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Public Pensions and Salary Spiking: A Cautionary Tale of Data Inaccuracy Leading to Erroneous Results

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Abstract

Analyses of public policy issues often rely on administrative data collected by state and local governments. The reliability of such analyses is contingent on the quality of the data and it is tempting for researchers to take the accuracy of administrative data for granted. In this paper we show how this can lead to spurious research findings. Specifically, we use two sets of administrative data on teacher compensation to study the issue of salary spiking (where end-of-career spikes in compensation are used to boost pension benefits) in Washington State. We illustrate how discrepancies in the reporting of pensionable compensation can lead one to strikingly different conclusions about the prevalence and financial implications of salary-spiking behavior. Our findings point to the importance of understanding how data collection processes and administrative uses of the data may (fail to) incentivize accuracy in reporting.

Keywords: pension, methodology

1. Introduction

Administrative data compiled by federal, state, and local governments have become increasingly available and are a vital part of policy research designed to inform decisionmaking.[1] While rarely collected explicitly for research purposes, it is often tempting for researchers to take the accuracy of administrative data for granted. But data are often collected because administrative rules require it, not because the data are particularly critical to any administrative process. In these cases, there is often little incentive to invest resources in verifying data accuracy or to correct mistakes. Therefore, in using administrative data, which are likely to be more complex and less well-documented than research-oriented data (such as U.S. Census Bureau or other survey data), it is important for researchers to understand how and why the data are collected and to assess a data set's accuracy with a degree of skepticism.

In this paper, we present an analysis using administrative data from Washington State that serves as a cautionary tale. Specifically, we study the prevalence and financial implications of salary spiking, where end-of-career increases in salary are used to boost the value of employees' defined benefit (DB) pensions. This is an important issue, for as described below, such increases in pension benefits tend to result in unfunded liabilities. Using the issue of salary spiking as a backdrop, we demonstrate how inconsistencies in teacher compensation records can generate misleading results. Our analysis uses employee-level compensation data reported by the state's public school districts to the Office of the Superintendent of Public Instruction (OSPI) and the Department of Retirement Services (DRS).[2] The data reported to OSPI include

[1] Indeed, we have used the administrative data discussed in this paper across many of our publications.
[2] Washington DRS describes the process by which employers should report data in the employer handbook, which can be found at http://www.drs.wa.gov/employer/handbook/chpt1/default.htm.

information on base salary as well as supplemental pay associated with additional time and responsibility, overtime, and buyback of unused leave.[3] The data reported to DRS include each employee's total pensionable compensation. During the period 2011 to 2016, the compensation data from OSPI and DRS overlap, allowing us to compare the pensionable compensation implied by the OPSI data to that recorded by DRS.

A naïve analysis of salary spiking using only OSPI data identifies nearly 30% of employees as salary spiking, with an implied cost to the pension system of $57 million for employees who separated from employment during the study 2011 to 2016 study period. In contrast, under a corresponding analysis incorporating DRS salary data, we find little evidence of salary spiking. The discrepancy between these estimates appears to be related to how school districts report compensation associated with the buyback of unused sick leave when employees exit employment, a form of compensation that is not pensionable.

In what follows, we provide background on the issue of salary spiking and its context in Washington State, describe the data used in the analysis, advance an empirical approach to identify salary-spiking behavior, and present findings on the prevalence and financial implications of salary-spiking behavior under the naïve and parallel analyses. A discussion section concludes.

[3] The term *buyback* is often expressed as *cashout*. We use *buy back* because it is more consistent with the language defining rules related to payments for unused leave in the Revised Code of Washington.

2. Background

2.1 Research on Administrative Data Quality

We are certainly not alone in calling attention to the fact that the ability of researchers to use administrative data to provide insights into important policy issues is limited by the quality of such data. For instance, in the context of using administrative data to assess the quality of medical care, Iezzoni (1997) found that issues of data quality related to coding accuracy, completeness of coding, and variable data quality across hospitals, limited researchers' ability to derive valid appraisals of quality of care using administrative data generated by hospitals. Looking more directly at the accuracy of data recorded in the course of providing health care, Peabody et al. (2004) found that only 57% of primary diagnoses were correctly recorded on administrative encounter forms.

The quality of administrative data has been shown to have important implications for causal findings. For example, Barreca et al. (2011) revisit research by Almond et al. (2010) that analyzed the marginal returns to medical care in the context of treatment thresholds for newborn babies with low birth weight. They find evidence that the birth weights recorded by hospitals were often imprecise, resulting in a clustering of observations at different levels of birth weight that was consistent with rounding practices or inexact measuring equipment. The findings in Almond et al. (2010) proved to be sensitive to the exclusion of observations clustered at the treatment threshold, leading Barreca et al. (2011) argue that the robustness of the original results were overstated.

One reason to be circumspect about the accuracy of administrative data is that data collection processes often fail to incentivize accurate reporting. As noted by Slemrod (2016), “[In] some cases, there may be consequences, negative or positive, for misstatements of the truth in submitting administrative data” (page 1,004). For instance, in an analysis of administrative data collection by national governments in Africa, Sandefur and Glassman (2015) found that student enrolment figures reported by frontline service providers diverged from survey estimates when the government’s funding mechanism shifted from a bottom-up fee based system to top-down per-pupil grants from the central government.

In the domain of public education, Dynarski et al. (2015) call for researchers to be more aware of potential pitfalls when working with data from the National Student Clearinghouse (NSC), which was born out of the student loan industry in 1993 and has more recently made efforts to integrate its data with state-level K-12 data. A primary data-quality concern is that students not appearing in NSC data are indistinguishable from students who do not enroll in college. Indeed, enrollment coverage in the NSC, which relies on institutions of higher education to participate and report accurate data on student enrollment, varies significantly across states, by type of institution, and over time. Using state-level data on college enrollment from Michigan, the authors demonstrate how failing to account for this variation in coverage can result in misleading findings.

To the best of our knowledge, ours is the first analysis to demonstrate how errors in the personnel data collected by states, and compensation data in particular, can generate dramatically misleading results. This is important because most states compile longitudinal administrative data generated by local school districts, and these data have been a tremendous asset for research on a wide variety of schooling issues (Figlio, Karbownik, & Salvanes, 2017).

Given this, it is important for researchers to understand how the collection process and ultimate administrative use (or nonuse) of the data may incentivize accuracy in reporting.

2.2 Salary Spiking in Public Pension Systems

Public pension systems have faced increasing scrutiny due to concerns about their fiscal sustainability. Many state pension systems are drastically underfunded, with estimates of total U.S. shortfalls exceeding several trillion dollars (Novy-Marx & Rauh, 2011; Biggs, 2015). The increasing levels of contributions required to pay down these unfunded pension obligations can put significant pressure on states and local governments which must raise taxes or reduce funding to government services (Zeehandelaar & Winkler, 2013; Malanga & McGee, 2018). The roles that overly optimistic actuarial assumptions, the over-promising of benefits, and persistent underfunding have played in producing these shortfalls have been addressed in the public pension literature (Novy-Marx & Rauh, 2009; Brown, Clark, & Rauh, 2011). Salary spiking, however, has received relatively little attention as a potential source of funding shortfalls in public defined benefit (DB) pension systems.

Salary-spiking activity might be expected given the design of traditional DB pension systems. DB pension plans provide members guaranteed monthly payments for the duration of their retirement and the size of the payment is typically a function of an employee's years of service and final average salary (FAS) level. The incentive to "spike" salary arises from the fact that a discrete spike in salary can be leveraged into receiving a higher level of compensation for the duration of one's retirement.

Under one of the teacher pension plans in Washington State (TRS1), for example, earning an additional $5,000 in salary during one's FAS averaging period would result in receiving an additional \$1,500 in benefits during each year of retirement.[4] Assuming a 4% discount rate, this would translate to an increase in the present value of the employee's DB annuity of \$20,385 if the employee lived for 20 years in retirement. While the additional compensation in this example would result in additional costs to the employee (in terms of contributions to the pension fund) and employer (in terms of compensation paid and contributions to the pension fund), they would be several times smaller than the additional pension benefits.[5]

While the definition of salary spiking is simple, there are nuances regarding what should or should not be characterized as salary-spiking behavior is not always clear. For example, most teachers exit the workforce with some amount of unused sick leave and in some states, buybacks of unused leave count as pensionable compensation. One teacher may accumulate a large amount of sick leave with the intention of boosting her pension benefit, while another may simply not happen to take many sick days. In the latter case, the accumulation of sick leave would have occurred with or without the pension system. Nonetheless, both individuals' pension benefits are boosted by the accumulation of sick leave, which will affect the state's unfunded liabilities. For the purposes of this paper, we would classify both individuals as salary spiking, even if in the latter case the spiking can be thought of as coincidental.

A second nuance is that salary spiking may operate through several different mechanisms. Continuing with the sick leave example above, the former teacher was engaging in

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[4] Under TRS1, the annual benefit is equal to $2\% * FAS * Years\ of\ Service$, where FAS is equal to average salary during an employee's two highest consecutive years of compensation. A one-time increase of \$5,000 during the FAS period would increase FAS by \$2,500, corresponding to an increase in the annual benefit of $0.02 * \$2{,}500 * 30 = \$1{,}500$, if the employee retires with 30 years of service.

[5] In 2014, the total employer and employee contribution rate to TRS1 was 13.7%. At that rate, additional compensation of \$5,000 would result in additional pension contributions of \$685.

"individual-driven spiking" in that she was accumulating sick leave for her personal benefit. The latter teacher was not engaging in individual-driven spiking but was nonetheless experiencing a boost in her pension. Hence, both teachers were benefiting from "structurally-driven spiking"—at some point, the decision to include sick leave buyback in the definition of pensionable compensation was negotiated (presumably) with knowledge of that decision's pension implications. Finally, some employees may benefit from "employer-driven spiking." For example, a principal may reward some teachers by making higher-paid positions available to them with the knowledge that the higher pay will be leveraged into a higher monthly benefit as well.

Perhaps the biggest challenge to empirically identifying salary-spiking behavior is obtaining detailed enough data to distinguish between pensionable and nonpensionable compensation. Depending on the pension plan, pensionable compensation may or may not include payments such as overtime, buyback of unused leave, performance or retirement bonuses, or expense reimbursements. Often, data on total compensation is insufficient.

The difficulty of obtaining salary data of sufficient quality may be one reason that the issue of salary spiking has received relatively little attention in the academic literature. To the best of our knowledge, the only published analysis of salary spiking is Fitzpatrick's (2017) study of the Illinois Teacher Retirement System. She obtained records on teachers' total compensation, which under the Illinois Teacher Retirement System (TRS), reflects pensionable compensation. These salary data were supplemented by information about teacher contracts codified in collective bargaining agreements, which were collected from a sub-sample of school districts. Fitzpatrick was also able to leverage a policy change in 2005 that required school districts to pay the full pension cost associated with end-of-career earnings increases above 6%—the threshold had previously been 20%—of the previous years' salary (i.e., the present value of the associated increase in pension benefits).

Fitzpatrick estimates that the pension costs associated with end-of-career salary increases received by Illinois TRS members prior to the policy change were costing state taxpayers about $116 million per year. While school districts were responsive to the policy change (school districts became less likely to award retirement bonuses of more than 6% and more likely to award retirement bonuses of exactly 6%), the rule change led some school districts that did not previously award bonuses to start providing them. Other districts that had been awarding bonuses above the 6% threshold avoided exceeding the threshold by spreading bonus compensation over multiple years of service. Consequently, the policy failed to reduce the overall costs associated with salary spiking.

2.3 Salary Spiking in the Context of Washington State's Teacher Retirement System

For salary spiking to be a viable mechanism for boosting pension benefits, teachers and school districts must be able to strategically augment end-of-career salaries. Here, we describe teacher compensation structures in Washington State and what they suggest about the ability of teachers and school districts to engage in salary-spiking behavior.

The largest component of teachers' salaries in Washington is determined and funded by the state. The state salary schedule sets compensation levels for certificated instructional staff based on years of service, degree level, and academic credits earned after degree. Teachers and districts have little ability to augment these state-funded base salaries.

In addition to base salaries, state law allows districts to pay additional compensation for additional time, responsibilities, and incentives. This supplemental pay, termed "TRI-pay," is determined in local negotiations between teachers and school districts and is codified in collective bargaining agreements (CBAs). In many districts, a portion of TRI-pay is determined by a supplemental salary schedule that builds on top of the state's base salary schedule in a proportional manner. This form of TRI-pay can be quite large—often exceeding $10,000—but also affords teachers and districts little opportunity to augment end-of-career salaries because it is strictly a function of experience, degree, and credits.

Teachers may also earn additional compensation under TRI-pay by taking on additional responsibilities or leadership positions. For example, a teacher could teacher summer school, serve as a department head, oversee extracurricular activities, serve as a mentor teacher, serve on short-term committees or projects (e.g., a curriculum revision committee), or undertake activities resulting in overtime pay. Depending on the nature of the work, compensation may be paid hourly or in the form of a stipend. Here, teachers and administrators do have some ability to augment end-of-career compensation by directing extra responsibilities toward individual teachers or groups of teachers.

Critical to how employers and employees can strategically boost end-of-career salaries, is the definition of "pensionable compensation." The rules governing pensionable compensation in Washington State vary depending on the plan in which teachers are enrolled.[6] Washington currently operates three plans under its Teacher Retirement System (TRS): TRS1,

[6] Pensionable compensation is defined in the state's administrative code (RCW 41.23.010). A detailed list of pensionable and nonpensionable types of compensation under TRS1 and TRS2/3 is available here: http://app.leg.wa.gov/wac/default.aspx?cite=415-112-401.

TRS2, and TRS3. Key features of these plans are presented in **Table 1**. Plan membership depends on date of hire and for some members (who were given a choice), whether they opted into TRS2 or TRS3. TRS1 and TRS2 are traditional DB plans with 5-year vesting periods and 2% benefit factors. TRS1 has a shorter FAS averaging period than TRS2 (2 years vs. 5 years) and its members can retire at younger ages. TRS3 is a hybrid DB-DC plan that provides a DB with a 1% benefit factor and a 10-year vesting period and a defined contribution (DC) component funded by employee contributions.

Pensionable compensation for TRS1 members includes “All salaries and wages paid by an employer to an employee member of the retirement system for personal services rendered during a fiscal year” (RCW 41.23.010, section (14)(a)(i)). This definition includes overtime payments and remuneration for unused annual leave (up to 30 days) but excludes remuneration for unused sick leave and retirement or termination bonuses. The definition of pensionable compensation for TRS2 and TRS3 is narrower in that it excludes remuneration for unused annual leave and all forms of severance pay.

While TRS1 does allow remuneration for unused annual leave to be included in FAS calculations, TRS members tend to have little opportunity to accumulate meaningful amounts of annual leave. In reviewing the collective bargaining agreements (CBAs) of a sample of Washington school districts, we found that teachers were provided between 1 and 3 days of personal leave per year and could accumulate between 2 and 5 days of leave. Therefore, any end-of-career buyback of unused leave would tend to be small. Ultimately, the ability to use unused leave buyback to boost pension benefits appears to be limited in Washington State.

In the context of salary spiking, two features of the TRS pension plans are worth highlighting. First, the FAS averaging period is shorter under TRS1 (2 years vs. 5 years), making it easier boost retirement benefits by augmenting end-of-career salaries. Second, the overall value of the DB annuity is largest under TRS1 and smallest under TRS3 due to TRS1 members being eligible to retire with full benefits earlier than members of TRS2 and TRS3 (age 55 vs. age 62), and the TRS3 benefit multiplier being smaller than that of TRS1 and TRS2 (1% vs. 2%). These differences in plan parameters translate to differential pay-offs to salary spiking, with the highest potential payoff under TRS1 and the lowest payoff under TRS3.

The teacher salary data in Washington State are seemingly well-suited to the task of identifying salary-spiking behavior. School districts are instructed by the Office of the Superintendent of Public Instruction (OSPI) to report total compensation and the amount of compensation associated with different assignments, including the base contract, supplemental contracts associated with additional time and responsibility, and buyback of leave. These variables would seem to provide a good approximation of pensionable salary, but some are not subject to strict reporting rules.

As noted above, some data are collected because administrative rules require it, not because the data are particularly critical to any administrative process. This is true of some of the data collected by OPSI in its S-275 personnel reporting system. In fact, the S-275 Personnel Reporting Handbook explicitly differentiates between data that affect the apportionment of state moneys and other data that are "informational only."[7] The S-275 data that affect the apportionment of state moneys are:

- Personnel information used to place certificated employees on the state salary schedule (i.e., degrees, credits, and certificated years of experience)
- Full-time equivalents (FTEs)
- Assignment codes and percentage of time assigned to duties associated with basic education, special education, and state institution education programs

Documentation requirements for these data are specified in the Washington Administrative Code (WAC). Other data reported to the S-275 are "informational only and may be documented in any reasonable manner" (Office of the Superintendent of Public Instruction, 2015, page 14). The data elements that do affect the apportionment of state funds are subject to audit by the Washington State Auditor's Office (SAO). For example, Seattle Public Schools was recently audited by the SAO on their reporting of staff mix and the SAO identified 15 errors that resulted in an underpayment of $41,018.[8]

What is important in the context of our use of the S-275 data is that some variables do *not* affect the apportionment of state moneys and are therefore subject to less stringent documentation and auditing requirements. And because data on total compensation, for example, does not affect the apportionment of state moneys, both school districts and OSPI

[7] The Handbook is available here: http://www.k12.wa.us/bulletinsmemos/Bulletins2015/B066-15Attach1.pdf, accessed on 6/19/2018.

[8] See https://www.seattleschools.org/UserFiles/Servers/Server_543/File/District/Departments/Internal%20Audit/13-14%20Audits/13-14%20Audits%20ADA/Final%20S-275%20Staff%20Mix%20Report%20-%20ADA%20Compliant.pdf, visited on 6/19/2018.

have relatively little incentive to invest resources into verifying the accuracy of that data and correcting mistakes when they are identified.

In contrast, there are strong incentives for ensuring the accuracy of the salary data collected by the Department of Retirement Services (DRS) because the figures reported to DRS are directly linked to two administrative outcomes. First, they are used to determine the size of each employee's DB annuity and second, they determine how much employers and employees contribute to the pension system. Also, employer and employee contributions (which are untaxed income) have important federal tax implications, creating a secondary incentive to record accurate data. As discussed below, we find substantial differences in the compensation data reported to DRS and that collected by OPSI.

3. Data

In this section, we describe the data used in the analysis, discuss measures of teacher compensation, and analyze differences in the salary data recorded by OPSI and the salary data recorded by DRS.

3.1 Data Sources

Our analysis of Washington State uses two administrative data sets. The first is the S-275 personnel reporting system maintained by the Washington State OSPI. The S-275 data include information on teacher names, school district, demographics, position assignment, position assignment salary, total compensation, and experience. Unique certification ID numbers facilitate the tracking of employment over time. We construct a panel of data that spans the school years ending between 1996 and 2017.[9]

The second data set is from DRS. It identifies each active (i.e., employed) member in TRS during the fiscal years ending between 2011 and 2017 and provides records on member name, plan membership (e.g., TRS1, TRS2, or TRS3), status (e.g., new member, active, re-entry), total service credits, school district, and pensionable compensation. The DRS data are matched to the S-275 administrative data using information on employee name, school year, and school district. We linked 86,433 individuals in the S-275 data to records in the DRS data, or 91% of certificated employees.

3.2 Measures of Compensation

Of primary interest to our analysis are data on teacher compensation, and more specifically, pensionable compensation. As discussed above, not all types of compensation are pensionable under the Washington's TRS plans.[10] Buyback of unused sick and vacation time is a potentially large confounder of pensionable salary because teachers can accumulate as much as a full year of sick leave (180 contract days) that can be cashed out at 25% of their regular rate of pay. In principal, the OSPI data allows us to construct a reasonable measure of pensionable compensation that removes pay associated sick leave buyback. As stated in the S-275 Personnel Reporting Handbook, "Districts need to examine all staff salary amounts to determine whether each assignment and salary are reported and which duty code suffix to use" (page 42).[11] The

[9] S- 275 data date back to 1984, but salary definitions in the years prior to 1996 are inconsistent with current definitions.

[10] For a list of pensionable, and nonpensionable, forms of compensation, see http://app.leg.wa.gov/wac/default.aspx?cite=415-112-401. Accessed on July 24, 2018.

[11] The Handbook is available here: http://www.k12.wa.us/safs/INS/PER/1516/S-275,%202015-16.pdf. Accessed on July 24, 2018.

Handbook specifies a duty code for "payments to an individual for certificated sick leave buyback or certificated vacation buy out" (page 62).[12] We construct a measure of pensionable salary by taking the difference between the total compensation reported in the S-275 and the compensation identified under the certificated buy-back duty code.[13]

Table 2 presents summary statistics for the sample teachers identified as separating from employment, reported by pension plan and overall. The primary variables of interest for this study are the two measures of compensation. In the final year of employment, the average pensionable salary implied by the S-275 data is $81,530 while the average pensionable salary reported by DRS is substantially lower at $76,223. The difference between these two measures varies from about $4,000 to $7,000 across pension plans. In contrast, the average difference between the two measures in the year before individuals exit is fairly small ($547). The average teacher in our sample is near retirement age and relatively experienced: 60.4 years and 26.3 years, respectively.[14] Most teachers in the sample have an advanced degree (71%), are female (71%), and are in a classroom teaching position (8%). That said, a sizable portion of our population serves as either an administrator or in another position (7% and 13%).

[12] Note that the duty code does not distinguish between sick leave and vacation buy back, and vacation buy back is pensionable for TRS1 employees.

[13] Lisa Dawn-Fisher, Chief Financial Officer for OSPI, indicated that OSPI would not advise anyone use the compensation data recorded in the S-275 as a source of information about pensionable salaries. In addition to leave buy back (which is associated with a specific duty code), other types of nonpensionable compensation are included in the total compensation reported by OSPI that are not associated with any duty code. Therefore, at best, the compensation data in the S-275 can be expected to provide only an imperfect measure of pensionable compensation (personal communication, July 19, 2018). This is reflected in **Figure 1a**, which shows the distribution of the difference between OSPI- and DRS-based measures of pensionable compensation away from the teachers' final year of service, when sick leave buy back is not being awarded.

[14] Note that our empirical approach, discussed below, demands that we observe compensation over a period of years. Therefore, teachers who exit during their first several years of employment (when exit rates are high) are excluded from our sample.

We further compare our two measures of pensionable compensation in **Figure 1a**, which shows the distribution of the difference between the S-275- and DRS-based measures of pensionable compensation during 2011 to 2016—the years in which our S-275 and DRS data overlap. On average, the S-275-based measure appears to perform fairly well. The distribution is centered on zero (the median difference is $0.46) with a moderate degree of variance (the standard deviation is $3,274).

While the S-275-based measure performs well on average, there are a substantial number of errors of large magnitude. Even if the errors were randomly distributed, this would result in the pattern of compensation falsely appearing to spike in the final year of service for some proportion of individuals. A systematic distribution of errors could exacerbate the false appearance of end-of-career spikes in salary. We explore this possibility in **Figure 1b**, in which the sample is restricted to the year in which a teacher separates from employment.

In contrast to **Figure 1a**, **Figure 1b** shows a strong tendency for the S-275 data to overstate pensionable compensation in the year an employee separates from employment. The mean difference in pensionable salary among employees represented in **Figure 1b** is $3,832 and the median is $506. For roughly 30% of the employees represented in **Figure 1b**, the pensionable salary implied by the S-275 data exceeds that reported by DRS by between $5,000 and $20,000. We do not observe this pattern of deviation in other years of service, and the timing and magnitude of the differences represented in the wide right-hand tail of the distribution suggests sick leave buyback as a potential source of error.

3.3 Leave Buyback and Pensionable Compensation

Since 1984, teachers have been able to accumulate a maximum of 180 days of sick leave for the purpose of buyback (see WAC 392-136-075). When a school district employee separates from employment, accumulated sick leave can be bought back if the employee is at least age 55 and: (1) employment is terminated due to retirement or death, or (2) the employee has accumulated 15 YOS under TRS2 or 10 YOS under TRS3. Sick leave is bought back at the rate of 25% of the full-time daily rate of compensation at the time of separation from employment. Therefore, sick leave buyback amounts can be quite large. For example, a teacher who accumulates 180 days of sick leave and earns annual compensation of $60,000 would take home $15,000 of additional compensation in his or her final year of service—an amount consistent with the large differences in compensation visible in **Figure 1b**.

While the S-275 Personnel Reporting Handbook instructs school districts to report compensation from the buyback of unused leave with the appropriate duty assignment code, most school districts do not report compensation from leave buyback for *any* individuals.[15] For individuals with at least some reported buyback, **Figure 1c** shows the distribution of reported compensation. The pattern strikingly similar to the distribution of errors shown in **Figure 1b**, suggesting that the nonreporting of leave buyback in the S-275 data is the primary driver of those errors.

Why some districts report buyback salary while others do not is unclear. To this end, we contacted a large district to help us understand the S-275 reporting process. The district uses an

[15] During the period 2011 to 2016, 133 out of 294 school districts did not report compensation coded as buy back for any individuals in our study sample.

automated HR data system to track compensation for all individuals within the district, including detailed information on types of compensation. This system is used to automatically export data reports to the S-275. While compensation received for leave buyback is included in the figures on total compensation reported to OSPI, the district does not generate a separate line item identifying it as such.

When leave buyback *is* reported, the S-275-based measure of pensionable compensation performs fairly well. **Figure 1d** shows the difference between S-275 and DRS measures of pensionable compensation in the final year of service among individuals for whom a positive amount of leave buyback is reported. In contrast to **Figure 1b**, the mass of observations to the right of zero are almost entirely absent. However, a handful of errors are clustered around $5,000 and $15,000. This could be due to districts reporting vacation buyback but not reporting sick leave buyback, or due to other nonpensionable payments that are not identified in the S-275. That said, about 92% of the difference between the mean error in final and nonfinal years appears to be explained by reported buyback.[16]

4. Empirical Approach

In this section, we describe our empirical approach. First, we develop an empirical model for identifying salary-spiking behavior. Second, we lay out a strategy for comparing the prevalence and financial implications of salary spiking under results derived from S-275 compensation data and results that incorporate DRS compensation data in the year an employee separates from employment.

[16] Overall, the average error in the final year of service is $3,832, but is only $303 among those with a positive amount of buy back reported in the S-275.

4.1 Identifying Salary-Spiking Behavior

In general terms, *salary spiking* is defined as using end-of-career increases in salary to boost pension benefits; to the best of our knowledge, a more precise definition has not been advanced in the literature. Given that salaries generally increase over time and are generated by a stochastic process, one would expect most end-of-career salaries to increase as a matter of course. So what magnitude of salary growth warrants the label of *salary spiking*? Below, we advance a statistical definition of salary spiking based on the extent to which end-of-career salary deviates from a teacher's observed pattern of compensation prior to the end of his or her career. This accounts for the magnitude of end-of-career salary growth as well as the extent to which it differs from the pattern of growth in preceding years.

Our empirical strategy centers on modeling patterns of compensation in order to define a range of end-of-career salaries that are "within expectations" for each individual. To define this range of salaries, we use simple forecasting methods that regress salary on year of employment for the years preceding the final year of the teacher's career:

(1) $$Salary_{it} = a_i + \beta_i Y_t + \varepsilon_{it}, t < T.$$

We estimate these models separately for each individual because, consistent with the definition of *salary spiking*, we are interested in identifying end-of-career deviations from each teacher's *own prior pattern* of compensation. In contrast, a model estimated across individuals would identify spiking as a deviation from the *average pattern* of compensation.[17]

[17] For example, a teacher may have a persistently higher salary (or higher salary growth rate) than other teachers. A pooled model would identify that teacher's end-of-career salary as being outside the range of expected salaries even when it was entirely consistent with that teacher's overall pattern of compensation.

The estimated parameters from the individual-level regressions represented in equation (1) above are used to forecast end-of-career salary,

(2) $$\hat{S}_{iT} = \hat{\alpha}_i + \hat{\beta}_i Y_T,$$

and the 95% confidence interval above $\hat{S}_{iT}$:

(3) $$CI_{iT} = \left[\hat{S}_{iT},\ \hat{S}_{iT} +\ T_{0.05} * S_e * \sqrt{1 + h_T}\right],$$

where $T_{0.05}$ is the t-statistic for a one-tailed test, S_e is the standard error of the regression, h_T is the Tth diagonal element of the projection matrix given by $x_T{}'(X'X)^{-1}x_T$, X is the matrix of independent variables in equation (1), and x_T Tth row of X.[18] For our primary specification, we use a 95% confidence level in defining the T-statistic.[19]

Given the range of expected salaries defined by CI_{it}, we define the indicator variable $Spike_i$ as follows:

(4) $$Spike_i = 1 \textbf{ IF } S_{iT} > \max[CI_{iT}] \textbf{ AND } FAS_{iT} > FAS_{i,T-1}; \textbf{ELSE } Spike_i = 0$$

In other words, an end-of-career increase in salary is characterized as salary spiking when the difference between actual salary and forecast salary is positive and statistically significant and results in an increase in FAS. The latter qualification means that an end-of-career increase in salary will only be classified as salary spiking if it also results in an increase in benefits.[20]

In specifying equation (1) above, we must consider a number of practical considerations related to identifying the analytical sample including panel length, the treatment of part-time

[18] See Greene (2003) for a detailed discussion of this statistic on page 111.
[19] We find qualitatively similar estimates using an 80% confidence level to define the T-statistic.
[20] This is a binding constraint for only about 3% of individuals identified as spiking in our primary model specification.

employment, gaps between years of employment, and the range of years over which to forecast salary. We discuss these issues here and as noted below, results from alternative model specifications are presented in Appendix A.[21]

Regarding the treatment of part-time employment, we exclude teacher-year observations where the level of employment is less than 1.0 FTE. Its inclusion would be inappropriate because the functional form of the model is ill-suited to accommodating the large shifts in compensation that may occur when, for example, an employee shifts from 1.0 to 0.5 FTE. This could generate biased forecasts of end-of-career salary and over-stated levels of variance.

Regarding the functional form of the regression models, our primary specification is a simple linear model controlling for school year. Given that teacher salaries tend to increase at a steady rate as they move across salary schedules defined by experience and degree, a linear specification is a sensible place to start. That said, there are reasons to expect nonlinear salary growth. For instance, if salaries grow at a constant percentage, they will grow by increasing amounts over time. Conversely, if teachers reduce effort by taking on fewer compensated duties as they approach the end of their career, salary growth may taper off over time. As a robustness check, we estimate quadratic and log-log model specifications to allow for curvature in the pattern of compensation and find qualitatively similar results.

Regarding panel length, our primary model specification uses all available years of employment data for each individual. This approach has the appeal of using the full set of

[21] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

information available. We also consider the possibility that forecasts could be improved by using only the most recent data, since an individual's early-career level of pay may be a poor predictor of pay many years later. To this end, we estimate models restricted to the 10 most recent observations, which generate very similar results.[22]

Lastly, one must decide how many years to forecast. Our primary model specification generates a forecast only for final-year salary (S_T). This corresponds to the inclusion of $[S_{T-n}, \ldots, S_{T-1}]$ in the regression model specified in equation (1). There is, however, a financial incentive to engage in salary-spiking behavior throughout the FAS averaging period (not just in the final year) so we estimate alternative model specifications that expand the range of years for which we forecast salaries to those in the FAS averaging period: 2 years for TRS1 and 5 years for TRS2 and TRS3.

4.2 Comparing Findings Between Datasets

An important element of the empirical analysis is the comparison of results derived from two different measures of compensation. As described in the previous section, DRS salary is available for a short period of years, from 2011 to 2016, so we do not estimate the forecast models using DRS data.[23] Rather, we use measures of pensionable compensation derived from the S-275 data to estimate the regression models (equation (1)), forecast expected salary (equation (2)), and generate the 95% confidence interval above forecast salary (equation (3)).

[22] For example, see discussion by Clark and McCracken (2009) on the bias-variance tradeoff in forecasting, or Greene (2003, page 112), for a practical example of this tradeoff.
[23] Using only DRS data to predict final-year salary would use at most, 5 years of data to forecast the 6th year, and regression models with only three degrees of freedom. Also, these models would only forecast compensation in 2016, making the results sensitive to time-varying factors affecting teacher compensation.

We identify salary spiking (equation (4)) using first, the measure of compensation derived from the S-275 data and second, the pensionable compensation reported in the DRS.

A potential concern regarding the use of S-275 data to forecast end-of-career salaries is that the S-275 data do not provide a precise measure of pensionable compensation, even where buy-back is not an issue (see **Figure 1a**). As discussed above, however, the S-275 data perform fairly well away from the final year of service. Below, we explore the robustness of our findings by modeling salary spiking for teachers *not* observed separating from employment, and consistent with the notion that S-275 is a good measure of pensionable salary for nonfinal years, we identify similar levels of salary spiking whether the forecast level compensation is tested against the DRS- or S-275-based measures of pensionable salary.

5. Results

Here we present findings on the prevalence and financial implications of salary-spiking behavior. As described above, we estimate two sets of salary-spiking results: one using measures of pensionable compensation derived from the S-275 data and the other using the pensionable salary reported by DRS in each employee's final year of service. As shown in **Figures 1a** to **1c**, the S-275-based measure of pensionable compensation tends to overstate pensionable compensation in the final year of service and we expect the former analysis to identify a greater prevalence of salary spiking than the latter analysis.

5.1 The Prevalence of Salary-Spiking Behavior

The proportion of teachers identified as salary spiking and the magnitudes of the spikes in salary are presented in **Table 3**. Column (1) presents the results when the S-275-based measure of pensionable salary is used to define S_{iT} in equation (4). Column (2) presents the results when the pensionable salary reported by DRS is used to define S_{iT}. The magnitude of the salary spike is calculated for each individual identified as spiking as the difference between actual final-year salary S_{iT} and forecast final-year salary $\hat{S}_{iT}$. For individuals *not* identified as spiking, the magnitude is defined as zero.

The results generated from the two analyses are strikingly different. The proportion of teachers identified as salary spiking in column (1) is nearly an order of magnitude greater than the proportion identified in column (2): (28.6% vs 3.2%). The former result suggests that salary spiking is an important policy concern in Washington State, whereas the latter suggests spiking is not a significant concern. This is also reflected in the average magnitude of the spike in salary which is $3,290 in column (1) vs $301 in column (2). This difference is primarily driven by the smaller proportion of teachers identified as spiking when DRS salary data are used to define S_{iT} rather than S-275 salary data.

These findings are robust to model specification. As discussed in the previous section, we estimate alternative model specifications with functional forms that accommodate curvature in the pattern of compensation, panel lengths restricted to an individual's final 10 years of service, narrower confidence intervals, and a wider range of years over which salary is forecast. We find qualitatively similar results under these alternative specifications, which are presented in **Appendix A**, **Table A1**.[24]

We also find results that are consistent with those presented in **Table 3** when separately considering each cohort of exiters (i.e., 2011, 2012,…, 2016). **Table 4** shows the proportion of

[24] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

teachers identified as salary spiking in each cohort. The gap between the proportion identified as salary spiking under the two different definitions of S_{iT} is consistently large. This suggests that the misreporting of compensation is a persistent problem.

5.2 Falsification Test Fails to Address Bias

The results above show that S-275 salary data can generate misleading results regarding the prevalence of salary spiking. If researchers had access to S-275 data but no access to DRS data, would it be possible to address this source of bias? In this section we consider a falsification test that repeats the preceding analysis over a sample of teachers who have no incentive to spike salaries. Specifically, we look at patterns of compensation among "nonexiters"—teachers who are not observed separating from employment as of the 2017–18 school year. These teachers have little pension-driven incentive to boost compensation as because if their salaries continue to grow, they will be outside their FAS averaging periods during 2011 to 2016. If errors in the data are driving results, and those errors are uncorrelated with t, nonexiters should exhibit a prevalence of salary spiking similar to that found among those separating from employment.

We estimate the regression models specified by equation (1) on the sample of nonexiters, defining false exit years of 2011, 2012,…, 2016 for each individual actively employed during those years,[25] and analyze the prevalence and magnitude of salary spiking. As in our primary analysis, we estimate two sets of results presented in **Table 5**: one using S-275 data to define S_{iT} and the other using DRS data to define S_{iT}.

[25] For instance, we would estimate 6 different salary forecast models for a teacher employed in each year between 2011 and 2016.

Among nonexiters, our analysis identifies a small proportion of teachers as salary spiking in the models using S-275 data to define S_{iT}. Because the finding that identified nearly 30% of teachers as salary spiking does not persist under the falsification test, a researcher using S-275 salary data might (incorrectly) conclude that there is strong evidence of pension-driven, salary-spiking behavior among Washington State teachers. As discussed above, errors in the data are concentrated in in the final year of service, making any falsification test that relies on the timing of an individual's FAS window particularly ill-suited to accounting for these errors.

Turning to the analysis using DRS salary data to define S_{iT} (column (2)), we find a similar prevalence of salary spiking in the falsification test (4.7%) as we do in the primary analysis (3.4%). In short, the finding that there is no evidence of pension-driven, salary-spiking behavior among members of Washington State's Teacher Retirement System is bolstered by the falsification test.

5.3 The Financial (Mis)Implications of Salary-Spiking Behavior

The policy concern underlying salary spiking is that end-of-career spikes in pensionable compensation lead to unfunded pension liabilities. As presented in an example above, a one-time boost in salary of $5,000 for a member of TRS1 would result in an increase in the present value of the employee's retirement annuity of roughly $20,000 and additional contributions to the pension system of only $685. Hence, the liabilities resulting from end-of-career shifts in pay tend to be underfunded by the corresponding shifts in contributions.

We calculate the financial implications of salary spiking for Washington's TRS pension system as the increase in pension wealth that is associated with salary-spiking behavior, which is representative of the increase in pension liabilities to the pension system.[26] Specifically, for each individual identified as salary spiking, we calculate the difference between pension wealth when final-year salary (S_{iT}) is equal to actual salary and pension wealth when final-year salary is equal to forecast salary ($\hat{S}_{iT}$).[27] We do this using results from both the S-275 and DRS-based analyses to illustrate the implications of using mis-reported data.[28] The pension wealth liabilities associated with salary spiking are presented in **Table 6**.

The liabilities derived from the analysis that uses S-275 data to define final-year salary (column (1)) dramatically overstate the financial implications of salary spiking among TRS members. Among the cohorts separating from employment during 2011 to 2016, the total additional liabilities associated with salary spiking implied by the S-275-based analysis exceed $57 million whereas the additional liabilities implied by the DRS-based analysis are only $4 million. From a policy standpoint, the S-275-based analysis incorrectly suggests that salary spiking is an issue that urgently needs to be addressed.

We emphasize that these liabilities are calculated only for those individuals in our study sample. This represents a narrow slice of the population of employees in each pension plan, and a natural question is, "how much would the S-275 data overstate liabilities for all TRS plan members?" Looking just at TRS1, which closed enrollment in 1977, the teachers exiting during

[26] Unfunded liabilities will be moderated slightly be the increase in contributions associated with increased salary. A back-of-the-envelope calculation using the spiking magnitudes from Table 3 suggests that an increase in contributions will be about 6.6% of the total increase in liabilities.
[27] Due to the nature of our confidence interval for identifying spiking, we may expect to incorrectly identify 5% of individuals as spiking due to noise in salary. This would lead us to overstate the financial implications of salary-spiking behavior.
[28] The pension wealth calculations are detailed in **Appendix B**. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

2011 to 2016 represent just 16% of all TRS1 members identified as retired during 2003 to 2016 using data on retirees from DRS.[29] Spiking-driven liabilities for TRS1 were overstated by roughly $40 million for TRS1 members in our sample, which would translate to an overstatement of roughly $250 million among all retirees drawing benefits during 2003 to 2016.

6. Discussion

Administrative data collected by state and local governments has become increasingly available to research targeted at informing public policy decisions. In many cases, the data are collected because administrative rules require it, not because the data are critical to an important administrative outcome, such as the allocation of funds. This raises the question, how accurate are these types of data and to what degree can data errors influence research findings?

Others have pointed out that data collection processes often fail to incentivize accurate reporting (e.g., Sandefur & Glassman, 2015), and at times appear to do the opposite (e.g., Iezzoni, 1997). This paper contributes to that literature by demonstrating how errors in personnel data compiled by states can lead to dramatically misleading results. We use two administrative data sets from Washington State to study the issue of salary spiking. In comparing the compensation data reported by OPSI and DRS, we find large discrepancies concentrated in an employee's final year of service. Specifically, our measure of pensionable compensation derived from the OSPI data frequently overstates the amount of pensionable

[29] This would include TRS1 members who exited employment well before 2003, but were still drawing a benefit during the period 2003 to 2016.

reported in the DRS data by thousands of dollars.[30] Consequently, analysis of the prevalence and financial implications of salary-spiking behavior lead to opposite conclusions depending on whether we used OSPI- or DRS-based measures of pensionable compensation in an employee's final year of service. Using the OPSI data, we identified 28.8% of TRS members as salary spiking, corresponding to an average cost to the system of $3,444 per exiting employee. In contrast, using the DRS data, we identified 3% of TRS members as salary spiking, corresponding to an average cost to the system of $343 per employee.

To the best of our knowledge, ours is the first analysis to demonstrate how errors in the personnel data collected by states, and compensation data in particular, can lead dramatically misleading results. This is important because most states compile longitudinal administrative data collected from local school districts. As these data are increasingly used in policy research it will be important for researchers to understand how the collection process and ultimate use (or nonuse) of the data may incentive accuracy in reporting. For instance, the compensation data from OSPI are "informational only" in that they do not directly influence any administrative process (such as the allocation of state funds). So it is perhaps not surprising that we found significant discrepancies between OSPI- and DRS-based measures of pensionable compensation.

The state of Washington does not appear to be alone regarding the "informational" aspect of elements of the personnel data it compiles. For example, the Wisconsin Department

[30] As discussed in Section 3, this appears to be driven by many districts including sick leave buy back in the total compensation reported to OSPI, but not identifying it with a specific assignment code as the instructions in the reporting manual suggest. Sick leave buy back is only collected when an employee separates from employment and is not pensionable compensation. Our OPSI-based measure of compensation relies on being able to reliably identify and subtract sick leave buy back from total compensation.

of Public Instruction makes staff data publicly available for researchers, including data on compensation, but notes that it is not validated by their office. Similarly, Illinois introduced legislation in 2010 requiring districts to report employee information, though as far as we can tell, there are no audit mechanisms in place to encourage accuracy.[31] Given the potential for longitudinal personnel data to inform policy, if data are going to be collected it would be prudent to adopt policies to incentivize accurate reporting and verify data quality. As demonstrated by our analysis, incorrect data have the potential to be less informative than no data at all.

Another contribution of this work is to introduce an empirical method for identifying salary spiking that allows one to assess the prevalence and financial implications of salary-spiking behavior. Our approach can be applied elsewhere (provided that suitable longitudinal compensation data are available) and provides consistent metrics that can be compared across jurisdictions (e.g., different pension systems of states). Such cross-jurisdictional work is important to understanding the relationship between pension plan structures, member characteristics, and the issue of salary spiking. We also introduce a falsification test that, while particularly vulnerable to the pattern of errors in our OSPI data, should be applied as a robustness check in future analyses of salary-spiking behavior.

We also note that an intent to increase pension benefits underlies the definition salary spiking, but administrative data does not reveal this directly. Future work could attempt to determine to what degree spiking behavior reflects the actions of individual employees, groups of employees, employers, or some combination thereof.

[31] See Illinois School Code Sections 10-20.47 and 34-18.38.

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Tables

Table 1. Key Features of Washington State's Teacher Retirement System

Feature	*TRS1*	*TRS2*	*TRS3*	
Membership definition	Hired pre-1977 (mandated)	Hired 1977–96 (default) Hired 2007–present (opt in)	Hired 1977–96 (option to transfer) Hired 1996–2007 (mandated) Hired 2007–present (default)	
Type	Traditional DB	Traditional DB	DB component	DC component
Vesting period	5 years	5 years	10 years	N/A
Employee contributions	6% of salary	Set by legislature	N/A	5%–15% (employee's choice)
Benefit formula	$0.02 * (FAS) * (YOS)$	$0.02 * (FAS) * (YOS)$	$0.01 * (FAS) * (YOS)$	N/A
FAS period	2 consecutive highest paid years	5 consecutive highest paid years	5 consecutive highest paid years	N/A
Retirement eligibility	60 years of age, or Any age & 30 YOS, or 55 years of age & 25 YOS (full benefit)	65 years of age, or 62 years of age & 30 YOS (full benefit), or 55 years of age & 20 YOS (reduced benefit)	65 years of age, or 62 years of age & 30 YOS (full benefit), or 55 years of age & 10 YOS (reduced benefit)	Withdrawal ages and penalties for early withdrawal dependent on federal tax rules

Note: DB is defined benefit; DC is defined contribution; FAS is final average salary; YOS is years of service. The TRS1 benefit is capped at 60% of an employee's FAS.

Table 2. Characteristics of Exiting Employees

	(1) Total	(2) TRS1	(3) TRS2	(4) TRS3
Salary				
Final-year S275	81,530	85,358	81,060	80,404
Final-year DRS	76,223	78,273	75,586	75,710
Prior-year S275	75,816	77,815	75,667	75,206
Prior-year DRS	75,269	77,381	75,127	74,715
Characteristics				
Age	60.4	63.8	62.8	58.7
Experience	26.3	33.4	26.5	23.9
Advanced Degree	0.71	0.64	0.69	0.74
Female	0.71	0.77	0.73	0.69
Teaching position	0.80	0.80	0.81	0.79
Administrator position	0.07	0.08	0.05	0.07
Other position	0.13	0.12	0.14	0.14
Observations	11,910	2,471	1,776	7,663

Note: The sample is composed of individuals who are identified as retired in DRS data and have at least 8 observations. This leads to 11,910 unique individuals in our data. Characteristics are reported as of the final year of employment. Teacher position means that the primary duty assignment is a classroom assignment; administrator positions include principals, superintendents, and other district administration positions; other positions include all other roles than teaching and administration.

Table 3. Prevalence and Magnitude of Salary Spiking in Washington Among Exiting Employees

	(1) S-275 final-year salary	(2) DRS final-year salary
Proportion identified as spiking	0.286	0.032
Average magnitude of spike in salary	\$3,266	\$288
Observations	11,910	11,910
Average magnitude of spike in salary among teachers identified as spiking	\$11,423	\$8,853
Observations	3,405	387

Note: Results for this table are produced from separate regressions for all 11,910 unique individuals in our data. Final-year salary is forecast using all available prior years of salary data. Sample restricted to employees with at least 9 years of salary data available. Regression models are linear and final years of employment range between 2011 and 2016.

Table 4. Prevalence of Salary Spiking Across Exiting Cohorts of Employees

Exit Year	(1) S-275 final-year salary	(2) DRS final-year salary	(3) Observations
2011	0.357	0.034	1,846
2012	0.255	0.013	1,864
2013	0.223	0.013	2,083
2014	0.259	0.020	2,128
2015	0.258	0.034	2,154
2016	0.382	0.086	1,835
Total	0.286	0.032	11,910

Note: Results for this table are produced from separate regressions for all 11,910 unique individuals in our data. Final-year salary is forecast using all available prior years of salary data. Sample restricted to employees with at least 9 years of salary data available. Regression models are linear and final years of employment range between 2011 and 2016.

Table 5. Prevalence of Salary Spiking Among Nonexiting Teachers

	(1) S-275 final-year salary	(2) DRS final-year salary
Proportion identified as spiking	0.053	0.047
Average magnitude of spike in salary	$552	$468
Observations	128,892	128,892
Average magnitude of spike in salary among teachers identified as spiking	$10,505	$9,849
Observations	6,774	6,120

Note: Results for this table are produced from separate regressions for all 128,892 unique individuals who we observe employed in 2017–18. For each individual, we produce separate regressions for each possible false-exit year, between 2011 and 2016. Final-year salary is forecast using all available years of salary data prior to the false-exit year. Sample restricted to employees with at least 9 years of salary data available. Regression models are linear.

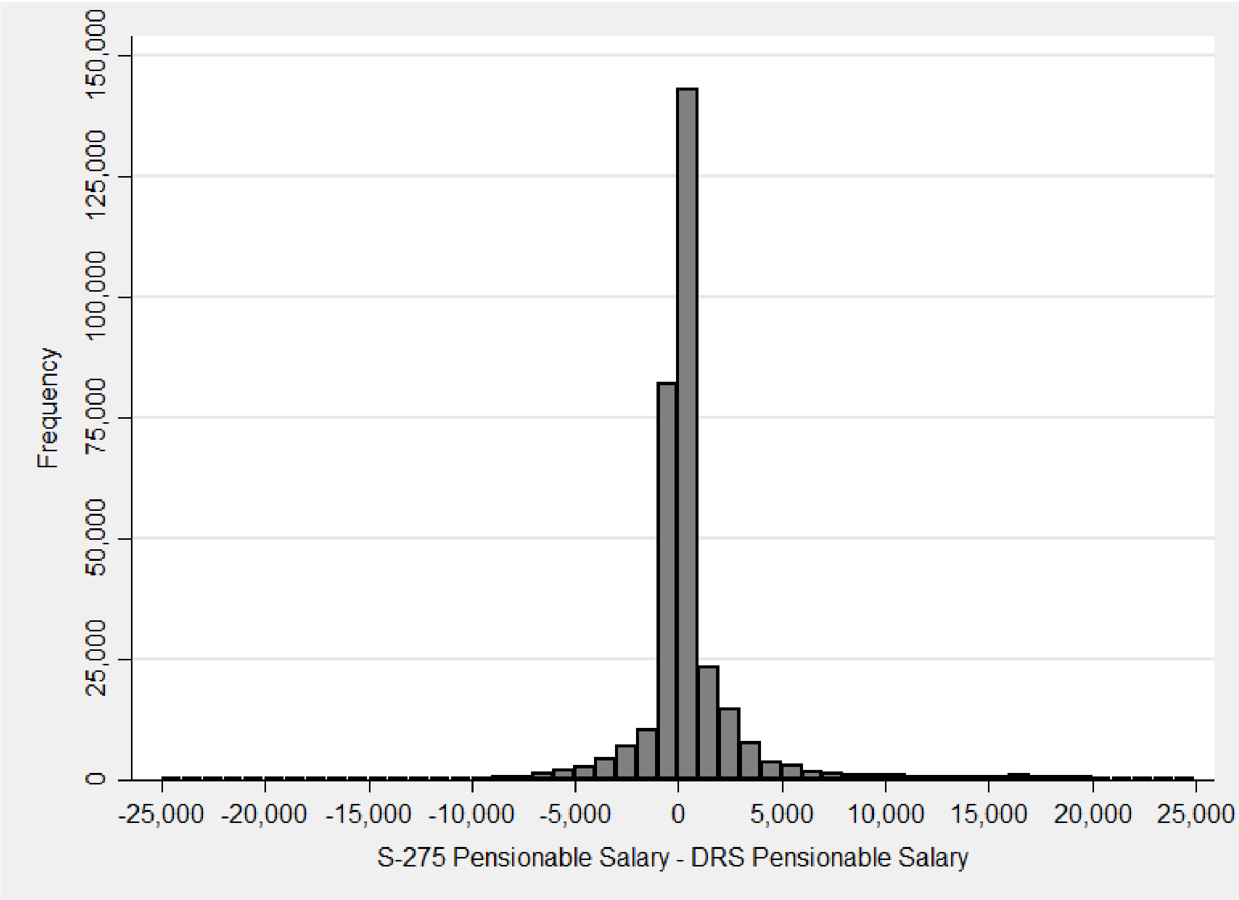
Table 6. The Present Value of Pension Liabilities Associated With Salary Spiking

	(1) S275 final-year salary	(2) DRS final-year salary
Total liabilities	$57,145,731	$3,832,587
Average liabilities	$4,798	$322
Average liabilities for spikers only	$16,862	$10,059
Observations	11,910	11,910

Note: These results are produced using pension wealth calculations described in Appendix B, and estimated values from separate regressions for all 11,910 unique individuals in our data. Magnitudes are equal to zero for all individuals who are not identified as spiking. Final-year salary is forecast using all available prior years of salary data. Sample restricted to employees with at least 9 years of salary data available. Regression models are linear Final years of employment range between 2011 and 2016.

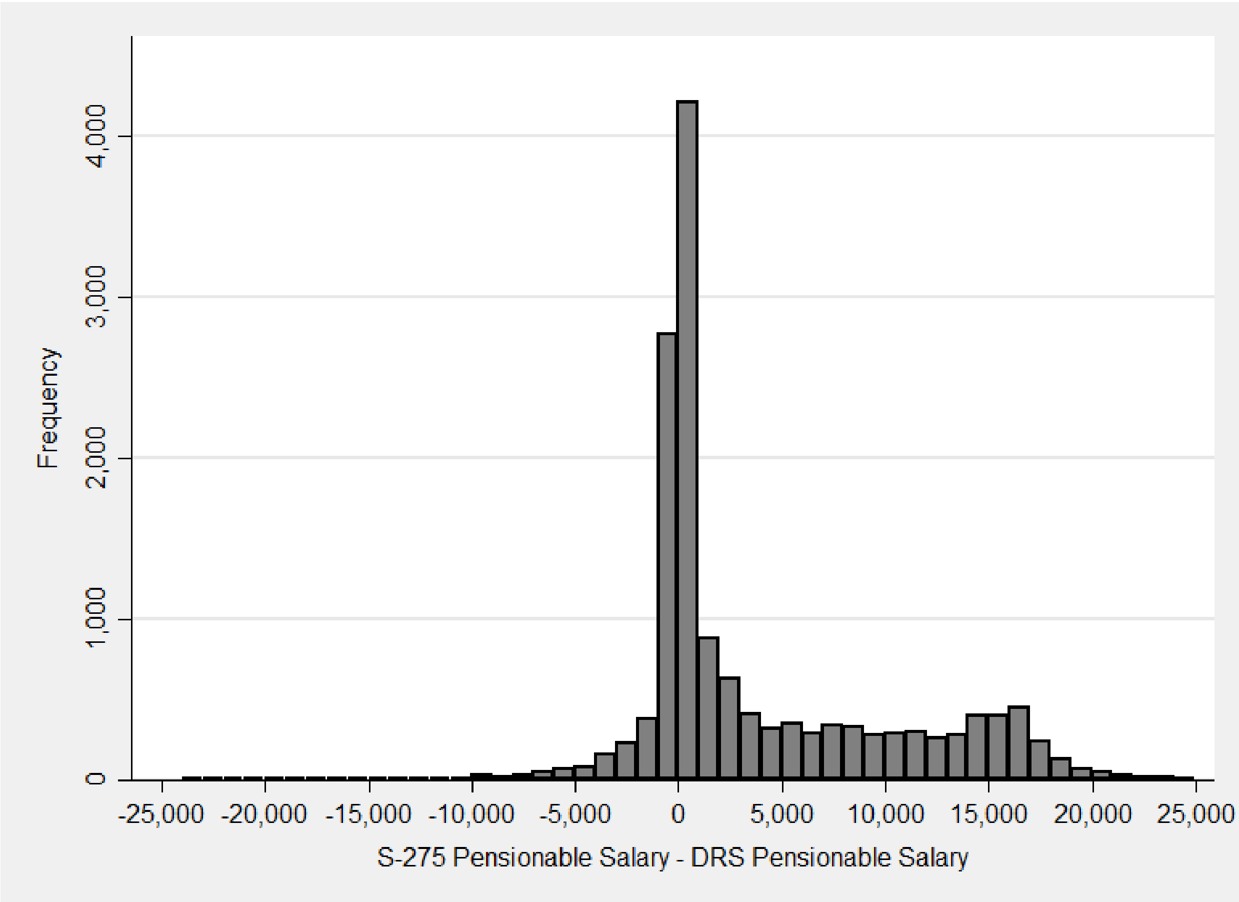
Figures

Figure 1a. Distribution of the Difference Between S-275 and DRS-Based Measures of Pensionable Salary in Years Preceding Separation From Employment



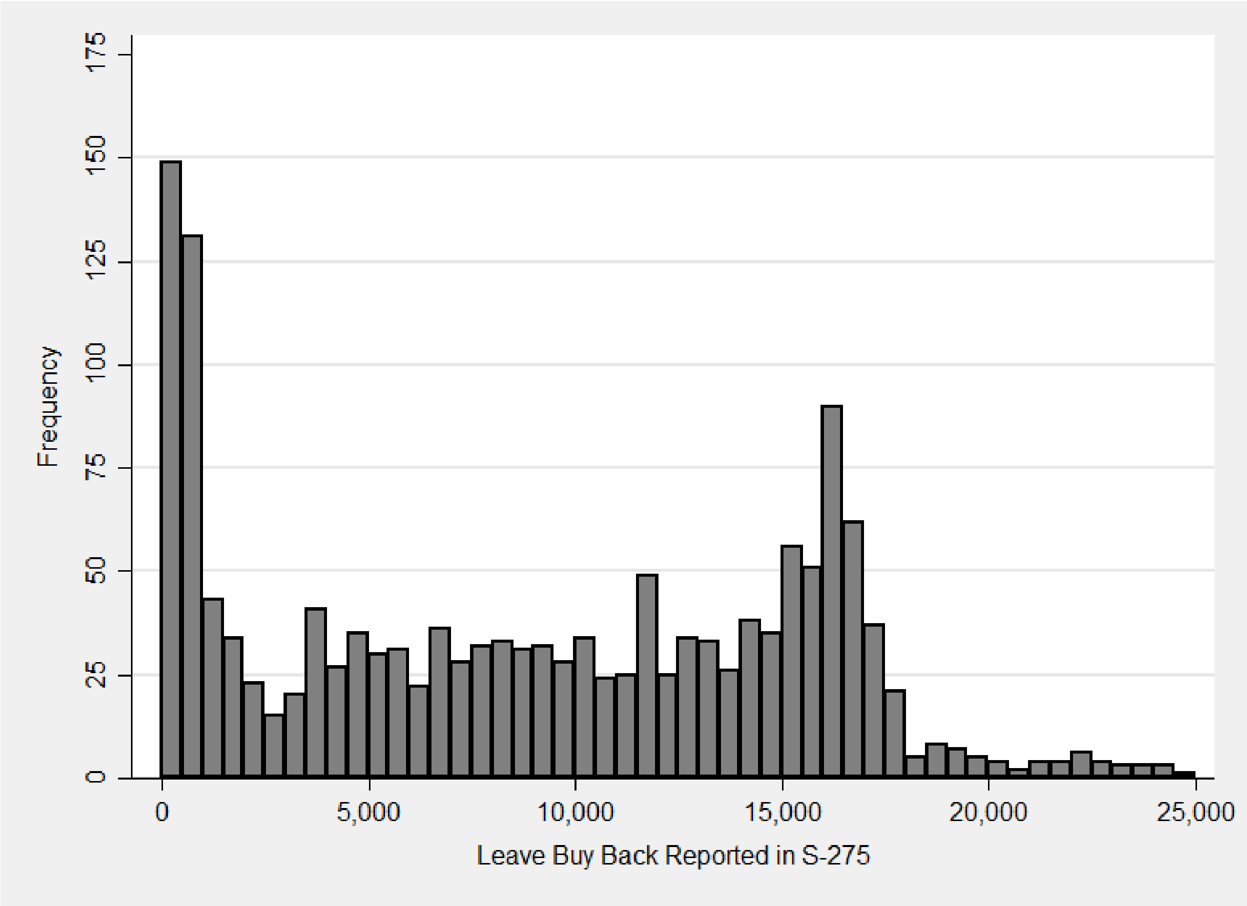
Note: The sample represented in **Figure 1a** is restricted employees in full-time equivalent, certificated teaching positions. For the purposes of presentation, the distribution is truncated at +/- $25,000.

Figure 1b. Distribution of the Difference Between S-275 and DRS-Based Measures of Pensionable Salary in Year of Separation From Employment



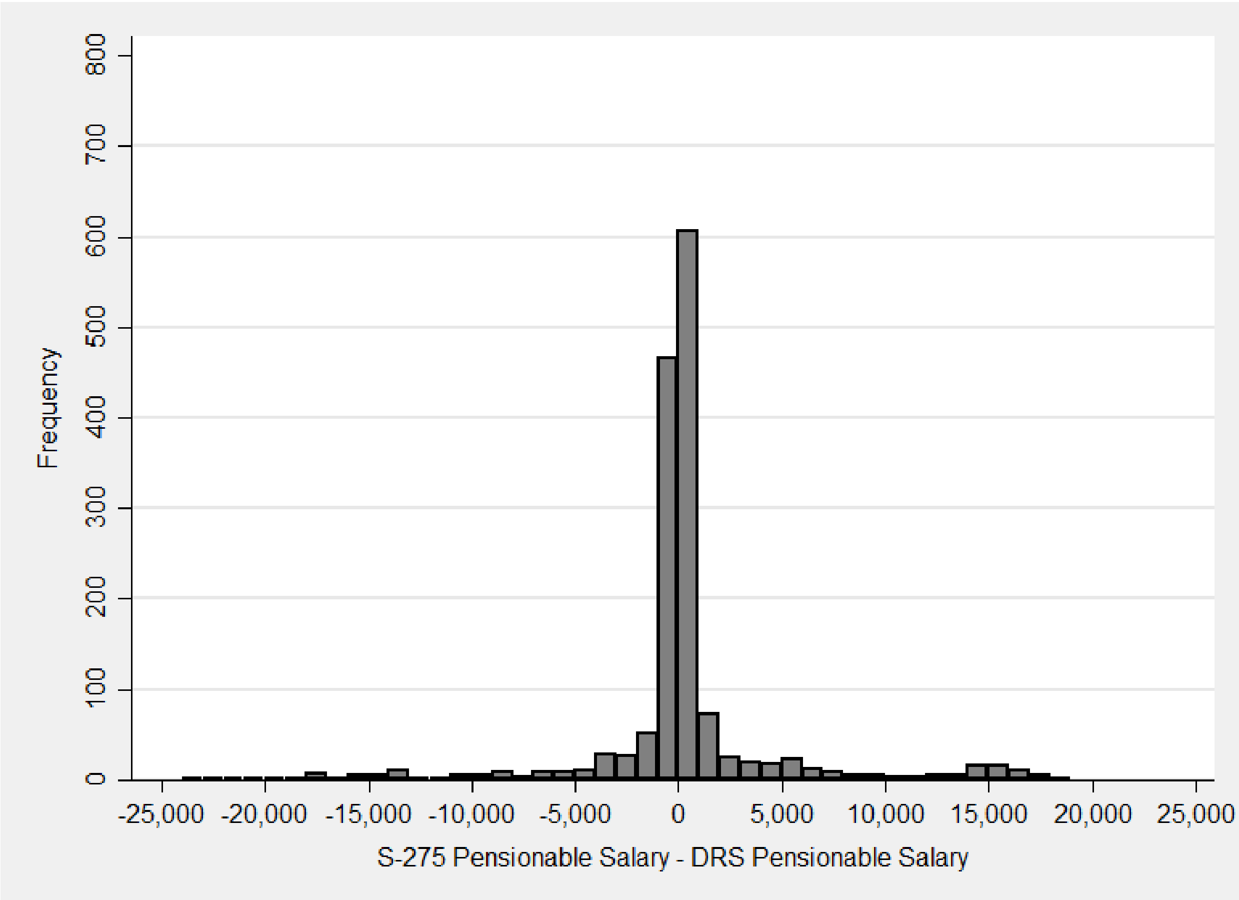
Note: The sample represented in **Figure 1b** is restricted employees in full-time equivalent, certificated teaching positions, who are separating from employment. For the purposes of presentation, the distribution is truncated at +/- $25,000.

Figure 1c. Distribution of Buyback Salary Reported in the S-275 in the Year of Separation From Employment When Buyback Is Greater Than Zero



Note: The sample represented in **Figure 1c** is restricted employees in full-FTE, certificated teaching positions, who are separating from employment, with a positive amount of buyback salary reported. For the purposes of presentation, the distribution is truncated to the interval $[\$1, \$25{,}000]$.

Figure 1d. Difference Between S-275 and DRS-Based Measures of Pensionable Salary in Year of Separation From Employment for Individuals With Some Amount of Reported Buyback



Note: The sample represented in **Figure 1d** is restricted employees in full-FTE, certificated teaching positions, who are separating from employment, which a positive amount of buyback salary reported. For the purposes of presentation, the distribution is truncated to the interval $[\$1, \$25{,}000]$.

Appendix A: Alternative Specifications for Salary-Spiking Models

Table A.1 Alternative Specifications of Primary Model

	Primary Model	80% CI	Quadratic Term	Log-Log Model	10-Year Model	Predict All FAS Years
Proportion spiking using:						
Salary with reporting error	0.286	0.372	0.286	0.155	0.294	0.277
Pensionable salary	0.032	0.074	0.032	0.011	0.036	0.063
Difference	0.253	0.298	0.253	0.144	0.258	0.214
Observations	11,910	11,910	11,910	11,910	11,910	11,910

Note: Results for this table are produced from separate regressions for all 11,910 unique individuals in our data. Sample restricted to employees with at least 9 years of salary data available and have final years of employment range between 2011 and 2016. The first column reproduces results from Table 3; subsequent columns introduce single modifications to the primary model.

Table A2. Alternative Specifications for Counterfactual Group

	Primary Model	80% CI	Quadratic Term	Log-Log Model	10-year Model
Proportion spiking using:					
Salary with reporting error	0.053	0.126	0.056	0.012	0.057
Pensionable salary	0.047	0.114	0.051	0.010	0.052
Difference	0.005	0.012	0.005	0.002	0.006
Observations	128,892	128,892	128,892	128,892	126,633

Note: Results for this table are produced from separate regressions for all 11,910 unique individuals in our data. Sample restricted to employees with at least 9 years of salary data available and have final years of employment range between 2011 and 2016. The first column reproduces results from Table 3; subsequent columns introduce single modifications to the primary model.

Appendix B: Pension Wealth Calculations

To determine the liabilities associated with a change in final average salary, we define pension wealth as the net present value of future pension payments at the moment an individual retires:[32]

$$PV_{DB}(A_S, A_R) = \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF(A_S, \mathrm{YOS}) * YOS * AFC$$

This gives the pension wealth of an individual who separates at A_S and retires at age A_R. The first term inside the summation, $(1+r)^{(A_R - A_S)+\mathrm{t}}$, discounts the value of the payment by the number of years until retirement $(A_R - A_S)$ and the year of the payment t.[33] r is the teacher's assumed discount rate. The second term, $f(A_t|\mathrm{A})$, is the probability of survival, conditional on surviving to the current age.[34] Survival probabilities are calculated using CDC mortality tables. We assume a discount rate of 7.5%, and a COLA of 2%.[35] Lastly, the value of the annuity is determined by $b * ERF(A_S, \mathrm{YOS}) * AFC * YOS$, where $b = 0.02$ for TRS1/2 and $b = 0.01$ for TRS3, ERF represents the penalty for early retirement, YOS is the teacher's years of service at separation, and AFC is the teacher's average final compensation.

Salary spiking is directly related to the variable AFC. We define the change in liabilities associated with salary spiking as:

$$Change\ in\ wealth = PV_{DB}\left(A_S, A_R, AFC_{Spike}\right) - PV_{DB}\left(A_S, A_R, AFC_{NoSpike}\right)$$

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[32] This is common practice in the pension literature; see (XYZ).

[33] For example, when individuals separate and retire in the same year, the first payment is not discounted because $(A_R - A_S) + \mathrm{t} = 0$.

[34] We assume that survival probability prior to retirement is equal to 1.

[35] We choose a 7.5% discount rate to match the assumptions of the Washington State pension system.

Conveniently, AFC is constant across all pension payments, so that AFC can be factored out of the summation:

$$PV_{DB}\left(A_S, A_R, AFC_{Spike}\right) - PV_{DB}\left(A_S, A_R, AFC_{NoSpike}\right)$$

$$= \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF * YOS * AFC_{Spike}$$

$$- \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF * YOS * AFC_{NoSpike}$$

$$= AFC_{Spike} * \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF * YOS \; - AFC_{NoSpike}$$

$$* \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF * YOS$$

$$= \sum_{t=0}^{\mathrm{T}} (1+r)^{(A_R - A_S)+\mathrm{t}} * f(A_t|\mathrm{A}) * COLA_t * b * ERF(A_S, \mathrm{YOS}) * YOS * \Delta AFC$$

As such, we estimate liabilities using the change in AFC due to spiking.[36]

The equation for pension wealth depends on the assumed retirement age A_R through the index on the summation, discounting, and the benefit factor b. For simplicity, we assume an individual chooses the retirement age that maximizes pension wealth; this assumption implies that teachers who quit before 30 YOS will retire at age 65. With the accumulation of 30 YOS, it is optimal to retire as soon as possible due to the more generous ERFs.

[36] By construction, all individuals in our setting have the same assumed retirement age, separation age, etc. If this does not hold in other settings, one must estimate liabilities for spiking and nonspiking separately. This could occur if, for example, researchers are modeling exit timing is endogenous to salary spiking.