t}\}$, effort levels $n - a_t$ for $t \in \{1, \ldots, \bar{t}\}$ and e_t^* for period $t \in \{\bar{t} + 1, \ldots, T\}$ produce a sufficient level of performance for tenure receipt.

For $t \in \{1, \ldots, \bar{t}\}$, teachers prefer $e_t = e_t^*$ to $e_t = n - a_t$ if:

[51] It is not possible that $n - a_t > r - \bar{a}$ for all $t \leq T$ because $r > n$ and $a_t \geq \bar{a}$ for some t by definition of $\bar{a}$.

$$V_t(e_t^*) \geq V_t(n - a_t)$$

$$u_t(e_t^*) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) \geq u_t(n - a_t) + V_{t+1}$$

$$V_{t+1} \leq u_t(e_t^*) - u_t(n - a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).$$

For the next case, suppose $e_t^* + \overline{a} < r$ and $a_1 + e_t^* \geq n$. To receive tenure, teachers need $\sum_{\tau=1}^{T} \frac{e_t}{T} \geq r - \overline{a}$. Since there is no discounting and the utility curve is concave and decreasing near the global optimum (e_t^*), teachers evenly distribute effort throughout the pretenure years, so $e_1 = e_2 = \cdots = e_T$.[52].

Since e_t^* is sufficient to meet the annual retention requirements by assumption, I must compare the utility from $e_t = e_t^*$ for $t \in \{1, \ldots T\}$ to the utility from $e_t = r - \overline{a}$ for $t \in \{1, \ldots T\}$ plus the future utility from keeping their job with tenure (V_{T+1}). This decision should be made in year 1 to optimize, which is feasible due to perfect foresight. Thus, I compare the stream of utility from year 1. This occurs when:

$$V_1(e_t = e_t^* \text{ for } t \in \{1, \ldots, T\}) \geq V_1(e_t = r - \overline{a} \text{ for } t \in \{1, \ldots, T\})$$

$$\sum_{t=1}^{T} u_t(e_t^*) + \sum_{\tau=T+1}^{\overline{T}} f(a_\tau, \tau) \geq V_{T+1} + \sum_{t=1}^{T} u_t(r - \overline{a})$$

$$V_{T+1} \leq \sum_{t=1}^{T} \Big(u_t(e_t^*) - u_t(r - \overline{a}) \Big) + \sum_{\tau=T+1}^{\overline{T}} f(a_\tau, \tau).$$

For the next case, suppose $e_t^* + \overline{a} < r$, $a_t + e_t^* < n$ for $t \in \{1, \ldots, \overline{t}\}$, and $r - \overline{a} \geq n - a_1$. There are three potential options:

1. Provide effort e_t^* and lose the job in the next period if $t \leq \overline{t}$.

[52] I assumed that e_t does not interact with a_t for $t \neq 1$ multiplicatively. The first order condition for e_t does not depend on t and the shape of the utility curve is constant in e_t over time. Consequently, it is optimal to evenly distribute effort throughout the pretenure period

2. Provide effort $n - a_t$ and maintain employment until the next period (only for $t \leq \bar{t}$, otherwise e_t^* is sufficient).

3. Provide effort $r - \bar{a}$ until period T and receive tenure.

Please note that options (1) and (2) are redundant for periods $t > \bar{t}$, so I focus on option (1) on that interval.

In this case, $e_t = e_t^*$ if the utility from option (1) exceeds the utility from options (2) and (3). For the utility from option (1) to exceed the utility from option (2) in the first $\bar{t}$ periods, I need:

$$
\begin{aligned}
V_t(e_t^*) &\geq V_t(n - a_t) \\
u_t(e_t^*) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) &\geq u_t(n - a_t) + \overline{V_{t+1}} \\
\overline{V_{t+1}} &\leq u_t(e_t^*) - u_t(n - a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau)
\end{aligned}
$$

where $\overline{V_{t+1}}$ only provides future teaching value up to tenure receipt, as the performance level is inadequate to earn tenure.

For the utility from option (1) to exceed the utility from option (3) in the first $\bar{t}$ periods, I need:

$$
\begin{aligned}
V_t(e_t = e_t^*) &\geq V_t(e_s = r - \bar{a} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(e_t^*) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) &\geq \sum_{s=t}^{T} u_s(r - \bar{a}) + V_{T+1} \\
V_{T+1} &\leq u_t(e_t^*) - \sum_{s=t}^{T} u_s(r - \bar{a}) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).
\end{aligned}
$$

For the utility from option (1) to exceed the utility from option (3) in periods $t \in \{\bar{t}, \ldots, T\}$, I need:

$$
\begin{aligned}
V_t(e_t = e_t^*) &\geq V_t(e_s = r - \overline{a} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(e_t^*) + \overline{V_{t+1}} &\geq \sum_{s=t}^{T} u_s(r - \overline{a}) + V_{T+1} \\
V_{T+1} - \overline{V_{t+1}} &\leq u_t(e_t^*) - \sum_{s=t}^{T} u_s(r - \overline{a}).
\end{aligned}
$$

Next, I compare the utility from option (2) and (3). The teacher will choose option (2) in periods $t \in \{1, \ldots, \overline{t}\}$ if the following holds:

$$
\begin{aligned}
V_t(e_t = n - a_t) &\geq V_t(e_s = r - \overline{a} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(n - a_t) + \overline{V_{t+1}} &\geq \sum_{s=t}^{T} u_s(r - \overline{a}) + V_{T+1} \\
V_{T+1} - \overline{V_{t+1}} &\leq u_t(n - a_t) - \sum_{s=t}^{T} u_s(r - \overline{a}).
\end{aligned}
$$

For the final case suppose $e_t^* + \overline{a} < r$, $a_t + e_t^* < n$ for $t \in \{1, \ldots, \overline{t}\}$, and $r - \overline{a} < n - a_t$ for $t \in \{1, \ldots, \widehat{t}\}$. There are three potential options:

1. Provide effort e_t^* and lose the job in the next period if $t \leq \overline{t}$.

2. Provide effort $n - a_t$ and maintain employment until the next period (only for $t \leq \overline{t}$, otherwise e_t^* is sufficient).

3. Provide effort $n - a_t$ until the period $\overline{\tau}$. For the remaining pretenure years, the teacher provides effort $\frac{T(r-\overline{a}) - \sum_{t=1}^{\overline{t}}(n-a_t)}{T-\overline{\tau}-1}$. Let $\overline{\tau}$ be defined as the largest $t \in \mathbb{Z}$ such that $\frac{T(r-\overline{a}) - \sum_{t=1}^{\overline{t}}(n-a_t)}{T-\overline{\tau}-1} < n - a_t$. In this case, the teacher can evenly split his or her effort and still receive tenure.

Again, please note that options (1) and (2) are redundant for periods $t > \overline{t}$, so I focus on option (1) on that interval. In addition, options (2) and (3) are redundant for periods $t \leq \overline{\tau}$, so I focus on option (2) on that interval.

To calculate the values for option (3), I define $\overline{\tau}$ as the period where I can evenly split remaining effort and still meet the minimum annual requirements. I know that it is optimal to evenly distribute effort across the remaining periods since the utility function is concave and decreasing above e_t^*. Thus, $e_{\overline{\tau}} = e_{\overline{\tau}+1} = \cdots = e_T$. Then, I solve the following equation showing the minimum effort needed to earn tenure after year $\overline{\tau}$ for e_t:

$$
\begin{aligned}
T(r-\overline{a}) &= \sum_{t=1}^{\overline{\tau}}(n-a_t) + \sum_{t=\overline{\tau}+1}^{T} e_t \\
(T-\overline{\tau}-1)e_t &= T(r-\overline{a}) - \sum_{t=1}^{\overline{t}}(n-a_t) \\
e_t &= \frac{T(r-\overline{a}) - \sum_{t=1}^{\overline{t}}(n-a_t)}{T-\overline{\tau}-1}
\end{aligned}
$$

where $\overline{\tau}$ occurs as the largest $t \in \mathbb{Z}$ such that $\frac{T(r-\overline{a})-\sum_{t=1}^{\overline{t}}(n-a_t)}{T-\overline{\tau}-1} < n-a_t$. To simplify notation, let $\overline{e} = \frac{T(r-\overline{a})-\sum_{t=1}^{\overline{t}}(n-a_t)}{T-\overline{\tau}-1}$.

The relationship between options (1) and (2) are the same as the previous case, so I focus on the relationship between options (1) and (3) and options (2) and (3).

If $\overline{\tau} < t < \overline{t}$, option (1) is preferred to option (3) when:

$$
\begin{aligned}
V_t(e_t = e_t^*) &\geq V_t(e_s = \overline{e} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(e_t^*) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau) &\geq \sum_{s=t}^{T} u_s(\overline{e}) + V_{T+1} \\
V_{T+1} &\leq u_t(e_t^*) - \sum_{s=t}^{T} u_s(\overline{e}) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau, \tau).
\end{aligned}
$$

If $\overline{t} < T < \overline{T}$, option (1) is preferred to option (3) when:

$$
\begin{aligned}
V_t(e_t = e_t^*) &\geq V_t(e_s = \overline{e} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(e_t^*) + \overline{V_{t+1}} &\geq \sum_{s=t}^{T} u_s(\overline{e}) + V_{T+1} \\
V_{T+1} - \overline{V_{t+1}} &\leq u_t(e_t^*) - \sum_{s=t}^{T} u_s(\overline{e}).
\end{aligned}
$$

Finally, I must compare the utility from option (2) and (3). The streams of efforts are identical until $\overline{\tau}$ in these two cases, so I only consider $t \in \{\overline{\tau}, \ldots, \overline{t}\}$. The teacher will choose option (2) if the following holds:

$$
\begin{aligned}
V_t(e_t = n - a_t) &\geq V_t(e_s = \overline{e} \text{ for } s \in \{t, \ldots, T\}) \\
u_t(n - a_t) + \overline{V_{t+1}} &\geq \sum_{s=t}^{T} u_s(\overline{e}) + V_{T+1} \\
V_{T+1} - \overline{V_{t+1}} &\leq u_t(n - a_t) - \sum_{s=t}^{T} u_s(\overline{e}).
\end{aligned}
$$

Combining these solutions, I find the following effort levels:

$$
e_t = \begin{cases}
n - a_t, & t \le \bar{t} \\
& \text{and } \Big\{ \Big(e_t^* + \bar{a} \ge r \text{ and } a_t + e_t^* < n \text{ for } t \in \{1,\dots,\bar{t}\} \text{ and } V_{t+1} > u_t(e_t^*) - u_t(n-a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \Big) \\
& \text{or } \Big(e_t^* + \bar{a} < r \text{ and } a_t + e_t^* < n \text{ for } t \in \{1,\dots,\bar{t}\} \text{ and } r - \bar{a} \ge n - a_1 \\
& \text{and } \overline{V_{t+1}} > u_t(e_t^*) - u_t(n-a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \text{ and } V_{T+1} - \overline{V_{t+1}} \le u_t(n-a_t) - \sum_{s=t}^{T} u_s(r-\bar{a}) \Big) \\
& \text{or } \Big(e_t^* + \bar{a} < r \text{ and } a_t + e_t^* < n \text{ for } t \in \{1,\dots,\bar{t}\} \text{ and } r - \bar{a} < n - a_t \text{ for } t \in \{1,\dots,\widehat{t}\} \\
& \text{and } \overline{V_{t+1}} > u_t(e_t^*) - u_t(n-a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \\
& \text{and } \Big\{ t \le \bar{\tau} \text{ or } \Big(t > \bar{\tau} \text{ and } V_{T+1} - \overline{V_{t+1}} \le u_t(n-a_t) - \sum_{s=t}^{T} u_s(\bar{e}) \Big) \Big\} \Big) \Big\} \\
r - \bar{a}, & t \le T \text{ and } \Big\{ \Big(e_t^* + \bar{a} < r \text{ and } a_1 + e_t^* \ge n \text{ and } V_{T+1} > \sum_{t=1}^{T} \big(u_t(e_t^*) - u_t(r-\bar{a}) \big) + \sum_{\tau=T+1}^{\overline{T}} f(a_\tau,\tau) \Big) \\
& \text{or } \Big(e_t^* + \bar{a} < r \text{ and } a_t + e_t^* < n \text{ for } t \in \{1,\dots,\bar{t}\} \text{ and } r - \bar{a} \ge n - a_1 \\
& \text{and } \Big\{ \Big(t \le \bar{t} \text{ and } V_{T+1} > u_t(e_t^*) - \sum_{s=t}^{T} u_s(r-\bar{a}) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \\
& \text{and } V_{T+1} - \overline{V_{t+1}} > u_t(n-a_t) - \sum_{s=t}^{T} u_s(r-\bar{a}) \\
& \text{or } \Big(t > \bar{t} \text{ and } V_{T+1} - \overline{V_{t+1}} > u_t(e_t^*) - \sum_{s=t}^{T} u_s(r-\bar{a}) \Big) \Big\} \Big) \Big\} \\
\bar{e}, & \bar{\tau} < t \le T \text{ and } e_t^* + \bar{a} < r \text{ and } a_t + e_t^* < n \text{ for } t \in \{1,\dots,\bar{t}\} \text{ and } r - \bar{a} < n - a_t \text{ for } t \in \{1,\dots,\widehat{t}\} \\
& \text{and } \Big\{ \Big(t < \bar{t} \text{ and } V_{T+1} > u_t(e_t^*) - \sum_{s=t}^{T} u_s(\bar{e}) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \\
& \text{and } V_{T+1} - \overline{V_{t+1}} > u_t(n-a_t) - \sum_{s=t}^{T} u_t(\bar{e}) \Big) \\
& \text{or } \Big(t > \bar{t} \text{ and } V_{T+1} - \overline{V_{t+1}} > u_t(e_t^*) - \sum_{s=t}^{T} u_s(\bar{e}) \Big) \Big\} \\
y - a_t, & t > T \text{ and } e_t^* < y - a_t \text{ and } V_{t+1} > u_t(e_t^*) - u_t(y-a_t) + \sum_{\tau=t+1}^{\overline{T}} f(a_\tau,\tau) \\
e_t^*, & \text{otherwise.}
\end{cases}
$$

Let T be the last pretenure year, $\bar{t}$ be the last year such that $e_t^* < n - a_t$, $\widehat{t}$ be the last year such that $r - \bar{a} < n - a_t$, $\bar{\tau}$ be the last year such that $\frac{T(r-\bar{a}) - \sum_{t=1}^{\bar{t}}(n-a_t)}{T-\bar{\tau}-1} < n - a_t$, $\bar{e} = \frac{T(r-\bar{a}) - \sum_{t=1}^{\bar{t}}(n-a_t)}{T-\bar{\tau}-1}$, and $\sum_{\tau=1}^{T} \frac{a_t}{T} = \bar{a}$. Let V_t be the future utility value, while $\overline{V_{t+1}}$ is the future value when dismissed at tenure receipt. The utility from the outside option is $f(a_t, t)$.

To solve the vector of effort inputs, I use backward induction. In retirement year $\overline{T}$, the optimal level of effort is e_t^* because future employment is irrelevant. Using this utility value, I solve the optimal decision for experience year $\overline{T}-1$. Teachers leave the profession if they are not offered continued employment (when student performance fails to achieve the minimum standards) or quit (when the utility from the outside option exceeds that from teaching). In this case, I replace the future recursive value with the stream of utility from the outside option, so $V_{\overline{T}-1} = u_{\overline{T}-1}(e_t^*) + f(a_T, T)$. I then iterate back to experience year 1 to solve the stream of effort and performance levels.

A.4.1 Simulating Model

When mapping TEACHNJ's standardized tenure receipt to increases in the tenure receipt requirements (r), the model identifies r as a potential source of bias.[53] These requirements may be more stringent for those hired after TEACHNJ, which would increase effort and performance in the first three years relative to the fourth year. The teacher fixed effects may overestimate teacher quality for those hired after TEACHNJ and attribute some of the fourth-year pretenure effort to innate ability. In the difference-in-differences design, this will underestimate the pretenured group's effort relative to that of the tenured group and bias the estimated productivity effects upward.

I simulate data to estimate these changes. I suppose initial teacher ability (a_1) follows a standard normal distribution. I assume teachers retire after 25 years because it is the minimum time needed to collect early retirement. Following Figure 2 of Wiswall (2013), I allow ability to increase by one standard deviation over 24 years of experience. Specifically, ability in experience year t is defined as $a_t = a_1 + \sqrt{\frac{t-1}{24}}$. I assume the outside option is defined as $f(a_t, t) = \kappa a_t - \mathrm{e}^{-\mathrm{t}}|\mathrm{s}|$, where $\kappa = 0.3$ and $s \sim N(0, 100)$.

Suppose teacher utility is $u_t(e_t) = bp_t - e_t^2$, where b gives the relative utilities of student test scores and teacher effort. With perfect job security, the teacher's optimal effort is

[53] I connect the standardized removal and streamlined appeals to increases in annual standards (n and y). However, they do not bias the estimates as they did not differ for those hired before and after TEACHNJ.

$e^* = \frac{b}{2}$, which does not depend on t. Student test scores are then $p_t = a_t + \frac{b}{2}$. For Table A5, I set the performance standards to reflect worst-case scenario decreases in tenure receipt rates after TEACHNJ. For those hired before TEACHNJ, 30% of teachers left the district before tenure. Figure 3 shows the annual difference in retention between the top of the 95% confidence interval before TEACHNJ and the bottom of the 95% confidence interval after TEACHNJ is about 6 percentage points. This would increase turnover by about 24 percentage points over the four pretenure years and equate to a 54% pretenure turnover rate. Thus, I set $y = 2.2$ and $n = 2.7$ in all models. Before TEACHNJ, I set $T = 3$ and $r = 3.05$. After TEACHNJ, I set $T = 4$ and $r = 5.45$. These values do not have simple interpretations other than they allow the model to match actual tenure receipt rates.

Using the simulated data and these worst-case parameters, I estimate equation (2). The results are presented in Table A5. First, I simulate the data when only extending T from three to four years. I show the results in Column (1), which estimates the productivity effects of tenure. Second, I simulate the data when changing T from three to four years and increasing the tenure receipt standards. In Column (2), I present the estimated productivity effects of tenure that are biased by the change in performance standards. The estimated effects in Column (2) are only biased upward by 0.012 units relative to Column (1). This difference is less than 0.4% of the true value, so the bias from increasing tenure receipt standards is unlikely to meaningfully impact the estimates.

In fact, the increased performance standards theoretically have limited scope to bias the results. The estimated productivity effects primarily capture the difference between the performance standards and innate ability of those who remain in the district for four years. The increased standards will induce some lower quality, marginal teachers to leave the profession prior to tenure receipt. As a result, the large performance declines associated with removing incentives from these lower quality teachers would not impact the estimates. In turn, some higher quality educators will become marginal teachers who may not receive tenure. Since the new marginal educators have higher innate ability, the estimated productivity declines following tenure receipt capture the difference between the new higher standards and the more talented marginal teachers. This difference is similar in size to the effects calculated in Column (1) based on lower standards and less talented marginal teachers.

A.5 Bounding Exercise

As discussed in the labor market effects section, being hired after TEACHNJ reduces the likelihood that the teacher remains in the district. This may generate selection bias, as lower quality fourth-year teachers hired after TEACHNJ may be dismissed at higher rates.

To account for these concerns, I follow the bounding exercise from Lee (2009).[54] Without the bounding exercise, I estimate:

$$\hat{\beta} = E[Y|D = 0, Z^* \geq 0] - E[Y|D = 1, Z^* \geq 0]. \tag{8}$$

In this equation, Y is the potential performance in experience year 4, while D is an indicator for being hired after TEACHNJ. The remaining term, Z^*, is the latent retention into year 4. This value depends on D and is positive when the applicant is retained into year 4. Unfortunately, $\hat{\beta}$ is not equal to the coefficient of interest, $\beta = E[Y|D = 0] - E[Y|D = 1]$.

To proceed, I must make the following assumptions. First, I assume that treatment is independent of potential performance and retention. Specifically, I assume D is independent of (Y_1^*, Y_0^*, S_1, S_0), where Y_1 (Y_0) is the potential performance for treated (control) states and S_1 (S_0) is defined analogously for potential retention. I also make a monotonicity assumption. I assume that being hired after TEACHNJ weakly decreases the probability of retention. Even though tenure receipt occurs one year later, turnover rates in each experience level are higher for those hired after TEACHNJ.

Next, I calculate the excess mass of retained fourth-year teachers hired before TEACHNJ

[54] Although I condition all expectations on average pretenure summative rating, race, gender, and district fixed effects, I omit these terms to simplify notation. I do not condition on experience fixed effects because I focus on fourth-year teachers to define performance and retention.

scaled to the number of retained teachers. This value is $p = \frac{Pr[Z^* \geq 0|D=0] - Pr[Z^* \geq 0|D=1]}{Pr[Z^* \geq 0|D=0]} \approx 0.2$.[55]

I then provide upper (lower) bounds for performance of dismissed teachers by trimming the bottom (top) p percentile of performance among retained fourth-year teacher. These bounds assume worst-case scenarios where the excess mass of retained teachers are the highest or lowest performers. Using this procedure, the math value-added, ELA value-added, and summative rating effects are bound by $[-0.059, 0.001]$, $[-0.037, 0.059]$, and $[-0.043, -0.003]$, respectively.

A.6 Productivity Effects Heterogeneity

Though I find weak productivity effects of tenure, these estimates may vary by teacher, school, and student characteristics. Directed tenure reforms may be effective if, for example, teachers in high-income schools are particularly responsive to tenure. To conduct this analysis, I reestimate the main model by interacting the independent variables with these traits.

First, I investigate which types of teachers are most responsive to tenure. Columns (1)–(3) of Table A6 show no differences in value-added by gender. However, the difference in summative ratings across genders is statistically significant at the 5% level, as shown by the p-value from an F-test of equality in Column (4). This finding aligns with previous teacher incentive research, which shows men are more responsive than women to performance pay (Jones, 2013) and increased pressure to remain employed due to weak outside options (Nagler et al., 2015). In addition, Niederle and Vesterlund (2007) find men prefer working in a competitive environment relative to women. These factors would facilitate a performance decline after tenure receipt when the competitive environment to receive tenure vanishes.

Next, I estimate the productivity effects by race in Columns (4)–(7) of Table A6. The results are similar, though Hispanic teachers experience no change in math value-added and an increase in ELA value-added. The differences rely on fewer than 300 teachers, so I

[55] To keep the samples similar before and after the law, I measure retention into year 4 among the entire sample of second-year teachers.

interpret them cautiously.

The effects may be concentrated among certain subsets of teachers that are particularly sensitive to value-added. Specifically, standardized test scores only affect the ratings of math teachers from grades 4 to 7 and ELA teachers from grades 4 to 8. In Column (8) of Table A6, I reestimate the main model using these high stakes subject-grades.[56] Although the future employment of these teachers is directly tied to test scores, their productivity effects remain nearly identical to the average effect of all teachers in the main results.

I then evaluate which types of schools are most impacted by the productivity effects of tenure in Table A7. I consider indicators for having at least 20% Black (Columns (1)–(3)), Hispanic (Columns (4)–(6)), and FRPL eligible (Columns (7)–(9)) students. In Table A8, I conduct a similar analysis using 50% math (Columns (1)–(3)) and ELA (Columns (4)–(6)) proficiency rates as thresholds. Although I find no statistically significant differences in summative ratings, the negative value-added effects are concentrated among wealthier schools with few minority students and high proficiency rates. These differences are statistically significant for the percentage of Hispanic, FRPL eligible, and math proficient students.

To test the robustness of these results, I estimate which types of students are most impacted by the productivity effects of tenure. I only consider value-added because I cannot separate ratings by student characteristics. Table A9 shows the results by student gender (Columns (1)–(3)), race (Columns (4)–(7)), and FRPL eligibility (Column (8)–(10)). Male students suffer more than female students when paired with a tenured teacher. This finding reflects the main results by teacher gender. Similarly, Hispanic and FRPL eligible students experience less of a decline in their teachers' math and ELA value-added relative to their counterparts. These results align with school characteristics in Table A7.

From a policy perspective, tenure is often criticized for protecting low-performing teachers in impoverished districts. However, these results show the negative effects are concentrated in wealthier, higher-achieving schools with few minority students. This suggests tenure reforms

[56] Students in other grades take these exams but their scores do not impact their teachers' ratings.

should target these schools. However, almost all the impacts remain smaller than the returns to experience in the first four years.[57] As a result, the efficacy of targeted reforms is limited.

[57] The only point estimate that is larger than early career returns to experience (0.043 ELA standard deviations) is the ELA value-added productivity effects for schools with few FRPL eligible students (-0.050 standard deviations). However, the two values are statistically indistinguishable from each other.

A.7 Appendix Tables

Table A1: Summative Rating Weights By Year and Subject

	2014, 2017, 2018		2015, 2016	
	ELA 4-8 Math 4-7	Other	ELA 4-8 Math 4-7	Other
Teacher Practice	55%	85%	70%	80%
SGO - District	15%	15%	20%	20%
mSGP - State	30%		10%	

Notes: This table shows summative rating weights. The first two columns record the weights for the academic years ending in 2014, 2017, and 2018. The first column provides weights for high stakes subjects where standardized tests impact the summative ratings. The second column provides weights for all other teachers. The third and fourth columns are defined similarly for the academic years ending in 2015 and 2016. In this table, SGO and mSGP are acronyms for Student Growth Objectives and median Student Growth Percentiles, respectively.

Table A2: Sample Restrictions

	Math VA	ELA VA	Ratings
All Teachers	50,835	56,445	154,670
Has Non-Missing Student Data	38,715	43,082	51,814
Has Value-Added in Years 2 and 3	3,199	3,562	6,480
Has Summative Ratings in Years 2 and 3	NA	NA	3,871

Notes: This table shows the number of observations remaining after each sample restriction. The first column records the number of teachers used for the math value-added analysis. The second and third columns are defined similarly for ELA value-added and summative ratings, respectively. The first row includes all teachers with the performance measure listed in the column header. In the second row, I restrict the sample to math and ELA teachers in tested grades with non-missing student, class, and school characteristics. In the third row, I restrict the sample to teachers with value-added in years 2 and 3. This provides multiple observations of performance prior to tenure receipt. In the final row, I restrict the sample to teachers with summative ratings in years 2 and 3. I only use this restriction for the summative rating analysis.

Table A3: Tenure Effects on Class Composition

	(1) Size	(2) % Black	(3) % Hisp.	(4) % Female	(5) % FRPL	(6) % Spec. Ed.	(7) % ELL	(8) New Grade
Tenure	0.191	-0.017*	0.003	0.002	0.024*	-0.003	-0.005	-0.080***
	(0.390)	(0.010)	(0.012)	(0.006)	(0.014)	(0.014)	(0.005)	(0.015)
Num Classes	22,718	22,572	22,624	22,624	22,622	22,496	22,623	18,312

Notes: This table shows γ from equation (4). The column headers define the dependent variables.
Standard errors in parentheses and clustered at the school level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A4: Productivity and Selection Effects at Tenure Receipt

	(1) Math VA	(2) ELA VA	(3) Ratings
Tenure	-0.014	0.004	-0.003
	(0.012)	(0.013)	(0.013)
	[-0.045]	[0.016]	[-0.008]
Num Schools	1,867	1,895	1,568
Num Teachers	3,199	3,562	3,871
Obs	514,487	645,807	13,960

Notes: This table shows γ from a modified version of equation (2) that excludes teacher fixed effects (ψ_j). Only Column (3) includes school and year fixed effects. The column headers define the performance measure.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* p<0.10, ** p<0.05, *** p<0.01

Table A5: Tenure Receipt and Length Reform Estimates Worst Case Scenario

	(1) Tenure Length	(2) Tenure Receipt and Length
Tenure Receipt	-3.085***	-3.073***
	(0.008)	(0.010)
Obs	257,410	257,410

Notes: This table shows γ coefficients from equation (2) when using the model defined in Section A.4. The estimates are parameterized to depict the worst-case scenario 6% annual decrease in retention attributable to TEACHNJ (see Figure 3). The parameterization is described in Appendix Section A.4.1. Column (1) shows the effect when only extending the time to tenure from three to four years. Column (2) shows the effect when extending the time to tenure and increasing the tenure receipt requirements.

Standard errors in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table A6: Productivity Effects Heterogeneity

Panel A: Math Value-Added

	(1) Male	(2) Female	(3) P-Value	(4) White	(5) Black	(6) Hispanic	(7) P-Value	(8) High Stakes
Tenure	-0.034	-0.032***	0.935	-0.033***	-0.047*	0.000	0.493	-0.032***
	(0.022)	(0.011)		(0.012)	(0.028)	(0.030)		(0.011)
	[-0.110]	[-0.104]		[-0.108]	[-0.151]	[0.001]		[-0.104]
Num Schools	1,023	1,765		1,822	425	381		1,528
Num Teachers	651	2,548		2,796	196	215		2,569
Obs	122,780	391,707		448,306	31,860	34,930		331,446

Panel B: ELA Value-Added

	(1) Male	(2) Female	(3) P-Value	(4) White	(5) Black	(6) Hispanic	(7) P-Value	(8) High Stakes
Tenure	0.010	0.008	0.945	-0.001	0.041	0.080**	0.095	0.008
	(0.037)	(0.011)		(0.012)	(0.035)	(0.040)		(0.012)
	[0.036]	[0.027]		[-0.003]	[0.143]	[0.278]		[0.028]
Num Schools	854	1,832		1,830	494	480		1,572
Num Teachers	505	3,057		3,069	245	261		3,099
Obs	90,858	554,949		560,965	42,216	44,549		564,811

Panel C: Summative Ratings

	(1) Male	(2) Female	(3) P-Value	(4) White	(5) Black	(6) Hispanic	(7) P-Value	(8) High Stakes
Tenure	-0.118***	-0.002	0.015	-0.008	-0.137*	-0.066	0.187	-0.020
	(0.044)	(0.016)		(0.016)	(0.082)	(0.047)		(0.016)
	[-0.367]	[-0.006]		[-0.024]	[-0.426]	[-0.204]		[-0.062]
Num Schools	572	1,471		1,484	225	225		1,264
Num Teachers	671	3,200		3,371	229	282		2,965
Obs	2,420	11,540		12,241	775	976		10,213

Notes: This table shows γ from equation (2) for the performance measure listed in the panel title. Only Panel C includes school and year fixed effects. Columns (1) and (2) show the effect by interacting each independent variable with teacher gender. Column (3) provides the p-value from an F-test of equality for the coefficients. Columns (4)–(7) are defined similarly for teacher race. For race, the F-test evaluates whether the coefficients for Black and Hispanic teachers are jointly different from the coefficient for White teachers. Column (8) shows the effect on grades 4 to 7 math and 4 to 8 ELA teachers.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A7: Productivity Effects by School Characteristics

Panel A: Math Value-Added

	(1) Black: 20%+	(2) <20%	(3) P-Value	(4) Hispanic: 20%+	(5) <20%	(6) P-Value	(7) FRPL: 20%+	(8) <20%	(9) P-Value
Tenure	-0.026	-0.043***	0.460	-0.001	-0.058***	0.006	-0.011	-0.062***	0.020
	(0.018)	(0.013)		(0.014)	(0.015)		(0.012)	(0.018)	
	[-0.084]	[-0.138]		[-0.004]	[-0.189]		[-0.035]	[-0.201]	
Num Schools	942	1,566		1,160	1,357		1,427	951	
Num Teachers	1,021	2,326		1,431	1,919		2,063	1,262	
Obs	147,591	362,219		218,622	291,188		311,242	198,568	

Panel B: ELA Value-Added

	(1) Black: 20%+	(2) <20%	(3) P-Value	(4) Hispanic: 20%+	(5) <20%	(6) P-Value	(7) FRPL: 20%+	(8) <20%	(9) P-Value
Tenure	0.018	-0.002	0.414	0.053***	-0.037**	0.000	0.038***	-0.050***	0.000
	(0.021)	(0.014)		(0.017)	(0.015)		(0.015)	(0.018)	
	[0.064]	[-0.008]		[0.186]	[-0.128]		[0.133]	[-0.176]	
Num Schools	946	1,582		1,155	1,408		1,444	975	
Num Teachers	1,086	2,623		1,565	2,181		2,272	1,455	
Obs	163,238	477,281		255,192	385,327		375,390	265,129	

Panel C: Summative Ratings

	(1) Black: 20%+	(2) <20%	(3) P-Value	(4) Hispanic: 20%+	(5) <20%	(6) P-Value	(7) FRPL: 20%+	(8) <20%	(9) P-Value
Tenure	-0.049	-0.010	0.271	-0.033	-0.010	0.450	-0.019	-0.019	0.994
	(0.031)	(0.016)		(0.023)	(0.018)		(0.021)	(0.020)	
	[-0.151]	[-0.031]		[-0.101]	[-0.031]		[-0.061]	[-0.060]	
Num Schools	403	1,138		608	933		903	638	
Num Teachers	1,085	2,938		1,647	2,390		2,383	1,647	
Obs	3,533	10,362		5,561	8,334		8,235	5,660	

Notes: This table shows γ from equation (2) for the performance measure listed in the panel title. Only Panel C includes school and year fixed effects. Column (1) shows the effect for schools with at least 20% Black students, while Column (2) shows the effect for schools with less than 20% Black students. Column (3) provides the p-value from an F-test of equality for the coefficients. Columns (4)–(9) are defined similarly for school Hispanic and FRPL compositions.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A8: Productivity Effects by School Proficiency

Panel A: Math Value-Added

	(1) Math Prof: 50%+	(2) <50%	(3) P-Value	(4) ELA Prof: 50%+	(5) <50%	(6) P-Value
Tenure	-0.051***	-0.010	0.056	-0.045***	-0.007	0.108
	(0.013)	(0.017)		(0.013)	(0.019)	
	[-0.166]	[-0.031]		[-0.144]	[-0.024]	
Num Schools	1,492	1,038		1,632	846	
Num Teachers	2,150	1,227		2,461	868	
Obs	333,238	175,600		393,503	115,335	

Panel B: ELA Value-Added

	(1) Math Prof: 50%+	(2) <50%	(3) P-Value	(4) ELA Prof: 50%+	(5) <50%	(6) P-Value
Tenure	-0.015	0.040**	0.024	-0.001	0.014	0.600
	(0.014)	(0.020)		(0.013)	(0.026)	
	[-0.052]	[0.140]		[-0.004]	[0.049]	
Num Schools	1,501	1,025		1,664	845	
Num Teachers	2,438	1,295		2,777	925	
Obs	444,206	194,578		509,792	128,992	

Panel C: Summative Ratings

	(1) Math Prof: 50%+	(2) <50%	(3) P-Value	(4) ELA Prof: 50%+	(5) <50%	(6) P-Value
Tenure	-0.014	-0.031	0.600	-0.012	-0.053	0.315
	(0.017)	(0.027)		(0.016)	(0.038)	
	[-0.045]	[-0.096]		[-0.039]	[-0.165]	
Num Schools	1,019	507		1,189	337	
Num Teachers	2,624	1,449		3,067	941	
Obs	9,176	4,690		10,850	3,016	

Notes: This table shows γ from equation (2) for the performance measure listed in the panel title. Only Panel C includes school and year fixed effects. Column (1) shows the effect for schools with at least 50% math proficient students, while Column (2) shows the effect for schools with less than 50% math proficient students. Column (3) provides the p-value from an F-test of equality for the coefficients. Columns (4)–(6) are defined similarly for ELA proficiency rates.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* p<0.10, ** p<0.05, *** p<0.01

Table A9: Productivity Effects by Student Characteristics

Panel A: Math Value-Added

	(1) Male	(2) Female	(3) P-Value	(4) White	(5) Black	(6) Hispanic	(7) P-Value	(8) FRPL	(9) Not FRPL	(10) P-Value
Tenure	-0.055***	-0.010	0.000	-0.047***	-0.030*	-0.007	0.046	-0.014	-0.048***	0.019
	(0.011)	(0.012)		(0.014)	(0.018)	(0.014)		(0.012)	(0.013)	
	[-0.178]	[-0.034]		[-0.153]	[-0.098]	[-0.022]		[-0.046]	[-0.157]	
Num Schools	1,761	1,737		1,737	1,737	1,737		1,676	1,721	
Num Teachers	3,198	3,186		3,186	3,186	3,186		3,085	3,156	
Obs	263,745	250,742		283,497	88,682	142,308		205,879	308,608	

Panel B: ELA Value-Added

	(1) Male	(2) Female	(3) P-Value	(4) White	(5) Black	(6) Hispanic	(7) P-Value	(8) FRPL	(9) Not FRPL	(10) P-Value
Tenure	-0.016	0.030**	0.000	-0.019	0.007	0.056***	0.002	0.040**	-0.014	0.004
	(0.012)	(0.013)		(0.013)	(0.020)	(0.019)		(0.016)	(0.013)	
	[-0.055]	[0.105]		[-0.067]	[0.023]	[0.195]		[0.138]	[-0.050]	
Num Schools	1,797	1,782		1,782	1,782	1,782		1,730	1,769	
Num Teachers	3,558	3,541		3,541	35,41	3,541		3,429	3,507	
Obs	332,165	313,642		375,751	98,289	171,767		244,551	401,256	

Notes: This table shows γ from equation (2) for the performance measure listed in the panel title. Column (1) shows the effect for male students, while Column (2) shows the effect for female students. Column (3) provides the p-value from an F-test of equality for the coefficients. Columns (4)–(10) are defined similarly for student race and FRPL eligibility.

Standard errors in parentheses and clustered at the school level. Performance units rescaled to standard deviation 1 in the dataset are included in brackets.

* p<0.10, ** p<0.05, *** p<0.01

A.8 Appendix Figures

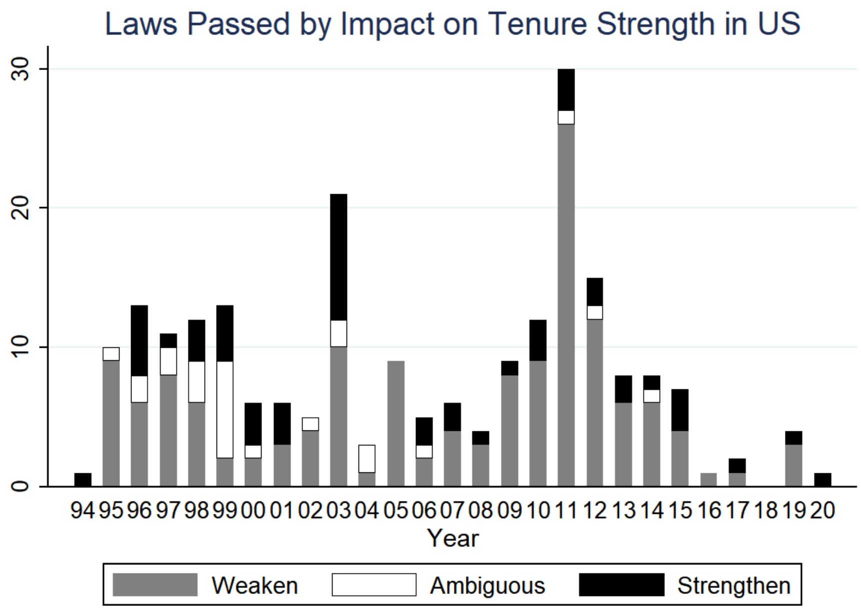
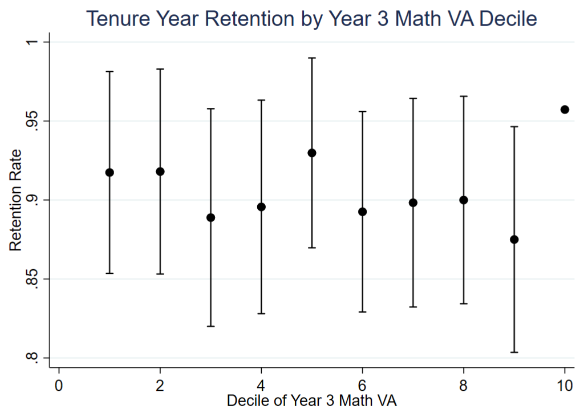


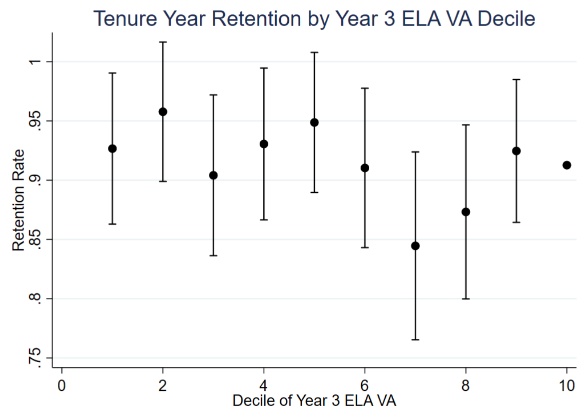
Figure A1: Laws Passed by Impact on Tenure Strength in the US

Notes: This figure records the number of tenure laws passed in the United States. The x-axis defines the year from 1994 to 2020, while the y-axis counts the number of laws. The laws are divided by their impact on tenure. Some examples of weakened tenure protections include extended pretenure periods and streamlined tenure dismissal policies. Some examples of strengthened tenure protections include shortened pretenure periods and narrowed scope for contract non-renewals. Laws that strengthen and weaken different components of tenure are listed as ambiguous. In total, this figure records 222 tenure laws across 49 states. This figure uses data from the Education Commission of the States.

Panel A: Math Value-Added



Panel B: ELA Value-Added



Panel C: Summative Ratings

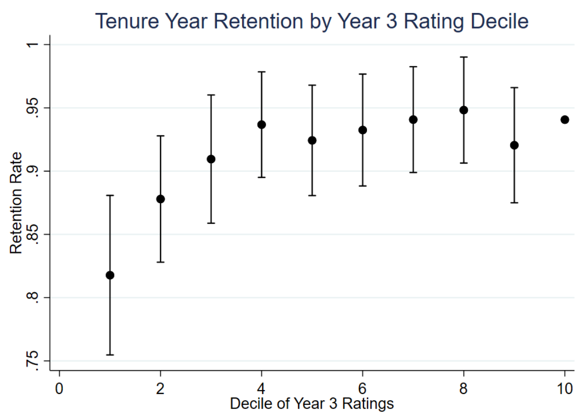


Figure A2: Tenure Year Retention by Decile

Notes: This figure plots retention rates and 95% confidence intervals by decile of year 3 performance. The x-axis records the decile of year 3 math value-added (Panel A), ELA value-added (Panel B), or summative rating (Panel C). The y-axis measures the retention rates. The omitted group is the top decile of year 3 performance.

Panel A: Education Bachelor's Degrees *Panel B: Education Master's Degrees*

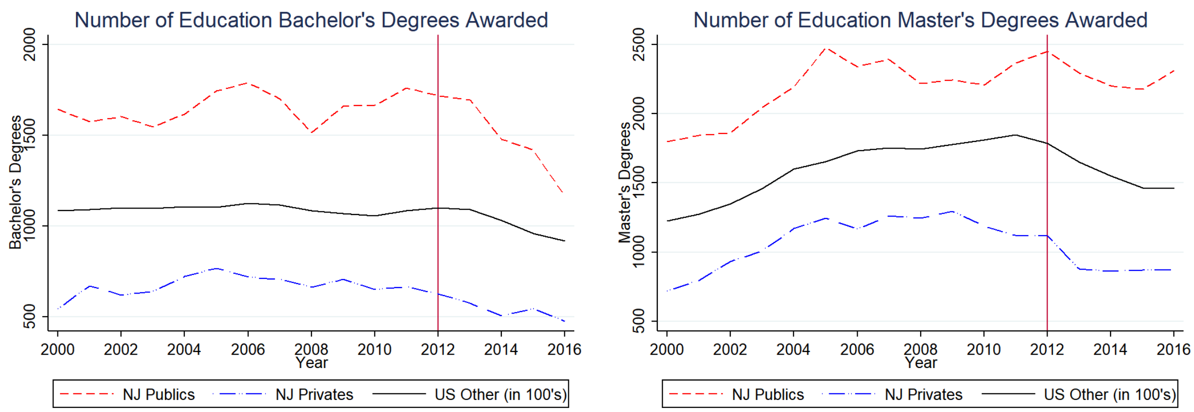


Figure A3: Trends in Education Degrees

Notes: This figure shows the number of bachelor's (Panel A) and master's (Panel B) degrees awarded by New Jersey public colleges, New Jersey private colleges, and all other United States colleges. The x-axis records the year, while the y-axis records the number of degrees awarded. The dashed red lines show New Jersey public colleges. The dashed and dotted blue lines show New Jersey private colleges. The solid black lines show all other United States colleges in hundreds of degrees. The red vertical lines illustrate the passage of TEACHNJ in 2012. This figure uses data from the Integrated Postsecondary Education Data System (IPEDS) of the National Center for Education Statistics.

Panel A: Turnover Rates by Experience *Panel B: Turnover Rates by Calendar Year*

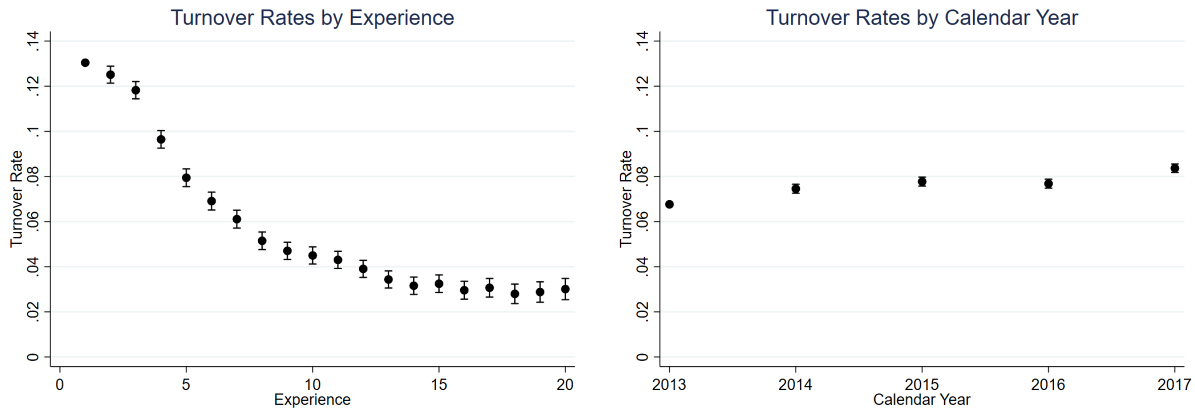


Figure A4: Turnover Rates

Notes: This figure shows the turnover rates and 95% confidence intervals by experience and calendar year. The omitted groups are teachers with 1 year of experience (Panel A) and teachers in 2013 (Panel B). In Panel A, I also omit teachers with more than 20 years of experience.