New Evidence on Teacher Pay

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Abstract

I document new and robust empirical evidence of earnings differences between teachers and non-teachers. First, I employ three complementary approaches that were not considered previously to alleviate pay differentials related to individual or job characteristics. These three approaches provide unifying estimates that turn an earnings penalty between female teachers and non-teachers of around 10%, based on a standard approach in the literature, into an earnings premium on the order of 5% to 10%. Likewise, estimates based on these approaches erase up to two-thirds of the earnings gap between male teachers and non-teachers. Second, going beyond the traditional focus on the mean, I decompose the pay gap across the entire earnings distribution. Estimates show that while teachers have a substantial earnings premium at the bottom of the distribution, they also have a large earnings penalty at the top.

JEL: I22, J20, J24, J31, J38

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1 Introduction

An enduring debate in public education is whether school teachers are adequately compensated, as teachers are a critical input in children's achievement function and, consequently, an important determinant of children's long-term educational and labor market outcomes in adulthood.[1] In the United States, teachers' wages are set by state or school districts' decree, legislative fiat, and collective bargaining. Federal, state, and local government funding determines school districts' ability to compensate teachers. Growing budget constraints on the parts of states and school districts, along with the rigid wage schedule, has made the long-standing question regarding the teachers' labor market more relevant: How are teachers *paid* relative to similar workers in other sectors? Missing in the literature is a conclusive answer because of the difficulty in recovering counterfactual salaries for teachers.

It is important to understand the pay gap for compensation planning and management, as they can presumably lead to big efficiency gains to schools (Podgursky 2011).[2] Studies have shown that teachers earn less than non-teachers with similar observable skills (e.g, Taylor 2008 and Allegretto and Mishel 2016). Further, as studies in the literature have attempted to connect teachers' relative pay, their quality (e.g., Stoddard 2003 and Hanushek and Rivkin 1997), and their labor supply, credible and comprehensive estimates of the pay gap facilitate a more nuanced view of the connection.[3]

A critical challenge confronted in the teacher pay analysis is the inability to have a directly comparable group of non-teachers to recover teachers' counterfactual earnings because teachers and non-teachers are not randomly assigned. I use three main empirical approaches not considered previously in order to tackle various potential biases and to document systematically new and robust empirical facts about the earnings gap.

First, I control for field-of-study fixed effects in the standard Mincer regression to erase a bias arising from individuals' career preferences, aspirations, and, to some extent, abilities. To do so, I leverage newly available data on field of study from the American

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[1] E.g., Hanushek (1992), and Chetty et al. (2011).
[2] For example, the United States spent $230 billion on public school teachers' salaries and another $93 billion on their benefits in the 2015/16 fiscal year (the U.S. Department of Education).
[3] Studies provide evidence that higher wages in teaching relative to nonteaching occupations decrease the likelihood of teachers leaving their profession (e.g., Dolton and van der Klaauw 1999 and Murnane and Olsen 1990). On the link between teacher pay and quality, the evidence is mixed (e.g., Figlio 2002).

Community Survey (ACS), covering 2009-2017. Second, I address omitted variable bias stemming from the differential pay for the variable nature of job characteristics by controlling for measures of a given occupation's task contents. Occupations differ in terms of the content of tasks involved, leading to differential compensations. Following Autor and Dorn (2013), I use three broader measures of tasks at the three-digit occupation level: abstract, routine, and manual. Third, I employ a propensity score matching (PSM) strategy to disentangle the relative earnings of teachers from observable differences in their characteristics. I match teachers with non-teachers based on their demographic characteristics, time and geographic fixed effects, and field of study.

All these approaches provide similar trends, in that female teachers earn around 5% to 10% more than that of comparable non-teachers. This is contrary to the finding of approximately 10% lower earnings for teachers based on a standard Mincer regression, which is commonly adopted in the teacher pay literature. Similarly, these approaches erase up to two-thirds of the earnings gap between male teachers and non-teachers.

To provide further insights into earnings differences, I next move beyond the traditional focus on the mean to look at earnings gaps across the entire distribution. The average pay gap is at the center of policy debates on teacher pay. And it misses important pay gap patterns, complicating the problem regarding teacher compensation structures and hindering school districts' ability to identify potential policies to address the problem. Given the compressed and rigid nature of teachers' salary schedule, their pay is the manner of "high-floor and low-ceiling." A high floor leads to a situation in which a teacher at the lower part of the distribution is potentially paid higher than an otherwise similar non-teacher, resulting in a substantial unexplained differential for teachers' earnings. Conversely, a low-ceiling pay structure prevents teachers from being adequately compensated at the top of the distribution.

I apply a quantile decomposition approach based on the recentered influence function (RIF) and provide the first empirical evidence of earnings differences beyond the mean and the potential sources behind such differences in the teachers' labor market. I partition the earnings gap at a given percentile into (i) a component that is explained by individual or group characteristics (explained gap) and (ii) a component that reflects differential wage schedules across the two sectors (unexplained gap). My results provide interesting patterns in heterogeneous returns to teachers. While many teachers enjoy a significant earnings premium at the lower end of the distribution, others face a substantial earnings penalty at the top.

2 Relation to Existing Work

This paper contributes to, and connects with, several strands of the existing literature. First, it substantially improves a long literature that analyzes the relative wages of teachers. The findings reach a consensus of a decline in teacher pay (see Podgursky and Springer 2011 and Podgursky 2011 for review). The most recent studies show the earnings gap between teachers and non-teachers in the range of around 7% to 14% (Taylor 2008, Allegretto and Mishel 2016, and West 2014). West (2014) provides new insight into teacher pay by controlling for the number of hours worked per week by making use of the time-use diary data from the American Time Use Survey (ATUS). The author finds that teachers work, on average, 34.5 hours per week annually as compared to 39.8 hours per week worked by non-teachers, and that based on estimated hours of work, high school teachers earn around 7% to 14% lower than those of non-teachers. Taylor (2008) uses PUMA fixed effects to account for the geographical sorting between teachers and non-teachers, given the fact that teachers are located in all parts of the country while non-teachers tend to be located in cities. She finds that teachers earn around 8% less than that of non-teachers. Using the Current Population Survey (CPS) data, Allegretto and Mishel (2016) document the weekly wage gap between teachers and non-teachers on an annual basis. The wage penalty for female teachers was 7.7% in 2009 and 13.9% in 2015, the latest year of their analysis. Richwine and Biggs (2011) offer an initial analysis of the wage gap between teachers and non-teachers using the panel data. In a related study, Schanzenbach (2015) re-examines the public-sector pay gap using AFQT and college majors. The author finds that individuals with lower skills select into the public sector and that the public-sector pay gap decreases considerably after controlling for fields of study.

By virtue of using the measures of task contents of occupations, this paper contributes to a growing body of work that examines how tasks affect the wage distribution. Using a British survey, Fernández and Nordman (2009) find that different job attributes such as "repetitive," "requiring literacy skills" and "requiring customer handling skills" become a substantial source of wage differentials across jobs, creating wage premiums and penalties. Likewise, Deming (2017), Acemoglu and Autor (2011), Autor, Levy, and Murnane (2003), and Atalay et al. (2020) explore the importance of various skills or tasks in explaining wage inequalities across groups in the labor market.

By applying a propensity score matching (PSM) approach, this paper is connected to the literature using PSM to explain the wage gap. For example, Mizala, Romaguera, and Gallegos (2011) apply the matching approach to explain the public-private wage gap in Latin America. Frölich (2007) employs this approach to investigate the gender wage gap among graduates in the U.K. Nopo (2008) explains the methodology of a matching approach for investigating wage differences across genders.

Another innovation of this paper is to apply the quantile decomposition technique based on recentered influence functions (RIF) regressions to understand the earnings gap between teachers and non-teachers across the entire distribution. In being the first study to apply this decomposition approach in the context of the earnings gap between teachers and non-teachers, this paper is related to an emerging literature that evaluates the distributional effects of public policies (Dube 2019 and Aaberge et al. 2010) and the gender wage gap, employing this approach. Kassenboehmer and Sinning (2014) apply this approach to explain the gender wage gap in the U.S., while Bhalotra and Fernandez (2018) use it to illustrate the role of women's labor force participation in the gender wage gap.

To summarize, two broader contributions stand out. First, it offers new, robust empirical facts about the relative earnings of teachers by being the first to control for college major fixed effects and for task contents of occupations and being the first to use a matching approach. Since each strategy has its own advantages in improving the direct comparison between teachers' and non-teachers' baseline characteristics or content of work, their collective use should combat varying potential biases and produce more credible estimates. Second, it offers the first investigation into the earnings gap across the entire distribution, using a quantile decomposition.

3 Data

3.1 American Community Survey

I use data from the 2009-2017 American Community Survey (ACS) extracted from the Integrated Public Use Microdata Series (Ruggles et al. 2019). The ACS samples 1% of the total population in the U.S. Note that the ACS has only been reporting the chosen fields of study for individuals pursuing bachelor's degrees since 2009. I restrict the sample to prime-age working people, aged 25 to 54. I exclude those below 25 years old to avoid the issues related to youth unemployment and early career choices and above 54 years old to avoid retirement issues. As the teaching profession requires at least a four-year college degree, I limit the sample to those having a bachelor's degree or beyond. Additionally, I exclude self-employed, unemployed, unpaid family workers, and those in the armed forces.

The ACS reports an individual's pre-tax salary income received from an employer during the past 12 months. I deflate annual incomes to 2009 dollars. As Bollinger and Hirsch (2006) show that earnings imputation in household surveys biases estimates, I exclude those individuals whose earnings are imputed. Similarly, the survey provides information on a respondent's number of weeks worked during that period in intervals, such as 1-13 weeks, 14-26 weeks, 27-39 weeks, and 40-52 weeks. I drop respondents who have missing values for the number of weeks worked or have zero income, which could also reflect their non-working status during the period.

To define teachers and non-teachers, I use the variable "OCC1990," which uses the 1990 Census Bureau occupational classification scheme. I classify individuals into teachers if they report being kindergarten and earlier school teachers, primary school teachers, secondary school teachers, and special education teachers.[4] I exclude private school teachers as public and private school teachers have different compensation mechanisms and working environments. I also drop those who report their occupation as "*teachers not mentioned elsewhere from,"* as it is not obvious if they are full-time regular school teachers or represent non-school teachers such as private tutors.

Panel A of Table 1 reports descriptive statistics for female teachers and non-teachers and Panel A of Table 2 for male teachers and non-teachers. The raw income is lower for teachers than that of non-teachers. Another striking difference is observed for the variable

[4] Kindergarten and earlier school teachers may be quite different from other regular school teachers. Even when I exclude kindergarten and earlier school teachers from my analytical sample, the results are similar.

"master's degree." Around 52% of female and 51% of male teachers have a master's degree, while approximately 25% of female and male non-teachers have such a degree. Teachers are more likely to have been married and to have a higher number of children.

3.2 Survey of Income and Program Participation

I use the 2008 Survey of Income and Program Participation (SIPP) panel which overlaps the time frame of the ACS. It is a nationally representative longitudinal survey that lasted from 2008 to 2013. I define teachers in the SIPP in a similar manner to that of the ACS. I drop family workers and non-workers (those whose occupation is missing). As in the ACS data, I restrict the sample to those who were at least 25 years at the beginning of the survey and did not exceed 54 years of age throughout the sample. Income refers to monthly earnings from an individual's job.[5] Panel B of Table 1 reports descriptive statistics for female teachers and non-teachers and Panel B of Table 2 for male teachers and non-teachers, both of which provide qualitatively similar patterns to those from the ACS. It is worth noting that the SIPP measures income on a monthly basis while the ACS reports annual income. That is why there is a visible discrepancy between the ACS and SIPP data in terms of income.

4 Empirical Estimations and Results

4.1 Baseline Estimation and Results

I first use the standard Mincer regression to examine the pay difference between teachers and non-teachers. In particular, I estimate the regression model of the following form:

$$ln(earnings_i) = \alpha + \tau T_i + X_i'\beta + \gamma_s + \lambda_t + \epsilon_i, \quad (1)$$

where T_i is a dummy variable that takes a value of one for teachers, and X_i is a vector of demographic variables such as education, age, age-squared, race, marital status, and the number of children.[6] γ_s and λ_t are vectors of state fixed and year fixed effects.

[5] I use the sum of variables "*tpsum1*" which measures earnings from the first job and "*tpsum2*" which measures earnings from a second job or other additional jobs for those individuals holding multiple jobs in the reference month. As in the ACS sample, I drop imputed earnings from my analysis.

[6] I divide education into four categories: a bachelor's degree, a master's degree, a professional degree, and a PhD. Likewise, I classify race into non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other race.

One potential issue estimating this standard model calculating the relative earnings of teachers is its inability to disentangle the earnings gap from the cost of living. Taylor (2008) argues that unlike college-educated workers in the non-teaching sector, teachers tend to be scattered across the state, including rural areas, and failure to control for labor market areas biases the relative wage estimates. Taylor (2008) uses Public Use Microdata Areas (PUMAs) fixed effects. The PUMAs are geographic units, each containing at least 100,000 persons, within a state. However, the PUMAs are not delineated to reflect similar labor markets or economic characteristics. Therefore, they may not be a good measure of the cost of living.

To better control for the cost of living, I compare teachers and non-teachers in the same labor market, defined as the commuting zone (CZ). The CZ is defined on the basis of journey-to-work data and includes counties having similar labor market conditions. There are approximately 740 CZs, covering the whole U.S. They can extend across state borders.

Using population data from the most recent decennial census, the Census Bureau changes the PUMA boundaries every 10 years. To map PUMAs to CZs for the ACS samples from 2009 to 2011, which are based on the 2000 Census, I use a crosswalk following Autor and Dorn (2013). For the ACS samples from 2012 to 2017, which are based on the 2010 Census, I use a crosswalk following Autor, Dorn, and Hanson (2019).

PUMAs can include a county or a cluster of counties. Most of the PUMAs are matched to unique CZs. However, some PUMAs extend across multiple counties falling into different CZs. That means PUMAs are mapped into more than one CZ. For individuals from such PUMAs, I re-weight their census weights by a new weight that is the proportional probability of each individual from each PUMA belonging to a given CZ, as in Autor and Dorn (2013).

4.1.1 Baseline Estimates

I begin by reporting the results based on Equation (1). Panel A of Table 3 contains the results for women. As shown in Column 1, I find that female teachers are paid $100\times(e^{0.093}-1)$ = 9.7% lower than non-teachers . Since the dependent variable is measured in logs, I convert the coefficient on the dummy variable "*Teacher*" in this way throughout the analysis. Next, I control for the commuting zone (CZ) fixed effects to adjust for the differences in the cost of living in teachers' and non-teachers' labor markets. The pay gap decreases to 7.8% (Column 2). In comparison, Taylor (2008) who uses the PUMA fixed effects in the 2000 Decennial Census data finds that teachers (both female and male) earn around 8.5% less than non-teachers.

Next, I estimate the earnings gap between male teachers and non-teachers. As reported in Panel B of Table 3, the results from the standard Mincer regression show that the earnings of male teachers are around 45% lower than the earnings of non-teachers (Column 1). When I control for CZ fixed effects, the earnings gap reduces to approximately 39% (Column 2).

4.1.2 Importance of College Majors

College major choices are one important factor underlying earnings differences. Such choices could reflect the ability-based sorting of individuals (Arcidiacono 2004) or preferences for a particular occupation based on non-pecuniary returns (see Altonji, Blom, and Meghir 2012 for review). Heterogeneous returns to the field of study raise the importance of controlling for college majors to account for the self-selection of individuals into occupations.[7] Therefore, I further add college major fixed effects. There are 176 fields of study in which individuals obtain their bachelor's degrees in my sample. As reported in Table 3, I find that for women, the earnings of teachers are 5.2% higher than those of similar non-teachers (Column 3 of Panel A). For men, when I add field-of-study fixed effects, the earnings gap reduces to 19% (Column 3 of Panel B). Additionally, I examine the wage profiles of teachers and find that the return to experience is lower in teaching than that of non-teaching jobs.[8]

[7] To explore who are more likely to select themselves into teaching, I examine the relationship between the proportion of teachers who join teaching from a particular field of study and their relative pay. Figure 1 presents the association between the proportion of individuals who become teachers by their field of study and the relative pay of teachers in that field. This elucidates clear patterns of self-selection into teaching based on fields of study which should reflect individual ability and taste. The proportion of individuals who are likely to join teaching is high from fields of study that provide a relatively higher pay. Such fields of study seem to be a few. Most of the fields of study have a lower relative pay and lower participation of its recipients in teaching.

[8] For female teachers, the additional year of experience has a return that is approximately 1% lower than non-teachers. For male teachers, the return is lower by around 1.1% than that of non-teachers. I calculate experience as the maximum of zero and age minus six minus years of schooling.

In this analysis, I compare teachers and non-teachers who hold a degree in the same field of study but pursue career in different sectors (teaching versus non-teaching). The estimates are obtained under the assumption that individuals majoring in the same field of study have a similar set of skills and talents. However, a potential concern is that those who choose a similar college major but embark on different career paths may have different underlying characteristics and backgrounds. For example, it is possible that those who major in education but do not go to become a teacher were not successful in teaching or have different underlying ability distribution and career preferences than those who become teachers.

Work Hours. One noticeable discussion in the teacher pay literature is that workers tend to work shorter hours. The problem with the survey data in measuring work hours is that workers tend to overstate their work hours (West 2014). Therefore, I turn to the American Time Use Survey (ATUS) that uses time-use diaries of individuals. Using these diaries from 2009 to 2017, I find that female teachers work around 34.16 hours per week, compared to 35.34 hours worked per week by non-teachers.[9] I re-estimate Equation (1), adjusting for weekly hours worked. To do that, I first calculate the average annual work hours for each group by multiplying average weekly work hours by 52. Then, I divide the earnings of each individual in each sector by the respective average annual work hours. The pay premium for female teachers increases to 9% (Column 4 of Table 3). I find a big difference in the number of hours worked per week between male teachers and non-teachers. Male teachers work 36.5 per week, while male non-teachers work 42.6 hours per week. When I adjust this discrepancy in hours worked, the earnings gap declines to around 1.9% (Column 4 of Table 3). Though these estimates are illustrative of a general pattern of pay differences related to work hours, a caveat is that these are derived extrapolating the annual number of hours worked.[10]

[9] The hours worked include all activities related to work, including those performed on-site and at home. It is important to note the nature of work schedules between teaching and non-teaching while comparing the hours worked. Teachers may spend more time at home for work-related activities, such as preparing lesson plans and grading than other professionals in the non-teaching sector. Individuals may value the time spent at home for work more than that spent on-site because of its flexibility to balance work and family. Similarly, teachers' working hours typically align with their own children's school hours, which can provide an additional advantage in child care (Podgursky 2004).

[10] Because of this caveat, I do not adjust for weekly hours worked throughout the remainder of the analysis.

Heterogeneous Returns. Considering that teachers typically tend to be drawn from among individuals majoring in the field of education (see Table B2 in Online Appendix), analysis of the pay gap experienced by those with and without having majored in education can provide more nuanced insights.[11] Being a conventional route to a teaching career, education majors can reflect self-selection of aspiring educators into teaching. Therefore, I separately estimate the pay differences for these two groups: education and non-education majors.

Table 4 contains these results. Columns 1 and 3 present the results without controlling for detailed fields of degree for those majoring in education and outside education, respectively. Columns 2 and 4 add detailed field-of-degree fixed effects. As shown in Panel A, female teachers who majored in education earn around 38.5% more than non-teachers who majored in education. However, the results revealed what amounts to a penalty in pay of around 15.9% for female teachers who hold non-education degrees as opposed to those non-teachers who hold non-education degrees. Likewise, male teachers majoring in education do not face any pay penalty. Those male teachers who did not pursue education majors earn around 34.1% less than similar non-teachers. Overall, this analysis provides a detailed insight into pay differentials, indicating the potential self-selection of individuals into majoring in education and subsequently becoming teachers.

4.1.3 Importance of Occupational Tasks

As noted earlier, college majors account for omitted variables bias resulting from individuals' ability and skills which are homogenous among individuals within a field of study. Still, estimates may suffer from other potential biases arising from differential skill and work effort requirements across occupations. Some occupations involve carrying out repetitive tasks, while others could require intense knowledge and analytical skills. This has natural implications for the salary in the teachers' labor market. Teachers could be paid less as their job characteristics are different from those held by other college graduates.

[11] More precisely, I use Education Administration and Teaching field reported in the ACS, which includes various specific majors such as General Education, Educational Administration and Supervision, School Student Counseling, Elementary Education, Mathematics Teacher Education, Physical and Health Education Teaching, Early Childhood Education, Science and Computer Teacher Education, Secondary Teacher Education, Special Needs Education, Social Science or History Teacher Education, Teacher Education, Language and Drama Education, Art and Music Education, and Miscellaneous Education.

One way to tackle such biases, isolating the relative earnings of teachers is to add direct measures of different skills and work effort required in a particular job to the standard Mincer regression. To do so, I use the task measures, which help to characterize the type of work performed across occupations. An emerging literature uses this "task approach" to analyze earnings inequality (see Autor 2013 and Acemoglu and Autor 2011 for review). Using the task content measures in the analysis of the relative earnings of teachers seems relevant to derive more nuanced estimates. Following Autor and Dorn (2013), I use three broader measures of tasks: abstract, routine, and manual for each occupation. The authors classify tasks into these three measures using the US Department of Labor's Dictionary of Occupational Titles. These task contents are measured at the three-digit occupation level.[12] The value of abstract measure ranges from 0 to 9, of routine measure from 1.19 to 8.65, and of manual measure from 0 to 10.[13]

I re-estimate Equation (1) using controls for these three measures of task contents of occupations. The findings reveal similar patterns to those that emerged from a specification using field-of-study fixed effects. Table 5 contains the results. Column 1 reports without controlling for CZs fixed effects and Column 2 adds them. I find that female teachers are paid around 4% to 5.5% higher than those of non-teachers. Likewise, these controls of the task measures erase a substantial pay gap for male teachers.

Overall, this analysis improves the standard Mincer regression, which relies on basic characteristics such as education and experience for explaining the earnings differences, by incorporating occupation-specific task prices to the regression. In other words, I include previously omitted variables regarding the role that the returns to the measures of task content plays in the overall pay differences between the teaching and non-teaching sectors, thus more credibly isolating the relative earnings of teachers.

Conditioning on these task content measures and basic demographic characteristics, along with time and location differences, the analysis assumes that the remaining earnings gap between teachers and non-teachers is attributable to differential wage structures across the two sectors. Additional assumption needed to address the problem of omitted variables

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[12] I retrieve data from the author's website at https://www.ddorn.net/data.htm, accessed July 10, 2020.
[13] I list occupations similar to teaching in terms of these task measures in Table B4 in Online Appendix.

bias arising from job characteristics is that these task measures can fully capture unobserved differences in skill sets and work requirements and that task contents within an occupation are uniform. However, it is plausible that job tasks within an occupation are heterogeneous, which can bias estimates. Likewise, task scores are calculated by mapping a large number of task contents provided by the DOT to broader measures for each occupation, which raises the possibility of measurement error. And, it is possible that there are other unmeasured contents of tasks specific to jobs, which influence pay.

4.2 Propensity Score Matching

Estimates of the earnings gap between teachers and non-teachers could be driven by imbalances in characteristics between teachers and non-teachers. As randomization is practically infeasible in the teachers' labor market, the closest approach that can be adopted in my setting is propensity score matching (PSM). The PSM approach that is widely used in the treatment evaluation is equally relevant for analyzing wage differences between two groups (Nopo 2008). Therefore, I use the PSM approach as yet another strategy to erase a confounding effect that results from systematic differences in baseline characteristics between teachers and non-teachers.

To implement the PSM in my context, I use a nearest-neighbor matching of nonparametric nature and follow a newly developed procedure in calculating standard errors for the post-matched regression. I apply one-to-one matching without replacement, which matches each teacher to the most comparable non-teacher. The main advantages of this matching approach are transparency and straightforwardness.

To execute it empirically, in the first step, I calculate the propensity score of being a teacher. The score represents the predicted probability derived from a logit model (Rosenbaum and Rubin 1985 and Imbens 2004). I regress an indicator variable for teacher on demographic variables such as education, race, and children, fields of study fixed effects, state fixed effects, year fixed effects, and commuting zone fixed effects. Formally, I use the following model:

$$teacher_i = \alpha + X_i'\beta + FieldStudy_f + \gamma_s + \lambda_t + CZ_c + \epsilon_i, \qquad (2)$$

where $FieldStudy_f$ is a vector of the field-of-study fixed effects and CZ_c a vector of the commuting zone fixed effects. After calculating the propensity score for each individual, I select the best-matched non-teacher for each teacher. Note that the nearest-neighbor matching estimator without replacement allows us to use a non-teacher match only once. The identifying assumption is that conditional on these observable characteristics, other unobservable factors do not jointly determine an individual's decision to join teaching and his/her earnings. In practice, this assumption is untestable.

One issue in running the post-matched regression is how to correctly calculate standard errors that take into account the uncertainty involved in the estimation of the propensity score in the first stage. The literature has widely used a bootstrap technique to address this problem. However, Abadie and Imbens (2008) explain that bootstrap standard errors are not generally valid. In a recent paper, Abadie and Spiess (2019) derive asymptotically valid standard errors in the post-matched regression based on nearest-neighbor matching without replacement. Note that since this paper uses a nearest-neighbor matching strategy without replacement to match teachers and non-teachers, Abadie and Spiess (2019) is highly relevant in the context of this analysis. The authors show that the OLS standard errors in the post-matched regression are valid as long as (i) matching is done without replacement and (ii) the regression is correctly specified relative to the population regression. They also suggest using clustered standard errors at the matched-pair level when the post-matching regression is not correctly specified. In this paper, I follow Abadie and Spiess (2019) and cluster standard errors at the matched-pair level**.**

4.2.1 Evidence from a Matching Approach

To make the estimation strategy simple, and for the purpose of illustration, I begin my analysis by matching each teacher to a non-teacher regardless of the closeness of the match. That permits me to keep all teachers. Therefore, the comparison group represents non-teachers who resemble similar characteristics to teachers. I report the results in Table 6. I estimate the three main baseline specifications. First, I use individual controls, year fixed effects, and state fixed effects. Second, I add CZ fixed effects. Finally, I further add field-of-study fixed effects. Across all three specifications, the results are similar. The robustness to additional controls highlights the quality of the match performed. In terms of magnitude, in my preferred specification, female teachers have around 10.2% higher earnings than non-teachers (Panel A, Column 3). Likewise, for male teachers, the PSM technique lowers the gap to 13.4% (Panel C, Column 3), accounting for over two-thirds of the earnings gap witnessed in the baseline regression.

Next, I match teachers and non-teachers within a specific caliper width, which is calculated as the difference in the propensity score of the matched pair. In the literature, there is no unanimous caliper width that should be adopted in the empirical analysis. However, Rosenbaum and Rubin (1985) and Cochran and Rubin (1973) suggest that a caliper width that is 0.2 of the standard deviation of the logit of the propensity score erases about 98% of bias resulting from the measured confounders. Therefore, I re-estimate the PSM approach using the suggested caliper width. I am able to match around 50% female teachers and 90% male teachers to their comparable non-teachers. Specifically, the treatment group here represents those teachers whom I am able to match with similar non-teachers (the comparison group). As shown in Column 3 of Panel B of Table 6, female teachers earn around 7.2% more than non-teachers. Likewise, for male teachers, the pay gap stands at approximately 15.7% (Column 3 of Panel D of Table 6), down from 45% found in the model based on Equation 1.

It is important to note that estimates are conditional on the identifying assumption that observable characteristics entirely explain individuals' underlying ability or productivity determining their earnings. Note that this approach selects a comparison group based on those observed characteristics only. It is possible that teachers and non-teachers are different in terms of other unobserved characteristics, which can influence earnings. Likewise, they might be choosing teaching and non-teaching jobs based on their underlying productivity, potentially violating the assumption.

4.3 Panel Data Approach

I make use of the panel data to employ an alternative approach to tackle a critical concern on whether omitted variables like fixed unobserved workers' productivity are contributing to the observed pay difference. I obtain the data from the 2008 panel of the Survey of Income and Program Participation (SIPP). As this longitudinal survey lasts for about five years, I can observe an individual's occupation over time and subsequently salary in both the teaching and non-teaching sectors if s/he switches her/his occupation. I use the specification parallel to Equation (1), controlling for individual fixed effects.

$$ln(earnings_i) = \alpha_i + \tau T_i + X_i'\beta + \gamma_s + \lambda_t + \epsilon_i, \quad (3)$$

where variables are defined as above, except that α_i represents individual fixed effects. Earnings here are measured on a monthly basis. I use the survey weight in my estimations and cluster standard errors at the state level. In this estimation strategy, I am able to compare the earnings of individuals who switch between teaching and non-teaching professions. This strategy illustrates how teachers would have performed in the non-teaching sector had they joined it.

4.3.1 Evidence from the Panel Data

In this sub-section, I present the results estimated using the panel data from the SIPP. Table 7 presents the results. I first estimate the effects of being a teacher on monthly earnings based an ordinary least squares estimation using individual-level control variables and state fixed effects. As shown in Column 1 at the top of Panel A, female teachers are paid around 3.5% less than non-teachers. This estimate is smaller than the estimate from the ACS data, which could be because of sample variation. Next, I control for individual fixed effects, which turn a negative earnings gap into an earnings premium. Specifically, female teachers earn around 12.7% more than non-teachers (Column 2 at the top of Panel A). One concern in this analysis is that it is possible for teachers to work in another occupation during the summer months when schools are off. To address such a concern, I drop months of June, July, and August from my analysis and re-estimate Equation 3. Column 3 at the top of Table 7 presents the results derived without individual fixed effects, and Column 4 controlling for individual fixed effects. Dropping summer months yields similar results. Another feature of the SIPP is that it reports the number of hours worked per month, enabling me to calculate hourly earnings.[14] I re-estimate my models on hourly earnings. I estimate parallel models for men and the results are presented in Panel B of Table 7. Controlling for individual fixed effects erases most of the earnings penalty for male teachers.

[14] I drop those individuals who have imputation in the number of hours worked. As a result, the sample sizes for monthly earnings and hourly wages are different.

While the panel data are helpful to purge unmeasured individual heterogeneities in the pay gap analysis, it is important to keep a drawback in mind while interpreting the results. Individuals who move into and out of teaching include a small subset who may be self-selecting into occupations based on the suitability of their skills. Their decision to switch jobs may be driven by various life events, such as marriage, health, children, spousal labor supply, and location preferences. A pursuit for an optimum labor-leisure choice or preferences for different nature of works in terms of predictability and stability may also motivate individuals to change their careers. If such underlying factors are driving their move in and out of teaching, the results are biased here.

6 Quantile Decomposition of the Earnings Gap

So far, as in the literature, this analysis focuses on the pay gap at the mean only. In order to provide further insights into earnings differences, I move beyond the mean to look at earnings gaps across the entire distribution. This analysis is highly relevant because of the implications of the “low-ceiling-and-high-floor” nature of the wage schedules prevailing in the teaching sector. A high floor leads to a situation in which a teacher at the lower part of the distribution is paid higher than an otherwise similar non-teacher. This culminates in a substantial unexplained wage differential for teachers, a wage premium. On the other hand, a low-ceiling pay structure prevents teachers at the top of the distribution from being appropriately compensated for their skills, a wage penalty.

I base my analysis, related to pay gaps and their sources over various percentiles, on the American Community Survey (ACS) data. Offering further explanations on what are driving pay differentials can help to reconcile my baseline findings. As we saw above, my baseline findings differ from the estimates of the pay gap in the literature. Using a rich set of relevant controls or using a more comparable control group eliminates (considerably reduces) the gap for female (male) teachers. This highlights the relative importance of the returns to individual characteristics or skills across the two sectors. These findings are in line with a prediction of Hoxby and Leigh (2004) that the compressed wage structure brings larger returns to low-skilled individuals but smaller returns to skilled workers. Against this background, it is a desirable exercise to uncover the extent to which individual or group characteristics explain the gap (explained gap) and the extent to which differential wage schedules across the two sectors (unexplained gap) play the role. In the context of the teachers' labor market, one reasonable source of the unexplained gap should be rigid salary schedules governed by school district laws, legislative fiat, and collective bargaining.

For this purpose, I use the decomposition methodology advanced by Firpo, Fortin, and Lemieux (2009, 2007),[15] which decomposes wage differentials for quantiles in a similar manner to the standard Blinder-Oaxaca decomposition for the mean differential (Oaxaca 1973 and Blinder 1973). Since the decomposition builds on the concept of the influence function (IF), first let's formalize the IF for quantile τ as:

$$IF(w; q_\tau, F_w) = \frac{\tau - \mathbf{1}[w \le q_\tau]}{f_w(q_\tau)}. \quad (4)$$

In this setting, the IF is an indicator that equals to $-(1-\tau)/f_w(q_\tau)$ when w (the log of earnings) is below the quantile τ and that equals to $\tau/f_w(q_\tau)$ when w is above the quantile τ. $f_w(q_\tau)$ is the marginal distribution of w at the quantile τ. Adding the τ^{th} quantile of the unconditional distribution of the log earnings, q_τ, to the IF leads to what Firpo, Fortin, and Lemieux (2009) call the *recentered influence function* (RIF). The RIF is:

$$RIF(w; q_\tau) = q_\tau + IF(w; q_\tau F_w). \quad (5)$$

The conditional expectation of the RIF can be expressed as a linear function of the explanatory variables. That permits us to use the RIF-regression model in a framework of the Ordinary Least Squares (OLS) regression. Formally, the earnings function of the RIF takes the following form:

$$E[RIF(w; q_\tau, g)|X] = X_g' \beta_g, \quad (6)$$

where $g \in \{tch, ntch\}$ and X is a vector of individual and group covariates as described earlier, including field-of-study fixed effects.[16] The sample analogous is $\widehat{RIF}(w; q_\tau, g)|X = X_g' \widehat{\beta_g}$. This exercise involves a two-fold approach. First, I estimate the

[15] Their approach is similar to that outlined in Chernozhukov, Fernández-Val and Melly (2013) but is computationally less cumbersome while one needs to use big data and to bootstrap standard errors.
[16] However, I do not use commuting zone fixed effects as it is computationally cumbersome to use these and calculate bootstrap standard errors. It is worth mentioning that they should not alter the interpretation of the results here as we saw earlier that the inclusion of CZ fixed effects changes the baseline estimates only slightly.

RIF for quantile τ for teachers and non-teachers, respectively. I replace the dependent variable *log(earnings)* by the RIF estimate for each quantile τ. Second, I use the standard decomposition approach to partition the effect into a part attributed to individual and group characteristics (the composition effect) and into a part attributed to differential prices of skills (the wage structure effect). Specifically, it can be expressed as:

$$\underbrace{\Delta q_{\tau}(w)}_{Overall} = \underbrace{(\overline{X}_{tch} - \overline{X}_{ntch})\hat{\beta}_{ntch}, \tau}_{Composition} + \underbrace{\overline{X}_{tch}(\hat{\beta}_{tch}, \tau - \hat{\beta}_{ntch}, \tau)}_{Wage \quad Structure}, \qquad (7)$$

where $\widehat{\beta_{(.)}}$ represents the estimated coefficients from the RIF-regressions and $\overline{X}_{(.)}$ includes averages of individual and group characteristics as described above. Likewise, $\Delta q_{\tau}(w) = q_{\tau,tch}(w) - q_{\tau,ntch}(w)$ represents the earnings difference between teachers and non-teachers at the quantile τ. I compute bootstrap standard errors with one hundred replications. An important feature of this approach is that it permits us to decompose the earnings gap between teachers and non-teachers at a given percentile. The estimates are obtained under the assumption of a selection-on-observables (controlling for observable characteristics, the decision to join teaching or non-teaching sectors is as close as randomly assigned) and under the assumption that expectation of RIF is linear in observable characteristics, X. It is important to note that, in this specification, I analyze the composition and wage-structure effects relative to averages of baseline characteristics of non-teachers and averages of the returns to their characteristics. Therefore, the wage-structure effect (unexplained component) here is interpreted as the extent of higher or lower wages that teachers would have received had they paid according to the wage schedules of non-teachers.

Figure 2 provides the basic insights into this approach, following Fortin, Lemieux, and Firpo (2011). F_{tch} represents the cumulative distribution function (CDF) of teachers' earnings and F_{ntch} the CDF of non-teachers' earnings. And the density is the slope of the CDF of the earnings. The vertical axis represents the CDF of the earnings distribution, and the horizontal axis shows the values of corresponding earnings at each quantile. The two CDFs illustrate earnings gaps at various quantiles. For example, at the median, the earnings gap is $q_{tch,0.5}$ - $q_{ntch,0.5}$. The approach intends to find the values of counterfactual distributions of teachers' earnings between the two CDFs. In other words, this approach would generate the estimates of teachers' earnings if they faced the earnings structure of non-teachers. To find the value of the counterfactual distribution of teachers at the median, we move down, along the dashed density line, from the counterfactual proportion. And the actual and counterfactual earnings gap of teachers at the median is $q_{tch,0.5}$ - $q^{C}_{tch,0.5}$.

Before presenting the results related to the decomposition, I present the earnings gaps across different percentiles in Figure A1 for female teachers and in Figure A2 for male teachers, employing unconditional quantile regressions. The quantile coefficients on teachers can be interpreted as the effect of a change in the distribution of teachers, i.e., a proportional increase in the share of teachers, on the earnings distribution. This exercise can be helpful in shedding light on teacher pay since the provision of teachers' rigid salary schedules affects both the earnings gap between teachers and non-teachers at the mean and the distribution of earnings within teachers by not allowing an appropriate pay difference between high-skilled and low-skilled teachers. Estimates reveal interesting patterns in that the gap is positive at the bottom section of the distribution but becomes substantially negative at the upper section.

Next, I go on to present the results for the decomposition based on Equation 7. The results exhibit the patterns of pay gaps and the returns to (individual and group) characteristics at different points of the distribution. As presented in Figure 3, estimates indicate that the estimate of the overall difference between female teachers and non-teachers is substantially positive up to the 40th percentile.[17] The most striking is the result found at the 10th percentile, with the earnings differential between teachers and non-teachers being around 0.39 log points (approximately 47.7%).[18] Notably, an unexplained component is around 0.97 log points. That means, the wage schedule in the teaching sector favors teachers at the 10th percentile markedly, thus enabling them to enjoy a large wage premium. Overall, the wage structure effect illustrates that the earnings of female teachers up to the 60th percentile were not justified by their observed characteristics. In other words, they are paid a higher price for their skills than non-teachers. On the other hand, at the 90th percentile, the pay difference between female teachers and non-teachers is -0.41 log points (-50.67%). Of

[17] Table A1 also contains the results of the compositions for selected percentiles.
[18] Note that it is calculated as $(exp^{0.47} - 1) \times 100$.

this difference, 0.15 log points is an unexplained component. That means that those who are in higher percentiles of the distributions face a wage penalty for being teachers.

For male teachers (Figure 4), the wage premium seems to be concentrated up to the 20th percentile. At the 10th percentile, the earnings gap between male teachers and non-teachers is 0.22 log points (24%). The unexplained gap is 0.44 log points, exhibiting a substantial wage premium. The overall wage premium for male teachers is not as high as that of female teachers. It disappears from the 20th percentile. And, the gap is negative and profound at the 90th percentile. The total difference at the 90th percentile for male teachers is -0.72 log points, and their characteristics, both individual and group, do not explain around 0.54 log points. This could be viewed as a wage premium for working in the non-teaching sector (and consequently a wage penalty for working in the teaching sector).

These findings underpin how teaching is monetarily rewarding for some but provides a wage penalty for others. These differential effects at various percentiles explain why it is difficult to attract teachers from the top quantile of the ability distribution (Hoxby and Leigh 2004, Bacolod 2007, and Corcoran, Evans, and Schwab 2004).

7 Discussion and Conclusion

In this paper, I document new and robust findings concerning the earnings gap between teachers and non-teachers, using various techniques not previously considered in the literature. This paper provides evidence that a standard regression model that only controls for basic characteristics such as race, age, and education severely biases pay gap estimates between teachers and non-teachers. After addressing various biases, I show that female teachers earn 5-10% more than similar non-teachers. Estimates in this paper of the earnings penalty between male teachers and non-teachers are up to two-thirds lower than estimates obtained using a standard regression model used in the previous literature.

In interpreting the results, one caveat is worthy of note. This study does not consider other important aspects of compensation, including fringe benefits, such as health insurance, retirement benefits, and job security. Unlike regular salaries, it is challenging to quantify how generous fringe benefits in the teaching sector are relative to the non-teaching sector due to the paucity of data in household surveys. Nevertheless, it is crucial to consider a few critical fringe benefits while interpreting the results in this paper.

First, one notable feature of the teaching profession is job security. Amid job instability becoming a common feature of the modern labor market (Farber 2010) and job loss producing several monetary and psychological costs, individuals should place importance on having a secure job like teaching. Richwine and Biggs (2011) provide suggestive evidence that job security in teaching can carry a compensation of up to 8 percent. Second, retirement health insurance is another significant perk of being a teacher (see Podgursky 2011). Upon retirement, teachers can continuously utilize the health insurance coverage provided during their employment. This is important considering that individuals who retire before reaching 65 years when they become eligible for Medicare must pay a substantial premium for medical coverage. However, employer-provided medical benefits upon retirement are not widespread; instead, they are declining among private-sector professionals. Third, pension constitutes an attractive benefit to teachers. Koedel and Podgursky (2016) note that around 90 percent of teachers are enrolled in defined benefit (DF) pension plans. Teachers receive annuity based on their salary and years of service. However, private-sector professions are typically enrolled in defined contribution (DC) plans. Under the DC plan, employers make an annual contribution to a worker's retirement funds as long as the worker is employed and does not receive any pension.

This study's findings, along with those of the previous studies, invite the question of why the pay gap between teachers and non-teachers persists. Under the standard theory of competitive labor markets, it is expected that in equilibrium, both the demand for and supply of labor determine wages, with the "law of one price" holding a central role. Such conditions lead teachers and non-teachers with similar skills to earn similar wages, thereby erasing the pay gap. However, frictions in both teaching and non-teaching sectors such as a licensure requirement, transferability of skills across sectors, tenure for teachers, and school administrators' preferences for and ability to identify highly competent teachers hinder movement between the sectors. Thus, the labor market is not able to clear the earnings gap.

This study yields several implications for designing K-12 education policies. Framing the findings using a Roy's (1951) model of occupational choice provides helpful insights into how school districts could improve their policies. Using a comparable comparison group turns an earnings penalty between female teachers and non-teachers into an earnings premium and erases most of the earnings gap between male teachers and non-teachers, indicating the possibility of their skill-based sorting. The wage rigidity in the teaching sector should have made it an attractive occupation for individuals with relatively lower skills. Conversely, highly skilled individuals may have self-selected into occupations that yield higher prices for their skills. Relatedly, one explanation for a rising gap in unadjusted earnings, in recent decades, between teachers and non-teachers documented in the literature could be that the rising prices of skills in the non-teaching sector and the skill-based sorting have led to higher earnings in the non-teaching sector. When such sorting occurs, a standard regression, which is applied in the literature controlling for basic demographic information such as education and race, biases pay gap estimates.

These findings also highlight the implication that policymakers should carefully assess the differential ability distribution of teachers and non-teachers to devise an optimum teachers' salary schedule. Instead of merely considering the salary of non-teachers, school districts should focus on how various teachers' skills are priced in the non-teaching sector. The decomposition of earnings across the entire distribution offers additional corroborating evidence on the potential selection of individuals into teaching based on their ability. The prevailing, rigid pay schedules that do not support differential pay structures based on qualification and competence are the main reason why some teachers enjoy a wage premium while others face a wage penalty. Therefore, school districts should adopt a teacher's compensation mechanism that provides differential and appropriate returns to skills. Specifically, they may want to differentiate the salary schedule according to the teacher type (e.g, primary or secondary) and by their subject of teaching. Doing that can help school districts attract and retain qualified individuals and avoid over-paying some teachers, leading to efficiency gains in its resource allocation.

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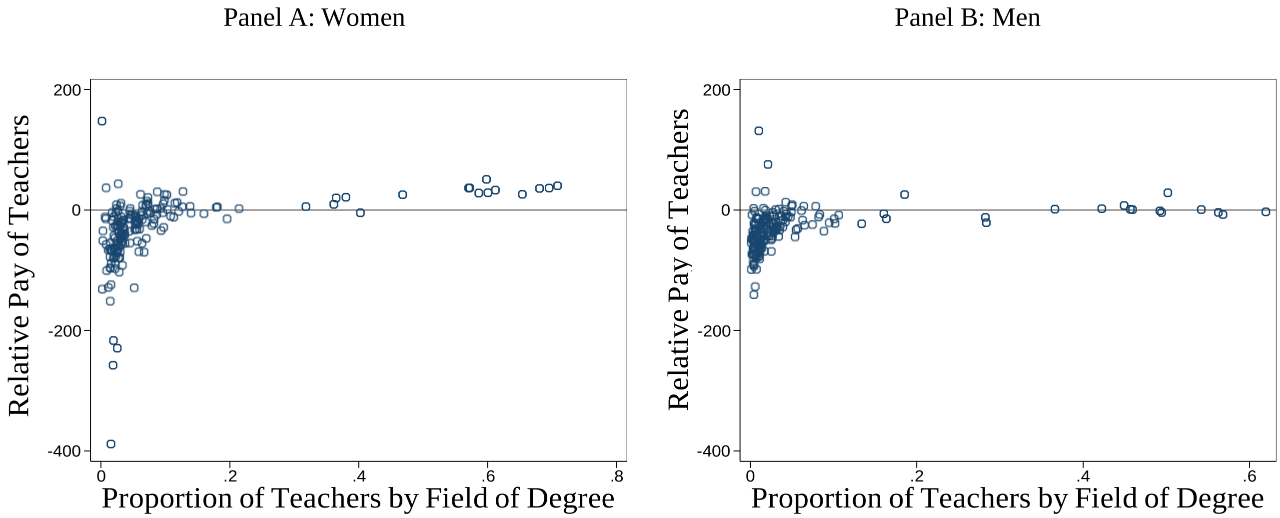
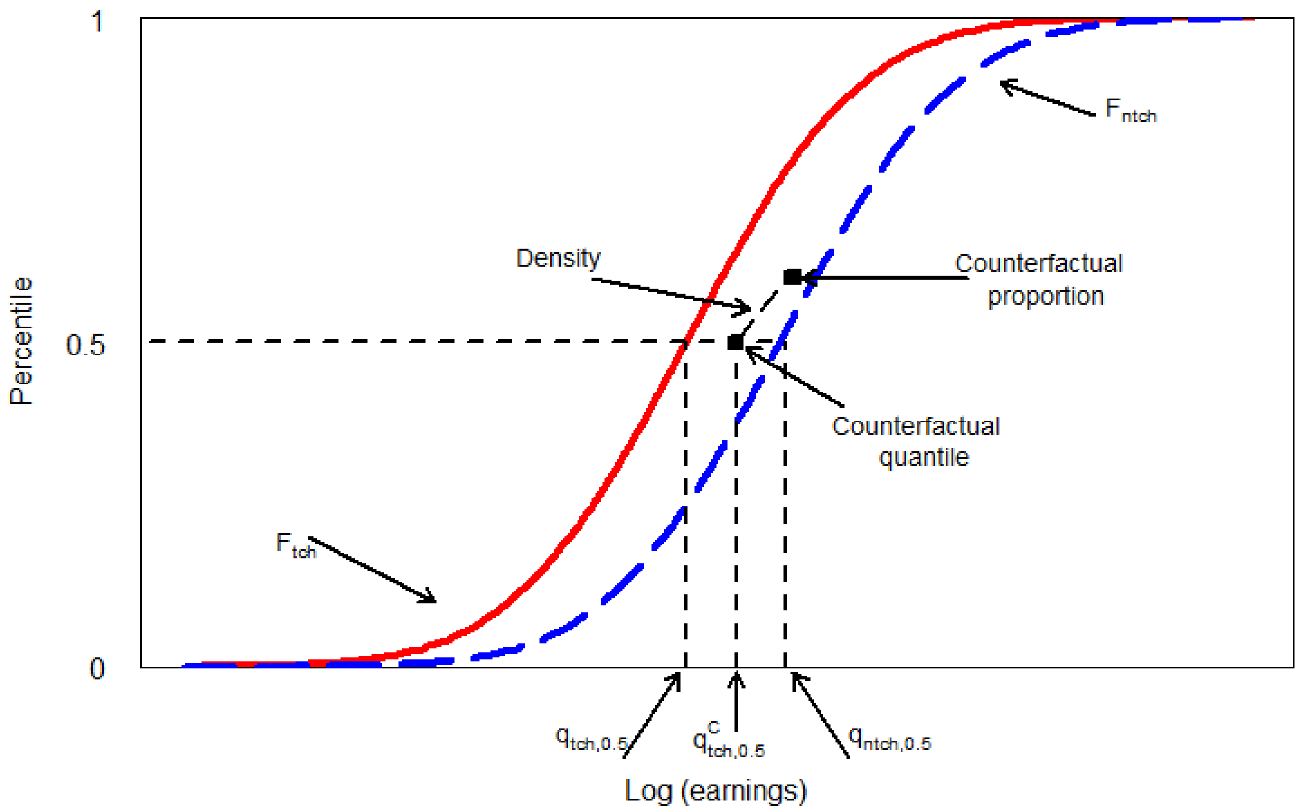
Figure 1: Relative Teacher Pay and Proportion of Teachers by Field of Study



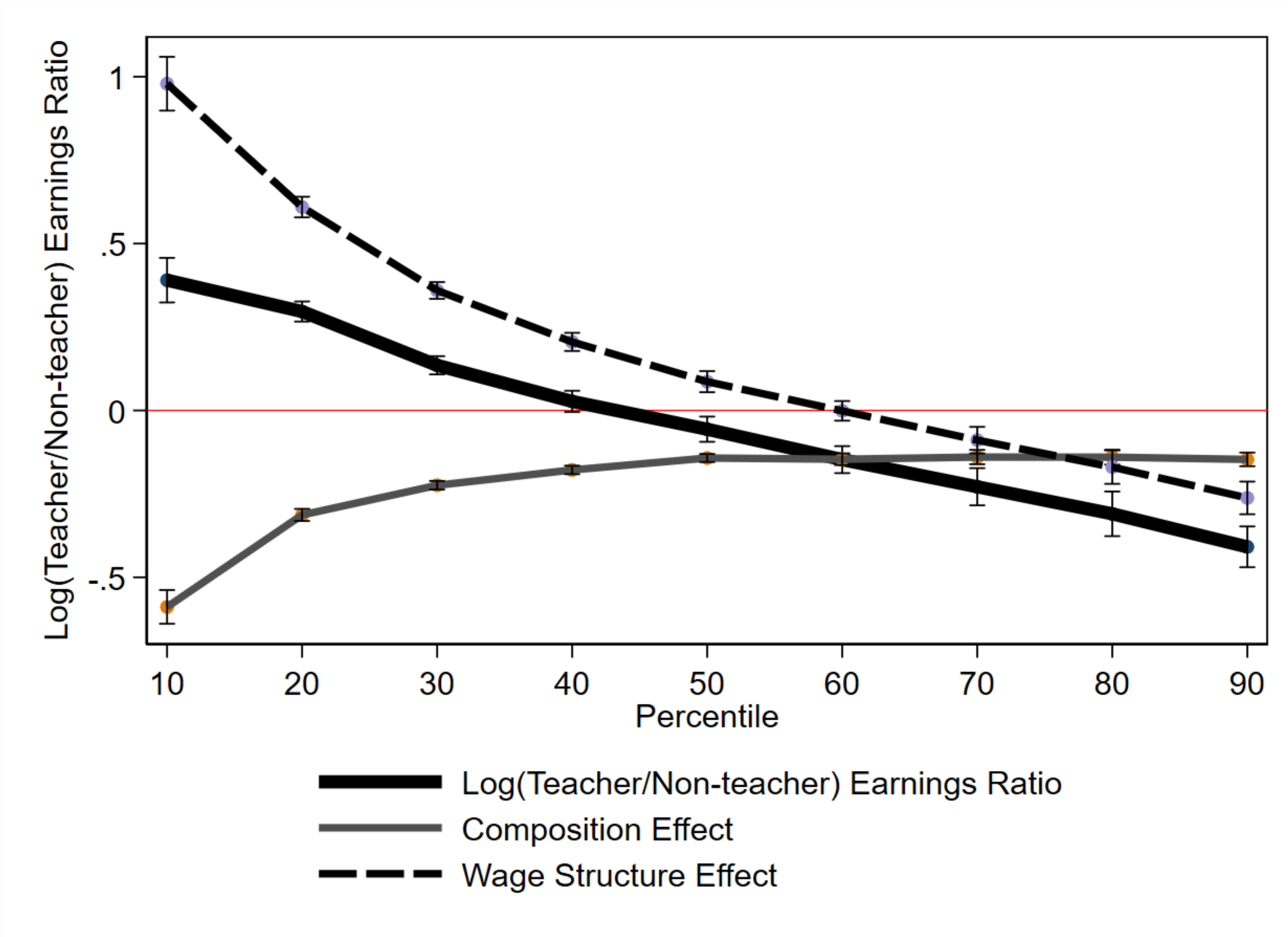
Notes: I estimate the relative earnings of teachers in each field of study, using the American Community Survey for the period 2009-2017, by comparing earnings differences between teachers and non-teachers. Then I plot the relative earnings of teachers (in percent) in a particular field of study against the proportion of individuals becoming teachers from that field of study.

Figure 2: Illustration of Quantile Decompostion Approach



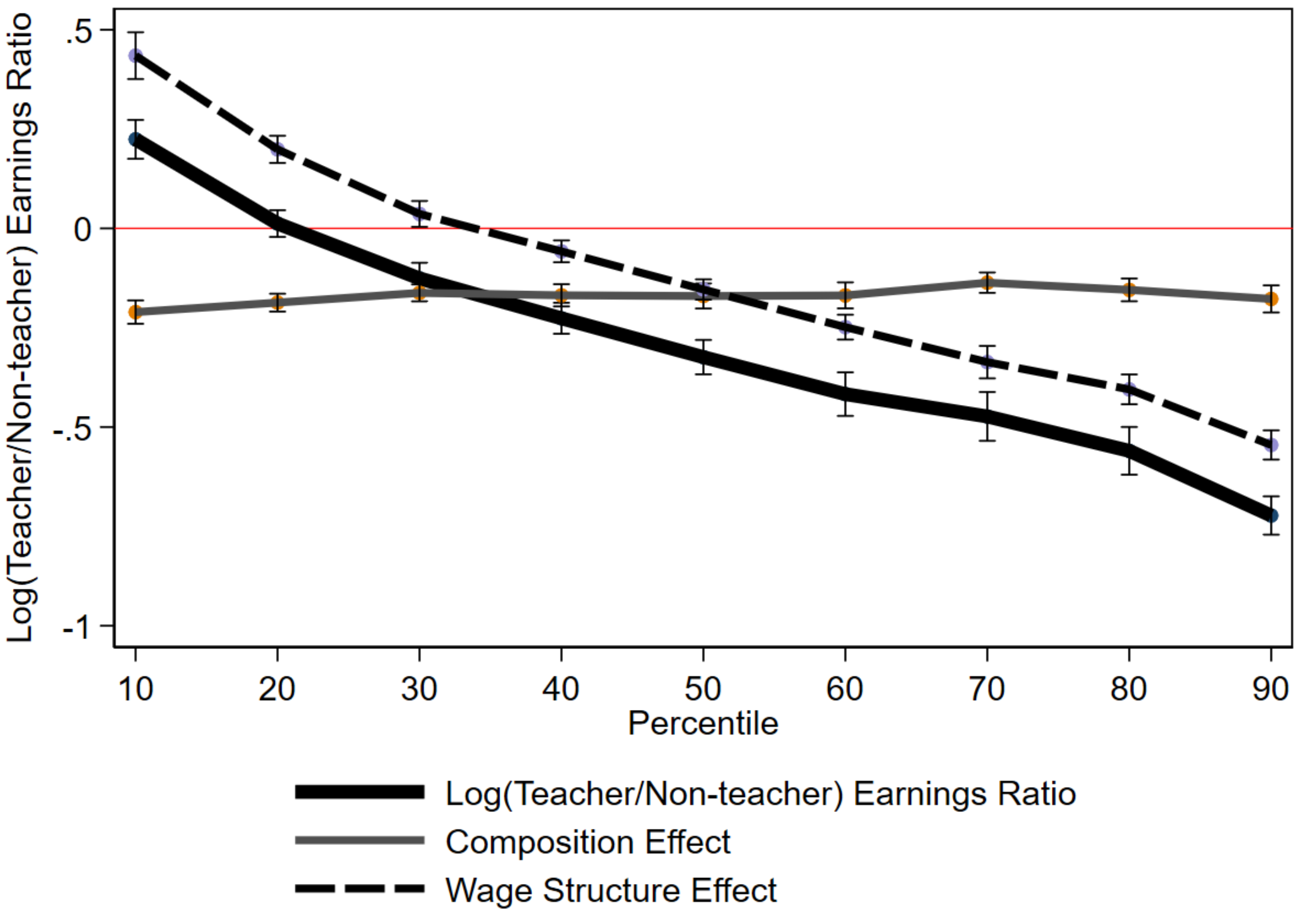
Notes: The figure provides the basic insights into the decomposition approach based on recentered influence function (RIF). F_{tch} represents the cumulative distribution function (CDF) of teachers' earnings and F_{ntch} the CDF of non-teachers' earnings. At the median, the earnings gap between teachers and non-teachers is $q_{tch,0.5}$ - $q_{ntch,0.5}$. The counterfactual earnings of teachers at the median is $q^{C}_{tch,0.5}$. See the text for detail.

Figure 3: Quantile Decomposition of the Pay Gap: Women



Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. I employ the quantile decomposition technique based on the recentered influence function (RIF) approach to calculate these estimates. Bootstrap standard errors are calculated with one hundred replications. The earnings gap at a given percentile is decomposed to a part attributed to individual and group characteristics (composition effect) and to a part attributed to wage schedules (wage structure effect). The overall difference represents the ratio of the log earnings of teachers to the log earnings of non-teachers, i.e., $q_{\tau,tch}\big(ln(earnings)\big) - q_{\tau,ntch}\big(ln(earnings)\big)$.

Figure 4: Quantile Decomposition of the Pay Gap: Men



Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. I employ the quantile decomposition technique based on the recentered influence function (RIF) approach to calculate these estimates. Bootstrap standard errors are calculated with one hundred replications. The earnings gap at a given percentile is decomposed to a part attributed to individual and group characteristics (composition effect) and to a part attributed to wage schedules (wage structure effect). The overall difference represents the ratio of the log earnings of teachers to the log earnings of non-teachers, i.e., $q_{\tau,tch}\big(ln(earnings)\big) - q_{\tau,ntch}\big(ln(earnings)\big)$.

Table 1: Summary Statistics for Women

	Teachers		Non-teachers	
	Mean	SD	Mean	SD
Panel A: ACS Sample				
Log Earnings	10.59	0.761	10.66	0.968
Bachelor's Degree	0.444	0.497	0.65	0.477
Master's Degree	0.521	0.5	0.251	0.434
Professional Degree	0.029	0.168	0.06	0.237
PhD	0.007	0.081	0.039	0.193
Married	0.708	0.455	0.599	0.49
Age	39.404	8.458	38.471	8.63
Number of Children	1.201	1.126	0.918	1.075
White	0.804	0.397	0.7	0.458
Hispanic	0.083	0.276	0.079	0.27
Black	0.072	0.258	0.093	0.29
Other Race	0.042	0.2	0.128	0.334
Observations	337,249		1,717,120	
Panel B: SIPP Sample				
Log Earnings	8.213	0.535	8.243	0.783
Bachelor's Degree	0.461	0.498	0.648	0.477
Master's Degree	0.507	0.5	0.249	0.432
Professional Degree	0.02	0.139	0.055	0.228
PhD	0.007	0.081	0.04	0.196
Married	0.735	0.441	0.633	0.482
Age	42.077	9.332	41.781	9.071
Number of Children	0.968	1.051	0.799	1.011
White	0.79	0.407	0.745	0.436
Hispanic	0.056	0.229	0.06	0.237
Black	0.099	0.299	0.091	0.288
Other Race	0.055	0.228	0.104	0.306
Observations	28,649		174,630	

Notes: I provide summary statistics for women. Panel A reports summary statistics calculated from the American Community Survey and Panel B from the Survey of Income and Program Participation. The statistics are calculated applying weights as described in the text.

Table 2: Summary Statistics for Men

	Teachers		Non-teachers	
	Mean	SD	Mean	SD
Panel A: ACS Sample				
Log Earnings	10.762	0.592	11.09	0.893
Bachelor's Degree	0.447	0.497	0.657	0.475
Master's Degree	0.511	0.5	0.234	0.424
Professional Degree	0.031	0.174	0.061	0.239
PhD	0.011	0.103	0.048	0.214
Married	0.707	0.455	0.67	0.47
Age	39.213	8.316	39.134	8.532
Number of Children	1.139	1.199	1.021	1.181
White	0.8	0.4	0.725	0.446
Hispanic	0.091	0.287	0.074	0.262
Black	0.071	0.256	0.063	0.243
Other Race	0.039	0.194	0.138	0.345
Observations	101,751		1,668,637	
Panel B: SIPP Sample				
Log Earnings	8.346	0.474	8.623	0.711
Bachelor's Degree	0.41	0.492	0.657	0.475
Master's Degree	0.557	0.497	0.224	0.417
Professional Degree	0.021	0.144	0.057	0.231
PhD	0.01	0.101	0.055	0.227
Married	0.764	0.425	0.722	0.448
Age	41.855	8.528	41.896	8.823
Number of Children	1.057	1.165	0.962	1.14
White	0.841	0.366	0.762	0.426
Hispanic	0.082	0.274	0.064	0.244
Black	0.055	0.227	0.063	0.244
Other Race	0.022	0.148	0.111	0.314
Observations	9,844		184,184	

Notes: I provide summary statistics for men. Panel A reports summary statistics calculated from the American Community Survey and Panel B from the Survey of Income and Program Participation. The statistics are calculated applying weights as described in the text.

Table 3: Relative Earnings of Teachers

	(1)	(2)	(3)	(4)
Panel A: Women				
Teacher	-0.093***	-0.075***	0.051***	0.087***
	(0.014)	(0.014)	(0.014)	(0.014)
Observations	2,054,369			
Panel B: Men				
Teacher	-0.373***	-0.332***	-0.174***	-0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	1,770,388			
Indiv. Controls	Y	Y	Y	Y
Field-of-Study Fixed Effects	N	N	Y	Y
Hours Worked Adjustment	N	N	N	Y
CZ Fixed Effects	N	Y	Y	Y

Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. The dependent variable is the log of annual earnings. All regressions include individual controls including age, age-squared, race (non-Hispanic black, Hispanic, and non-Hispanic other race), marital status, education (a master's degree, a professional degree, and a PhD), the number of children, state fixed effects, and year fixed effects. Column 1 reports the results derived from Equation (1), Column 2 from adding commuting zone (CZ) fixed effects, and Column 3 from further adding 176 college major fixed effects. Likewise, in Column 4, I report the results calculated after adjusting for the number of hours worked using the American Time Use Survey. Panel A presents the results for women and Panel B for men. Standard errors are clustered at the state level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 4: Heterogeneous Returns

	Education Majors		Non-education Majors	
	(1)	(2)	(3)	(4)
Panel A: Women				
Teacher	0.317***	0.326***	-0.241***	-0.148***
	(0.012)	(0.011)	(0.023)	(0.023)
Observations	349,123		1,705,246	
Panel B: Men				
Teacher	0.018	0.025	-0.415***	-0.294***
	(0.017)	(0.017)	(0.014)	(0.015)
Observations	119,163		1,651,225	
Indiv. Controls	Y	Y	Y	Y
Field-of-Study Fixed Effects	N	Y	N	Y
CZ Fixed Effects	Y	Y	Y	Y

Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. The dependent variable is the log of annual earnings. Each column in each panel presents estimates from a separate regression that controls for basic characteristics such as education, age, race, marital status, and the number of children. Each regression also includes state fixed and year fixed effects. Columns 1 and 3 present the results without controlling for detailed fields of degree for those majoring in education and outside education, respectively. Columns 2 and 4 add detailed field-of-study fixed effects. Panel A reports the results for women and Panel B for men. Standard errors are clustered at the state level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 5: Controlling for Task Measures of Occupations

	(1)	(2)
Panel A: Women		
Teacher	0.039**	0.054***
	(0.016)	(0.016)
Observations	2,054,369	
Panel B: Men		
Teacher	-0.273***	-0.241***
	(0.016)	(0.016)
Observations	1,770,388	
Indiv. Controls	Y	Y
CZ Fixed Effects	N	Y

Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. The dependent variable is the log of annual earnings. Each column in each panel presents estimates from a separate regression. Each regression includes individual controls such as education, age, race, marital status, and the number of children. Each regression also includes state fixed and year fixed effects. Further, each regression controls for three task measures: abstract, routine, and manual. Column 1 reports the results based on Equation (1), Column 2 from adding commuting zone (CZ) fixed effects. Panel A reports the results for women and Panel B for men. Standard errors are clustered at the state level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 6: Propensity Score Matching Approach: Comparing All Teachers to their Matched Non-Teachers

	(1)	(2)	(3)
		Women	
Panel A: No caliper			
Teacher	0.104***	0.107***	0.098***
	(0.003)	(0.003)	(0.004)
Observations		674,498	
Panel B: 0.2 SD Caliper			
Teacher	0.068***	0.068***	0.070***
	(0.004)	(0.004)	(0.004)
Observations		390,906	
		Men	
Panel C: No caliper			
Teacher	-0.134***	-0.131***	-0.126***
	(0.005)	(0.005)	(0.005)
Observations		203502	
Panel D: 0.2 SD Caliper			
Teacher	-0.150***	-0.149***	-0.146***
	(0.005)	(0.005)	(0.005)
Observations		174,144	
Indiv. Controls	Y	Y	Y
Field-of-Study Fixed Effects	N	N	Y
CZ Fixed Effects	Y	Y	Y

Estimates are based on the American Community Survey (ACS) for the period 2009-2017. The dependent variable is the log of annual earnings. Each column in each panel presents estimates from a separate regression. Column 1 reports the results derived from Equation (1) that controls for basic characteristics such as education, age, race, marital status, and the number of children. Each regression also includes state fixed and year fixed effects. Column 2 adds commuting zone (CZ) fixed effects, and Column 3 further adds 176 college major fixed effects. Panels A and B report the results for women and Panels C and D for men. Panels A and C report the results based on the model that matches teachers with non-teachers without any caliper restriction. Panels B and D use a caliper of a 0.2 standard deviation of the propensity score of the logit model. Standard errors are clustered at the matched-pair level, following Abadie and Spiess (2019). * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 7: Relative Monthly Earnings of Teachers: Using the SIPP Data

	(1)	(2)	(3)	(4)
Panel A: Women				
	Monthly Earnings			
Teacher	-0.034***	0.126***	-0.038***	0.148***
	(0.004)	(0.020)	(0.005)	(0.023)
Observations	203,279	203,279	151,541	151,541
	Hourly Wages			
Teacher	-0.131***	0.033*	-0.131***	0.055***
	(0.003)	(0.019)	(0.004)	(0.021)
Observations	187379	187379	139641	139641
Panel B: Men				
	Monthly Earnings			
Teacher	-0.325***	0.019	-0.324***	0.044
	(0.006)	(0.029)	(0.006)	(0.032)
Observations	194,028	194,028	143,350	143,350
	Hourly Wages			
Teacher	-0.316***	-0.074**	-0.312***	-0.057*
	(0.005)	(0.031)	(0.006)	(0.033)
Observations	178,480	178,480	131,781	131,781
Indiv. Controls	Y	Y	Y	Y
Indiv. Fixed Effects	N	Y	N	Y

Notes: Estimates are based on the 2008 Survey of Income and Program Participation (SIPP) panel. Each column in each panel presents estimates from a separate regression. Column 1 reports the results calculated using the ordinary least squares (OLS) regression and column 2 adds individual fixed effects. Each regression also includes state fixed and year fixed effects. The results in columns 3-4 are estimated in similar ways to those in columns 1-2 but summer months (June, July, August) are dropped. Panel A reports the results for women and Panel B for men. The top part of each panel reports the results based on a model that uses monthly earnings as the dependent variable while the bottom part of each panel uses hourly wages. While calculating hourly wages, I drop observations having imputed work hours. Standard errors are clustered at the state level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Appendix A

American Time Use Survey

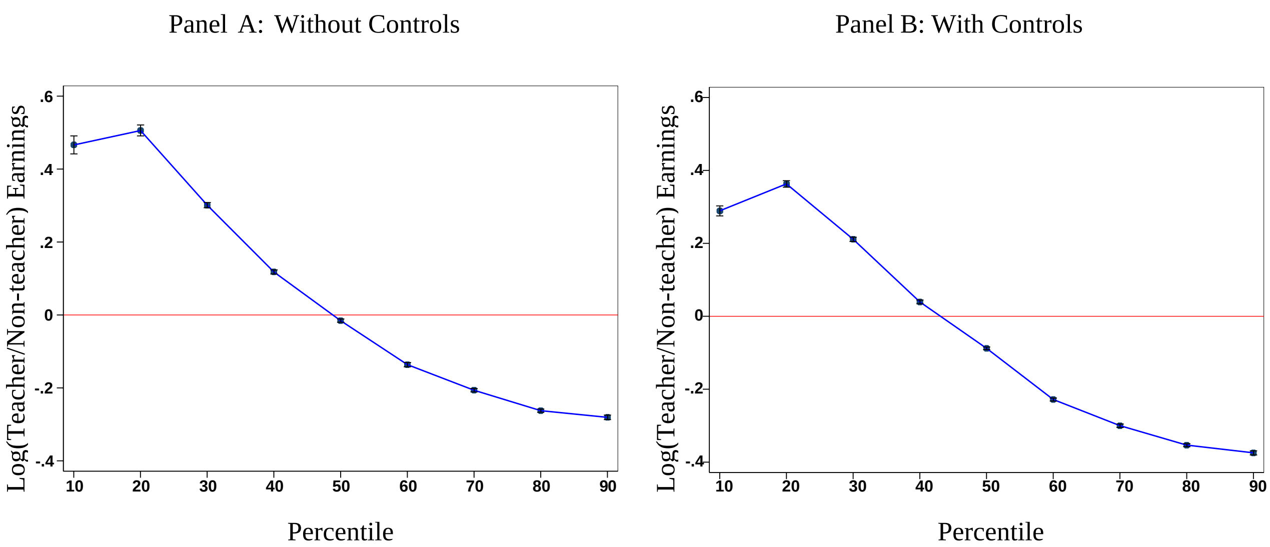
I use the American Time Use Survey (ATUS) from 2009 to 2017, corresponding to the period of my main analysis. The nationally representative survey includes the time-use diary, reporting activities, such as paid work, child care, volunteering, and socializing, done by respondents in a 24-hour window, beginning at 4 am on the previous day of the interview.

I restrict the sample in a similar manner to that of the American Community Survey sample. I use 6-digit activity codes and find activities related to paid work. As in West (2014), I define activity codes from 50100 to 50199, and from 50200 to 50299 as related to paid work. I use the ATUS final weight to calculate the average time worked by teachers and non-teachers as

$$\overline{T_g} = \frac{\sum_i W_i * I_g * T_{ig}}{\sum_i W_i * I_g},$$

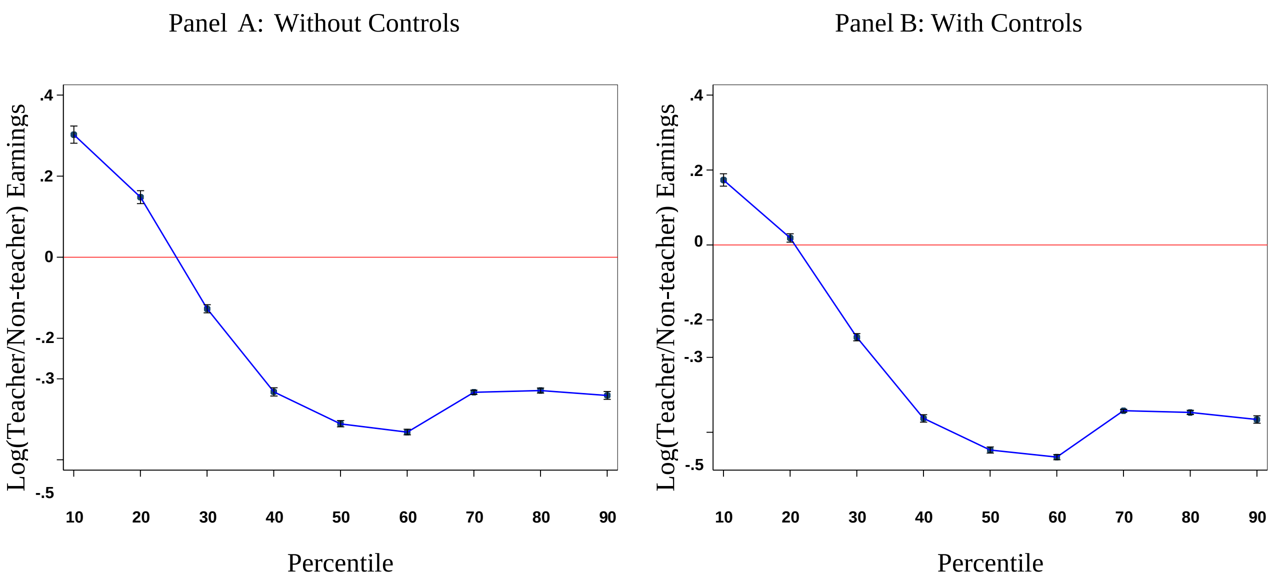
where W_i is the final weight of the respondent, $g \in$ {teacher, non-teacher}, and I_g is indicatorfor a group, that is, the teacher or the non-teacher.

Figure A1 The Earnings Gap across the Distribution: Women



Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. Panel A shows the earnings gaps across the distribution using unconditional quantile regression based on the recentered influence function (RIF) regressions. Panel B reports the results using control variables such as indicators for race, indicators for education, marital status, age, age-squared, the numberof children, college major fixed effects, state fixed effects, and year fixed effects. The analysis is limited to women.

Figure A3: The Earnings Gap across the Distribution: Men



Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. Panel A shows the earnings gaps across the distribution using unconditional quantile regression based on the recentered influence function (RIF) regressions. Panel B reports the results using control variables such as indicators for race, indicators for education, marital status, age, age-squared, the numberof children, college major fixed effects, state fixed effects, and year fixed effects. The analysis is limited to men.

Table A1: Decompositions of the Earnings Gap between Teachers and Non-teachers for Select Percentiles

	10^{th}	50^{th}	90^{th}
Panel A: Women			
Overall Difference	0.390***	-0.056***	-0.409***
	(0.034)	(0.019)	(0.031)
Overall Composition Structure	-0.589***	-0.142***	-0.147***
	(0.026)	(0.006)	(0.010)
Overall Wage Structure	0.979***	0.086***	-0.262***
	(0.041)	(0.016)	(0.025)
Panel B: Men			
Overall Difference	0.224***	-0.324***	-0.723***
	(0.025)	(0.022)	(0.025)
Overall Composition Structure	-0.211***	-0.170***	-0.178***
	(0 .015)	(0.016)	(0.017)
Overall Wage Structure	0.435***	-0.154***	-0.545***
	(0.030)	(0.013)	(0.019)

Notes: Estimates are based on the American Community Survey (ACS) for the period 2009-2017. I employ the quantile decomposition technique based on the recentered influence function (RIF) approach to calculate these estimates. Bootstrap standard errors are calculated with one hundred replications. The earnings gap at a given percentile is decomposed to a part attributed to individual and group characteristics (composition effect) and to a part attributed to wage schedules (wage structure effect). The overall difference represents the ratio of the log earnings of teachers to the log earnings of non-teachers, i.e., $q_{\tau,tch}\big(ln(earnings)\big) - q_{\tau,ntch}\big(ln(earnings)\big)$. Panel A presents the results for men and Panel B for women.

Appendix B

Table B1: Propensity Score Matching Approach: Using Various Caliper Widths

	(1)	(2)	(3)
		Women	
Panel A: 1 SD Caliper Width			
Teacher	0.069***	0.066***	0.066***
	(0.004)	(0.004)	(0.004)
Panel B: 0.75 SD Caliper Width			
Teacher	0.070***	0.067***	0.067***
	(0.004)	(0.004)	(0.004)
Panel C: 0.5 SD Caliper Width			
Teacher	0.069***	0.067***	0.068***
	(0.004)	(0.004)	(0.004)
		Men	
Panel D: 1 SD Caliper Width			
Teacher	-0.148***	-0.150***	-0.147***
	(0.005)	(0.005)	(0.005)
Panel E: 0.75 SD Caliper Width			
Teacher	-0.148***	-0.149***	-0.146***
	(0.005)	(0.005)	(0.005)
Panel F: 0.5 SD Caliper Width			
Teacher	-0.149***	-0.149***	-0.146***
	(0.005)	(0.005)	(0.005)
Indiv. Controls	Y	Y	Y
Fields-of-Study Fixed Effects	N	N	Y
CZ Fixed Effects	N	Y	Y

Notes: Estimates are based on the American Community Survey (ACS) for the period 2009- 2017. The dependent variable is the log of annual earnings. Each regression also includes state fixed and year fixed effects. Column 1 reports the results derived from Equation (1), Column 2 from adding commuting zone (CZ) fixed effects, and Column 3 from further adding 176 college major fixed effects. I use three different caliper widths for both women and men: 0.5, 0.75, and 1 standard deviation of the propensity score of the logit model. Standard errors are clustered at the matched-pair level, following Abadie and Spiess (2019). * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table B2: Share of Teachers by Field of Study

Field of Study	Share
Panel A: Women	
Education Administration and Teaching	62.58%
Business	4.22%
Psychology	3.92%
English Language, Literature, and Composition	3.79%
Social Sciences	3.12%
Liberal Arts and Humanities	2.42%
Fine Arts	2.39%
Biology and Life Sciences	2.1%
Communications	2.07%
Family and Consumer Sciences	1.65%
Mathematics and Statistics	1.46%
Linguistics and Foreign Languages	1.42%
Medical and Health Sciences and Service	1.39%
History	1.37%
Physical Sciences	1.11%
Panel B: Men	
Education Administration and Teaching	49.7%
Business	5.86%
History	5.62%
Social Sciences	5.03%
English Language, Literature, and Composition	3.96%
Fine Arts	3.44%
Mathematics and Statistics	3.01%
Biology and Life Sciences	3%
Physical Fitness, Parks, Recreation, an	2.49%
Communications	2.45%
Physical Sciences	2.38%
Psychology	2.37%
Liberal Arts and Humanities	1.68%
Engineering	1.53%
Linguistics and Foreign Languages	1.02%

Notes: I present the top field of studies from which teachers are drawn, using the American Community Survey (ACS) data for the period 2009-2017. Panel A presents estimates for women and Panel B for men.

Table B3: Major Occupations for Education Majors

Occupation	Share
Panel A: Women	
School teachers	62.06%
Executive, Administrative, and Managerial Occupations	8.67%
Postsecondary Teachers	2.44%
Secretaries, Stenographers, and Typists	2.42%
Management Related Occupations	2.14%
Social Scientists and Urban Planners	2.01%
Cleaning and Building Service Occupations	1.84%
Sales Representatives, Commodities	1.83%
Sales Occupations	1.17%
Adjusters and Investigators	1.16%
Panel B: Men	
School teachers	44.95%
Executive, Administrative, and Managerial Occupations	16%
Postsecondary Teachers	3.28%
Sales Representatives, Commodities	3.17%
Management Related Occupations	2.53%
Social Scientists and Urban Planners	2.49%
Sales Occupations	2.46%
Writers, Artists, Entertainers, Athletes, Lawyers, and Judges	2.28%
Mathematical, Computer Scientists, Engineers, Architects, and Surveyors	1.83%
Transportation Occupations	1.33%

Notes: I present major occupations in which individuals majoring in education work, using the American Community Survey (ACS) data for the period 2009-2017. Panel A present estimates for women and Panel B for men.

Table B4: Occupations Similar to Teachers in terms of Task Contents

Abstract	Routine	Manual
Inspectors and compliance officers	Managers in education and related field	Geologists
Registered nurses	Dietitians and nutritionists	Archivists and curators
Urban and regional planners	Subject instructors	Computer and peripheral equipment operation
Clergy and religious workers	Secondary school teachers	Other law enforcement: sheriffs
Lawyers	Social scientists	Health aides, except nursing
Health record tech specialists	Social workers	Nursing aides, orderlies, and attendant
Radiologic tech specialists	Lawyers	Supervisors of cleaning and building
Biological technicians	Advertising and related sales jobs	Baggage porters
Insurance sales occupations	Bill and account collectors	Aircraft mechanics
Advertising and related sales jobs	Housekeepers, maids, butlers, stewards	Heavy equipment and farm equipment mechanics
Repairers of data processing equipment	Fire fighting, prevention, and inspection	Elevator installers and repairers
Ship crews and marine engineers	Farmers (owners and tenants)	Glaziers
	Farm managers, except for horticultural	Dressmakers and seamstresses
	Garage and service station related occupation	Shoemaking machine operators

Notes: I present select occupations which have task measures close to teachers. Column 1 list similar occupations in terms of abstract task measure, Column 2 routine task measure, and Column 3 manual task measure.