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ARTICLE

The incidence of Social Security taxes on teacher wages and employment

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Abstract

We study the incidence of Social Security taxes on teacher wages and employment. On average, we estimate teachers with Social Security coverage take home 9.6 percent less in wages than observationally similar teachers in similar districts without Social Security coverage. This accounts for about three-fourths of the 12.4-percent total Social Security tax. Moreover, our analysis suggests this is likely a lower-bound estimate of the true incidence of Social Security taxes – under reasonable assumptions, we cannot rule out full (100%) tax incidence on teacher wages. We find no evidence of tax incidence on teacher staffing levels.

Keywords: Social Security; tax incidence; teacher retirement costs and benefits; teachers and Social Security

JEL Codes: H22; H55; I20; J32

1. Introduction

Public workers in the United States, including teachers, were not covered by Social Security when it was first introduced in the 1930s. Beginning in the 1950s, groups of public workers were permitted to opt into coverage if desired. In most states, teachers either remained uncovered or opted into coverage together. However, in several states school districts made individual choices, resulting in within-state variation in social security coverage across school districts. We leverage variation in one of these states – Texas – to estimate the incidence of social security taxes on teacher wages and employment.

Our interest in the incidence of social security taxes on teachers is motivated by policy proposals to enroll teachers in social security in states where they are not currently enrolled (Kan and Aldeman, 2014; Gale *et al.*, 2015; Koedel and Gassmann, 2018).[1] Proponents argue this would make teacher retirement compensation more equitable (Kan and Aldeman, 2014). It would also diversify the risk in teachers' retirement portfolios, most notably because unlike retirement wealth in most state plans, social security is portable across occupations and states. Thus, expanding social security coverage among teachers would dampen the risks they face of occupational and geographic mobility. Teachers also face risk associated with the poor financial health of most state retirement plans; dual coverage in social security would help teachers diversify away from some of this risk as well (Gale *et al.*, 2015).

[1]Like in states where teachers already have social security coverage, teachers would pay into and receive benefits from both the state retirement plan and social security. Practically speaking, these proposals should be viewed as applying to new hires (Gale *et al.*, 2015).

In addition, proponents point to the strong association between the financial health of state retirement plans and social security coverage. Although causal inference is difficult, teacher retirement plans in states without dual social security coverage are in much worse financial condition than plans with dual coverage (Backes *et al.*, 2016).[2] A likely explanation is that in states without social security, the demands of providing for a full retirement exacerbate the influence of actuarial practices that lead to underfunding. Several aspects of actuarial practices are problematic, but the first-order issue is that public pension actuaries consistently understate future liabilities by discounting them at too high of a rate (Novy-Marx and Rauh, 2009; Brown *et al.*, 2011). Plans in states without dual social security coverage tend to offer more generous pension benefits, amplifying this problem.[3] Beyond the risk borne by teachers due to the poor funding of state plans, districts and states are also at risk because underfunding can lead to higher long-term costs, reducing the level of resources available to provide government services (Melnicoe *et al.*, 2019; Kim *et al.*, 2021).

If states without social security coverage for teachers were to push for coverage, or if the federal government mandated it, tax incidence is an important consideration. We are not aware of any prior research on tax incidence in the teacher labor market specifically (for any tax), though two insights from the general literature suggest the incidence of social security taxes on teachers is likely high. First, tax incidence is higher for the more inelastic side of the market and labor supply is typically more inelastic than labor demand (Fullerton and Metcalf, 2002). Second, social security taxes are linked to benefits at the individual level, and tax incidence on workers is higher when the tax corresponds to a directly linked benefit (Summers, 1989).

However, these insights may not generalize to the teacher labor market, which has unique features and is highly non-competitive. For example, on the supply side, teaching is a licensed occupation and most states have stringent requirements. Occupational licensing restricts labor supply by increasing the cost of entry, which could give teachers more leverage in salary negotiations than typical workers in unlicensed occupations. Alternatively, on the demand side, a somewhat unique feature of the teacher labor market is that school district boundaries are non-overlapping. Noting that the private education sector in the United States is very small, this creates frictions in employment opportunities that may reduce teachers' negotiating power if, as research suggests, they have highly localized geographic employment preferences (Boyd *et al.*, 2005; Reininger, 2012). More broadly, the fact that school districts are non-competitive, publicly funded entities could lead to a different incidence outcome than in the private sector. Building on the logic of Glaeser and Ponzetto (2014), one possibility is that if local voters are uninformed about social security costs and benefits, districts with coverage could pass all or part of the costs onto local taxpayers. The combined effect of these and other factors on the incidence of social security taxes in the teacher labor market is theoretically ambiguous, motivating our empirical investigation.

We estimate tax incidence on teacher salaries and staffing levels using an administrative data panel covering all public school teachers in Texas from 1996 to 2020. An analytic challenge we face is that like other covered public employers, most Texas school districts with social security coverage opted into coverage in the mid-20th century, prior to the availability of credible data on teacher wages and employment. Thus, we cannot exploit variation over time in social security coverage for identification and must rely on cross-sectional variation.

Working within this constraint, we begin by estimating the *unconditional* gap in take-home pay between teachers in covered and uncovered school districts. Teacher pay is about 5 percent lower in covered districts. After controlling for observable teacher and district characteristics, we estimate the *conditional* pay gap widens, to 9.6 percent. Taken at face value, the conditional gap implies teachers pay 77 percent of the 12.4-percent total social security tax in the form of lower wages. Moreover, the

[2] Gale *et al.* (2015) further show this is true of state plans that cover all types of government workers.

[3] Clark and Craig (2011) show that teacher pension plans in states without social security coverage offer more generous benefits but with higher costs. Novy-Marx and Rauh (2009) document the underfunding of state and local pension plans broadly and discuss the role played by actuarial practices in greater depth.

direction of observed sorting suggests this estimate is likely a lower bound. Using modern techniques to adjust for sorting on unobservables (Oster, 2019), under reasonable assumptions we cannot rule out that teachers pay 100 percent of the total social security tax in the form of lower wages.

We also conduct a parallel investigation of tax incidence on teacher staffing levels. We find no evidence of incidence along this dimension. This result is consistent with research in other contexts showing that tax incidence on labor supply is primarily on wages, not employment, though there are some exceptions (see discussion below).

Our finding that teachers bear most or all of the cost of social security taxes makes expanding their enrollment in social security appealing from a fiscal perspective, especially if states can leverage social security to bolster the financial stability of their state retirement plans. The effect on teacher well-being is less certain and depends on how much teachers value social security benefits. The best evidence on this question comes from survey experiments conducted by Fuchsman *et al.* (2023), who estimate teachers are willing to pay 10.7 percent of their salaries for social security coverage. This estimate is similar to what we estimate for teachers' tax incidence, suggesting the consequences for teacher well-being will be minimal, at least on average.

2. Brief review of previous research on payroll tax incidence

The incidence of payroll taxes in the larger labor market has been widely studied. Gruber (1997) estimates tax incidence after a reform in Chile that privatized the public social security system, lowering the payroll tax. Wages went up by the same amount as the reduction in taxes, which is the expected result if tax incidence is fully on wages. Similarly, Anderson and Meyer (2000) study a policy in Washington state that changed firms' tax rates for unemployment insurance. They find that tax increases at the industry level were largely passed onto workers through lower earnings. Saez *et al.* (2012) and Saez *et al.* (2019) study payroll tax increases and decreases, in Greece and Sweden respectively, concentrated on young workers. Saez *et al.* (2019) show that tax reductions are passed onto workers through higher wages overall – which is consistent with tax incidence falling on workers – but both studies show, somewhat unexpectedly, that the tax wedge between young and old workers does not translate into a gap in wages. Saez *et al.* (2019) offer as an explanation that firms are effectively operating under internal wage equity constraints, preventing them from passing on tax incidence differentially to different types of workers.

Bozio *et al.* (2019) study a series of tax reforms in France with the goal of isolating the role of linked benefits in driving tax incidence. The reforms in France also led to tax changes for different types of workers, this time based on income levels. For payroll taxes without linked benefits, Bozio *et al.* (2019) replicate the findings in Saez *et al.* (2012, 2019) that firms do not to differentiate tax incidence among workers. However, they find evidence of differential tax incidence when there is a clear tax–benefit linkage. They interpret their results as showing linked benefits are a key determinant of tax incidence at the individual level.[4]

Most studies find workers collectively bear most or all of the incidence of payroll taxes, and do so in the form of lower wages, but there are exceptions. Examples include Bennmarker *et al.* (2009) and Benzarti and Harju (2021), who study payroll tax cuts in Sweden and Finland, respectively. Both studies find the majority of the tax incidence is on firms. Of the incidence that does fall on workers, they also find evidence of incidence on employment, which is less common (in Benzarti and Harju (2021), incidence also fluctuates with the business cycle).

Despite some mixed findings, a reasonable prediction based on prior studies is that teachers are likely to bear the bulk of the incidence of US social security taxes, and to do so in the form of lower wages. This prediction is reinforced by evidence from Bozio *et al.* (2019) on the importance

[4]As an alternative to the 'fairness norms' model in Saez *et al.* (2019), Bozio *et al.* (2019) put forth a model where in the absence of linked benefits, unions with strong bargaining power and preferences for wage equality prevent differential tax incidence among workers.

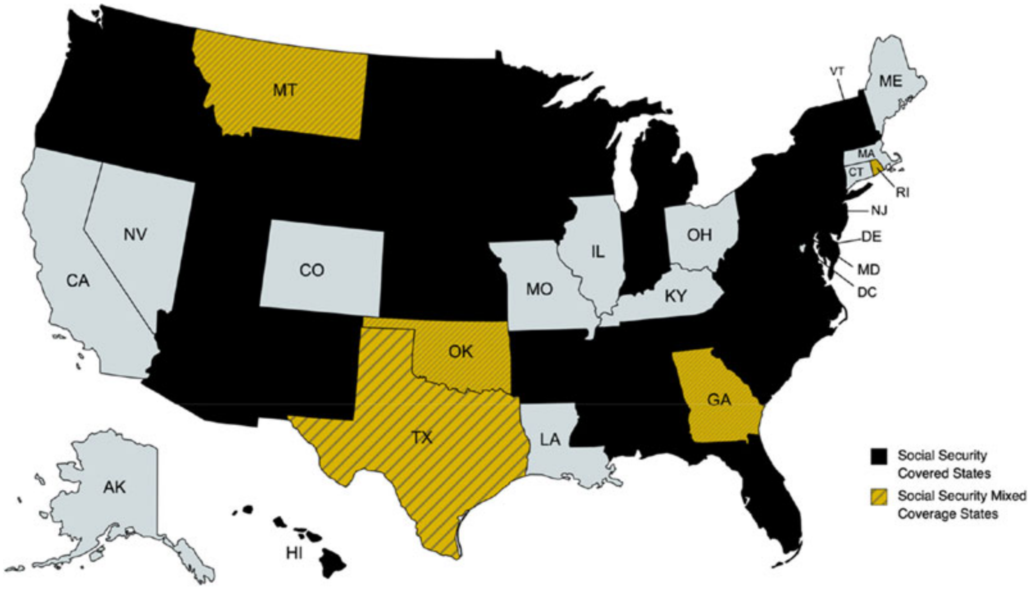

Figure 1. State-level social security coverage in the United States for public school teachers.
Notes: Teachers in 33 states are covered by social security (fully shaded), teachers in 12 states and the District of Columbia do not have social security coverage (Aldeman, 2019*a*), and there is mixed coverage of teachers across school districts in five states (partially shaded).

of linked benefits in determining tax incidence, as linked benefits are a key feature of social security. However, we are not aware of any prior teacher-specific research on tax incidence, or for that matter, any prior research focused on public workers, and the extent to which evidence from the private sector will generalize to the public sector is unclear.[5]

3. Social security and retirement benefits in Texas public schools

Most but not all workers in the United States are covered by social security. Uncovered workers are concentrated primarily in state and local governments, including public schools (Quinby *et al.*, 2020). Overall, about 40 percent of teachers in US schools lack social security coverage (Morrill and Westall, 2019; Aldeman, 2019*a*). In most states, districts either all offer coverage (33 states) or are all uncovered (12 states). Texas is one of the just five states with mixed social security coverage across districts within a state. Figure 1 documents the national landscape of social security coverage among teachers.

Figure 2 illustrates the variation in social security coverage across school districts in Texas. Teachers in 27 of the 1,059 Texas school districts – accounting for about 4.5 percent of the Texas teaching workforce – are covered. In raw numbers, Texas employs approximately 330,000 full-time equivalent (FTE) teachers, of which about 15,000 are in social security districts. Although districts with social security coverage employ only a small fraction of Texas teachers, owing to the state's large size, they are greater in number than the entire teaching workforce in several states (Snyder *et al.*, 2019).[6] Figure 3 shows most districts in Texas that opted into social security did so in the 1950s and 1960s. Since 1996, which is the first year of our administrative data panel, just six districts opted into social security coverage.[7]

[5]Teaching is the largest public-sector occupation in the United States, accounting for over 3 million US workers (Bureau of Labor Statistics, 2024).

[6]Texas denies collective bargaining rights to public employees, including public school teachers.

[7]Two of these are new districts that opened for the first time with social security coverage, and four others switched from uncovered to covered status. Switches in the other direction – from covered to uncovered status – are not permitted by social

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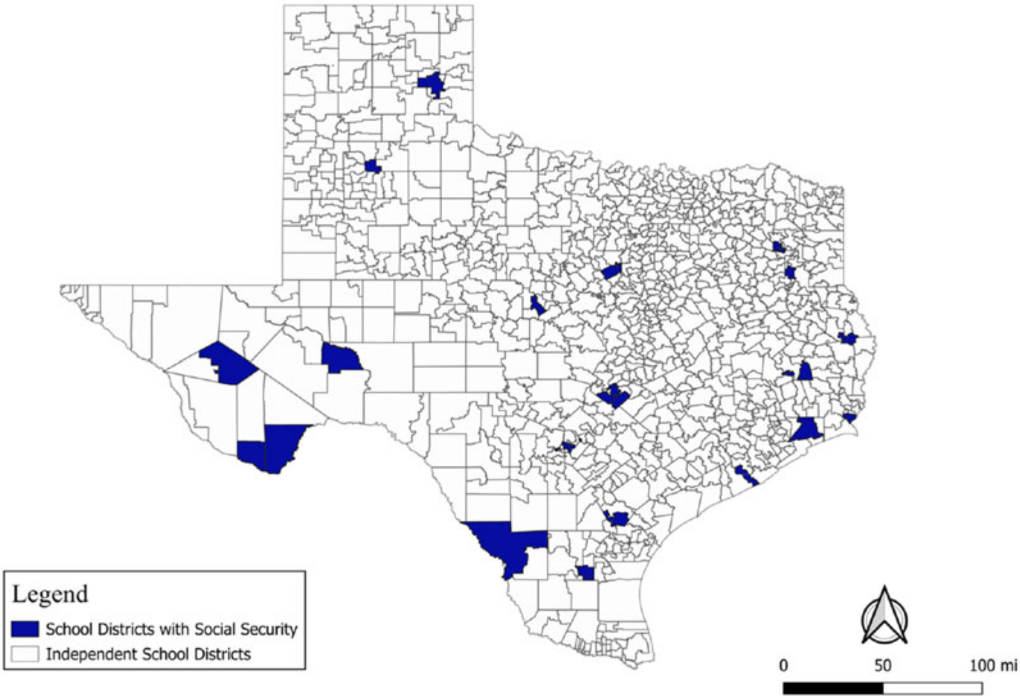

Figure 2. District-level social security coverage in Texas for public school teachers.
Notes: Teachers in 27 school districts are covered by social security (shaded).

Regardless of social security coverage, all teachers in Texas public schools participate in the same state pension plan: the Teacher Retirement System of Texas (TRS). Teachers in districts covered by social security receive retirement benefits from both social security and TRS, and teachers in uncovered districts receive benefits from TRS only. TRS requires the employer to contribute 8.3 percent and teachers to contribute 7.7 percent of teacher salaries, for a total contribution rate to the retirement plan of 16 percent. For teachers in social security districts, employers and employees additionally (and evenly) split the 12.4 percent total social security tax.[8]

security rules. Of the four district switchers, we observe post-social security wages and employment for three (the fourth switched after 2020). These districts may seem like an appealing group to study using a difference-in-differences-style research design. However, in addition to being few in number, they are small, rural, and have some peculiar attributes. For instance, on average the district switchers combine to contain just five schools and employ 33 full-time-equivalent teachers annually. Two of these districts also have the two absolute lowest pupil-to-teacher ratios in the state of Texas. In short, the district switchers are a small and unique group, and unlikely to provide generalizable insights about the incidence of social security taxes.

[8]A complication on the benefit side is that teachers who split their teaching careers between districts with and without social security coverage may be affected by social security's windfall elimination provision (WEP). The WEP reduces the social security benefits of teachers who receive both (a) social security benefits and (b) pension benefits from employment in a non-social security district. The case of Texas teachers is somewhat unique in that non-covered employers have the same external retirement benefit package (through TRS) as covered employers, but the WEP applies nonetheless. The WEP affects the value of the benefits tied to social security taxes for teachers who move between covered and uncovered districts. Per above, to the extent teachers realize this, it may affect tax incidence. In the empirical analysis below, we show that our incidence findings are not sensitive to WEP-induced changes in the tax–benefit linkage by focusing on a subsample non-mobile teachers. This does not rule out a broader effect of the WEP on the labor market because it could affect whether teachers are willing to move between covered and uncovered employment, but at least conditional on observed labor mobility, our findings do not differ substantively depending on whether we include teachers whose social security benefits are affected by the WEP.

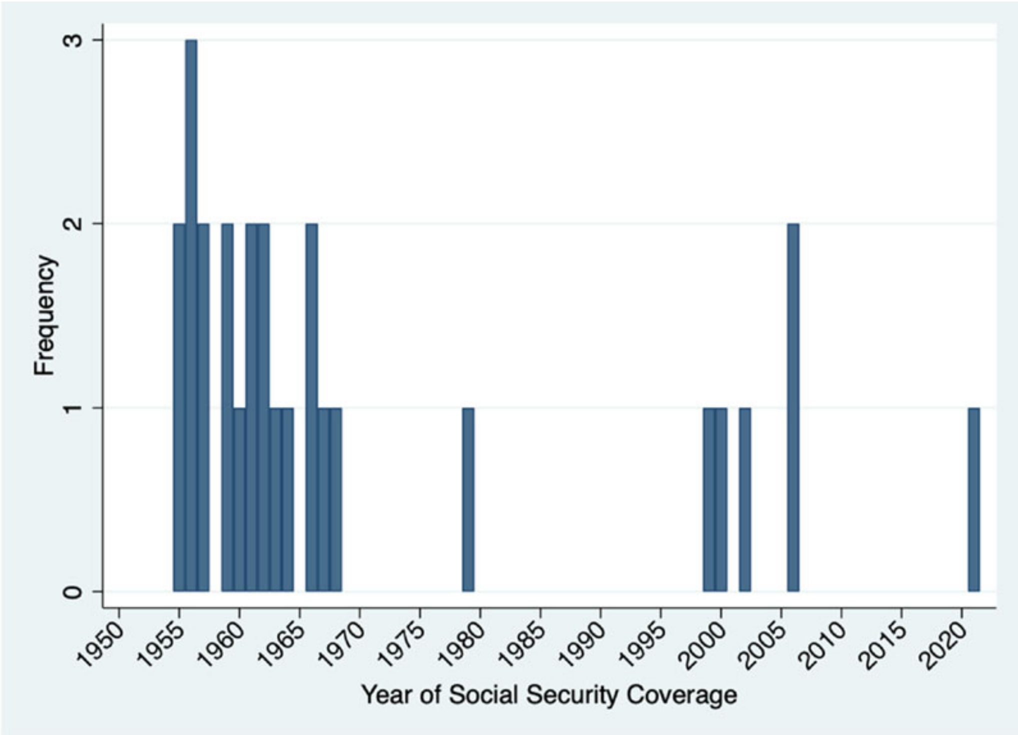

Figure 3. The Year of social security implementation.
Notes: The initial year of social security coverage is defined as the first school year with social security coverage.

Our ability to observe teachers with the same state pension coverage, but who differ by social security coverage, is an important advantage of our setting. In contrast, cross-state comparisons are difficult because state pension plans have evolved differently in states with and without social security. For example, a typical teacher's replacement rate from their state pension plan is about 10 percentage points higher in states without social security coverage (Clark and Craig, 2011). Plans in uncovered states also have considerably more debt (Backes *et al.*, 2016). The incidence of both of these (i.e., state-plan benefit costs and debt servicing costs) on teachers is unclear and can confound inference about the incidence of social security taxes in cross-state studies. Our analysis within Texas holds these important aspects of pension costs fixed among teachers with and without social security coverage.

4. Data

Our analysis is based on a teacher-level administrative data panel from the Public Education Information Management System (PEIMS) managed by the Texas Education Agency. The PEIMS data cover all teachers in Texas public schools and include information on teacher age, gender, race/ethnicity, school and district of employment, years of experience, highest education level, base pay, and total pay (inclusive of supplemental pay). We merge in district characteristics including district size and urbanicity, student demographics, local revenue, total revenue, pupil–teacher ratios, and benefit costs for instructional employees, from the Common Core of Data published by the US Department of Education.

Table 1 provides summary statistics for our data panel, which spans the years 1996–2020 (we use the spring year to denote the school year – e.g., 1995–96 as 1996). All dollar figures are in 2020 dollars. Net of their direct social security taxes (i.e., the 6.2% of salaries taken out of worker pay), Table 1

Table 1. Summary statistics: teacher and district characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		SS districts		Non-SS districts	
Variables	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Teacher characteristics						
1(SS coverage)	0.045	0.206				
Total salary (net of SS)[1]	56,410	10,392	53,664	10,080	56,538	10,389
Base salary (net of SS)[1]	55,006	9,847	52,108	9,269	55,141	9,852
Age	42.02	11.07	42.04	11.01	42.02	11.07
Experience in the state	11.41	9.31	11.74	9.50	11.40	9.30
Experience in the district	8.03	7.64	8.88	7.98	7.99	7.62
1(Graduate degree)	0.235	0.424	0.265	0.441	0.234	0.423
1(African American)	0.092	0.289	0.084	0.277	0.092	0.289
1(Hispanic)	0.217	0.412	0.410	0.492	0.207	0.406
1(Female)	0.771	0.420	0.769	0.422	0.771	0.420
District characteristics						
Log of Total enrollment	9.63	1.62	10.50	1.27	9.59	1.62
Pupil–Teacher ratio	15.03	1.72	15.25	1.34	15.02	1.74
Log of Total revenue per pupil	9.35	0.18	9.46	0.22	9.34	0.17
Log of Local revenue per pupil	8.50	0.69	8.74	0.65	8.49	0.69
% English language learners	14.49	12.04	21.45	10.83	14.17	11.99
% Free/Reduced lunch status	50.51	22.39	60.51	17.52	50.05	22.49
% African American students	13.28	13.17	10.76	10.55	13.39	13.27
% Hispanic students	45.98	27.57	67.84	23.71	44.96	27.32
% Charter status	1.83	13.40	0.28	5.25	1.90	13.66
% City schools	43.47	49.57	86.83	33.81	41.45	49.26
% Suburb schools	30.95	46.23	1.81	13.33	32.31	46.77
% Town schools	10.97	31.26	3.09	17.30	11.34	31.71
% Rural schools	14.61	35.32	8.27	27.54	14.90	35.61
N (teacher-years)	7,088,769		315,737		6,773,032	

Notes: SS = Social Security. Salaries and revenues are expressed in 2020 dollars. Data on ELL rates are unavailable for TX school districts in the Common Core of Data prior to 1999; for the three years prior (1996–98), we impute districts' ELL rates to the first observed value in 1999.
[1]All salary values are net of employee social security payments (i.e., 6.2%) when applicable. Total salary is equal to base salary plus supplemental pay.

shows teachers in social security districts earn $53,664 per year in total salary, on average, over the course of our data panel, which is just over 5 percent lower than the average in non-social security districts. In addition to the salary difference, teachers in covered districts are more likely to have a graduate degree (26.5% versus 23.4%) and more likely to be Hispanic (41% versus 20.7%), which is the predominant minority group in Texas. District characteristics, which are teacher-weighted in the table, also vary considerably by social security coverage. Teaching positions in covered districts are more likely to be in traditional (non-charter) districts in urban areas, with higher enrollments, higher per-pupil revenues, more English Language Learners (ELL), more students enrolled in free and reduced-price lunch programs, and more Hispanic students.

The differences by coverage status in Table 1 – and other differences they may imply along unobserved dimensions – are potential confounders in our efforts to estimate the incidence of social security taxes. To gain insight into how these differences are likely to affect our analysis, we estimate several versions of the following linear regression:

$$SS_{idt} = \delta_0 + X_{idt}\delta_1 + Z_{dt}\delta_2 + \lambda_t + \eta_{idt} \tag{1}$$

In the equation, SS_{idt} is an indicator equal to one if teacher i in district d and year t is covered by social security, and zero otherwise. The vectors X_{idt} and Z_{dt} include the teacher and district characteristics listed in Table 1, respectively. For teacher age and experience, we include linear and quadratic terms. λ_t is a year fixed effect and η_{idt} is the error term, which we cluster at two levels: by district

Table 2. Observable differences by Social Security coverage

Variables	(1)	(2) 1(Social Security coverage)	(3)
Log of District enrollment		0.0131	0.0133
		(0.0206)	(0.0206)
Log of Total revenue per pupil		0.1910	0.1897
		(0.1565)	(0.1575)
Log of Local revenue per pupil		0.0248	0.0262
		(0.0326)	(0.0334)
% Hispanic students		0.0010	0.0009
		(0.0011)	(0.0011)
% African American students		−0.0009	−0.0008
		(0.0013)	(0.0012)
% English Language Learners		−0.0007	−0.0007
		(0.0027)	(0.0027)
% Free/Reduced lunch status		0.0006	0.0006
		(0.0005)	(0.0005)
1(Charter)		0.0607	0.0669
		(0.0889)	(0.0903)
1(Suburb district)		−0.0553*	−0.0549*
		(0.0324)	(0.0322)
1(Town district)		−0.0501	−0.0493
		(0.0337)	(0.0330)
1(Rural district)		−0.0268	−0.0256
		(0.0362)	(0.0353)
Age	−0.0004		0.0005
	(0.0004)		(0.0006)
Age^2	0.0000		−0.0000
	(0.0000)		(0.0000)
Experience in state/1,000	−0.6376*		0.0857
	(0.3734)		(0.3155)
Experience in state^2/1,000	0.0142**		0.0089
	(0.0061)		(0.0055)
Experience in district/1,000	1.7082		0.3799
	(1.1537)		(0.4147)
Experience in district^2/1,000	−0.0328		−0.0182
	(0.0236)		(0.0189)
1(Graduate degree)	0.0093		0.0011
	(0.0092)		(0.0058)
1(African American)	0.0074		−0.0137
	(0.0147)		(0.0152)
1(Hispanic)	0.0527		0.0132
	(0.0352)		(0.0152)
1(Female)	0.0006		0.0043
	(0.0012)		(0.0025)
Year fixed effects	X	X	X
R^2	0.0119	0.0904	0.0916
Observations (teacher-years)	7,088,769	7,088,769	7,088,769

Notes: We divide all experience variables by 1,000 to illuminate the values of very small coefficients. Standard errors are two-way clustered by district and TRS entry year.
***p < 0.01, **p < 0.05, *p < 0.1.

and by the year of entry into the Texas teaching workforce.[9] We estimate a version of equation (1) that omits Z_{dt}, then a version that omits X_{idt}, then the full version as shown. The results are provided in Table 2.

[9]We cluster by the individual entry year for most of the entry year distribution (from 1981 to 2010), but combine entry years in the tails of the distribution to avoid using small clusters. Specifically, in the tails we bin teachers by their entry year as follows: (1) 1975 and before, (2) 1976 to 1980, (3) 2011 to 2015, and (4) 2016 and after. There are 34 entry-year clusters in total.

The first takeaway from Table 2 is that conditional on district characteristics, there is no evidence of observed differences between teachers with and without social security coverage. In column (1), before we condition on district characteristics, teacher experience is the only characteristic that is a significant predictor of social security status. In column (3), after we add district characteristics, none of teacher characteristics are significant. Moreover, the model R^2 is essentially unchanged going from column (2), which includes only district characteristics, to column (3), which includes both district and teacher characteristics (it increases by just 0.0012).

In contrast, district characteristics explain about 9 percent of the total variation in social security coverage across teachers. Many of the district characteristics are highly correlated with each other, making inference from the individual regression coefficients in Table 2 difficult. But reviewing the evidence in Tables 1 and 2 holistically, teaching positions with social security coverage are more likely to be in districts that are larger, urban, have more revenue, and serve more disadvantaged student populations. These observed differences also raise concerns about unobserved differences, which we address below.[10]

5. Empirical strategy

5.1 Main specifications

We begin with the following linear regression of teacher salaries on social security coverage and teacher and district characteristics:

$$Ln(Y_{idt}) = \beta_0 + \beta_1 SS_{dt} + X_{idt}\beta_2 + Z_{dt}\beta_3 + \theta_t + \varepsilon_{idt} \tag{2}$$

In equation (2), Y_{idt} is the salary for teacher i in district d and year t, net of the 6.2 percent employee social security tax for teachers in covered districts (i.e., we multiply gross salaries for covered teachers by 0.938).[11] The other terms in equation (2) are as defined in equation (1) (although we remove the i subscript on social security coverage because it does not vary across teachers within district-years). The parameter of interest in equation (2) is β_1, which indicates the incidence of social security taxes on wages.

When we subtract the social security employee tax from the dependent variable prior to estimation, we impose a variant of what Zoutman *et al.* (2018) dub the 'Ramsey Exclusion Restriction'. This is important so that we do not misattribute the employee tax as take-home pay. Note, however, this does not make any assumption about the incidence of the employee tax – it is merely an accounting tool. For example, our model still allows districts to pay all or part of the employee tax by raising teacher pay, in which case the net-of-tax salaries in social security districts would rise to reflect this, putting positive pressure on β_1.

Equation (2) models tax incidence on wages, where prior research suggests it is most likely concentrated. We also test for incidence on staffing levels using a district-level model of the pupil–teacher ratio. The model is specified similarly to equation (2) but uses the district pupil–teacher ratio as the dependent variable and collapses the data to the district-year level as follows:

$$R_{dt} = \gamma_0 + \gamma_1 SS_{dt} + \bar{X}_{dt}\gamma_2 + Z_{dt}\gamma_3 + \phi_t + \xi_{dt} \tag{3}$$

In equation (3), R_{dt} is the pupil–teacher ratio for district d in year t, $\bar{X}_{dt}$ includes district-average teacher characteristics, and the other terms are as defined above.

Equations (2) and (3) will allow us to recover unbiased estimates of tax incidence if the differences between teachers with and without social security coverage are along observed dimensions only, and if

[10]We also briefly considered the potential for district mergers and annexations to influence our findings. Over the course of our data panel in Texas there were 22 instances of district mergers and annexations, all among districts without social security coverage. In results suppressed for brevity, we confirm our findings are substantively unaffected if we drop all school districts involved in a merger or annexation.

[11]The social security tax applies to earnings up to a ceiling, but the ceiling is ignorable because very few teachers reach the ceiling (fewer than 0.1% of teacher salaries exceed the ceiling amount, which in 2020 was $137,700 in annual earnings).

the provision of other benefits is independent of social security coverage. While possible, this identification condition seems unlikely. Our evaluation setting mitigates what is arguably the biggest threat in terms of correlated benefits because all teachers in our sample share a common state pension plan. This prevents districts from offsetting their social security expenditures by reducing other employer-provided retirement benefits. However, other benefits – most notably health benefits, which combined with retirement benefits constitute the vast majority of benefit costs for teachers (Bruno, 2019; Aldeman, 2019*b*) – could be problematic. In addition to the possibility of correlated benefits, a myriad of other unobservables could potentially affect our estimates.

We explore the potential for bias in our estimates in two ways. First, we test directly for correlated benefit costs by estimating a district-level regression specified similarly to equation (3), but where the dependent variable is the district ratio of total benefit costs to gross salaries. If social security coverage is independent of other employer benefit costs, then it should correspond to an increase in total benefit costs of 6.2 percent of gross salaries (i.e., the employer share of the social security tax). A value above 6.2 percent would imply coverage reflects a general proclivity of social security districts to offer benefit-heavy compensation packages, which would bias our estimate of β_1 in equation (2) negatively, and/or γ_1 in equation (3) positively (assuming other benefit costs have at least some incidence on workers). Alternatively, a value below 6.2 percent would imply social security coverage substitutes for other costly employee benefits and cause bias in the other direction.

Second, and more broadly, we follow the approach of Oster (2019) to provide a bounded estimate of tax incidence under assumptions about bias from unobserved differences between districts (and teachers) that differ by social security status. The intuition behind Oster's approach is that differences along observed and unobserved dimensions likely cause bias in the same direction (also see Altonji *et al.*, 2005). With knowledge of (1) the direction of bias caused by observed differences and (2) the explanatory power of observables over outcomes, both of which can be estimated, and by making assumptions about (3) the relative magnitudes of observed and unobserved differences and (4) the explanatory power of unobservables over outcomes, one can estimate and adjust for the impact of unobservables. Formally, Oster (2019) proposes that a parameter adjusted for bias from *unobservables* can be recovered from an ordinary least squares (OLS) estimate that conditions on *observables* as follows:

$$\beta * \approx \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{\max} - \tilde{R}}{\tilde{R} - \dot{R}} \tag{4}$$

In equation (4), β^* is the bias-adjusted estimate of the parameter of interest. Four of the parameters on the right-hand side of the equation are directly estimable: $\tilde{\beta}$ is the estimate from an OLS model with full controls for observables, $\dot{\beta}$ is the estimate from a sparse OLS model with no controls (i.e., the model includes just an intercept and the parameter of interest, which in our case is an indicator for social security coverage), and $\tilde{R}$ and $\dot{R}$ are the R^2 values from these models, respectively. δ and $R_{\max}$ are unknown and must be parameterized by the researcher. Oster (2019) describes δ as the 'coefficient of proportionality' – it is the ratio of the magnitude of unobserved to observed selection. $R_{\max}$ is the total explanatory power of observables and unobservables over the outcome. The maximum value of $R_{\max}$ is 1.0, but for most outcomes the feasible value is less than 1.0.[12]

For our preferred bounding exercise we set $\delta = 1.0$, or in words, we parameterize the magnitudes of selection on observables and unobservables to be the same. This is a common parameterization in the use of this and related methods in the literature (also see Altonji *et al.*, 2005). We set $R_{\max} = \tilde{R} + (\tilde{R} - \dot{R})$, or in words, we assume unobservables explain as much of the outcome variation as observables. Given the rich observable information available about teachers and districts in our dataset, this parameterization allows for a substantial role of unobservables in influencing our tax-incidence estimates. We also show results under alternative parameterizations of δ and $R_{\max}$.

[12]For example, if some of the variation in the outcome is due to measurement error, or if there is some conditional randomness in outcomes, the feasible value will be below 1.0.

Table 3. Incidence of Social Security taxes on total salary

	(1)	(2)	(3)	(4)
Variables	Log of total salary			
1(Social Security coverage)	−0.050	−0.061	−0.094	−0.096
	[−0.098, −0.001]	[−0.099, −0.021]	[−0.160, −0.029]	[−0.159, −0.033]
Teacher characteristics		X		X
District characteristics			X	X
Year fixed effects	X	X	X	X
R^2	0.0150	0.3415	0.0883	0.4092
Observations (teacher-years)	7,088,769	7,088,769	7,088,769	7,088,769

Notes: The teacher and district characteristics included in the models are as shown in Table 2. Coefficients for controls are reported in Appendix Table A3. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

6. Results

6.1 Main results

Table 3 shows estimates from several versions of equation (2) where we use total teacher salary as the dependent variable.[13] In presenting the results, the conventional approach would be to denote statistical significance under the null hypothesis that tax incidence is zero. However, this seems unlikely. Because the expected incidence in our setting is uncertain, we instead simply report our point estimates and 95 percent confidence intervals. We construct the confidence intervals based on our two-way clustered standard errors throughout.

Column (1) of Table 3 shows that unconditionally, teachers covered by social security have salaries that are 5 percent lower than their uncovered counterparts, on average, net of their own social security contributions. This matches the descriptive statistics in Table 1. Column (2) shows this point estimate changes very little if we condition on observable teacher characteristics, which is notable because teacher characteristics (primarily experience) explain about 33 percent of the variation in teacher salaries. The stability of the incidence parameter reflects the lack of selection on observables at the teacher level. Columns (3) and (4) add district characteristics, in isolation in column (3), and in addition to the teacher characteristics in column (4). While district characteristics explain much less of the variation in teacher salaries, their inclusion in the model has a more significant impact on our estimate of the incidence parameter – in total, it increases in magnitude by 94 percent from column (1) to column (4). The point estimate from the full model indicates teachers covered by social security earn 9.6 percent less than uncovered teachers, conditional on observables. Taken at face value, this implies covered teachers pay 77 percent of the total social security tax in the form of lower wages.[14]

In Table 4 we conduct a parallel investigation of tax incidence on staffing levels using equation (3).[15] The district data are weighted by the teacher sample size to maintain comparability with the teacher-level results in Table 3 (results from unweighted analogs to the weighted regressions are similar and reported in Appendix Table A4). In the full model in column (4), the conditional difference in the

[13]Total salary is equal to base salary plus supplemental pay. Table 1 shows that supplemental pay is small, and it follows that our findings are qualitatively similar if we estimate tax incidence using base salary instead of total salary (see Appendix Table A1).

[14]We also confirm this result using two types of placebo tests, shown in Appendix Figure A1 and Table A2. In the first one, we drop all teachers in social security districts, then run a permutation test where we randomly assign false social security coverage to Texas districts 1,000 times. At each iteration we calculate the effect of false social security coverage. Our true estimate is well outside of the 95 percent confidence interval of the estimates under random assignment to social security coverage. In the second test, we again drop all teachers in social security districts, then falsely code uncovered districts that are immediately adjacent to a social security district as covered. As expected, our tax incidence estimate under this placebo condition is small and not statistically different from zero.

[15]We calculate the pupil–teacher ratios using the Common Core of Data based on student enrollment and the number of FTE teachers. These data are available in the Common Core for 99.7 percent of the district-years represented in the Texas administrative data. The small number of district-years with missing data are dropped from this portion of our analysis.

Table 4. Incidence of Social Security taxes on the pupil–teacher ratio

	(1)	(2)	(3)	(4)
Variables	Pupil–teacher ratio			
1(Social Security coverage)	0.238	−0.382	0.119	0.072
	[−0.511, 0.986]	[−0.673, −0.090]	[−0.528, 0.765]	[−0.326, 0.469]
Teacher characteristics		X		X
District characteristics			X	X
Year fixed effects	X	X	X	X
R^2	0.0375	0.3576	0.5519	0.5829
Observations (district-years)	27,100	27,100	27,100	27,100

Notes: The district-level models are weighted by number of teachers. The teacher and district characteristics included in the models are as shown in Table 2. The mean value of the pupil–teacher ratio (the dependent variable) is 15.0. We calculate the pupil–teacher ratios using the Common Core of Data based on student enrollment and the number of FTE teachers. These data are available in the Common Core for 99.7% of the district-years represented in the Texas administrative data. The small number of district-years with missing data are dropped from this portion of our analysis. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using clustered standard errors by district.

Table 5. Impact of Social Security coverage on the ratio of districts' total benefit costs to total salaries for instructional employees

	(1)	(2)	(3)	(4)
Variables	Ratio of benefit to salary costs			
1(Social Security coverage)	0.061	0.056	0.051	0.051
	[0.039, 0.084]	[0.031, 0.080]	[0.030, 0.073]	[0.030, 0.072]
Teacher characteristics		X		X
District characteristics			X	X
Year fixed effects	X	X	X	X
R^2	0.3157	0.3935	0.4070	0.4252
Observations (district-years)	27,100	27,100	27,100	27,100

Notes: The district-level models are weighted by number of teachers. Total benefit costs and instructional salaries are available in the Common Core for 95.9% of the district-years represented in the Texas administrative data. The small number of district-years with missing data are dropped from this portion of our analysis. The teacher and district characteristics included in the models are as shown in Table 2. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using clustered standard errors by district.

pupil–teacher ratio between covered and uncovered districts is just 0.07. This point estimate is very small, corresponding to just 0.5 percent of the sample-average pupil–teacher ratio of 15, and the 95 percent confidence interval comfortably includes zero. This result gives no indication of tax incidence on teacher staffing levels.

6.2 Bias and robustness

In Table 5 we test for potential bias in our estimates due to the presence of correlated benefits. We estimate versions of equation (3) at the district level that use as the dependent variable the ratio of total employer benefit costs to total salaries.[16] The employer social security tax is 6.2 percent of salary; if other benefits are correlated with social security benefits, we would expect the coefficient on social security coverage to differ from 6.2 percent. Importantly, and unlike in our preceding models, we do *not* net out the employee social security tax from total salaries in the denominator of the dependent variable for this test. The reason is that we are no longer testing for tax incidence; rather, this supplementary regression is designed to test whether social security coverage is correlated with other employer benefit costs. The 6.2-percent social security tax on employers is levied on gross salaries,

[16]Benefit-cost data are unavailable in PEIMS so we construct the ratio of benefit costs to total salaries using data from the Common Core. Benefit-cost data are available in the Common Core for about 96 percent of the district-years represented in the Texas administrative data. The small number of district-years with missing data are dropped from this portion of our analysis. Benefit costs and salaries are reported for all instructional employees – these are primarily teachers but also include other education personnel.

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Table 6. Estimates of Social Security tax incidence on total salaries allowing for sorting into Social Security coverage on unobservables

Estimated inputs				
Sparse-model OLS coefficient ($\dot{\beta}$)				−0.050
Full-model OLS coefficient ($\tilde{\beta}$)				−0.096
R^2 from sparse-OLS model ($\dot{R}$)				0.015
R^2 from full-OLS model ($\tilde{R}$)				0.409
Bias-adjusted treatment effects (β^*)				
Researcher-specified inputs		Max explanatory power of observables / unobservables ($R_{\max}$)		
		0.50	0.803	1.00
Coefficient of proportionality (δ)	0.50	−0.102	−0.119	−0.131
	1.00	−0.107	**−0.142**	−0.165
	1.50	−0.113	−0.165	−0.200

Notes: The adjustment is following Oster (2019) as described in equation (4). The parameters reported in the first horizontal panel inform the adjustment. The values in the lower table are the adjusted incidence estimates. The symbols in parenthesis identify the parameters used in the adjustment procedure as denoted in equation (4). The bolded entry is for our preferred adjustment.

so in order for our model to be informative for this test, we must use gross salaries in the denominator of the dependent variable.

Column (1) of Table 5 shows that unconditionally, benefit costs as a percent of gross salaries are 6.1 percent higher in social security districts. Conditional on observables, this estimate attenuates to 5.1 percent in column (4). Throughout the table, our confidence intervals cannot rule out that social security coverage corresponds to a 6.2 percent of salary increase in total benefit costs. Thus, we cannot reject the null hypothesis that social security coverage is independent of other employer-provided benefits. We interpret this result as ruling out correlated benefits as a source of (meaningful) bias in our estimates of tax incidence.

Noting that this is our preferred interpretation, we can also ignore statistical significance in Table 5 and take the point estimates at face value. Given that they are below 6.2 percent, this would imply social security and other employer-provided benefits are weak substitutes. We believe this interpretation is a stretch given the confidence intervals around our estimates in Table 5, but if true, it would suggest our estimates of tax incidence in Table 3 are biased positively (i.e., toward zero) as long as other benefit costs have at least some incidence on wages. That is, it would imply the true magnitude of the incidence parameters in Table 3 are understated due to correlated benefits.

Table 7. Estimates of Social Security tax incidence on the pupil–teacher ratio allowing for sorting into Social Security coverage on unobservables

Estimated inputs			
Sparse-model OLS coefficient ($\dot{\beta}$)			0.238
Full-model OLS coefficient ($\tilde{\beta}$)			0.072
R^2 from sparse-OLS model ($\dot{R}$)			0.038
R^2 from full-OLS model ($\tilde{R}$)			0.583
Bias-adjusted treatment effect (β^*):			
Researcher-specified inputs		Max explanatory power of observables / unobservables ($R_{\max}$)	
		0.75	1.00
Coefficient of proportionality (δ)	0.50	0.047	0.008
	1.00	0.021	**−0.055**
	1.50	−0.005	−0.119

Notes: The adjustment is following Oster (2019) as described in equation (4). The parameters reported in the first horizontal panel inform the adjustment. The values in the lower table are the adjusted incidence estimates. The symbols in parenthesis identify the parameters used in the adjustment procedure as denoted in equation (4). The mean value of the pupil–teacher ratio (the dependent variable) is 15. The bolded entry is for our preferred adjustment.

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Next, in Tables 6 and 7 we show incidence estimates for wages and employment, respectively, after we adjust for unobservables following Oster (2019). To reflect the uncertainty inherent to this adjustment, we present a range of adjusted values over different parameterizations of δ and $R_{\max}$. Our preferred parameterizations of $\delta = 1.0$ and $R_{\max} = \tilde{R} + (\tilde{R} - \dot{R})$ are in bold.

We begin with our wage estimate in Table 6. The pattern of results in Table 3 indicates the direction of observed sorting into social security with respect to wages is positive and accordingly, the Oster (2019) adjustment for bias from unobservables increases the magnitude of our tax-incidence estimate. Using our preferred parameterization, the adjusted social security coefficient in Table 6 is −0.142, implying wage incidence above 100 percent of the total social security tax. While it is theoretically possible for tax incidence to exceed 100 percent (e.g., if workers value the benefits above the cost), we suspect this high number is more likely the product of our liberal parameterization of δ and $R_{\max}$. Use of smaller values for δ and $R_{\max}$ yields smaller incidence estimates. In what we view as a conservative parameterization, where δ and $R_{\max}$ are both set to 0.50, we estimate the tax incidence on teacher wages is 10.2 percent.

In Table 7, the adjustments for bias from unobservables have no substantive impact on our estimate of the tax incidence on staffing levels. (Note that in our staffing models, observables explain more than 50 percent of the variation in the outcome. Thus, in Table 7 we present adjusted estimates over a restricted range of $R_{\max}$ values.)

Under the assumption that any bias from unobservables is in the same direction as observables, our estimates from the full models in Tables 3 and 4 are lower bounds on the tax incidence of social security. Incorporating our preferred adjustment based on Oster (2019) and focusing on wages – where our analysis suggests the incidence is concentrated – a reasonable range of tax-incidence estimates is between 77 and 100 percent. However, it is also possible that bias from sorting on unobservables is in the opposite direction of observed sorting. While this is an uncommon assumption, it could happen in our context if teachers who select into employment in social security districts value social security coverage more than other teachers, in which case their willingness-to-pay would be higher than in the full population. These teachers would accept lower wages to work in covered districts, causing negative bias in our estimate of the incidence parameter – that is, leading it to be overestimated in our sample relative to a global coverage policy.

While we cannot rule out this possibility with certainty, we believe it is unlikely. One reason is that there is no evidence that social security coverage, or retirement benefits in general, are a first-order concern among teachers when they select where to work (Boyd *et al.*, 2005; Horng, 2009; Reininger, 2012; Fuchsman *et al.*, 2023). This is especially likely to be true for young teachers, who prior research suggests will place less value on their retirement benefits compared to older teachers, and who are less knowledgeable about retirement (French and Jones, 2012; Quinby, 2020). In fact, among US teachers with zero to –nine years of experience, Fuchsman *et al.* (2024) find that over 20 percent do not correctly answer a basic question about whether they have social security coverage.

If social security is more important to older teachers, we would expect to see older teachers systematically sort into social security districts, but there is no evidence of this type of sorting in our data (per Table 2). It is also possible that districts could respond. One way covered districts could respond is by flattening their salary schedules – that is, raising relative pay for younger teachers and lowering it for older teachers – compared to uncovered districts, reflecting differential teacher preferences for social security. This suggests a testable implication: the wage gap between teachers in covered and uncovered districts will be largest among older and more experienced teachers, and smallest among younger teachers. We test for this possibility in Table 8 by estimating tax incidence separately for teachers with less than five years of experience and more than 15 years of experience. The results in the first two columns of the table give no indication that incidence is lower among inexperienced teachers or higher among experienced teachers.[17]

[17]We design these tests around teacher experience because districts cannot explicitly differentiate pay by age, but they can differentiate pay by experience.

Table 8. Robustness: incidence of Social Security taxes on total salary

Subset of teachers Variables	(1) Less than 5 years of exp.	(2) More than 15 years of exp.	(3) No change in SS coverage	(4) No change in district
	Log of total salary			
1(Social Security coverage)	−0.095	−0.089	−0.094	−0.092
	[−0.160, −0.030]	[−0.147, −0.032]	[−0.160, −0.028]	[−0.154, −0.030]
Teacher characteristics	X	X	X	X
District characteristics	X	X	X	X
Year fixed effects	X	X	X	X
R^2	0.1941	0.3884	0.4121	0.5329
Observations (teacher-years)	2,107,122	2,329,759	6,830,270	3,940,476

Notes: The teacher and district characteristics included in the models are as shown in Table 2. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

We also impose restrictions on the teacher sample to minimize the potential for endogenous sorting during the career. First, in column (3) of Table 8, we restrict the sample to teachers who do not change social security status during our data panel. Next, in column (4), we restrict the sample to teachers who do not change districts during our data panel at all. The restricted mobility of teachers in these samples reduces the potential for endogenous sorting into social security coverage, but our findings are similar regardless of whether we use the full teacher sample or either of the restricted subsamples.[18]

Finally, we explore the potentially confounding effect of a reform to the TRS passed in 2005. Several rules changed after the reform, the most notable of which is that the career length required to be eligible for full TRS retirement benefits increased. There is no clear theoretical expectation for how this reform would affect social security tax incidence, but to test for any potential impact, we estimate models separately for teachers subject to the pre- and post-reform TRS rules (i.e., grandfathered into the old rules, or subject to the new rules). The results, reported in Appendix Table A5, show tax incidence is substantively similar for both groups.

7. Conclusion

We study the incidence of social security taxes on public school teachers in Texas, which is one of the five of states where there is cross-district variation in social security coverage. At what is likely a lower bound, we estimate the incidence of total social security taxes on teacher wages is 77 percent. Under reasonable assumptions about sorting on unobservables, we cannot rule out incidence on wages of 100 percent. We find no evidence of tax incidence on teacher staffing levels using the same methods.[19]

To the best of our knowledge, we are the first to estimate social security tax incidence exclusively for workers in the public sector. Prior studies either exclude public workers, or analyze them in combination with private workers, who are much more common and disproportionately drive the estimates. Our findings for teachers are consistent with most of the literature on tax incidence in the private sector – namely, tax incidence is primarily concentrated on the supply side of the labor market, and on wages specifically. Among other things, this suggests local government agencies (in our case, school districts) are unable to offset the cost of providing social security benefits by raising additional local revenue.

[18]There are also reasons female teachers may value social security benefits less than male teachers. Most notably, female teachers who are married could be in line for spousal benefits that are comparable to or higher than their own benefits, especially among the older cohorts in our sample. However, because districts cannot pay differently by gender, we do not expect gender differences in benefit valuation to show up in our incidence estimates. We confirm this in results suppressed for brevity. It is also possible that if women value social security benefits less than men, they could self-select out of social security districts, but there is no evidence of this in Table 2.

[19]It is also possible that social security tax incidence could spill over into other aspects of school district budgets, such as the level of non-teacher staffing, capital expenditures, etc. We cannot rule this out, but our finding that most or all of the incidence is on teacher salaries makes spillovers along other dimensions less likely.

Our findings help to inform policy proposals to enroll teachers in social security in states where they currently lack coverage (Kan and Aldeman, 2014; Gale *et al.*, 2015; Koedel and Gassmann, 2018). We find no evidence to suggest the additional social security taxes would lead to changes in teacher staffing levels. Moreover, combining our wage-incidence estimates with evidence from Fuchsman *et al.* (2023) – who use survey experiments to estimate that teachers value social security coverage at about 10.7 percent of salary – suggests teachers will be roughly indifferent to social security enrollment. In other words, their tax incidence would be comparable to their valuation of benefits, on average. We conclude that policy proposals to enroll teachers in social security seem promising if states can leverage this to improve the fiscal health of their retirement plans.

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Appendix A

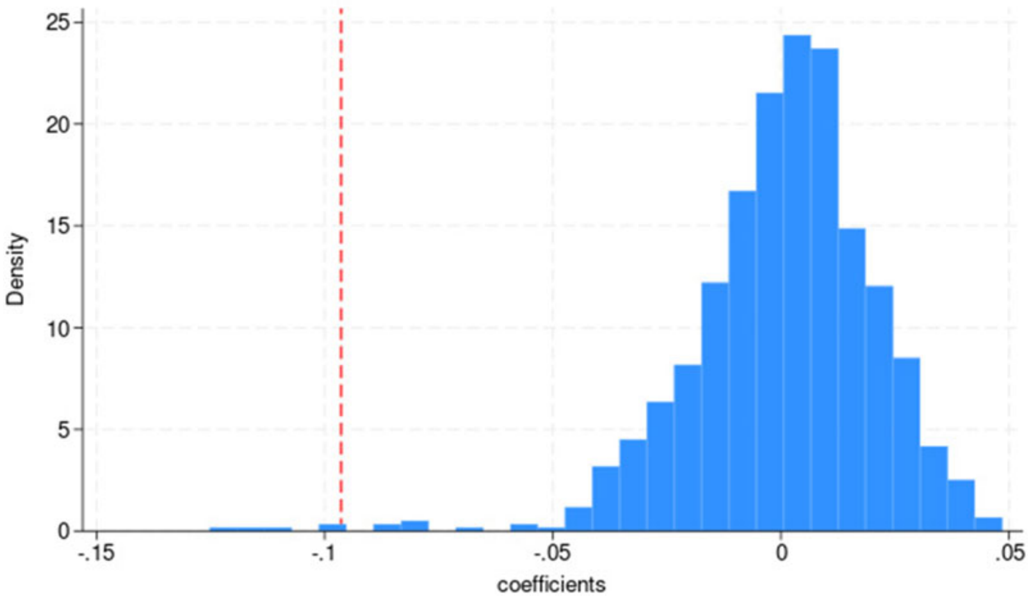

Figure A1. Permutation test: distribution of coefficients with random assignment of Social Security coverage status to school districts.
Notes: This figure shows results from a permutation test where we drop all districts with social security coverage, then in the remaining sample, randomly assign the same number of districts to false social security coverage 1,000 times. At each iteration we estimate the effect of false social security coverage. The histogram shows the distribution of estimates. The dashed vertical line marks the incidence parameter estimated using the real data.

Table A1. Incidence of Social Security taxes on base salary (analog to Table 3 in the main text)

	(1)	(2)	(3)	(4)
Variables	Log of base salary			
1(Social Security coverage)	−0.053	−0.064	−0.099	−0.102
	[−0.099, −0.008]	[−0.101, −0.027]	[−0.162, −0.037]	[−0.161, −0.042]
Teacher characteristics		X		X
District characteristics			X	X
Year fixed effects	X	X	X	X
R^2	0.0140	0.3393	0.0919	0.4128
Observations (teacher-years)	7,088,769	7,088,769	7,088,769	7,088,769

Notes: The teacher and district characteristics included in the models are as shown in Table 2 in the main text. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

Table A2. Placebo test: estimated incidence of Social Security taxes on total and base salary when Social Security coverage is falsely coded in school districts adjacent to districts with actual Social Security coverage

Variables	(1) Placebo Log of total salary	(2) Placebo Log of base salary
1(Pseudo-social security coverage)	0.005	0.007
	[−0.011, 0.021]	[−0.008, 0.022]
Teacher characteristics	X	X
District characteristics	X	X
Year fixed effects	X	X
R^2	0.4066	0.4100
Observations (teacher-years)	6,772,389	6,772,389

Notes: We exclude school districts with actual social security coverage from the sample and falsely code geographically adjacent school districts as having social security coverage. The expected tax incidence in the falsely coded districts is zero. The teacher and district characteristics included in the models are as shown in Table 2. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

Table A3. Estimated coefficients from the full models in Table 3

	(1)	(2)	(3)	(4)
Variables	Log of total salary			
Log of District enrollment			0.0280 [0.020, 0.036]	0.0288 [0.019, 0.038]
Log of Total revenue per pupil			0.0508 [0.016, 0.086]	0.0355 [−0.002, 0.073]
Log of Local revenue per pupil			0.0270 [0.012, 0.042]	0.0277 [0.010, 0.045]
% Hispanic students			0.0006 [0.000, 0.001]	0.0005 [0.000, 0.001]
% African American students			0.0003 [0.000, 0.001]	0.0005 [0.000, 0.001]
% English language learners			0.0001 [−0.000, 0.001]	0.0006 [−0.000, 0.001]
% Free/Reduced lunch status			−0.0004 [−0.001, −0.000]	−0.0004 [−0.001, −0.000]
1(Charter)			−0.0853 [−0.165, −0.006]	0.0163 [−0.058, 0.091]
1(Suburb district)			0.0226 [0.012, 0.033]	0.0338 [0.020, 0.047]
1(Town district)			−0.0173 [−0.036, 0.002]	−0.0205 [−0.041, −0.000]
1(Rural district)			0.0028 [−0.015, 0.021]	0.0084 [−0.014, 0.031]
Age		−0.0015 [−0.003, −0.000]		−0.0001 [−0.001, 0.001]
Age^2		−0.0000 [−0.000, 0.000]		−0.0000 [−0.000, −0.000]
Experience in state/1,000		20.1894 [17.473, 22.906]		21.2891 [18.513, 24.065]
Experience in state^2/1,000		−0.2067 [−0.207, 0.032]		−0.2179 [−0.287, −0.148]
Experience in district/1,000		3.1315 [1.755, 4.508]		0.6955 [−0.481, 1.872]
Experience in district^2/1,000		−0.0690 [−0.109, −0.029]		−0.0125 [−0.044, 0.019]
1(Graduate degree)		0.0597 [0.054, 0.065]		0.0442 [0.039, 0.049]
1(African American)		0.0397 [0.027, 0.052]		0.0010 [−0.007, 0.009]
1(Hispanic)		0.0204 [0.012, 0.029]		0.0011 [−0.005, 0.007]
1(female)		−0.0538 [−0.059, −0.048]		−0.0554 [−0.062, −0.049]
Year fixed effects	X	X	X	X
R^2	0.0150	0.3415	0.0883	0.4092
Observations (teacher-years)	7,088,769	7,088,769	7,088,769	7,088,769

Notes: The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

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Table A4. Incidence of Social Security taxes on the pupil–teacher ratio, unweighted (analog to Table 4 in the main text)

	(1)	(2)	(3)	(4)
Variables	Pupil–teacher ratio			
1(Social security coverage)	−0.285	−0.494	0.132	0.091
	[−1.202, 0.632]	[−1.217, 0.228]	[−0.389, 0.652]	[−0.397, 0.578]
Teacher characteristics		X		X
District characteristics			X	X
Year fixed effects	X	X	X	X
R^2	0.0059	0.2119	0.4627	0.4803
Observations (district-years)	27,100	27,100	27,100	27,100

Notes: District-level analysis (unweighted). The teacher and district characteristics included in the models are as shown in Table 2 in the main text. The mean value of the pupil–teacher ratio (the dependent variable) is 15.0. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using clustered standard errors by district.

Table A5. Heterogeneity: incidence of Social Security taxes on total and base salary

Subset of teachers	(1) Grandfathered in pre-2005 TRS rules	(2) Post-2005 TRS rules	(3) Grandfathered in pre-2005 TRS rules	(4) Post-2005 TRS rules
Variables	Log of total salary		Log of base salary	
1(Social Security coverage)	−0.083	−0.101	−0.090	−0.105
	[−0.138, −0.028]	[−0.165, −0.036]	[−0.146, −0.033]	[−0.164, −0.046]
Teacher characteristics	X	X	X	X
District characteristics	X	X	X	X
Year fixed effects	X	X	X	X
R^2	0.5884	0.3423	0.5812	0.3441
Observations (teacher-years)	1,336,658	5,752,111	1,336,658	5,752,111

Notes: TRS teachers are grandfathered into the pre-2005 pension rules if they meet one of three conditions in 2005: (1) the sum of age and experience add up to 70 or greater, (2) experience greater than or equal to 25, or (3) age greater than or equal to 50. The teacher and district characteristics included in the models are as shown in Table 2. The 95% confidence intervals reported in brackets below the coefficient estimates are calculated using two-way clustered standard errors by district and TRS entry year.

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