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Estimating Compensating Wage Differentials for Public School Teachers in High-Poverty and High-Minority Schools: Evidence from U.S. National Data, 1988–2018

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Using a hedonic wage framework, this paper estimates compensating wage differentials (CWDs) for teachers in high-poverty and/or high-minority schools, drawing on thirty years of nationally representative data from the School and Staffing Surveys (SASS), National Teacher and Principal Survey (NTPS), and Common Core of Data (CCD), 1988–2018. We also examine CWDs for teachers with STEM BA degrees and for rural teachers. Results indicate that salaries reflect positive CWDs in high-minority schools but consistent wage penalties in high-poverty schools. STEM BA teachers, despite generally earning a premium, face an additional 0.11% wage penalty for each 1-percentage-point increase in school poverty and an even larger penalty in rural areas. Rural teachers experience an added 0.07% penalty under the same conditions. These findings highlight enduring disparities in teacher compensation by school demographics, subject specialization, and geography, with implications for addressing teacher shortages in disadvantaged settings.

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Estimating Compensating Wage Differentials for Public School Teachers in High-Poverty and High-Minority Schools: Evidence from U.S. National Data, 1988–2018

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Data Availability

Restricted-use data used in this study can be obtained via an official application to the Institute of Education Sciences and the National Center for Education Statistics. For information regarding the computer programs and statistical codes used for this study, please contact the first author at nwg12@txstate.edu.

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Conflict of Interest

The authors declare that they have no conflict of interest to declare that is relevant to the content of this article.

Abstract

Despite longstanding concerns about staffing challenges in disadvantaged schools, little is known about how teacher compensation varies with school context across time and geography. Using a hedonic wage framework and thirty years of nationally representative data from the School and Staffing Surveys (SASS), National Teacher and Principal Survey (NTPS), and Common Core of Data (CCD), this paper estimates how teacher pay varies across school settings over three decades.

We find that teachers in schools with higher minority enrollments earn modest wage premiums, while those in high-poverty schools face persistent pay penalties—even after controlling for teacher and school characteristics. STEM-BA teachers, who generally receive higher salaries, experience an additional 0.11% wage penalty for each one-percentage-point increase in school poverty, with larger penalties in rural areas. Rural teachers overall face a 0.07% added penalty under similar conditions.

These findings reveal enduring disparities in teacher compensation by school demographics, subject area, and geography. The results underscore the structural challenges of recruiting and retaining teachers in high-need and rural schools, particularly those with STEM expertise.

Keywords: Compensating wage differentials, teacher salaries, hedonic wage model, high-poverty schools, high-minority schools

JEL Codes: C31, C51, I20, J31, J45

Teacher pay has consistently lagged behind that of other college-educated professionals, and the gap has widened over time. In 1996, teachers earned 15.7% less in average weekly wages than their college-educated peers; by 2021, the gap had nearly doubled to 32.9% (Allegretto 2022). Adjusted for inflation, teacher wages have remained largely stagnant since the mid-1990s, showing little growth from 1996 to 2002, throughout the 2000s, and again after 2010 (Allegretto 2022). Moreover, teacher salary structures typically fail to compensate for challenging working conditions. Teachers in high-poverty schools earn substantially less than their counterparts in low-poverty schools, about $5,600 less in base salary in 2015-2016, or roughly 9.5% of the average salary in low-poverty schools (Garcia and Weiss 2019). On average, the gap amounts to nearly 10% lower pay for teachers in high-poverty schools (Garcia and Weiss 2019).

Persistent shortages of teachers in high-poverty and high-minority schools undermine the quality of elementary and secondary education (Quartz et al. 2005; Peske et al. 2006). Many teachers migrate from these schools to those serving wealthier, Whiter student populations (Quartz et al. 2005; Simon et al. 2015). Prior research has examined factors influencing teachers' school and district choices (Chambers 1981; Levinson 1988; Boyd et al. 2003; Goldhaber, Destler, and Player 2010; Martin 2010). Teachers weigh both pecuniary and nonpecuniary rewards when choosing between occupations, within teaching subjects, and when selecting a specific school. Personal characteristics, such as age, gender, socioeconomic status, ethnicity, and experience, can shape these preferences for work environments and conditions (Chambers 1981; Simon et al. 2015). Evidence shows that teachers tend to prefer schools with lower proportions of minority or economically disadvantaged students (Greenberg and McCall 1974; Quartz et al. 2005; Prost 2013; Simon et al. 2015).

The theory of compensating wage differentials (CWDs) explains that workers require higher wages to accept jobs with less desirable characteristics, such as poor working conditions or a higher proportion of nonwhite students (Smith 1979; Levinson 1988; Villanueva 2007). Under hedonic pricing theory, workers in public-sector labor markets make trade-offs between wages and job disamenities (Rosen 1974, 1986; Smith 1979; Villanueva 2007). Prior studies generally find that schools with higher concentrations of minority students pay higher salaries (Levinson 1988; Boyd et al. 2003; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010; Martin 2010), though findings on CWDs for high-poverty schools are mixed (Boyd et al. 2003; Brunner and Imazeki 2010; Martin 2010; Winters 2011).

This paper examines whether teachers are compensated for working in high-poverty and/or high-minority schools over a thirty-year period, 1988–2018, focusing on three research questions:

1. Do teacher salaries reflect compensating wage differentials (CWDs) for working in high-poverty and/or high-minority schools, and how have these differentials evolved over time?
2. To what extent are teachers with STEM BA degrees compensated for working in high-poverty and/or high-minority schools, and how have these compensation patterns changed over time?
3. Do teachers in rural high-poverty and/or high-minority schools face a wage penalty compared to their peers in non-rural low-poverty and/or low-minority schools? Do STEM BA teachers face the same penalty? How does this trend vary over time?

We utilize nationally representative, cross-sectional teacher-level data from seven waves of the School and Staffing Survey (SASS; 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012) and two waves of the National Teacher and Principal Survey (NTPS; 2015-2016 and 2017-2018). These data are linked to school and student-level characteristics from the Common Core of Data (CCD), providing a comprehensive national view of CWDs in the teacher labor market. Unlike prior studies, which often rely on a few survey years or state-specific datasets (Alaska Department of Education and Early Development (DEED) data in Berman and DeFeo (2024); Wisconsin Longitudinal Survey (WLS) in Daw and Hardie (2012)), our analysis covers three decades of national dataset using a hedonic wage regression framework.

In addition to estimating overall CWDs, we analyze differences for STEM BA teachers and between rural and non-rural schools. The STEM teacher pipeline remains constrained in schools with high proportions of Black, Latino, and low-income students (Wolf 2015; McKinney et al. 2017). Recruiting teachers is particularly challenging in rural schools than urban schools (Rhinesmith et al. 2023), and half of U.S. states face equity gaps between rural and urban areas (Gagnon and Mattingly 2015). Our study bridges these strands of research, offering a long-term, nationally representative analysis of CWDs in the teaching profession, with a particular focus on STEM BA degree holders and rural schools.

Previous Literature

Compensating Wage Differentials

The theory of compensating wage differentials (CWDs), first introduced by Adam Smith in *The Wealth of Nations*, explains that individuals demand higher pay to offset the disutility of undesirable working conditions (Smith 1979). Rosen's (1986) hedonic pricing model formalizes this framework, explaining how adverse job attributes, such as difficult working environments, should result in higher wage differentials, as workers are less willing to accept such positions without adequate compensation. Personal characteristics, such as age, gender, socioeconomic background, ethnicity, and professional experience, also influence individuals' preferences for particular job environments (Chambers 1981).

Gustman and Clement (1977) find that inter-area salary differences across 83 U.S. cities and 48 states from 1968 to 1970 are strongly influenced by the opportunity costs of teachers. These costs stem from high real wages in alternative occupations, high local costs of living, and poor nonpecuniary job attributes (Gustman and Clement 1977). Controlling for other factors, they show that areas with higher opportunity costs offer higher salaries, consistent with the presence of CWDs that compensate for less desirable work environments (Gustman and Clement 1977).

CWDs have been documented not only in education but also across other public-sector labor markets (Schumacher and Hirsch 1997; Lanfranchi, Ohlsson, and Skalli 2002; Bender et al. 2006; Hall and Greenman 2015). For example, registered nurses in hospitals earn roughly 20% more due to hospital-related disamenities (Schumacher and Hirsch 1997), while janitors receive a 13.4% wage premium for higher injury risks (Bender et al. 2006). In contrast, undocumented workers receive little or no wage compensation for hazardous job conditions (Hall and Greenman 2015).

Empirical Studies in Education

Hedonic wage regression models have been widely employed to estimate CWDs in the teacher labor market (Levinson 1988; Harris 2006; Berger et al. 2008; Player 2009; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010; Martin 2010; Winters 2011; Boyd et al. 2003, 2013; Feng 2020). Several studies find positive CWDs for teaching in schools with higher proportions of nonwhite students (Levinson 1988; Boyd et al. 2003; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010; Martin 2010; Winters 2011). For instance, Levinson (1988) finds that a higher share of nonwhite students is associated with higher salaries for both white and nonwhite teachers, confirming earlier findings by Antos and Rosen (1975) on racial CWDs. Martin (2010) reports similar results of positive CWDs for working in school districts with higher shares of Black and Latino students. In Washington State, most teachers support extra pay for working in low-performing, high-need schools but oppose merit pay, particularly for experienced teachers (Goldhaber, DeArmond, and DeBurgomaster 2011).

Evidence on CWDs for teaching in high-poverty schools is mixed. Some studies find no wage differentials (Levinson 1988; Harris 2006; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010), while others report negative CWDs (Boyd et al. 2003; Martin 2010; Winters 2011) or positive CWDs (Brunner and Imazeki 2010). Financial incentive programs have been shown to improve recruitment and retention in high-poverty schools. For example, North Carolina's $1,800 annual bonus for certified math, science, and special education teachers reduced turnover (Clotfelter et al. 2008), and Washington State's financial bonus for National Board Certified Teachers in high-poverty schools increased teacher retention by 4 to 8 percentage points (Cowan and Goldhaber 2018). Tennessee's $5,000 bonus program for priority schools also boosted retention (Springer, Rodriguez, and Swain 2016). However, results are not universally positive: in France, bonuses failed to retain teachers in schools with more minority, low-income, and low-performing students (Prost 2013). These mixed findings may reflect short study periods, policy design differences, or unobserved teacher, school, and district characteristics. Building on this literature, our study uses cross-sectional survey data from 1988 to 2018 to estimate CWDs for teaching in high-poverty schools and/or high-minority schools.

STEM Teachers in High-Poverty and High-Minority Schools

STEM education in high-poverty and/or high-minority schools remains a persistent national concern (Wolf 2015; McKinney et al. 2017). High-poverty schools and rural districts face particular challenges in recruiting and retaining qualified STEM teachers (Harmon 2001; Wolf 2015). Early exposure to high-quality STEM instruction is crucial for developing students' long-term competence (McKinney et al. 2017). Yet in California, African American, Latino, and low-income students have less access to STEM learning opportunities and experience worse academic outcomes in STEM subjects (Wolf 2015). In Texas, beginning STEM teachers in high-poverty schools exhibit high attrition rates, negatively affecting student achievement (Fuller and Pendola 2019). The majority of these teachers enter through alternative certification programs, which often provide limited field experience and little or no clinical training (Fuller and Pendola 2019). Moreover, wage disparities between high-poverty schools and low-poverty schools persist. In 2012, STEM teachers in high-poverty schools earned about $6,100 less than those in low-poverty schools; by 2021, the gap had narrowed but remained at approximately $4,000 (Nguyen 2025).

Rural Wage Penalties

Previous studies find that teachers prefer suburban and urban schools over rural ones (Boyd et al. 2013; Gagnon and Mattingly 2015; Rhinesmith et al. 2023). Rural teachers often face wage penalties and significant rural-urban pay disparities (Collins 1999). Weaker union representation in rural areas may further contribute to wage penalties (Babcock and Engberg 1999). Beyond lower pay, teachers experience geographic and social isolation, harsh weather, long distances from large communities and family, and inadequate shopping as major deterrents to working in rural areas (Murphy and Angelski 1997).

To address recruitment and retention challenges in rural schools serving large proportions of low-income students and/or students of color, states and countries have employed strategies including "grow-your-own" programs, financial incentives, professional learning communities, and capacity-building initiatives (Lowe 2006; Burke and Buchanan 2022; Feng et al., n.d.). In U.S. rural districts, a loan forgiveness plan for new teachers and subsidized housing have been successful strategies along with bonuses and salary increases (Lowe 2006). In New South Wales, Australia, incentives such as salary supplements, monetary benefits to living allowances, and heavily subsidized rental arrangements have attracted teachers to rural and remote schools (Burke and Buchanan 2022). However, financial incentives are not always effective. Bonuses in some disadvantaged French schools failed to retain teachers (Prost 2013).

Urban districts facing staffing shortages have also used economic incentives to attract and retain high-quality teachers (Collins 1999; Figlio 2002; Feng et al., n.d.). While teachers prefer suburban schools to urban schools (Boyd et al. 2013), urban districts are more likely to employ financial incentives to recruit and attract teachers with advanced credentials, such as doctorates and National Board for Professional Teaching Standards (NBPTS) certification (Strunk and Zeehandelaar 2011).

This study extends the literature by examining whether CWDs exist for teaching in schools with higher shares of low-income students and/or minority students across rural, urban, suburban, and town contexts. Prior research has rarely conducted long-term rural and nonrural comparisons. By doing so, this paper addresses a key gap in understanding whether wage premiums offset the challenges of working in high-poverty and/or high-minority schools in rural areas.

Union Wage Premiums

A substantial body of research finds that unions contribute to CWDs and wage premiums in the public sector (Baugh and Stone 1982; Lipsky 1982; Barbezat 1989; Babcock and Engberg 1999; Hedrick et al. 2011; Winters 2011; Brunner and Squires 2013; Han and Keefe 2023). Using a spatial econometric framework, Winters (2011) estimates that union activity raises salaries for experienced teachers by 18 to 28%. Baugh and Stone (1982), through cross-section wage-level and cross-section wage-change regressions, find that by the late 1970s, unionized teachers earned 12 to 22% higher wages, and their real wages increased while those of non-unionized teachers declined from 1974 to 1978.

The impact of unions on teacher pay can differ across districts and among demographic groups. In states that mandate collective bargaining, beginning salaries and wage premiums for experienced teachers rise with district size, suggesting that larger, more powerful unions negotiate greater premiums (Brunner and Squires 2013). Moreover, disadvantaged demographic groups, such as Black and women workers, receive a higher union wage premium in the public sector (Kerrissey and Meyers 2021). Adjusting for cost-of-living differences, unobserved state-level effects, and potential endogeneity between unionization and wages, Hedrick et al. (2011)

still find a positive union wage premium, although the magnitude is smaller than in earlier studies.

Teacher unions may also influence CWDs in high-poverty and/or high-minority schools. To account for this possibility, our robustness checks incorporate union membership and collective bargaining variables into additional hedonic wage regressions. Details on variable construction appear in the Data Sources section, and regression results are reported in the Robustness Checks section.

Data and Methodology

Data Sources

We utilize nationally representative teacher-level cross-sectional data from the School and Staffing Surveys (SASS), covering seven waves: 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012. The SASS collects detailed information on public and private schools, principals, school districts, and teachers, providing comprehensive descriptive data on U.S. elementary and secondary education. Our analysis focuses on the public teacher survey, administered by the National Center for Education Statistics (NCES), which contains detailed information on teacher compensation, demographics, general school conditions, and student composition. In 2012, the NCES redesigned SASS and named it the National Teacher and Principal Survey (NTPS) with an increased emphasis on teacher labor markets. We merge the SASS waves with the 2015-2016 and 2017-2018 NTPS waves.

For each teacher, we observe variables such as age, gender, race (White, Black, Asian, Latino/Hispanic, American Indian, and two or more races), years of experience, union membership, collective bargaining, degree attainment (BA, MA, and STEM BA), certification status (fully certified; uncertified or holding a temporary license), and main teaching subject (non-STEM, science, mathematics, computer science, and special education). The dependent variable is the natural logarithm of the inflation-adjusted base salary, with 2017-2018 as the base year. Teacher salary excludes summer school pay, merit pay, income from non-teaching jobs, non-school income, and other external compensation.

The collective bargaining variable captures whether the school district has an agreement with a teachers' association or union for the purpose of collective bargaining. Union strength and activity are proxied by the legal status of collective bargaining (Winters 2011). Collective bargaining data are available for only five waves (1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012). Union membership is unavailable for the 1988-1989 and 1990-1991 waves; charter and magnet school indicators are missing for the 1988-1989, 1990-1991, and 1993-1994 waves; and minority student population data are missing in 2017-2018 wave.

We augment these teacher-level data with school-level characteristics from the Common Core of Data (CCD), including enrollment, average class size, school type (elementary, secondary, combined, charter, and magnet), and locale (urban, suburban/town, and rural). We measure school poverty by the percentage of students eligible for free lunch, not reduced-price lunch, which is consistently available across waves. Schools with greater than or equal to 50% free-lunch eligibility are classified as high-poverty schools in our analysis. Benchmarks of 50%, 70%, or 75% are common in the literature, given the absence of a standard NCES definition (Borg et al. 2012; Sass et al. 2012; Garcia and Weiss 2019). Minority students include African American, Hispanic, Native American, Asian, Native Hawaiian/Pacific Islanders, and multiracial students. Schools with greater than or equal to 50% nonwhite enrollment are classified as high-minority schools in our analysis.

Descriptive Profiles of Public School and STEM BA Teachers

Table 1 summarizes teacher and school characteristics for all public school teachers and those with a STEM BA degree. The average teacher earns $52,709, is 42 years old, and 65% female. Most are White (85.7%), hold a BA degree (98%), and nearly half (47.7%) hold a MA degree. Average experience is 14.3 years, and 92.7% are fully certified. By primary teaching field, non-STEM fields account for 84.5% of teaching assignments, with mathematics (8.4%), science (6.4%), computer science (0.7%), and special education (8.7%) making up the rest.

Regarding student populations, schools average 33.4% free lunch eligibility and 29.6% minority enrollment. About 23.2% of teachers work in high-poverty schools (≥ 50% free lunch eligibility), and 23.3% work in schools with high minority (≥ 50%) enrollment. By school type, 47.5% teach in secondary schools, 42.5% in elementary, and 10% in combined schools. More teachers work in charter schools (4.6%) than magnet schools (2.8%). Average school enrollment is 775 students, with an average class size of 24. In terms of locale, 49.1% of teachers work in rural areas, and 50.9% in non-rural areas (27.7% suburban/town and 23.2% urban).

Teachers with a STEM BA degree comprise 9.6% of the sample. Their base salary is, on average, $1,921 higher than the overall teacher average, and they are 11.5 percentage points less likely to be female. Their main teaching fields are science (40.7%), mathematics (36.6%), and computer science (1.5%), though 21.2% teach non-STEM subjects and 1.6% teach special education. They hold MA degrees at a higher rate (55.1%) than all teachers (47.7%). These teachers work in schools with slightly lower free lunch eligibility (29.7%) than the overall average (33.4%), and similar minority composition (29%). They are more likely to work in secondary schools (75.7%) than in elementary (14.1%) or combined schools (10.2%) and teach in schools with larger enrollments (1,005) compared to the full sample (775).

Trends in Teacher Base Salaries by School Poverty and Minority Composition

From 1988 to 2018, average teacher base salaries grew gradually, lagging behind the sharper increases in the shares of students eligible for free lunch and minority student enrollment. Teacher salaries increased typically by 1 to 3% between survey waves, with a notable decline in 2007-2008. The average base salary rose from approximately $49,900 in 1988-1989 to about $54,970 in 2017-2018, representing a total increase of roughly 10%. In contrast, demographic changes in schools were far more pronounced. The share of students eligible for free lunch nearly doubled, from 22.5% in 1988-1989 to 45.2% in 2017-2018. Similarly, minority student enrollment rose from 24.5% in 1988-1989 to 43.3% in 2015-2016. These increases in poverty and minority representation far outpaced the growth in teacher salaries.

We illustrate descriptive trends in base salaries by school poverty and minority status, respectively, with results reported separately for non-rural and rural schools and for the full teacher sample versus teachers with STEM BA degrees in Figures 2 and 3. Following Gilpin (2011), who finds that wage differentials matter primarily for teachers with fewer than six years of experience, we restrict these analyses to teachers with less than six years of total teaching experience. In Figure 2, for non-rural schools, teachers in high-poverty schools consistently earn more than those in low-poverty schools, suggesting a CWD. However, in rural areas, the pattern reverses: teachers in high-poverty schools earn less, indicating a wage penalty. These patterns are similar for STEM BA teachers, though the salary lines for high-poverty and low-poverty schools occasionally intersect. In Figure 3, high-minority schools generally offer higher average salaries than low-minority schools, particularly in non-rural areas, indicating a wage premium for teaching in high-minority contexts. However, in rural areas, STEM BA teachers working in high-minority schools often experience wage penalties.

Rural-Nonrural Salary Comparisons: Mean Difference Tests for Full and STEM BA Samples

Table 2 presents the results of t-tests comparing mean values between rural and non-rural schools for both the full teacher sample and the STEM BA teacher sample. The coefficients represent the mean difference, calculated as the non-rural mean minus the rural mean. For the full sample in the first two columns, teacher salaries in urban, suburban, or town areas exceed those in rural areas by $9,106.8, statistically significant at the 0.01 level. In terms of teacher demographics, most differences are statistically significant, except for the percentages of teachers whose main teaching field is in non-STEM or STEM categories. Non-rural areas have higher proportions of Black (0.0505), Latino/Hispanic (0.0383), Asian (0.0207), and multiracial teachers (0.00321), and lower proportions of White teachers (-0.100), compared to rural areas. Teachers in non-rural areas tend to have less total experience (-0.260) and a lower percentage of full certification (-0.0173). Differences in the proportions of teachers in STEM fields such as mathematics, science, and computer science, or in non-STEM fields, are not statistically significant. However, the proportion of teachers whose main teaching field is special education (0.0108) is higher in non-rural areas. Additionally, more teachers in non-rural areas hold BA (0.00183) and MA degrees (0.105), are union members (0.0597), and work in districts with collective bargaining (0.0841). In terms of school characteristics, non-rural schools have higher proportions of charter (0.0568) and magnet schools (0.0390), more elementary schools (0.0724), and fewer combined schools (-0.0708). They also tend to have larger enrollment (385.1) and average class sizes (3.288). Regarding student characteristics, non-rural schools have a 1.6 percentage point higher share of students eligible for free lunch, and an 18.9 percentage point higher minority student composition, statistically significant at the 0.01 level, compared to rural schools.

Empirical Strategy

We estimate a hedonic wage regression to test whether CWDs exist for teachers working in high-poverty and/or high-minority schools. We also examine whether these CWDs differ for all teachers, for teachers with STEM BA degrees, and across different locales. The baseline model is as follows:

$$\ln(W_{ijst}) = \beta_0 + \beta_1\, POV_{jst} + \beta_2\, MIN_{jst} + \beta_3\, (POV_{jst}*MIN_{jst}) + \beta_4\, X_{ijst} + \beta_5\, H_{jst} + \delta_s + \lambda_t + \varepsilon_{ijst}$$

The dependent variable, $\ln(W_{ijst})$, is the natural log of the adjusted annual base salary of teacher i working in school j, located in state s, and in year t. Our key predictors are the percentage of students eligible for free lunch (POV_{jst}), which measures poverty, and the percentage of minority students (MIN_{jst}). Their interaction term ($POV_{jst}*MIN_{jst}$) captures how the effect of one varies with the other. Control variables include teacher covariates (X_{ijst}) and school characteristics (H_{jst}). Specifically, teacher covariates are age, female, race (White, Black, Asian, and Hispanic), years of experience, union membership, education level (BA and MA), certification status, main teaching field (non-STEM, science, mathematics, computer science, and special education), and collective bargaining status. School characteristics include enrollment, school type (elementary, secondary, combined, charter, and magnet), and average class size. Additionally, we add state fixed effects (δ_s) and year fixed effects (λ_t). The state fixed effects control for unobserved state-level heterogeneity, such as legislative support or unobserved amenities, that might affect teacher salaries (Hedrick et al. 2011). The year fixed effects capture any unobserved variation or special events that may affect teacher salaries.

In additional specifications, we extend the model to address research questions 2 and 3, by including either a STEM BA degree indicator (STM_{jst}) or a rural school indicator (RUR_{jst}), interacting them with the percentage of students eligible for free lunch (POV_{jst}) and the percentage of minority students (MIN_{jst}). The simplified interaction forms are as follows:

$$\ln(W_{ijst}) = \beta_0 + \beta_1 \, POV_{jst}*MIN_{jst}*STEM_{ijst} + \beta_2 \, X_{ijst} + \beta_3 \, H_{jst} + \varepsilon_{ijst}$$

$$\ln(W_{ijst}) = \beta_0 + \beta_1 \, POV_{jst}*MIN_{jst}*RUR_{jst} + \beta_2 \, X_{ijst} + \beta_3 \, H_{jst} + \varepsilon_{ijst}$$

These specifications allow us to test whether STEM BA teachers or rural teachers receive different compensation in high-poverty and/or high-minority schools. We separately examine the effects of holding a STEM degree and working in a rural school. The triple interaction term ($POV_{jst}*MIN_{jst}*STEM_{ijst}$) captures whether the combined effect of poverty and minority composition on teacher salaries differs for teachers with a STEM BA. Similarly, the triple interaction term ($POV_{jst}*MIN_{jst}*RUR_{jst}$) captures whether the combined effect of poverty and minority composition on teacher salaries differs for teachers working in rural areas.

To estimate how wages vary with job amenities, we follow Lavetti (2023), who interacts worker characteristics with an observed job amenity, in his case, injury risk. In our setting, the worker characteristic is possession of a STEM BA degree, and the job amenity (or disamenity) is the school's poverty rate and minority share. We assume that teachers with STEM degrees may differ in productivity and that these productivity differences interact with the level of amenities. In particular, the productivity of STEM BA teachers may vary when teaching in schools with higher concentrations of poverty and/or minority students. Thus, the coefficient β_1 captures how the wage effects of poverty and minority composition scale with the teacher's STEM degree status.

Results

Teacher Salary on School Poverty Rates and Minority Shares

Columns 1 and 2 of Table 3 present regressions of the variables of interest on log teacher salary, controlling for teacher characteristics. In column 3, we add state fixed effects and year fixed effects, but do not include school characteristics due to missing data in some waves. This exclusion increases both the number of observations and the R-squared value. Column 4 reports hedonic wage regression results with teacher characteristics, school characteristics, state fixed effects, and year fixed effects.

Using a hedonic wage framework, we test whether teachers earn CWDs in high-poverty and/or high-minority schools. In Table 3, column 1, we regress only the percentage of free lunch eligible students on log teacher salary. The coefficient on student poverty is -0.0658 (0.00338), negative and statistically significant at the 0.01 level, indicating that school poverty is associated with lower teacher pay. This negative CWD is consistent with prior research (Boyd et al. 2003; Martin 2010; Winters 2011; Garcia and Weiss 2019).

In column 2, we regress only the percentage of minority students on log teacher salary. The coefficient on minority share is 0.130 (0.00255), positive and statistically significant at the 0.01 level, suggesting that schools with higher minority enrollment offer higher teacher salaries. This positive CWD aligns with earlier findings (Levinson 1988; Boyd et al. 2003; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010; Martin 2010; Winters 2011).

Because schools with high poverty rates often also have high minority enrollment, we include an interaction term to capture their combined effect. The interaction coefficient tells us how the effect of poverty changes when the minority share is higher, and vice versa. In column 4, each additional percentage point increase in both student poverty and minority is associated with a 0.0442% (= -0.165 + 0.0692 + 0.140) increase in teacher salary, statistically significant at the 0.01 level.

Holding the minority share at zero, higher poverty is associated with lower salaries (-0.165 in column 4, statistically significant at the 0.01 level), equivalent to about $87 less for each 1-percentage-point increase in poverty. Conversely, holding poverty proportion at zero, a higher minority share is associated with higher salaries (0.0692 in column 4, statistically significant at the 0.01 level), or roughly $35 more for each 1-percentage-point increase in minority share.

Teacher Salary on School Poverty Rates, Minority Shares, and STEM BA

We further investigate whether STEM BA teachers receive additional compensation for working in high-poverty and/or high minority schools. Across models, the coefficients for holding a STEM BA degree are positive and statistically significant at the 0.01 level (0.0300, 0.0278, and 0.0277 in columns 1, 2, and 3 of Table 4), indicating a STEM BA wage premium.

In contrast, the share of students eligible for free lunch is negatively associated with teacher salaries, with coefficients of -0.0626, -0.179, and -0.158 in columns 1, 3, and 4, all statistically significant at the 0.01 level, indicating a wage penalty in high-poverty schools. STEM BA teachers in schools with larger shares of low-income students experience an additional penalty of -0.0369 (column 1) and -0.111 (column 3), both statistically significant at the 0.01 level, the latter equivalent to roughly $59 less per 1-percentage-point increase in poverty, holding minority share at zero. This aligns with Nguyen (2025), who finds that STEM teachers in high-poverty schools earn less than their peers in low-poverty schools from 2012 to 2021.

The coefficients for the percentage of minority students are positive and statistically significant at the 0.01 level (0.132, 0.147, and 0.0768 in columns 2, 3, and 4), suggesting higher salaries in high-minority schools. Figure 7 illustrates these results. Overall, a one percentage point increase in both student poverty and minority shares is associated with a 0.0428% increase in STEM BA teacher salaries (i.e., -0.158 + 0.0768 + 0.124 in column 4).

Teacher Salary on School Poverty Rates, Minority Shares, and Rural School Status

We next examine whether CWDs exist in high-poverty and/or high-minority schools in rural and non-rural areas. The coefficients for rural schools are negative and statistically significant at the 0.01 level (-0.120, -0.127, -0.0924, and -0.0778 in columns 1-4 of Table 5), indicating a rural wage penalty.

The coefficients for the free-lunch share remain negative and statistically significant at the 0.01 level (-0.0334, -0.140, and -0.173 in columns 1, 3, and 4). Teachers in rural schools with a high proportion of low-income students face an additional wage penalty of -0.0728 (column 4), also statistically significant at the 0.01 level, corresponding to about $38 less per 1-percentage-point increase in poverty, holding minority share constant.

The coefficients for minority share remain positive and statistically significant at the 0.01 level (0.0748 and 0.0438 in columns 2 and 3). Figure 8 visualizes these findings. A one percentage point increase in both student poverty and minority shares corresponds to a 0.0978% decrease in teacher salaries in rural areas (i.e., -0.173-0.0778+0.151+0.198-0.196 in column 4).

To summarize the hedonic wage regression results, teacher salaries reflect CWDs in high-minority schools, yet a wage penalty prevails in high-poverty schools. STEM BA teachers earn a wage premium overall but still face a wage penalty in high-poverty schools. Rural teachers experience a wage penalty, which is amplified in high-poverty schools.

Predicted Teacher Salary Trends by School Poverty and Minority Composition

Predicted teacher salary trends (Figures 4 and 5) further illustrate these dynamics from 1988 to 2018. For STEM BA teachers, salaries in high-poverty schools are consistently lower than in low-poverty schools, with the wage penalty larger and more persistent in rural areas (Figure 4). Over time, STEM BA teachers' salaries have remained slightly higher than the overall teacher average, confirming the wage premium.

Regarding school minority status, STEM BA teachers are better compensated in high-minority schools, with the CWDs more evident in non-rural areas, where the high-minority salary line stays above the low-minority line across all survey waves (Figure 5). Finally, teacher salaries in rural schools remain consistently lower than in non-rural schools throughout the study period, underscoring the rural wage penalty.

Robustness Checks

Accounting for Union Membership and Collective Bargaining

We assess the robustness of our model and results by incorporating union membership and collective bargaining variables. Prior studies have shown that being a union member or working in a district with collective bargaining is associated with higher salaries (Baugh and Stone 1982; Winters 2011; Brunner and Squires 2013). Parallel to the previous findings, column

4 shows that union membership increases teacher salaries by 0.0354%, statistically significant at the 0.01 level, while the availability of collective bargaining increases teacher salaries by 0.00859%, statistically significant at the 0.05 level. This specification controls for teacher characteristics, including union membership and collective bargaining, school characteristics, and employs both state fixed effects and year fixed effects.

Consistent with our earlier findings, the percentage of students eligible for free lunch is negatively associated with teacher salary, with coefficients of -0.0640 (0.00437) and -0.124 (0.0129) in columns 1 and 3, both statistically significant at the 0.01 level. In contrast, the percentage of minority students is positively associated with teacher salary, with coefficients of 0.0161 (0.00325) and 0.0876 (0.0110), also statistically significant at the 0.01 level. An additional percentage point in student poverty or minority composition is associated with a 0.0408% increase in salary. The number of observations in this analysis (50,000) is smaller because the collective bargaining variable is available only for the 1988–1989, 1990–1991, 2011–2012, 2015–2016, and 2017–2018 waves.

Adjusting for Regional Cost of Living

Our second robustness check adjusts for cost-of-living differences using the Comparable Wage Index for Teachers (CWIFT) developed by the National Center for Education Statistics (NCES). The CWIFT accounts for regional variations in living costs and the competitiveness of local labor markets for college graduates in other professions, allowing for fairer salary comparisons across regions. Since urban, suburban, and town areas often have higher living expenses than rural areas, cost-of-living adjustments may influence observed salary differences.

CWIFT data are available only from 2015 to 2022, so we apply it to the 2015–2016 and 2017–2018 waves.

After adjusting for cost of living, the percentage of students in poverty remains negatively associated with teacher salaries, with coefficients of -0.0452 and -0.0395, both statistically significant at the 0.01 level. Rural area coefficients are also negative (-0.0510, -0.0449, and -0.0561) and statistically significant at the 0.01 level. STEM BA status coefficients remain positive but are not statistically significant. These results reinforce our earlier conclusion that higher poverty rates are linked to lower salaries, and teachers in rural areas face a persistent wage penalty. For STEM BA teachers in rural areas, a one percentage point increase in school poverty is associated with a 0.0082% salary increase.

Figure 6 displays predicted teacher salaries from 2015 to 2018 after the cost-of-living adjustment. In all cases, whether the sample is full or STEM BA, rural or non-rural, we find that high-poverty schools have lower predicted salaries than low-poverty schools. The wage gap is most pronounced for rural STEM BA teachers.

Conclusion

Prior research consistently finds positive compensating wage differentials (CWDs) for teachers in high-minority schools (Levinson 1988; Boyd et al. 2003; Brunner and Imazeki 2010; Goldhaber, Destler, and Player 2010; Martin 2010; Winters 2011), but the evidence on high-poverty schools remains mixed. While these studies offered valuable insights, few have examined how these differentials have persisted and evolved over a thirty-year period, nor have they systematically analyzed subgroups such as STEM BA teachers or rural teachers. By drawing on nationally representative teacher data spanning three decades, this study contributes new evidence on the long-term stability of CWDs and how they intersect with subject specialization and geography.

Our findings confirm that teachers in high-minority schools consistently receive wage premiums, while those in high-poverty schools bear persistent wage penalties. These patterns have remained remarkably stable from 1988 to 2018. Importantly, our study highlights additional disparities for STEM BA and rural teachers. STEM BA teachers generally earn a wage premium for their degrees, but they face greater negative CWDs in high-poverty schools, with an additional 0.11% penalty for each 1-percentage-point increase in school poverty. Similarly, rural teachers face an overall wage penalty compounded by an additional 0.07% penalty per 1-percentage-point increase in poverty. Yet, both groups earn positive CWDs in high-minority schools. To our knowledge, no prior study has directly examined how high-poverty wage penalties intersect with STEM qualifications or rural contexts. These findings underscore that while demographic composition matters, poverty concentration remains the most consistent determinant of wage penalties.

Robustness checks incorporating union membership and collective bargaining confirm these patterns, as does adjustment for local cost of living. The persistence of these patterns, even after accounting for institutional and geographic variation, suggests that wage penalties in high-poverty schools are structural features of the labor market rather than temporary or localized anomalies. Nevertheless, our study faces data limitations. Union membership is missing for early waves (1988–1991), collective bargaining data are available only in five survey years, and minority student population data are absent in the 2017–2018 wave. Additionally, while we control teacher and school characteristics, we do not capture and control all dimensions of working conditions, such as school climate or leadership, which may also shape teacher compensation and retention.

Our findings have broader implications for teacher compensation policy, particularly in addressing persistent inequities in high-poverty, rural, and STEM education. Persistent wage penalties for teaching in high-poverty schools threaten to exacerbate existing inequities in staffing and student learning opportunities. Prior work has shown that high-poverty schools suffer from frequent turnover, with departing teachers often replaced by less experienced, less effective ones (Springer, Rodriguez, and Swain 2016). If compensation structures continue to disadvantage teachers in these environments, shortages in critical areas like STEM and rural education will likely deepen, further stratifying educational quality.

Policy responses must therefore address both salary structures and broader working conditions. Financial incentives remain central: targeted signing or retention bonuses, salary differentials for teaching in high-poverty schools, and higher pay steps for additional years of experience can help attract and retain effective teachers (Clotfelter et al. 2008; Fulbeck 2014; Hendricks 2015; Springer, Rodriguez, and Swain 2016; Cowan and Goldhaber 2018). Beyond bonuses, differentiated pay scales for STEM and rural teachers, loan forgiveness or tuition reimbursement for teachers committing to disadvantaged schools, and housing subsidies can reduce the financial barriers to staying in these positions. Expanding union coverage and collective bargaining rights may also play a role, as unions have historically reduced inequities in pay across race and gender (Kerrissey and Meyers 2021).

At the same time, financial compensation alone may not be sufficient. States and districts should pair wage reforms with improvements in working conditions, including stronger administrative support, reduced class sizes, mentoring and induction programs for new teachers, and professional development tailored to high-poverty contexts. “Grow-your-own” pipelines that recruit teachers from within rural or high-poverty communities may also improve retention by reducing geographic and cultural mismatches.

This study provides a unique thirty-year perspective on teacher compensation patterns across poverty, minority concentration, subject specialization, and geography. By documenting persistent wage penalties in high-poverty schools and their disproportionate impact on STEM and rural teachers, we underscore the need for policy interventions that restructure salary schedules to better reflect school context and teaching demands. Addressing these disparities is essential not only for improving teacher labor market efficiency but also for ensuring equitable access to high-quality education in the nation’s most disadvantaged schools.

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Tables and Figures

Table 1: Summary Statistics for Public School Teachers and STEM BA Teachers, 1988-2018

	Full Sample		STEM BA	
	Mean	**Sd**	**Mean**	**Sd**
Teacher Demographics				
Adjusted base salary	52708.89	16622.83	54630.32	17152.55
Age	42.282	10.663	42.034	11.020
Female	0.652	0.476	0.537	0.499
White	0.857	0.35	0.865	0.342
Black	0.060	0.237	0.057	0.232
Asian	0.019	0.136	0.026	0.158
Latino/Hispanic	0.044	0.206	0.037	0.189
American Indian	0.013	0.113	0.008	0.088

Two or more races	0.007	0.083	0.008	0.088
Total experience	14.306	9.596	14.068	9.944
Fully certified	0.927	0.26	0.915	0.278
Main teaching non-STEM	0.845	0.362	0.212	0.408
Main teaching math	0.084	0.278	0.366	0.482
Main teaching science	0.064	0.245	0.407	0.491
Main teaching computer science	0.007	0.083	0.015	0.122
Main teaching special ed.	0.087	0.282	0.016	0.125
BA	0.980	0.140	1.000	0.000
MA	0.477	0.499	0.551	0.497
Union member	0.710	0.454	0.715	0.451
Collective bargaining	0.386	0.487	0.357	0.479
School Characteristics				
Charter	0.046	0.209	0.054	0.225
Magnet	0.028	0.166	0.037	0.189
Elementary	0.425	0.494	0.141	0.348
Secondary	0.475	0.499	0.757	0.429
Combined	0.100	0.300	0.102	0.303
Enrollment	775.226	619.605	1004.68	742.857
Average class size	23.729	13.735	23.250	11.541
Urban	0.232	0.422	0.234	0.423
Suburban/Town	0.277	0.447	0.295	0.456
Rural	0.491	0.500	0.471	0.499
Student Characteristics				
Free lunch eligibility %	0.334	0.25	0.297	0.231
Minority composition %	0.296	0.305	0.290	0.300
High-poverty 50% benchmark	0.232	0.422	0.180	0.384
High-poverty 75% benchmark	0.08	0.272	0.058	0.234
High-minority 50% benchmark	0.233	0.423	0.221	0.415
High-minority 75% benchmark	0.131	0.338	0.126	0.332
White students	495.889	461.032	643.74	546.548
Black students	113.296	231.457	147.131	284.519
Latino/Hispanic students	93.532	250.856	121.524	313.061
Asian students	30.044	107.113	39.639	118.414
Am. Indian/Alaskan students	12.371	48.434	12.237	43.937

Note: The STEM BA sample consists of teachers holding a bachelor's degree in a STEM field. The full sample includes 287,230 observations, of which 27,570 are in the STEM BA sample. Collective bargaining data are available for only five waves (1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012) of the nine survey waves. Union membership is unavailable for the 1988-1989 and 1990-1991 waves; charter and magnet school indicators are missing for the 1988-1989, 1990-1991, and 1993-1994 waves; and minority student population data are missing in 2017-2018 wave.
Source: U.S. Department of Education, National Center for Education Statistics (NCES), School and Staffing Surveys (SASS), 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and National Teacher and Principal Survey (NTPS), 2015-2016 and 2017-2018.

Table 2: T-test of Means Between Rural and Non-rural Schools for Full Sample and STEM BA Sample, 1988-2018

	Full Sample		**STEM BA**	
	Coefficient	**T-stat**	**Coefficient**	**T-stat**
Teacher Demographics				
Adjusted base salary	9106.8***	152.62	9136.5***	45.79
Age	0.252***	6.34	0.136	1.02
Female	0.0245***	13.81	0.0296***	4.92
White	-0.100***	-77.70	-0.0982***	-24.02
Black	0.0505***	57.42	0.0485***	17.42
Asian	0.0207***	41.11	0.0246***	12.96
Latino/Hispanic	0.0383***	50.02	0.0284***	12.54
American Indian	-0.0123***	-29.30	-0.00745***	-7.01
Two or more races	0.00321***	10.39	0.00397***	3.73
Total experience	-0.260***	-7.25	-0.638***	-5.32
Fully certified	-0.0173***	-17.87	-0.0214***	-6.37
Main teaching non-STEM	-0.00045	-0.33	-0.00114	-0.23
Main teaching math	0.000868	0.84	0.00673	1.16
Main teaching science	0.0000855	0.09	-0.00595	-1.00
Main teaching computer science	-0.000499	-1.61	0.000392	0.27
Main teaching special ed.	0.0108***	-10.27	0.00175	-1.16
BA	0.00183***	3.50	0	(.)
MA	0.105***	56.86	0.0931***	15.58
Union member	0.0597***	31.01	0.0398***	6.67
Collective bargaining	0.0841***	29.21	0.0565***	6.62
School Characteristics				
Charter	0.0568***	59.44	0.0657***	21.00
Magnet	0.0390***	48.89	0.0486***	17.63
Elementary	0.0724***	39.36	0.0297***	7.08
Secondary	-0.00162	-0.87	0.0445***	8.61
Combined	-0.0708***	-63.72	-0.0743***	-20.47
Enrollment	385.1***	175.21	570.2***	68.88
Average class size	3.288***	51.21	3.694***	25.90
Urban	0.456***	343.99	0.442***	101.43
Suburban/Town	0.544***	410.05	0.558***	128.10
Student Characteristics				
Free lunch eligibility %	0.0160***	15.13	0.00902**	2.92
Minority composition %	0.189***	158.14	0.188***	49.99
High-poverty 50% benchmark	0.0706***	39.64	0.0712***	13.88
High-poverty 75% benchmark	0.0500***	43.62	0.0279***	8.91
High-minority 50% benchmark	0.196***	116.00	0.193***	36.26
High-minority 75% benchmark	0.142***	104.66	0.136***	31.69
White students	153.0***	82.13	245.6***	34.95
Black students	118.7***	129.26	162.3***	45.07
Latino/Hispanic students	105.4***	104.56	133.7***	33.06

Asian students	40.54***	93.80	52.43***	34.33
Am. Indian/Alaskan students	-8.445***	-42.51	-4.519***	-7.78

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Table 3: (Main Results) Hedonic Wage Regression of Natural Log Teacher Salary on School Poverty and Minority Shares

	(1)	(2)	(3)	(4)
Free lunch eligibility %	-0.0658***		-0.188***	-0.165***
	(0.00338)		(0.00919)	(0.0142)
Minority composition %		0.130***	0.143***	0.0692***
		(0.00255)	(0.00729)	(0.0128)
Free lunch eligibility %*Minority composition %			0.0782***	0.140***
			(0.0124)	(0.0225)
Teacher controls	Yes	Yes	Yes	Yes
School controls	No	No	No	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
N	223160	236430	186180	80200
R^2	0.2276	0.2417	0.3509	0.3312

Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Table 4: (Main Results) Hedonic Wage Regression of Natural Log Teacher Salary on School Poverty and/or Minority Shares and STEM BA Teachers

	(1)	(2)	(3)	(4)
Free lunch eligibility %	-0.0626***		-0.179***	-0.158***
	(0.00348)		(0.00900)	(0.0126)

Minority composition %		0.132***	0.147***	0.0768***
		(0.00267)	(0.00760)	(0.0138)
STEM BA	0.0300***	0.0278***	0.0277***	0.0175
	(0.00416)	(0.00316)	(0.00753)	(0.0111)
STEM BA*Free lunch eligibility %	-0.0369***		-0.111**	-0.0425
	(0.0112)		(0.0374)	(0.0510)
STEM BA*Minority composition %		-0.0125	-0.0402*	-0.0458
		(0.00673)	(0.0183)	(0.0246)
Free lunch eligibility %*Minority composition %			0.0676***	0.124***
			(0.0125)	(0.0228)
STEM BA*Free lunch eligibility %*Minority composition %			0.135**	0.0950
			(0.0501)	(0.0668)
Teacher controls	Yes	Yes	Yes	Yes
School controls	No	No	No	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
N	222450	235350	185520	80100
R^2	0.2280	0.2424	0.3513	0.3311

Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Table 5: (Main Results) Hedonic Wage Regression of Natural Log Teacher Salary on School Poverty and/or Minority Shares and Rural School Status

	(1)	(2)	(3)	(4)
Free lunch eligibility %	-0.0334***		-0.140***	-0.173***
	(0.00414)		(0.0127)	(0.0192)
Minority composition %		0.0748***	0.0438***	0.0212
		(0.00334)	(0.00811)	(0.0156)
Rural	-0.120***	-0.127***	-0.0924***	-0.0778***
	(0.00236)	(0.00187)	(0.00359)	(0.00738)
Rural*Free lunch eligibility %	-0.0728***		-0.000819	0.0238

	(0.00590)		(0.0151)	(0.0241)
Rural*Minority composition %		-0.0330***	0.155***	0.151***
		(0.00467)	(0.0124)	(0.0215)
Free lunch eligibility %*Minority composition %			0.102***	0.198***
			(0.0165)	(0.0297)
Rural*Free lunch eligibility %*Minority composition %			-0.148***	-0.196***
			(0.0241)	(0.0402)
Teacher controls	Yes	Yes	Yes	Yes
School controls	No	No	No	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
N	223160	236430	186180	80200
R^2	0.2649	0.2721	0.3580	0.3318

Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Table 6: (Robustness Check) Hedonic Wage Regression of Natural Log Teacher Salary on School Poverty and Minority Shares with Union Membership and Collective Bargaining Controls

	(1)	(2)	(3)
Free lunch eligibility %	-0.0640***		-0.124***
	(0.00437)		(0.0129)
Minority composition %		0.161***	0.0876***
		(0.00325)	(0.0110)
Free lunch eligibility %*Minority composition %			0.0772***
			(0.0185)
Teacher controls	Yes	Yes	Yes
School controls	No	No	Yes
State FE	No	No	Yes
Year FE	No	No	Yes
N	100630	110360	50000
R^2	0.2915	0.3072	0.4432

Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects.

We add union membership and collective bargaining status in teacher controls. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

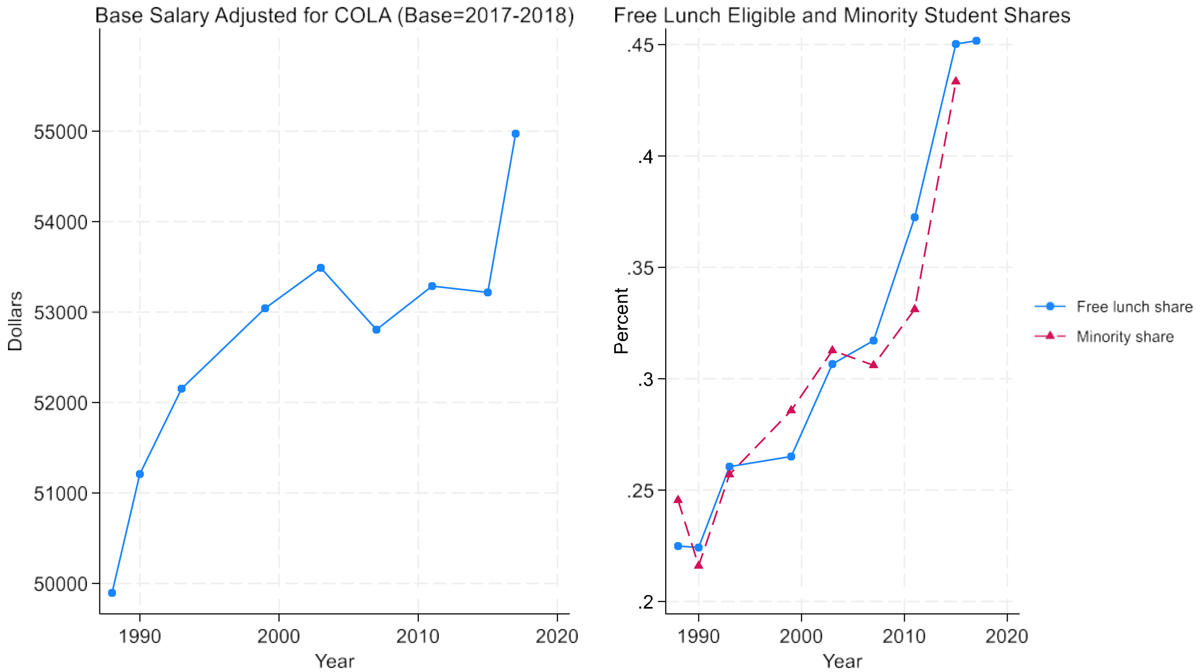
Table 7: (Robustness Check) Hedonic Wage Regression of Natural Log Teacher Salary Incorporating CWIFT on School Poverty Shares and Rural School Status, 2015-2018

	(1)	(2)	(3)	(4)
Free lunch eligibility %	-0.0452***	-0.0395***	-0.0172	-0.00814
	(0.00903)	(0.00743)	(0.00969)	(0.0147)
STEM BA		0.0219	0.0169	0.00274
		(0.0117)	(0.0115)	(0.0124)
Rural	-0.0510***		-0.0561***	-0.0449***
	(0.00665)		(0.00702)	(0.0112)
Rural*Free lunch eligibility %	0.0185		0.0643***	0.0525**
	(0.0139)		(0.0142)	(0.0196)
STEM BA*Free lunch eligibility %		-0.0221	-0.0105	0.0135
		(0.0264)	(0.0212)	(0.0224)
Rural*STEM BA			0.00508	0.0224
			(0.0231)	(0.0262)
Rural*STEM BA*Free lunch eligibility %			-0.0387	-0.0632
			(0.0640)	(0.0742)
Teacher controls	Yes	Yes	Yes	Yes
School controls	No	No	No	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
N	52180	52180	52180	30330
R^2	0.1485	0.1459	0.1987	0.2121

Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level.

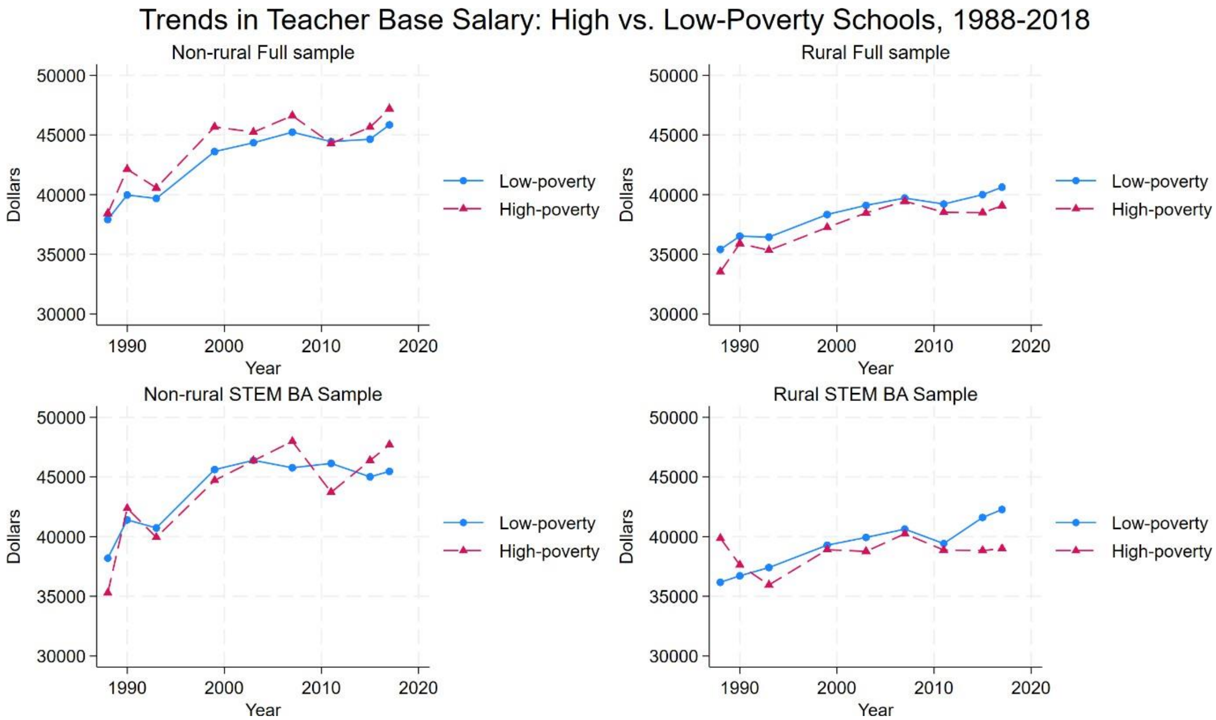
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: U.S. Department of Education, NCES, NTPS, 2015-2016 and 2017-2018.

Figure 1: Trend in Teacher Salaries, School Poverty Rates, and Minority Shares, 1988-2018



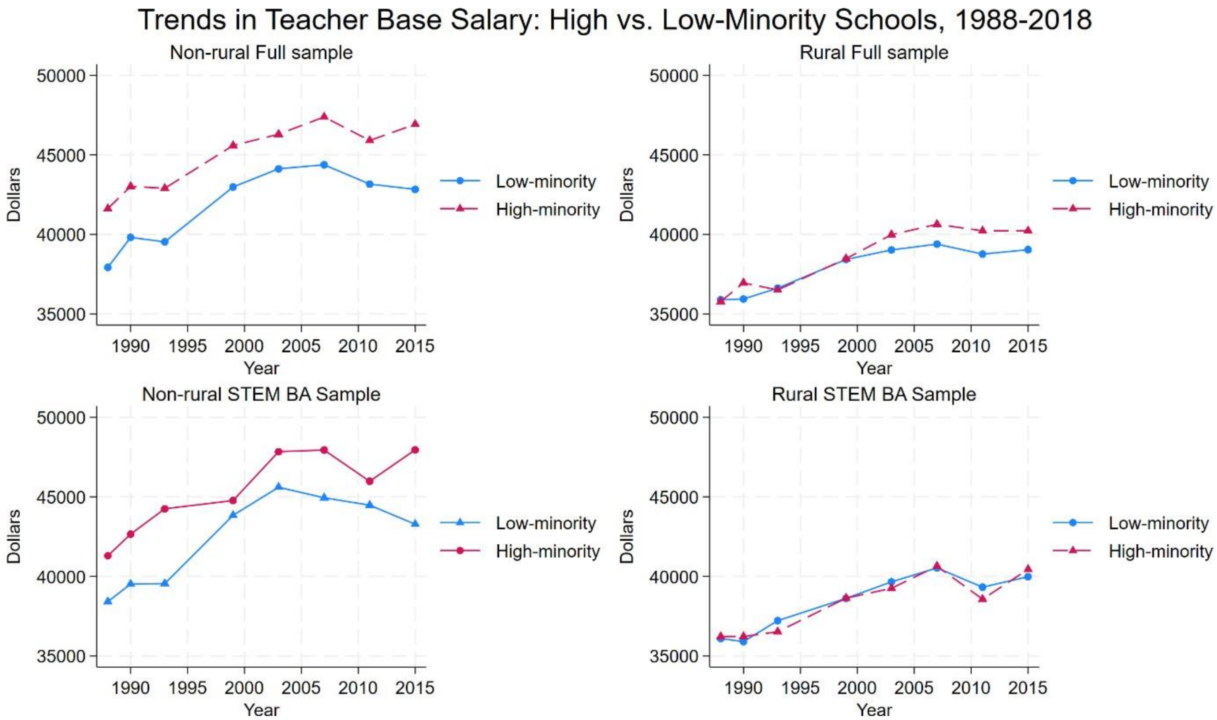
Source: U.S. Department of Education, National Center for Education Statistics, School and Staffing Surveys (SASS), 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and National Teacher and Principal Survey (NTPS), 2015-2016 and 2017-2018.

Figure 2: Trends in Teacher Base Salary for Teachers with Fewer than Six Years of Experience: High vs. Low-Poverty Schools, 1988-2018



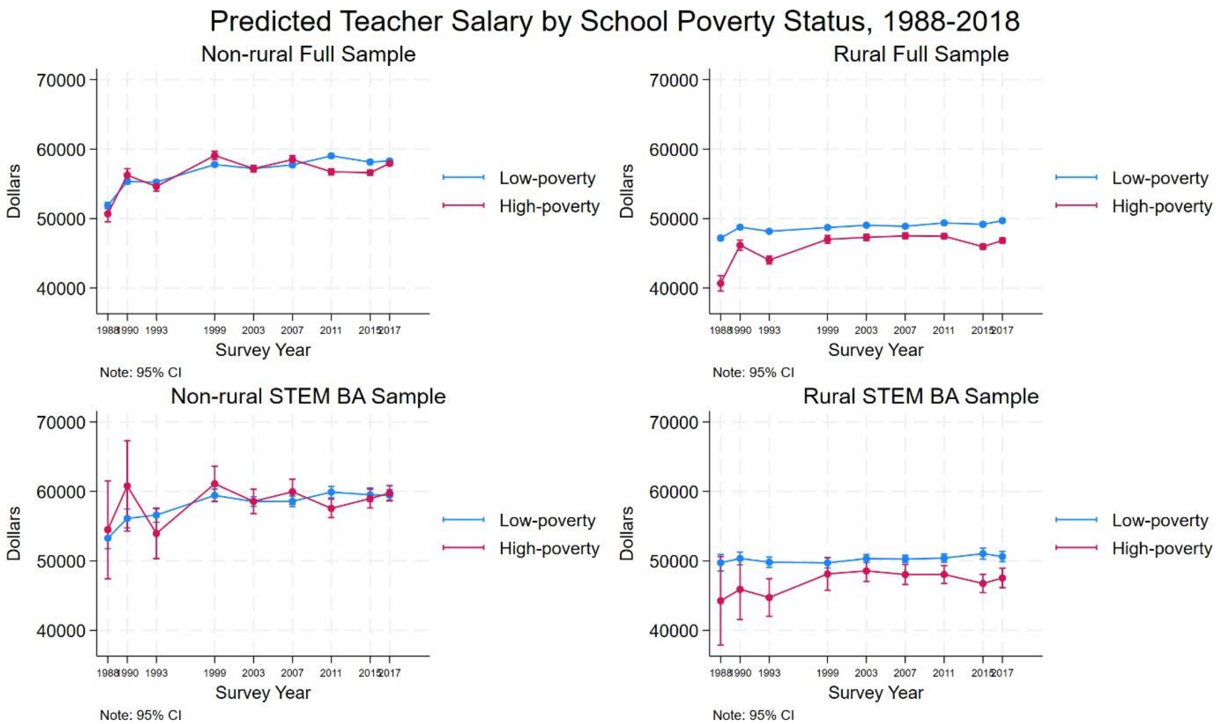
Note: We restrict these descriptive trends to teachers with less than six years of total teaching experience. Schools with greater than or equal to 50% free-lunch eligibility are classified as high-poverty schools.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Figure 3: Trends in Teacher Base Salary for Teachers with Fewer than Six Years of Experience: High vs. Low-Minority Schools, 1988-2018



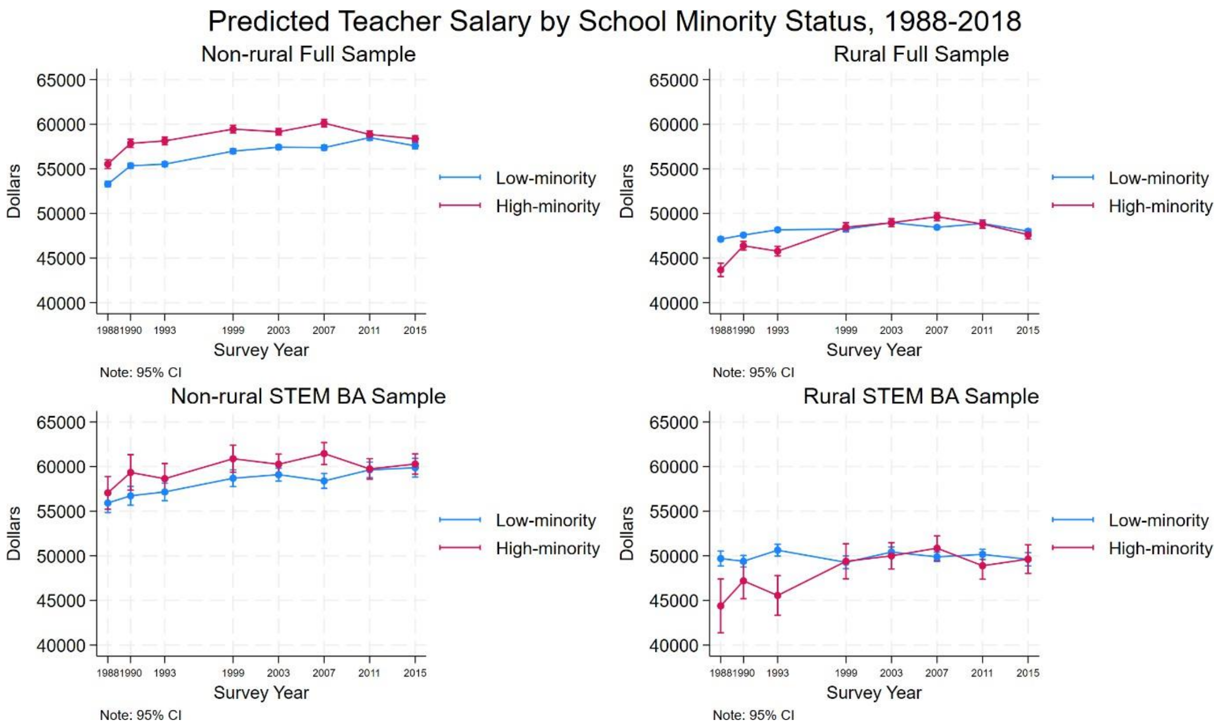
Note: We restrict these descriptive trends to teachers with less than six years of total teaching experience. Schools with greater than or equal to 50% nonwhite enrollment are classified as high-minority schools.
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Figure 4: Predicted Teacher Salary by School Poverty Status, 1988-2018



Note: Schools with greater than or equal to 50% free-lunch eligibility are classified as high-poverty schools. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

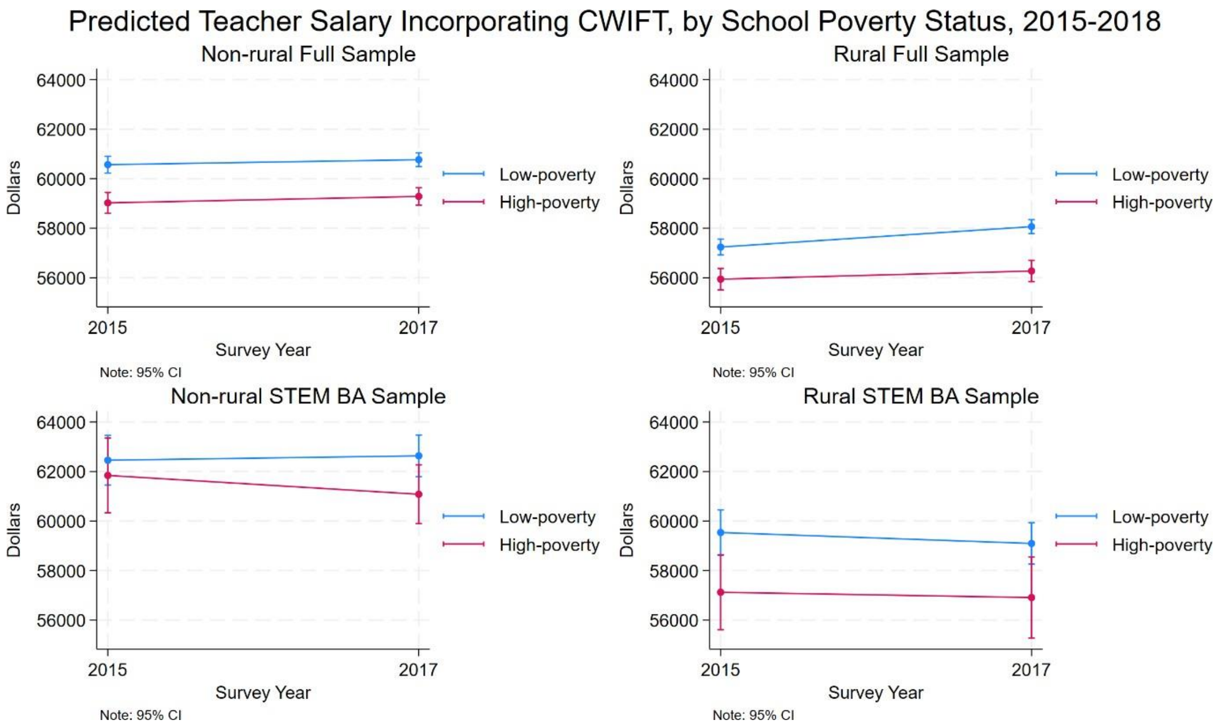
Figure 5: Predicted Teacher Salary by School Minority Status, 1988-2018



Note: Schools with greater than or equal to 50% nonwhite enrollment are classified as high-minority schools. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base).

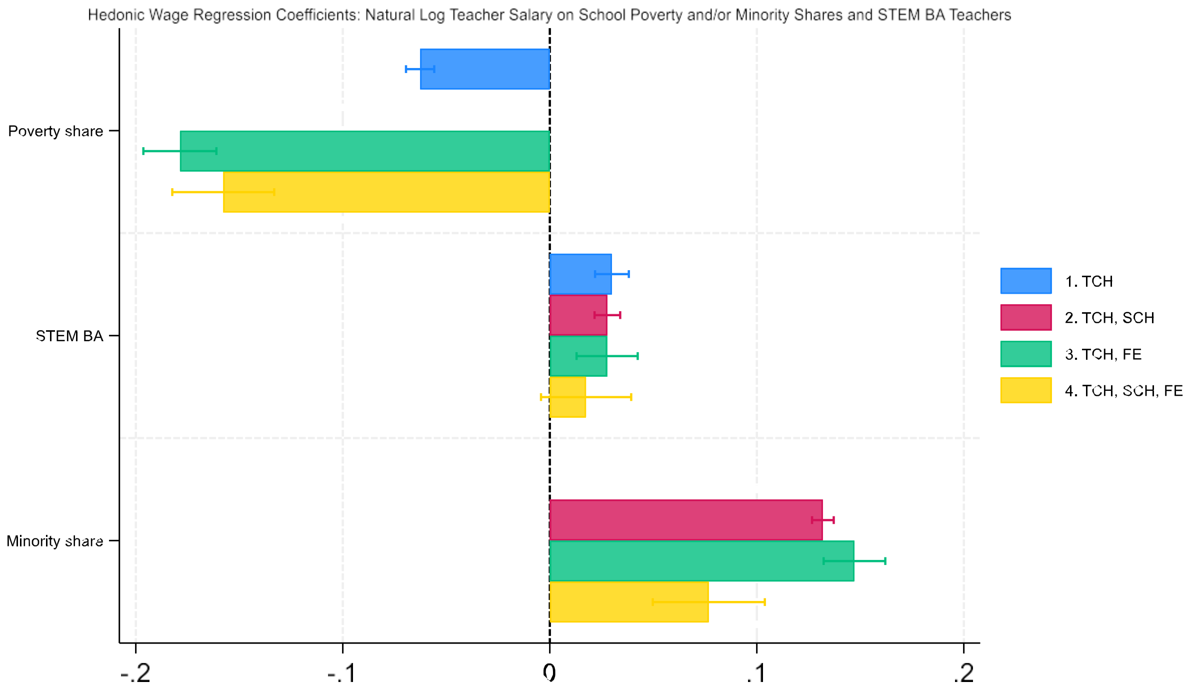
Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Figure 6: Predicted Teacher Salary Incorporating CWIFT, by School Poverty Status, 2015-2018



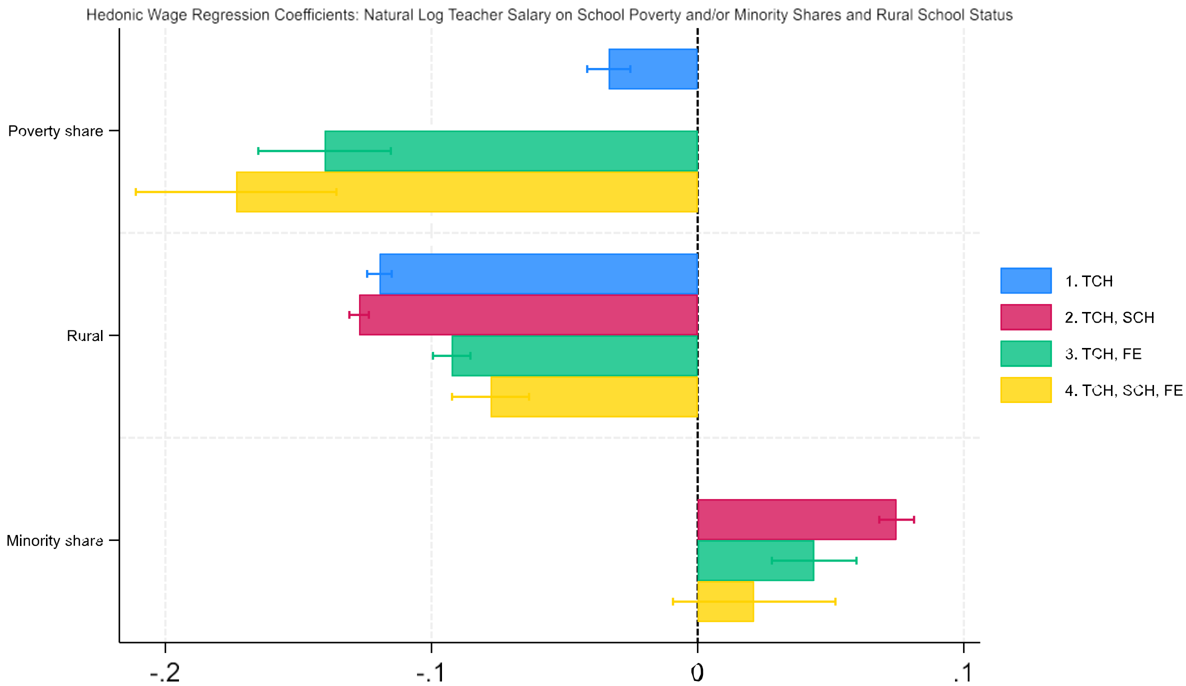
Note: Schools with greater than or equal to 50% free-lunch eligibility are classified as high-poverty schools. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). Source: U.S. Department of Education, NCES, NTPS, 2015-2016 and 2017-2018.

Figure 7: Hedonic Wage Regression Coefficients: Natural Log Teacher Salary on School Poverty and/or Minority Shares and STEM BA Teachers



Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.

Figure 8: Hedonic Wage Regression Coefficients: Natural Log Teacher Salary on School Poverty and/or Minority Shares and Rural School Status



Note: Model 1 includes teacher controls and school poverty. Model 2 includes teacher controls and school minority. Model 3 includes teacher controls, school poverty, and school minority, with state and year fixed effects. Model 4 includes teacher and school controls, school poverty, and school minority, with state and year fixed effects. Teacher controls include age, gender (female), race/ethnicity — White, Black, Asian, Latino/Hispanic, and American Indian (with multiple races as the base) — years of experience, master's degree, certification status (fully certified), and main teaching field — science, mathematics, computer science, or special education (with non-STEM as the base). School controls include total enrollment, average class size, school level — elementary or secondary (with combined schools as the base) — charter school, and magnet school. Standard errors clustered at the teacher level. Source: U.S. Department of Education, NCES, SASS, 1988-1989, 1990-1991, 1993-1994, 1999-2000, 2003-2004, 2007-2008, and 2011-2012, and NTPS, 2015-2016 and 2017-2018.