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While investing in the teacher workforce is central to improving schools, school resources are notoriously limited, forcing school leaders to make difficult decisions on how to prioritize funds. This paper examines a critical input to resource allocation decisions: teacher preferences. Using an original, online discrete choice survey experiment with a national sample of 1,030 U.S. teachers, we estimate how much teachers value different features of a hypothetical teaching job. The findings show that (a) teachers value access to special education specialists, counselors, and nurses more than a 10% salary increase or 3-student reduction in class size, (b) investments in school counselors and nurses are strikingly cost-effective, as the value teachers place on each of these support roles far exceeds the per teacher cost of funding these positions, and (c) teachers who are also parents treat a 10% salary increase and a child care subsidy of similar value as near perfect substitutes. These novel estimates of teachers' willingness to pay for student-based support professionals challenge the idea that inadequate compensation lies at the root of teacher workforce challenges and illustrate that reforms that exclusively focus on salary as a lever for influencing teacher mobility (e.g. transfer incentives) may be poorly aligned to teachers' preferences.

VERSION: February 2022

Suggested citation: Lovison, Virginia S., and Cecilia H. Mo. (2022). Investing in the Teacher Workforce: Experimental Evidence on Teachers' Preferences. (EdWorkingPaper: 22-528). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/fygj-e132>

Investing in the Teacher Workforce: Experimental Evidence on Teachers' Preferences

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While investing in the teacher workforce is central to improving schools, school resources are notoriously limited, forcing school leaders to make difficult decisions on how to prioritize funds. This paper examines a critical input to resource allocation decisions: teacher preferences. Using an original, online discrete choice survey experiment with a national sample of 1,030 U.S. teachers, we estimate how much teachers value different features of a hypothetical teaching job. The findings show that (a) teachers value access to special education specialists, counselors, and nurses more than a 10% salary increase or 3-student reduction in class size, (b) investments in school counselors and nurses are strikingly cost-effective, as the value teachers place on each of these support roles far exceeds the per teacher cost of funding these positions, and (c) teachers who are also parents treat a 10% salary increase and a child care subsidy of similar value as near perfect substitutes. These novel estimates of teachers' willingness to pay for student-based support professionals challenge the idea that inadequate compensation lies at the root of teacher workforce challenges and illustrate that reforms that exclusively focus on salary as a lever for influencing teacher mobility (e.g. transfer incentives) may be poorly aligned to teachers' preferences.

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Author contributions: V. Lovison is the lead author of the study, as she led all aspects of the research design, data collection, analysis, and writing of the manuscript. C. Mo secured funding for data collection and provided feedback on the research design, data collection, analysis, and manuscript. V. Lovison and C. Mo jointly conceptualized the paper.

The authors gratefully acknowledge the Berkeley Institute for Young Americans (#52801-13279-40) for funding this research. The authors would also like to thank Michela Carlana, Heather C. Hill, Chad Slife, Eric S. Taylor, attendees at the American Education Finance and Policy Conference, and seminar participants at the Economics of Education workshop at the Harvard Graduate School of Education for helpful comments and feedback.

Resolving quandaries about how to improve teacher recruitment and retention requires understanding how teachers make choices about where to work. With information on teachers' preferences, school leaders can better leverage what resources they have available to better attract, retain, and develop teachers. Further, appealing to teachers' preferences provides a decision framework for understanding how best to allocate resources under conditions of scarcity. Simply, faced with two cost-equivalent options for investing in the teacher workforce, the decision maker should choose the one that teachers value most. The challenge, then, is estimating how much teachers value different features of their job.

This paper takes up this challenge and estimates teachers' employment preferences using a discrete choice survey experiment with a nationally representative sample of 1,030 teachers with respect to grade level assignment, and the gender and race of teachers. Specifically, we presented teachers with pairs of hypothetical teaching jobs, and asked teachers which school in the pair they preferred. We defined each school according to seven features, which were salary, childcare benefits, class size, and four key teacher support roles: school counselors, nurses, special education specialists, and instructional coaches (Note 1). The values assigned to each of the seven features were randomly assigned, breaking the link between salary, school characteristics, and other unobservable factors that also correlate with teachers' employment decisions. We leverage this randomized design to test the causal effect of each job feature on the probability a teacher wanted to work at a given hypothetical school.

Overall, we identified four school features that teachers valued at least as much or more than a 10% increase in salary. These were working at a school that provided 1) a full-time nurse; 2) a full-time counselor; 3) a full-time special education paraprofessional; and 4) a full-time special education co-teacher. Additionally, we found that teachers' preferences for childcare

benefits hinged predictably on whether the teacher had children (and would thus be benefits-eligible) and on the size of the benefit. Eligible teachers valued a \$3,000 per child subsidy (with a \$6,000 annual cap) similarly to a 10% increase in salary, but strictly preferred a 10% increase in salary to a more modest childcare benefit of \$1,500 per child. Finally, we found that class size and instructional coaching had little effect on teachers' employment decisions.

We took advantage of the fact that each profile included salary details to estimate the strength of teachers' preferences for each job feature in terms of their preferences for earning more in salary (i.e. salary equivalents). We then use these estimates to address the key policymaker problem: faced with a choice between increasing teachers' salaries or investing in any of the six alternatives instead, which should they choose? In addressing this question, we focused on increasing teacher salaries by 10%, which is large enough to be substantively meaningful but not so large as to be politically intractable. Ten percent is also within the range of what a teacher might anticipate gaining (losing) by transferring to a contiguous state or district. We classify a benefit as "cost-effective" if the amount teachers are willing to forego in additional salary to receive the benefit exceeds the per teacher cost of the investment. In this exercise of assessing cost-effectiveness, we are assuming the cost of the investment would be evenly distributed across teachers.

These analyses yield three central findings. Assuming an average teacher salary of \$60,000 and an average of 33 teachers per school (NCES, 2020), we learn the following. First, investments in counselors and nurses are highly cost-effective. We estimate the average teacher is willing to trade off a 13% increase in salary (\$7,800) to work at a school with a nurse, which is more than five times the per teacher cost of employing a full-time nurse. Similarly, the average teacher is willing to trade off a 12.5% increase in salary (\$7,487) to work at a school with one

full-time counselor, which is more than four times the per teacher cost of employing a school counselor.

Second, of all the policy options we examined, investments in full-time, in-class special education support were most appealing to teachers, but least cost-effective. The average teacher would be willing to trade off a 16.6% increase in salary (\$12,611) for full-time support from a special education co-teacher and a 12.5% increase in salary (\$10,675) for full-time support from a special education paraprofessional. However, different from the case of the school counselor and nurse, the benefits accrued to teachers fail to offset the cost of hiring the full-time special education specialist, for both the paraprofessional and the co-teacher.

Third, we find that teachers with at least one child under 12 would be willing to substitute a 10% increase in salary for a \$3,000 per child benefit. For a hypothetical teacher making \$60,000 with two children under 12, the average cost to provide either the 10% raise or the childcare benefit would be about \$6,000 per year. However, providing childcare benefits is far less expensive than increasing salary in the long run because districts can cap the benefit at a fixed amount (i.e. we imposed a ceiling at \$6,000 in our design), only a subset of the teaching workforce is eligible, and the benefits expire as teachers' children age out. Notably, we also observe that teachers ineligible for a childcare benefit find working at a hypothetical school that offers childcare benefits more attractive than one that does not. One possible explanation for this result is that family-friendly policies serve as a positive signal of workplace quality. Another is that aspiring parents are anticipating future benefits.

Our work contributes to a growing literature on teachers' preferences (Alva et al., 2020; Fagernäs & Pelkonen, 2012; Fuchsman et al., 2021; Horng, 2009; Johnston, 2020; Viano et al., 2020). These insights into how teachers value various components of their jobs form a basis for

predicting how teachers will respond to policies that aim to influence their behavior, such as incentivizing teachers to stay in the classroom or attracting teachers to work in high-poverty schools. A major contribution of this extant scholarship is the consistent finding that teachers sort into schools located in wealthier neighborhoods for the better working conditions such as principal support, not for the racial or socio-economic composition of the student body (Hornig, 2009; Johnston, 2020; Viano et al., 2020), as many originally suspected (e.g. Hanushek et al. 2004).

We expand on the evidence that administrative support is central to teachers' employment decisions by focusing on concrete investments leaders can make to support their teaching faculties. In particular, we focus on personnel policy—the choices school leaders make about how to manage human resources. Though personnel costs are the single largest line item in a school budget, accounting for 80% of expenditures in the average public school (NCES, 2020), we know very little about the types of personnel investments that are meaningful from teachers' perspectives.

There is a rich debate on school finance and personnel that highlights both the substantial expense of non-instructional support staff (e.g., Roza, 2020) and the critical services these staff provide to students and teachers alike (e.g., Whitaker et al., 2019). On the one hand, investments in support staff *are* investments in the teaching workforce, insofar as non-instructional staff relieve teachers of peripheral responsibilities and enable teachers to prioritize core instructional tasks. On the other hand, funds dedicated to non-instructional staff are funds that could otherwise be allocated towards increasing teacher compensation, either through salary or other pecuniary benefits such as childcare subsidies. Absent from this debate is systematic information on how teachers consider these tradeoffs and what they would or would not be willing to forego in direct

personal benefits to work at a school that employs various support staff. This paper addresses this question directly for four specific staff roles—counselors, nurses, special education specialists, and instructional coaches.

Conceptually, teachers may prefer investments in support personnel over direct compensation, including childcare benefits, for several reasons. First, counselors, nurses, and special education specialists provide essential services that enhance student well-being, which teachers value, but may feel personally ill-equipped or otherwise unable to provide. Second, gains from specialization are possible when schools are staffed with adequate student-based support professionals. By redistributing tasks across several team members, school leaders can help free up teacher time for core instructional duties. Third, by sharing in the total work required to care for students, counselors, nurses, and special education specialists may help lighten teachers' overall workloads and reduce teacher stress, opening up more time for rest and leisure outside of school.

A robust literature documents the strong influence of teachers' working conditions on their employment decisions (Boyd et al. 2011; Johnson & Birkeland, 2003; Johnson et al., 2012; Johnson, 2019; Ladd, 2011; Kraft et al., 2016; Simon & Johnson, 2015). Nevertheless, the idea that inadequate pay lies at the root of teacher workforce challenges is deeply entrenched. Direct feedback from teachers that dissatisfaction with salary is rarely the reason they exit the profession (Goldring et al., 2014) has done little to abate the fixation on teacher salaries as a promising policy lever to attract and retain teachers. As evidence, a great deal of research and public debate focuses on increasing teacher salaries as a key means of addressing persistent teacher workforce challenges, such as chronically understaffed schools and high teacher turnover

(Carver-Thomas and Darling-Hammond, 2017; Glazerman et al. 2013; Goldhaber et al., 2007; Hanushek et al. 2004; Loeb et al., 2005; Nguyen et al., 2020; Rumberger, 1987).

This paper challenges the widely held belief that increasing salary is the most potent strategy to influence teachers' career decisions by identifying a set of alternative investments that teachers value as much or more than an increase to their own salary. Additionally, this study is the first to our knowledge to empirically examine the promise of offering childcare benefits as a policy to attract and retain teachers.

Context

In the average American public school, a teacher earns about \$60,000 annually (Bureau of Labor Statistics [BLS], 2019), receives no childcare benefits, is assigned a class of 21–25 students, and receives some, albeit limited, support from a special education specialist or an instructional coach (United States Department of Education, 2018). While three out of four American schools employ at least one full-time counselor, the average student to counselor ratio is 444:1, far exceeding the recommended ratio of 250:1 (Whitaker et al., 2018). The outlook for school nurses is even more troubling; one in three schools have no full-time nurse on staff (Willgerodt et al., 2018). One objective of this study is to understand whether and how adjusting staffing arrangements would influence teacher mobility—that is, teachers' decisions to work at one school versus another.

The policy decisions we examine share four common characteristics. First, each represents a specific choice that schools and districts must make about how to invest in employees and manage human resources. Second, building on research from Viano et al. (2020), each represents a malleable feature of schools rather than a fixed feature, such as the school's location or the students it serves. Third, each is associated with a knowable cost and can

therefore be incorporated into a cost–effectiveness framework. Fourth, each is theoretically relevant to teachers’ employment decisions.

Our study does not (and could not) cover an exhaustive list of policy choices that satisfy these four criteria. We include salary to facilitate our cost analyses and class size to benchmark our work to the existing literature on teachers’ preferences. We exclude, for example, tenure policies, performance incentives, health insurance, and retirement benefits, as prior work has carefully attended to the relevance of these personnel policies to teachers’ employment decisions (e.g., Strunk et al., 2017; Johnston, 2020; Viano et al., 2020). In comparison, far too little attention has been paid to teachers’ preferences for childcare benefits and school support personnel, thus they are our focus here. We expand on each in the sections that follow.

Childcare Benefits

To date, quantitative policy research on teachers’ preferences has largely overlooked the question of whether offering teachers childcare benefits would be a fruitful strategy to recruit or retain teachers. One reason this topic has yet to be carefully examined is that it is extraordinarily rare for school districts to offer childcare benefits to teachers (Schimke, 2018; Sparks, 2018). The lack of attention to the absence of childcare assistance in schools is surprising given that a robust body of evidence suggests childcare benefits increase women’s participation in the labor market (e.g., Brodeur & Connolly, 2013; Gelbach, 2002; Morrissey, 2017) and teaching is a female-dominated profession (NCES, 2020). In fact, the challenge of juggling family and professional responsibilities without institutionalized, family-friendly workplace supports has long been a top reason women exit the teaching profession (Stinebrickner, 2002). We therefore capitalize on the format of presenting hypothetical teaching jobs in this study to “introduce” this benefit to teachers and report on the response.

Counselors and Nurses

Schools that prioritize investing in student-based health professionals, like counselors and nurses, may be particularly attractive to teachers. Of first order importance, nurses and counselors take care of students' physical, mental, and emotional needs, improving student well-being and improving the chances that students arrive at class ready to learn. Moreover, teaching is emotional labor. When teachers perceive that they or their students lack the support they need to succeed, feelings of teacher burnout and compassion fatigue are common (Koenig et al., 2018). Nurses and counselors may help reduce this risk by providing an infrastructure of support for students and teachers alike. Finally, by narrowing the scope of teachers' professional responsibilities, nurses and counselors may make it possible for teachers to achieve a more sustainable work-life balance.

Instructional Coaches

Prior work suggests that teachers value the opportunity to work in schools that foster professional growth (Johnson, 2006). Employing an instructional coach to work one-on-one with teachers is one option schools have to support teachers' development. A meta-analysis by Kraft et al. (2018) suggested impressive gains in student achievement when teachers were provided with this type of individualized support. However, instructional coaching—particularly consistent, one-on-one coaching—is not yet a standard feature of most American public schools. At least one third of teachers work in schools without a single instructional coach on staff (US Department of Education, 2015) (Note 2). And while it is true that instructional coaches are concentrated in schools that struggle to attract and retain teachers (Domina et al., 2015), it is not clear whether there is strong demand among teachers for this type of support, or whether teachers

feel scarce resources should be allocated elsewhere. Our study helps address these open questions.

Personnel Support for Students with Disabilities

The two most common types of in-class special education support for general education teachers are special education co-teachers and paraprofessional aides. As Jones and Winters (2020) argued, providing teachers with special education support “may alter the allocation of resources in a way that could better leverage current teachers’ abilities” (p. 2). Over the past decade, federal requirements to include students with disabilities in the general classroom have led to a marked change in the composition of these classrooms (Gilmour, 2018). As of 2018, 95% of the 6.7 million U.S. students with disabilities attended regular public schools, and 63% spent the majority of the school day in a general education classroom (US Department of Education, 2018). Importantly, rising rates of inclusion have not been matched with corresponding improvements in academic achievement for these students (National Assessment of Educational Progress, 2015), which suggests teachers may be struggling to support their learning. Consistent with this theory, Gilmour and Wehby (2020) found that teacher turnover rates were higher when teachers were assigned to instruct greater numbers of students with disabilities. Altogether, these signs point to an unmet need for support, both for students with disabilities and for their general classroom teachers. Moreover, they underscore the potential importance of special education staffing to teachers’ employment decisions.

Data

Procedures

We pre-registered this study with the American Economic Association’s registry for randomized control trials. We collected data over a 2-month period using LUCID Marketplace,

from November 2020 to January 2021. Eligible participants received an email invitation with a link to take the survey. The survey took participants approximately 15 minutes to complete. In addition to the choice experiment, the survey included questions on teachers' career values, their beliefs about educational production, their current level of satisfaction in the workplace, their self-reported levels of burnout (following Maslach et al., 2009), and an assessment of whether they were likely to quit teaching in the near future. For a complete list of survey items, please see Appendix B.

The Choice Experiment

In each choice task, we presented teachers with the following prompt: “If two schools were otherwise identical in every other way—same building, same principal, same teaching assignment, same students—which school would you prefer?” Teachers then reviewed the two school profiles and indicated their preferred choice. Teachers repeated this choice exercise five times, and altogether, teachers rated 10,300 unique school profiles (see Appendix C for a sample choice task). As each successive choice task reduces measurement error, we included the maximum number of choice tasks while keeping the total survey length under 15 minutes. Research by Bansak et al. (2018) shows that on surveys like ours with relatively few choice tasks, the risk that respondent decision fatigue will affect response quality is low.

Each of the two school profiles in a choice task were defined by the same seven features, or attributes. In selecting the number of attributes, we aimed to provide sufficient coverage such that teachers felt they had enough information on the schools to make a decision while taking care not to overwhelm them with excess details. The rule of thumb from the market research literature is to keep the number of attributes fewer than 10 to prevent respondent fatigue

(Malhotra, 1982); we narrowed it further, to seven features, after cognitive testing our survey with a pilot sample of teachers.

We selected the values of each attribute for their potential relevance to policy and stakeholder decision making. For instance, each attribute contained a baseline or comparison condition. For the salary and class size attributes, the baseline condition was the status quo (i.e. “same as your current position”). For all other attributes, the baseline condition was the absence of the workplace support (i.e. “no nurse”, “no childcare benefits”). We then specified treatment conditions to maximize the treatment–comparison contrast while remaining pragmatic. Table 1 lists the set of discrete policy choices we examined, alongside their unit cost. We derived median wages from 2019 BLS data, excluding benefits; we calculated the cost of increasing teacher salary by 10% using the average teacher salary of \$60,000. Following Goldhaber et al. (2007), we conceptualized the cost of a 10% reduction in class size (2–3 students for the average classroom) as roughly equivalent to 10% of teacher salary. While the general idea is that reducing class sizes by 10% would require hiring 10% more teachers, we acknowledge that calculating the “true” cost of reducing class size is complex, and depends on a variety of local factors such as space constraints and teacher benefits. Given the geographic diversity of our sample, we adopt this approximate cost strategy for illustrative purposes and simplicity.

Sample

We contracted LUCID, a survey sampling platform, to recruit and survey a national sample of 1,030 U.S. K–12 teachers. Based upon national teacher workforce numbers, we had a hard grade level quota (50% elementary and 50% secondary school teachers), a soft gender quota (77% female), and a soft race quota (80% white). We further screened for occupation on our survey, excluding any individuals not currently working as teachers. To ensure a high-quality

online panel of teachers, we deployed five attention checks in our survey to flag inattentive respondents, and excluded anyone who did not pass all five checks.

Our sampling procedure was successful; much like the national teacher workforce, our sample was 75% female, 81% White, and included a fairly even share of primary and secondary teachers. The majority of teachers in the sample (85%) were working in public schools, and the modal teacher held 10 or more years of experience. Column 1 of Table 2 provides further descriptive statistics on the sample, and Column 2 provides population means for all US teachers as a reference. Compared to the national sample of public school teachers, our sample skewed slightly less experienced, and under-represented teachers from rural areas. Our core analysis did not include sampling weights given that we leverage a high quality online sample of verified teachers where all respondents passed a range of attention checks, our experimental design, and minimal theoretical reasons for large treatment heterogeneity (Miratrix et al., 2018; Coppock et al., 2018); however, including sampling weights does not substantively alter our research findings.

Identification and Model

A core challenge to understanding how teachers decide where to work using observational data is that schools differ along many dimensions. A teacher deciding between two schools might find one appealing for the promised salary and childcare benefits, but another appealing for the small class sizes and special education support. Even when we can observe the schools in a teacher's choice set—which is rare—it is ultimately difficult to say with confidence which feature or features of the preferred school ultimately tipped the scale. The choice experiment employed in the current study overcomes this limitation by presenting teachers with hypothetical school profiles where the school features were randomly assigned.

As Hainmueller et al. (2014) detail, this fully randomized discrete choice design affords several advantages. First, by introducing random variation in school features, we broke the link between school characteristics and unobservable factors that also correlate with teachers' employment decisions. This is an important advantage over observational studies since favorable job features, such as higher pay and better working conditions, tend to bundle together (e.g., Ladd, 2011), making it difficult to disentangle teachers' preferences. Second, by asking teachers to hold constant in their minds all unstated features of the schools in the pair (the principal, the students, the school location), we further reduced the risk that omitted variables account for the relationship between a specific school feature and teacher's decision about whether to work at that school. Third, we simultaneously estimated treatment effects for each of the policy choices examined in the study, a strong efficiency advantage over the modal experimental or quasi-experimental study that focuses on a single treatment at a time.

Estimation

We leveraged this design to estimate two quantities of interest. First, we estimated the probability a teacher would want to work at a school when the school offered a specific benefit (e.g., one full-time nurse) relative to a school without that benefit (e.g., no full-time nurse), holding fixed all other school characteristics. Second, we estimated teachers' willingness to pay for each specific benefit. We discuss each of these estimates in turn.

We estimate the causal effect of each school attribute on the probability a respondent preferred a school profile using simple ordinary least squares regression. Specifically, we regressed the binary choice outcome on a vector of indicator variables for each school attribute using the following model:

$$Y_{ijk} = \beta X_{jk} + \epsilon_{ijk}$$

where teachers are indexed with i , profiles with j , and tasks with k . The choice outcome variable, Y_{ijk} , is a binary variable equal to 1 if the teacher rated the profile as preferred, and 0 otherwise. X is a vector of indicator variables for each attribute. Because the attribute values were randomly assigned to profiles, and profiles were randomly assigned to teachers, the vector of coefficients β capture the independent effect of each attribute on the probability a teacher preferred a school, averaging over the randomization distribution of all other school attributes. Specifically, the coefficient on each treatment dummy represents the estimated average change in the probability a teacher prefers a school profile when the profile includes the attribute “treatment” value rather than the attribute “comparison” value, averaging across all other attributes. Following Hainmueller et al. (2014), hereafter, we refer to these estimates as “average marginal component effects” (AMCEs).

Standard errors are clustered at the teacher level to account for the stability in teachers’ preferences across choice tasks. We did not include choice set fixed effects in our model because unlike in an observational setting where the schools in a teacher’s choice set inherently contain information about teachers’ preferences, the randomization process guarantees school profiles within a given task are statistically independent. Thus, choice set fixed effects were not warranted.

To facilitate our discussion of costs and benefits, we then converted the AMCEs described above to salary equivalents, also called willingness-to-pay (WTP) estimates, by dividing the coefficient on each attribute by the coefficient on a 10% salary increase (see Fuchsman et al. 2020 and Johnston 2020 for related work taking a similar methodological approach). These salary equivalents provide suggestive insights on the amount teachers would be willing to forego in additional income to secure a specific job benefit. The general idea is that in

order to arrive at a decision regarding two schools that vary along multiple dimensions, teachers have to consider their preferences on salary and each of the other attributes presented in the task, as well as how willing they would be to tradeoff salary for other favorable attributes (Bansak et al., 2021). We see clear evidence of these tradeoffs occurring in the data. For instance, of all the school profiles featuring a 10% *decrease* in salary, over one-third were selected as preferred, suggesting teachers are willing to trade off salary for the right set of workplace supports (see Figure 2). We leverage this feature of the discrete choice survey design in order to approximate how much teachers value different features of hypothetical teaching jobs in dollar terms.

Assumptions

Three key assumptions underpin our results. First, interpreting our estimates as teachers' willingness-to-pay requires the assumption that teachers' preferences for salary *increases* are linear from 0 to approximately 21%, the largest willingness-to-pay estimate in the study. A 21% increase in pay represents the upper bounds of what teachers might realistically anticipate gaining by transferring to a contiguous state or district in the real world.

We can use the survey data to partially explore the plausibility of this assumption. The data contains estimates of teachers' preferences over three discrete salary propositions: a 10% increase in salary, a 10% decrease in salary, and no change in salary. A formal test of linearity indeed reveals evidence of loss aversion, and we reject the null hypothesis that teachers' salary preferences are linear along the interval from -10 to 10 ($\beta = -1.41, se = 0.197$). However, crucially, the WTP interpretation only assumes linearity along the *positive* interval from 0 to 21%. Thus, teachers' understandable aversion to a salary loss does not violate this assumption, nor would potential asymmetries in teachers' preferences for very large (and in most cases, unrealistic) salary increases.

Second, a causal interpretation of the results requires the assumption that teachers' preferences are independent of the specific features assigned to the hypothetical schools. This assumption should hold given features were randomly assigned to school profiles and school profiles were randomly assigned to teachers. Accordingly, a series of omnibus *F*-tests suggest no evidence of a systematic relationship between school features and teacher characteristics such as age, gender, race or teacher experience (Table 3).

Third, a causal interpretation of the results hinges on the assumption of "information equivalence" (Dafoe et al., 2018): we must assume that teachers did not update their beliefs about the background characteristics of a particular school within a pair upon reading the description of the school profile. The potential threat is that teachers may have inferred additional characteristics about the schools presented in the choice task, despite the survey instructions to assume the schools in the pair are otherwise identical. For instance, a teacher may have implicitly assumed that a school without a counselor on staff was poorly managed or that a school that employed a full-time school nurse was located in a wealthy school district. To reduce this risk, before every choice task we re-emphasized to teachers that the schools in the pair were located in the same building, served the same students, and were led by the same principal. Nevertheless, we cannot reject the possibility that teachers may have mentally associated the included features of the school with other unincluded school characteristics that may be correlated, at least in their experiences. In this regard, the experimental design does not entirely overcome the risk of omitted variable bias. However, encouragingly, Dafoe et al. (2018) shows that specifying the background variables (as we did, with respect to the students, school facilities, locale, and school principal) lessens this risk substantially.

With these assumptions in mind, we present our results below. Following the key findings, we share further evidence that teachers' preferences do not appear sensitive to specific design features, such as which attribute appears first or last in a task, the order in which the tasks are presented, or the order of the profiles within a task.

Results

Overall, we identify four investments that teachers value at least as much or more than a 10% increase in salary. These are funding for a full-time nurse, counselor, special education paraprofessional, and special education co-teacher. We also identify two investments that teachers value less than a 10% salary increase. These are funding for a three-student reduction in class size and one hour of instructional coaching per month. Finally, we identify that teachers' preferences for childcare benefits hinge on two predictable factors: i) whether the teacher currently has children, and ii) the size of the childcare benefit. Teachers currently with dependents under 12 value a \$3,000 childcare benefit (with a \$6,000 annual cap) similarly to a 10% increase in salary, but strictly prefer a 10% increase in salary to a more modest childcare benefit of \$1,500 per child.

Figure 1 provides a visual summary of teacher preferences over the specific attributes presented in the choice tasks. The plot presents the overall average effect of each attribute on teachers' hypothetical job choices, accounting for all other stated features of the school. For example, presenting a hypothetical school with a 10% salary increase rather than no change in salary, *ceteris paribus*, increased the probability a teacher chose that school by 12 percentage points. Additionally, all other things being equal, presenting a hypothetical school as providing full-time in-class support from a special education co-teacher rather than providing no in-class special education support increased the probability a teacher chose that school by 25 percentage

points. As a point of emphasis, estimates of the overall effect of each attribute are in reference to a specific baseline value (e.g. no salary increase; no in-class special education support), which we display along the x-intercept of each rectangular panel in Figure 1.

For the remaining presentation of results, to facilitate interpretability of our estimates, we rescale the estimates presented in Figure 1 into salary equivalents. We then use these estimates to ground a discussion regarding the cost effectiveness of each approach. We classify an investment as “cost-effective” if the amount teachers are willing to forego in additional salary to secure the benefit exceeds the per teacher cost of the investment. Table 4 presents the main results. Column 1 contains the WTP estimates in terms of a percentage increase in salary. Column 2 provides the estimated WTP in dollar terms, or salary equivalents, assuming a baseline average teacher salary of \$60,000 a year, which is the average teacher salary in the United States at the time of the survey (NCES, 2020). Column 3 presents the average unit cost of each investment per teacher, assuming that there are 33 teachers per school, which is the national average number of teachers per school at the time of our data collection (NCES, 2020). We discuss these results in detail in the sections that follow.

School Nurses

Though funding for school nurses is rarely discussed among strategies to attract and retain teachers, evidence from this experiment suggests school nurses are important to teachers. On average, we estimate that teachers are willing to trade off a 13% increase in salary (\$7,800) to work at a school with a nurse, which is more than five times the per teacher cost of employing a full-time nurse.

While these estimates, and those that follow, pertain to the average teacher, the substantive conclusion that teachers value nurses above and beyond what they cost to provide

holds under a wide range of plausible alternative assumptions. For instance, assuming treatment effects are constant across years of experience, an early career teacher making closer to \$40,000 would be willing to forego an estimated \$5,218 in additional salary to work at a school with a full-time nurse, which exceeds the per teacher cost of hiring a nurse even at very small schools employing as few as 10 teachers.

Counselors

Much like school nurses, school counselors are both important to teachers and cost effective to supply. We estimate that working at a school with one full-time counselor is worth \$7,487 in salary equivalents to teachers, more than four times the per teacher cost of employing a school counselor. Similarly, we estimate that working at a school that employs two full-time counselors is worth \$9,952 in salary equivalents to teachers, which is almost three times the per teacher cost of hiring two counselors. Thus, these results suggest funding up to two full-time school counselors is a smart investment even before factoring in the returns to students.

These school counselor results also highlight non-linearities in teachers' preferences. The value teachers place on working at a school with two counselors is less than double that of a school with just one counselor, suggesting the marginal utility of the provision of school counselors tapers off as the number of counselors increases further.

Special Education Support

Of all the investments we studied, teachers expressed the highest WTP for special education staffing support. The average teacher would be willing to trade off a 12.5% increase in salary (\$10,675) for full-time support from a special education paraprofessional and a 16.6% increase in salary (\$12,611) for full-time support from a special education co-teacher. However, the cost of providing teachers with this type of one-on-one support is far greater than teachers'

estimated WTP, with costs ranging from approximately \$28,000 per year for a full-time paraprofessional aide to \$61,000 per year for a full-time co-teacher. Thus, unlike school counselors and nurses, it is not possible to justify the expense of employing special education support staff on the basis of benefits to teachers alone. Nevertheless, teachers' relatively high WTP for special education support suggests schools' decisions on how to allocate resources towards special education staffing have important implications for the employment decisions of general education teachers. Consistent with this hypothesis, Gilmour and Wehby (2020) found that teacher turnover increased when teachers were assigned to teach more students with disabilities. Our results suggest that increasing investments in special education specialists may be a viable, albeit expensive, option for ameliorating these adverse effects.

These findings also imply that teachers do not appear to hold strong preferences over whether their in-class special education support comes from a paraprofessional or from a co-teacher. This is important given the cost of hiring a paraprofessional is nearly half the cost of hiring a co-teacher (Table 1). Additionally, recent research from North Carolina suggests teaching assistants improve student outcomes (Hemelt et al. 2021), further strengthening the case for investing in paraprofessionals.

Childcare Benefits

Table 5 presents the childcare results separately by eligibility status, where eligible teachers are those with at least one child under 12. Intuitively, we observe that the size of the childcare benefit is meaningful to eligible teachers, but irrelevant to ineligible teachers. Eligible teachers would be willing to trade off a 6% increase in salary (\$3,468) for a \$1,500 per child benefit and an 11% increase in salary (\$4,902) for a \$3,000 per child benefit. Meanwhile, the demand for childcare benefits among ineligible teachers is inelastic to price. Ineligible teachers

would be willing to trade off a 6% increase in salary to work at a school that offered either the \$1,500 per child benefit or the \$3,000 per child benefit.

Several key takeaways follow from these results. First, this data suggests a \$3,000 per child benefit appears to be a good substitute for a 10% increase in salary among teachers with children under 12.¹ However, given the choice between a more modest childcare benefit of \$1,500 per child and a 10% increase salary, both teachers with and without children are more likely to prefer the raise. Second, even teachers ineligible for a childcare benefit find working at a hypothetical school that offers childcare benefits more attractive than one that does not. One possible explanation for these results is that family-friendly policies serve as a positive signal of workplace quality. Another is that hopeful parents are anticipating future benefits. Third, on average across all teachers, a comparison of Columns 2 and 3 in Table 5 reveal that the benefits of implementing even a modest child care subsidy program exceed the per teacher cost.

As a final point, for a teacher with two kids under 12 making the average teacher salary of \$60,000 per year, the cost to provide the small and large benefit (\$3,000 and \$6,000, respectively) are remarkably consistent with our estimates of how much teachers value these benefits in dollar terms (Table 5, Column 2). In both cases, the confidence interval for the WTP estimate contains the true benefit amount. This strong alignment between the direct value of the childcare benefits and teachers' willingness to pay for such benefits provides reassuring evidence that teachers responded rationally to the choice tasks, and lends face validity to the WTP calculations.

Instructional Coaches

On the whole, teachers appear to strictly prefer investments in counselors, nurses, and special education specialists to investments in instructional coaching. However, while the offer

of coaching does not appear to strongly influence teachers' employment preferences, we nevertheless find that the value teachers place on coaching exceeds the cost. In particular, we estimate that coaches are worth about \$2,500 in salary equivalents to teachers, more than double what our back-of-the-envelope calculations suggest is the approximate per teacher cost of instructional coaching (Note 3).

We find it unlikely that our choice to operationalize instructional coaching as occurring for one hour per month weakened teachers' preferences for coaching. A meta-analysis by Kraft et al. (2018) showed that one hour of one-on-one coaching per month was well above the average frequency of coaching in most schools.

Class Size

While we observe that teachers generally prefer smaller classes to larger classes, among all of the school features we studied, teachers showed the lowest WTP for smaller class sizes. Teachers valued a three-student reduction in class size on par with a 3.2% increase in pay, or \$1,920 in salary equivalents. These estimates for class size are remarkably consistent with those reported by Johnston (2020), who found that teachers valued a 10-student reduction in class size on par with an 11.9% salary increase. (Note 4) Additionally, the class size effects are consistent with prior studies indicating that teachers generally prefer receiving more pay to teaching smaller classes, particularly when the proposed class size reductions are modest (Goldhaber et al., 2011; Johnston, 2020; Viano et al., 2020).

Heterogeneity in Teacher Preferences by Grade Span

Figure 3 presents preferences separately for primary (Grades K–6) and secondary (Grades 7–12) teachers. This analysis excludes the 12% of teachers who indicated teaching both primary and secondary grades. While teacher preferences appear fairly consistent across grade

spans, we observe a few modest (and statistically insignificant) differences in the strength of their preferences. In particular, elementary school teachers appear to hold slightly stronger preferences for working at a school that employs a full-time nurse and also appear to care more about class size and instructional coaching. Meanwhile, secondary teachers were somewhat more averse to taking a reduction in salary and held slightly stronger preferences for working at a school that employs school counselors.

Treatment-Treatment Interactions

Appendix Tables A2 (A3) present the 10 most (least) preferred school profiles. We observe that the 10 most attractive school profiles all have at least one counselor on staff as well as some combination of two out of three additional supports (nurse, instructional coach, or special education support). Meanwhile, the 10 least attractive schools profiles each featured a 10% decrease in salary and no counselor on staff.

This snapshot of teacher preferences prompts additional questions of whether certain combinations of attributes are particularly appealing or unappealing to teachers. To address this question, we estimated *average marginal interaction effects (AMIE)*, an estimand proposed by Egami and Imai (2018) which captures the causal interaction between two or more treatments in a conjoint experiment. A nice feature of the AMIE is that the estimated effects are invariant to the specified baseline category, an advantage in empirical settings like this one without a natural control or comparison group. We report the results of this analysis in Appendix Table A4. Because of the large number of possible treatment-treatment interactions, we use a data-driven selection process (e.g., LASSO regression) to reduce false discovery rates, and identify just two significant treatment interactions: Nurse x Salary and Nurse X Counselor. However, these interaction effects have a fairly narrow estimated range of two to three percentage points. We

take the absence of strong interaction effects as evidence consistent with what we would expect to observe if teachers adopted a holistic approach to selecting their preferred school, rather than basing their choices on a small handful of attributes.

Validity and Generalizability

Internal Validity

Our analysis pooled together data for each profile from each profile rated by each teacher. We implicitly treated each as an independent observation, assuming that teachers' preferences were not influenced by the order in which the profiles were presented within a task, the order the attributes were presented within a task, or the order of the tasks themselves (Hainmueller et al., 2014). We discuss each of these assumptions in turn.

No Task Order Effects

We assumed that for any possible combination of school profiles, a teacher would always prefer the same profile in the pair, irrespective of the order in which the task was presented. There are at least two scenarios that would violate this assumption. One possibility is that teachers would view a particular attribute value in a task that would then change their decision-making process for all subsequent tasks. To identify possible task order effects, we estimated AMCEs separately by task, and then examined confidence intervals for each attribute value across tasks. Figure A1 shows that the pattern of results was remarkably similar across tasks, allaying concerns that teachers' preferences were influenced by task order. Another possibility is that teachers would experience decision fatigue as they progressed through the tasks and grow increasingly inattentive. Encouragingly, Bansak et al. (2018) studied this possibility and showed that the risk of survey satisficing due to respondent decision fatigue was minimal on surveys that included many more choice tasks than the current survey.

No Profile Order Effects

We also assumed that for any teacher and task, a teacher would always prefer the same *profile* irrespective of the order with which the pair of profiles was presented within the task (first or second). To examine whether teachers were influenced by profile order, we estimated AMCEs separately by profile. As shown in Figure A2, the sign, magnitude, and statistical significance of each attribute value was consistent across profiles, supporting the assumption that profile order is ignorable.

No Attribute Order Effects

To minimize the risk for attribute order effects, we re-randomized attribute order for every teacher and every task. Thus, the assumption that the order of the attributes within a task was unrelated to teachers' preferences is plausible. To test this assumption, we estimated AMCEs for each attribute by row. For brevity, Figure A3 displays only a subset of these results. Overall, we found no evidence of a systematic relationship between teachers' preferences and the order with which attributes were presented on a profile.

External Validity

An implicit assumption of our design is that the choices teachers make in an online experimental setting offer good approximations of teachers' actual choices in real-world settings. While we cannot test this assumption directly, the broader research literature on choice experiments suggests a strong link between stated and revealed preferences. Most recently, Viano et al. (2020) undertook a validation exercise by pairing experimental data from a choice experiment like this one with administrative data on teachers' actual employment histories. The authors found that teachers' expressed preferences were strong predictors of their employment choices. Discrete choice experiments deployed in other public policy areas of healthcare (Quaife

et al., 2018; Telser & Zweifel, 2007) and transportation (Louviere & Woodworth, 1983) found similarly strong links between individuals' stated preferences on choice experiments and their revealed preferences in the authentic setting of interest.

While this literature establishes that it is possible to estimate real-world preferences using a discrete choice design, the degree to which any given experiment succeeds in this effort hinges crucially on the study details. Thus, we discuss three features of our discrete choice experiment that may influence generalizability: the realism of the choice tasks (i.e., face validity), the timing of the study, and the sample of participants. For each, we describe the steps we took to address each potential threat.

Face Validity

One important consideration for the external validity of a discrete choice experiment is the distribution of the attributes across tasks (de la Cuesta et al., 2021). Like most discrete choice experiments, we employed a uniform distribution, and thus the AMCEs we estimated implicitly assigned equal weights to each school profile. If in practice teachers systematically found some of the randomly generated school profiles more realistic than others, then the uniform weighting would be a suboptimal choice.

Considering this possibility, we selected both the attributes and the range of values assigned to the attributes such that no possible combination of attributes would feel far-fetched enough to teachers to discredit the realism of the thought experiment. A counterexample would be a school offering a 30% increase in salary, or a school with six counselors on staff. To assess whether we succeeded in our efforts to create feasible school profiles, we workshopped our set of attributes and values with a sample of 10 teachers across all four major census regions

(Northeast, Midwest, South, West) until we reached a consensus that the school profiles felt like realistic choices in all locales.

The one major exception to this was our decision to include the childcare subsidy attribute. While childcare benefits are common in sectors outside of education, they are rare in schools. It is thus possible that teachers may have found the prospect of childcare benefits becoming available in their own job market unrealistic. To test whether this influenced teachers' preferences, we subset our sample on the one third of school profiles that offered no childcare benefits ($n=3,410$) and re-estimated AMCEs for this group. As shown in Figure A4, though estimated less precisely, the AMCEs were consistent with those in the full sample, allaying concerns that this design choice influenced teachers' decision-making processes.

Study Timing

As mentioned, we collected data from late November 2020 to January 2021, a period marked by the COVID-19 pandemic. Here, we address the possibility that our findings are sensitive to the timing of the survey. The ideal way to test whether the pandemic may have influenced teachers' preferences would have been to run the experiment before the pandemic and run the experiment after the pandemic, and then compare the results. We approximated this approach as follows: After completing the last task of the choice experiment, we presented teachers with an exact replica of their final choice task. We then explicitly primed them to think back to before the pandemic and indicate whether their preferred school would have been different. Encouragingly, 90% of teachers indicated their choices would have been stable across the two time periods, assuaging concerns that the pandemic influenced how most teachers responded to our survey. This evidence is consistent with findings from Peyton et al. (2020), who

carried out the ideal experiment described above, and successfully replicated pre-pandemic results.

Study Participants

Because our study took place during a time when school districts appropriately suspended much research activity that did not directly pertain to immediate pandemic-response needs, we opted to deploy our study online. One advantage of recruiting an online sample rather than partnering with a specific education agency is that we could assemble a geographically diverse participant pool. A disadvantage is that preferences for teachers who participate in online research may differ from preferences of teachers who either choose not to participate in online research or are unaware of such opportunities.

Despite our best efforts to procure a high-quality sample that included only attentive, K–12 teachers, we cannot rule out the possibility that our teachers may have been unique in unobservable ways. However, the results of our experiment are consistent with those reported by Johnston (2020), who in 2016 deployed a similar choice experiment with a large urban school district in Texas and achieved an impressive response rate of 98% (Note 5). Both the present study and Johnston’s research estimated teachers’ willingness to pay for class size reductions, and the results are nearly identical. We take the stability of the results across both time and place as encouraging evidence that the results of our experiment are unlikely to be substantially biased due to sampling.

Discussion

To gain further descriptive insights into how teachers value various school personnel, we also included a series of items on the survey that asked teachers how valuable they find various support staff. In line with the experimental evidence highlighting the value that teachers place on

nurses, counselors, and special education paraprofessionals and co-teachers, an overwhelming majority of teachers rated nurses (88%), counselors (89%), special education paraprofessionals (92%), and special education co-teachers (93%) as “beneficial” or “very beneficial” (Appendix Table A5). These descriptive findings support our central claim regarding the importance of these support staff to teachers, a “feature” of schools that is too often overlooked in discussions of teachers’ working conditions.

A key limitation of this research is that treatment effects are defined in reference to a specific baseline category. This nuance is important for considering policy implications. For example, while this data clearly suggests that having full-time special education support instead of no special education support influences teachers’ decisions more strongly than the prospect of a 10% raise or no raise, it does not necessarily follow that we should expect to observe the same pattern of preferences if we had set the baseline level of special education support at half or quarter time. Intuitively, it could be that teachers are very averse to no support from a special education specialist, but find part-time support sufficient. While this level of nuance was beyond the scope of the current study, it provides a ripe area for future research, given how important special education staffing models appear to be to teachers’ employment decisions.

A second limitation of the current study is that our discussion of costs and benefits focuses solely on benefits to teachers, whereas the personnel policy choices we studied are likely to have an impact beyond teacher satisfaction. For example, we find that teachers would be willing to trade off approximately \$10,000–\$12,000 in additional salary for full-time support from a special education specialist, yet special education specialists cost a great deal more to provide. However, a more robust cost–effectiveness analysis would additionally incorporate returns to other important constituencies, such as students and their families.

A final limitation is that our sample focused squarely on the existing teacher workforce, not the prospective pool of teacher candidates. As such, our results are most applicable to explaining patterns in teacher sorting across schools, not to explaining teachers' decisions to teach or pursue other career opportunities in the first place. Along similar lines, because the teacher hiring process is often "information-poor" (Liu & Johnson, 2006) and because teachers may be promised supports during the hiring process they do not in turn receive (perhaps due to turnover of key personnel), the patterns we observe in this data may relate more strongly to why teachers leave a school than why they initially sign on to teach at that school. However, at minimum, these results suggest that schools that are staffed with counselors, nurses, and special education specialists should highlight these favorable working conditions to teachers during the recruitment process. This may be especially important for schools serving student populations with high needs.

These limitations notwithstanding, we find overall that reforms that exclusively focus on salary as a lever for influencing teachers' choices of where to work (e.g., transfer incentives) may be poorly aligned with teachers' preferences. More than a modest increase in pay, teachers want to work at a school where they will have the support of full-time counselors, nurses, and special education specialists. These are noteworthy findings precisely because these are not the policy levers typically featured in most debates on how to attract and retain teachers. While providing more teachers with their own full-time special education specialist is likely to be prohibitively expensive for many schools, filling vacant counseling and nursing positions is a far less costly alternative, and one that teachers value a great deal. As of 2019, five million US students attended a school lacking either a counselor, a nurse, or both (Whitaker et al., 2019). Prioritizing funding towards addressing these staffing shortages would both increase essential services for

students and, this study suggests, improve the likelihood a teacher would want to work at one of these schools above and beyond a financial incentive equivalent to a 10% salary increase.

One possible explanation for why teachers may value these student-support professionals more than a modest increase to their own salary is because these support staff members help teachers manage the stresses of teaching. Indeed, over half of teachers (54%) reported their work was emotionally exhausting “to a high degree” or a “very high degree” and 48% reported feeling burnt out because of their work to a high or very high degree (Appendix Table A5). Meanwhile, a small minority (29%) of teachers reported feeling like they have the support they need at school. Schools that invest in student-support professionals can alleviate some of this tension for teachers by ensuring that the enormous responsibility of caring for students is shared broadly across a team of individuals, rather than falling squarely on the shoulders of teachers alone. This shared sense of responsibility and collegiality may go a long way toward reducing work-related stress, preserving teachers’ work time for instructional activities, or increasing time for teachers’ own well-being, any of which could positively influence teachers’ professional satisfaction. For example, on the margin, a teacher could spend an additional hour counseling a student facing a personal hardship after school, or instead, refer that student to the school counselor and spend that hour completing a core instructional task or recuperating for the next day. We know that teachers want to work in schools where they feel they will be successful (Johnson 2019). This research highlights that an important part of this recipe for success may be support from counselors, nurses, and special education specialists.

Finally, this study also examined the impact of childcare subsidies on teachers’ hypothetical decisions on where to work. We find that the average teacher with children under 12 would be willing to trade off a 10% increase in salary for a childcare benefit of similar value,

suggesting that for teacher-parents, salary and childcare subsidies are good substitutes. That teachers' preferences are similar for two pecuniary benefits of similar value is intuitive but interesting since providing childcare benefits is a cheaper alternative to increasing salaries. Unlike across-the-board salary hikes which increase district costs in perpetuity, childcare benefits expire as a teacher's children age out of eligibility, lowering the total cost of the program. However, at least three points of caution are warranted. First, childcare subsidies only directly benefit a subset of the teaching workforce. While we find no evidence that teachers who are not parents are averse to a public investment in childcare subsidies, more careful attention to this question is needed given the opportunity costs of any type of education spending are high. Second, because teacher-parents treat childcare subsidies as interchangeable with salary, we should therefore anticipate that offering childcare benefits would impact teacher recruitment and retention similarly to increasing salary. That is, access to counselors, nurses, and special education specialists is likely more important to teachers than either type of pecuniary benefit. Finally, outside of this study, we know very little about teachers' preferences for childcare support as very few schools across the United States offer these benefits. One study is not sufficient to comprehensively substantiate a policy recommendation; however, this work demonstrates the need for further exploration of what role, if any, childcare benefits could play in shaping teachers' working conditions and employment preferences.

References

- Alva, C., Bobba, M., Ederer, T., León-Ciliotta, G., Neilson, C. A., & Nieddu, M. (2020). *Teacher compensation and structural inequality: Evidence from centralized teacher school choice in Peru* [Conference paper]. National Bureau of Economic Research. http://conference.nber.org/conf_papers/f145585.pdf
- Bansak, K., Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2018). The number of choice tasks and survey satisficing in conjoint experiments. *Political Analysis*, 26(1), 112–119. <https://doi.org/10.1017/pan.2017.40>
- Bansak, K., Hainmueller, J., Hopkins, D. J., Yamamoto, T., Druckman, J. N., & Green, D. P. (2021). Conjoint survey experiments. *Advances in Experimental Political Science*, 19.
- Boyd, D., Grossman, P., Ing, M., Lankford, H., Loeb, S., & Wyckoff, J. (2011). The influence of school administrators on teacher retention decisions. *American Educational Research Journal*, 48(2), 303–333. <https://doi.org/10.3102/0002831210380788>
- Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2005). The draw of home: How teachers' preferences for proximity disadvantage urban schools. *Journal of Policy Analysis and Management*, 24(1), 113–132. <https://doi.org/10.1002/pam.20072>
- Brodeur, A., & Connolly, M. (2013). Do higher child care subsidies improve parental well-being? Evidence from Quebec's family policies. *Journal of Economic Behavior & Organization*, 93(C), 1–16. <https://doi.org/10.1016/j.jebo.2013.07.001>
- Bureau of Labor Statistics. (2019). *Occupational outlook handbook*. Retrieved from <https://www.bls.gov/ooh/>
- Carver-Thomas, D., & Darling-Hammond, L. (2017). *Teacher Turnover: Why It Matters and What We Can Do about It*. Learning Policy Institute.
- Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *The Quarterly Journal of Economics*, 126(4), 1593–1660. <https://doi.org/10.1093/qje/qjr041>
- Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, 104(9), 2633–2679. <https://doi.org/10.1257/aer.104.9.2633>
- Clotfelter, C. T., Ladd, H. F., Vigdor, J. L., & Wheeler, J. (2006). High-poverty schools and the distribution of teachers and principals. *North Carolina Law Review*, 85, 1345–1379. https://scholarship.law.duke.edu/faculty_scholarship/1915

- Coppock, A., Leeper, T. J., & Mullinix, K. J. (2018). Generalizability of heterogeneous treatment effect estimates across samples. *Proceedings of the National Academy of Sciences*, *115*(49), 12441-12446.
- Dafoe, A., Zhang, B., & Caughey, D. (2018). Information equivalence in survey experiments. *Political Analysis*, *26*(4), 399-416.
- de la Cuesta, B., Egami, N., & Imai, K. (2021). Improving the external validity of conjoint analysis: The essential role of profile distribution. *Political Analysis*. Advance online publication. <https://doi.org/10.1017/pan.2020.40>
- Domina, T., Lewis, R., Agarwal, P., & Hanselman, P. (2015). Professional sense-makers: Instructional specialists in contemporary schooling. *Educational Researcher*, *44*(6), 359–364. <https://doi.org/10.3102/0013189X15601644>
- Egami, N., & Imai, K. (2018). Causal interaction in factorial experiments: Application to conjoint analysis. *Journal of the American Statistical Association*.
- Fagernäs, S., & Pelkonen, P. (2012). Preferences and skills of Indian public sector teachers. *IZA Journal of Labor & Development*, *1*(1), 1–31. <https://doi.org/10.1186/2193-9020-1-3>
- Fuchsman, D., McGee, J. B., and Zamarro, G. (2020). Teachers' Willingness To Pay For Retirement Benefits: A National Stated Preferences Experiment. (EdWorkingPaper: 20-313). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/m3b7-nn67>
- Gelbach, J. B. (2002). Public schooling for young children and maternal labor supply. *The American Economic Review*, *92*(1), 307–322. <https://doi.org/10.1257/000282802760015748>
- Gilmour, A. F. (2018). Has inclusion gone too far? Weighing its effects on students with disabilities, their peers, and teachers. *Education Next*, *18*(4), 8–16. <https://www.educationnext.org/has-inclusion-gone-too-far-weighing-effects-students-with-disabilities-peers-teachers/>
- Gilmour, A. F., & Wehby, J. H. (2020). The association between teaching students with disabilities and teacher turnover. *Journal of Educational Psychology*, *112*(5), 1042–1060. <https://doi.org/10.1037/edu0000394>
- Glazerman, S., Protik, A., Teh, B. R., Bruch, J., & Max, J. (2013). *Transfer incentives for high-performing teachers: Final results from a multisite randomized experiment* (No. 4269bc8810414c8a8f64d3c36fde8211). Mathematica Policy Research.
- Goldhaber, D., DeArmond, M., & DeBurgomaster, S. (2007). Teacher attitudes about compensation reform: Implications for reform implementation. *Working Paper 20*. Retrieved from <https://digitalarchives.wa.gov/do/9AEEE8C9CF8A6B2FD8919991FC97A82D.pdf>

- Goldhaber, D., Lavery, L., & Theobald, R. (2015). Uneven playing field? Assessing the teacher quality gap between advantaged and disadvantaged students. *Educational Researcher*, 44(5), 293–307. <https://doi.org/10.3102/0013189X15592622>
- Goldring, R., Taie, S., & Riddles, M. (2014). Teacher Attrition and Mobility: Results from the 2012-13 Teacher Follow-Up Survey. First Look. NCES 2014-077. *National Center for Education Statistics*.
- Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, 22(1), 1–30. <https://doi.org/10.1093/pan/mpt024>
- Hanushek, E. A., Kain, J. F., & Rivkin, S. G. (2004). Why public schools lose teachers. *The Journal of Human Resources*, 39(2), 326–354. <https://doi.org/10.2307/3559017>
- Hemelt, S. W., Ladd, H. F., & Clifton, C. R. (2021). Do teacher assistants improve student outcomes? Evidence from school funding cutbacks in North Carolina. *Educational Evaluation and Policy Analysis*, 0162373721990361.
- Hornig, E. L. (2009). Teacher tradeoffs: Disentangling teachers’ preferences for working conditions and student demographics. *American Educational Research Journal*, 46(3), 690–717. <https://doi.org/10.3102/0002831208329599>
- Jackson, C. K. (2009). Student demographics, teacher sorting, and teacher quality: Evidence from the end of school desegregation. *Journal of Labor Economics*, 27(2), 213–256. <http://dx.doi.org/10.1086/599334>
- Jackson, C. K. (2018). What do test scores miss? The importance of teacher effects on non–test score outcomes. *Journal of Political Economy*, 126(5), 2072–2107. <https://doi.org/10.1086/699018>
- Johnson, S. M. (2006). *The workplace matters: Teacher quality, retention, and effectiveness* [Working paper]. National Education Association. <https://files.eric.ed.gov/fulltext/ED495822.pdf>
- Johnson, S. M. (2019). *Where teachers thrive: Organizing schools for success*. Harvard Education Press.
- Johnson, S. M., & Birkeland, S. E. (2003). Pursuing a “sense of success”: New teachers explain their career decisions. *American Educational Research Journal*, 40(3), 581–617. <https://doi.org/10.3102/00028312040003581>
- Johnson, S. M., Kraft, M. A., & Papay, J. P. (2012). How context matters in high-need schools: The effects of teachers’ working conditions on their professional satisfaction and their students’ achievement. *Teachers College Record*, 114(10), 1–39.

- Johnston, A. C. (2020). Teacher preferences, working conditions, and compensation structure (EdWorkingPaper No. 21–202). Annenberg Institute at Brown University. <https://doi.org/10.26300/hr7y-1137>
- Jones, N., & Winters, M. (2020, November 11–13). *The effect of co-teaching on student performance* [Conference paper]. 2020 APPAM Fall Research Conference. Retrieved from <http://sites.bu.edu/voise/files/2020/06/Effect-of-Co-Teaching.pdf>.
- Koenig, A., Rodger, S., & Specht, J. (2018). Educator burnout and compassion fatigue: A pilot study. *Canadian Journal of School Psychology, 33*(4), 259–278. <https://doi.org/10.1177/0829573516685017>
- Kraft, M. A., Blazar, D., & Hogan, D. (2018). The effect of teacher coaching on instruction and achievement: A meta-analysis of the causal evidence. *Review of Educational Research, 88*(4), 547–588. <https://doi.org/10.3102/0034654318759268>
- Kraft, M. A., Marinell, W. H., & Yee, D. S-W. (2016). School organizational contexts, teacher turnover, and student achievement: Evidence from panel data. *American Educational Research Journal, 53*(5), 1411–1449. <https://doi.org/10.3102/0002831216667478>
- Ladd, H. F. (2011). Teachers' perceptions of their working conditions: How predictive of planned and actual teacher movement? *Educational Evaluation and Policy Analysis, 33*(2), 235–261. <https://doi.org/10.3102/0162373711398128>
- Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational Evaluation and Policy Analysis, 24*(1), 37–62. <https://doi.org/10.3102/01623737024001037>
- Leeper, T. J., Hobolt, S. B., & Tilley, J. (2020). Measuring subgroup preferences in conjoint experiments. *Political Analysis, 28*(2), 207–221. <https://doi.org/10.1017/pan.2019.30>
- Liu, E., & Johnson, S. M. (2006). New teachers' experiences of hiring: Late, rushed, and information-poor. *Educational Administration Quarterly, 42*(3), 324–360.
- Loeb, S., Darling-Hammond, L., & Luczak, J. (2005). How teaching conditions predict teacher turnover in California schools. *Peabody Journal of Education, 80*(3), 44–70. https://doi.org/10.1207/s15327930pje8003_4
- Louviere, J. J., & Woodworth, G. (1983) Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregate data. *Journal of Marketing Research, 20*(4), 350–366. <https://doi.org/10.2307/3151440>
- Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of consumer research, 8*(4), 419–430.

- Maslach, C., Leiter, M. P., & Schaufeli, W. (2009). Measuring burnout. In C. L. Cooper & S. Cartwright (Eds.), *The Oxford Handbook of Organizational Well Being* (pp. 86–108). <https://doi.org/10.1093/oxfordhb/9780199211913.003.0005>
- Miratrix, L. W., Sekhon, J. S., Theodoridis, A. G., & Campos, L. F. (2018). Worth weighting? How to think about and use weights in survey experiments. *Political Analysis*, 26(3), 275-291.
- Morrissey, T. W. (2017). Child care and parent labor force participation: A review of the research literature. *Review of Economics of the Household*, 15(1), 1–24. <https://doi.org/10.1007/s11150-016-9331-3>
- National Assessment of Educational Progress. (2015). The nation’s report card. Retrieved from https://www.nationsreportcard.gov/reading_math_2015/
- National Center for Education Statistics. (2020, April). *Public school expenditures*. https://nces.ed.gov/programs/coe/indicator_cmb.asp
- Nguyen, T. D., Pham, L. D., Crouch, M., & Springer, M. G. (2020). The correlates of teacher turnover: An updated and expanded meta-analysis of the literature. *Educational Research Review*, 31, Article 100355. <https://doi.org/10.1016/j.edurev.2020.100355>
- Peyton, K., Huber, G. A., & Coppock, A. (2020). *The generalizability of online experiments conducted during the COVID-19 pandemic*. SocArXiv. <https://doi.org/10.31235/osf.io/s45yg>
- Quaife, M., Terris-Prestholt, F., Di Tanna, G. L., & Vickerman, P. (2018). How well do discrete choice experiments predict health choices? A systematic review and meta-analysis of external validity. *The European Journal of Health Economics*, 19(8), 1053–1066. <https://doi.org/10.1007/s10198-018-0954-6>
- Roza, M. (2010). *Educational economics: Where do school funds go?* Urban Institute Press.
- Roza, M. (2020). *The big bet on adding staff to improve schools is breaking the bank*. Hoover Education Success Initiative. https://edunomicslab.org/wp-content/uploads/2020/03/roza_webreadypdf_revised.pdf
- Rumberger, R. W. (1987). The impact of salary differentials on teacher shortages and turnover: The case of mathematics and science teachers. *Economics of Education Review*, 6(4), 389–399. [https://doi.org/10.1016/0272-7757\(87\)90022-7](https://doi.org/10.1016/0272-7757(87)90022-7)
- Schimke, A. (2018, July 31). Can in-house child care keep young teachers in the classroom? These districts want to find out. *Chalkbeat Colorado*. <https://co.chalkbeat.org/2018/7/31/21105412/can-in-house-child-care-keep-young-teachers-in-the-classroom-these-districts-want-to-find-out>

- Simon, N. S., & Johnson, S. M. (2015). Teacher turnover in high-poverty schools: What we know and can do. *Teachers College Record*, 117(3), 1–36.
- Smith, T. M., & Ingersoll, R. M. (2004). What are the effects of induction and mentoring on beginning teacher turnover? *American Educational Research Journal*, 41(3), 681–714. <https://doi.org/10.3102/00028312041003681>
- Sparks, S. D. (2018, January 23). *Can child-care benefits keep teachers in the classroom?* Education Week. <https://www.edweek.org/leadership/can-child-care-benefits-keep-teachers-in-the-classroom/2018/01>
- Steiner, E. D. and Woo, A. Job-Related Stress Threatens the Teacher Supply: Key Findings from the 2021 State of the U.S. Teacher Survey. Santa Monica, CA: RAND Corporation, 2021. https://www.rand.org/pubs/research_reports/RRA1108-1.html.
- Stinebrickner, T. R. (2002). An analysis of occupational change and departure from the labor force: Evidence of the reasons that teachers leave. *The Journal of Human Resources*, 37(1), 192–216. <https://doi.org/10.2307/3069608>
- Strunk, K. O., Barrett, N., & Lincove, J. A. (2017). When tenure ends: The short-run effects of the elimination of Louisiana’s teacher employment protections on teacher exit and retirement. *Education Research Alliance Technical Report*.
- Telser, H., & Zweifel, P. (2007). Validity of discrete-choice experiments evidence for health risk reduction. *Applied Economics*, 39(1), 69–78. <https://doi.org/10.1080/00036840500427858>
- U.S. Department of Education (2018). Institute of Education Sciences, National Center for Education Statistics.
- U.S. Department of Education, National Center for Education Statistics, National Teacher and Principal Survey (NTPS), "Public School Data File," 2015–16.
- U.S. Census Bureau (2019). *U.S. Census Bureau United States Population Growth by Region*. Retrieved from https://www.census.gov/popclock/print.php?component=growth&image=/www.census.gov/popclock/share/images/growth_1561939200.png
- Viano, S., Pham, L. D., Henry, G. T., Kho, A., & Zimmer, R. (2020). What teachers want: School factors predicting teachers’ decisions to work in low-performing schools. *American Educational Research Journal*, 58(1), 201–233. <https://doi.org/10.3102/0002831220930199>
- Whitaker, A., Torres-Guillén, S., Morton, M., Jordan, H., Coyle, S., Mann, A., Sun, W-L. (2019). *Cops and no counselors. How the lack of school mental health professionals is harming students*. American Civil Liberties Union.

https://www.aclu.org/sites/default/files/field_document/030419-acluschooldisciplinereport.pdf

Willgerodt, M. A., Brock, D. M., & Maughan, E. D. (2018). Public school nursing practice in the United States. *The Journal of School Nursing, 34*(3), 232-244.

Tables and Figures

Table 1

Values and Unit Costs of Attributes Included in Study

Attribute	Value	Annual unit cost
One-on-one instructional coaching	No coaching	\$0
	One hour of coaching per month	\$66,000 per school
In-class support for students with special needs	No in-class support	\$0
	Full-time support from special education co-teacher	\$61,000 per classroom
	Full-time support from paraprofessional	\$28,000 per classroom
School counselor	No counselor	\$0
	One full-time counselor	\$50,000 per school
	Two full-time counselors	\$100,000 per school
School nurse	No nurse	\$0
	One full-time nurse	\$50,000 per school
Salary	Same as your current position	\$0
	10% more than your current position	\$6,000 per teacher
	10% less than your current position	(−\$6,000 per teacher)
Childcare subsidies ^a	No childcare subsidy	\$0
	\$1,500 per child	\$1,500 per child per eligible teacher; max benefit of \$6,000
	\$3,000 per child	\$3,000 per child per eligible teacher; max benefit of \$6,000
Average class size	Same as your current position	\$0
	3 students fewer than your current position	(−\$6,000 per classroom)
	3 students more than your current position	\$6,000 per classroom

Note. Median wages are derived from BLS (2019) data. Following Goldhaber et al. (2011), we conceptualized the cost of a 10% reduction in class size (2–3 students for the average classroom) as roughly equivalent to 10% of teacher salary and assumed an average teacher’s salary of \$60,000. ^aEligible expenses for reimbursement include cost of attendance at a licensed program (e.g., daycare, before/afterschool care, summer camp) for children ages 0–12.

Table 2*Characteristics of Study Sample and U.S. Teacher Workforce*

	Sample (%)	National (%)
Age (years)	40	42
Female (%)	75	77
Race (%)		
<i>Asian</i>	6	2
<i>Black</i>	9	7
<i>Latinx</i>	9	9
<i>Pacific Islander</i>	0.0	0.2
<i>Native</i>	0.0	0.5
<i>Other</i>	4	2
<i>White</i>	81	79
Teaching experience (years)		
<i>Less than 3 years</i>	12	9
<i>3–9 years</i>	39	28
<i>10 or more years</i>	49	63
School type (%)		
<i>Traditional Public</i>	76	82
<i>Charter</i>	9	5
<i>Private</i>	12	13
<i>Other</i>	4	--
School locale (%)		
<i>City</i>	34	28
<i>Suburb</i>	42	35
<i>Town</i>	12	13
<i>Rural</i>	11	24
School level (%)		
<i>Primary</i>	57	50
<i>Secondary</i>	55	50
Region (%)		
<i>Northeast</i>	23	17
<i>South</i>	35	38
<i>Midwest</i>	25	21
<i>West</i>	18	23
Observations	1,030	--

Note. National estimates are from the US Department of Education’s National Center for Education Statistics (2018). National region means are from the U.S. Census Bureau (2019) and account for the full population (i.e., estimates do not subset on teacher population). Percentages may not sum to 100 due to rounding. School-level percentages do not sum to 100 because teachers indicated teaching students from multiple grade levels.

Table 3*Relationship Between Attribute Values and Teacher Characteristics (Omnibus F Test)*

Teacher characteristic	<i>p</i> value
More than 10 years of experience	0.84
Works at a traditional public school	0.88
Works in the South	0.16
Teacher holds advanced degree	0.81
Teaches Grades K–6	0.80
Teaches Grades 7–12	0.63
Age	0.32
Female	0.52
Parent	0.96
White	0.05
Latinx	0.97
Black	0.36
Observations	1,030

Note. This table reports results from a series of hypothesis tests that the attribute values presented to the respondent jointly predict teacher characteristics. In separate regressions, we regressed each teacher characteristic on dummy variables for each attribute with standard errors clustered at the teacher level. The table reports the *p* value on the omnibus F test.

Table 4*Willingness to Pay Estimates*

Policy	(1) WTP (%)	(2) WTP (\$)	(3) Cost per teacher (\$)
\$1,500 childcare benefit	5.8 (1.1)	3,468 (666)	3,000
\$3,000 childcare benefit	8.2 (1.3)	4,902 (757)	6,000
Three-student reduction in class size	3.4 (1.0)	2,021 (602)	6,000
One full-time SPED paraprofessional	17.8 (2.0)	10,675 (1,221)	28,000
One full-time SPED co- teacher	21.0 (2.3)	12,611 (1,372)	61,000
One hour per week of instructional coaching	4.2 (0.9)	2,495 (520)	2,000
One full-time school nurse	13.0 (1.5)	7,828 (904)	1,515
One full-time school counselor	12.5 (1.5)	7,487 (920)	1,727
Two full-time school counselors	16.6 (1.9)	9,952 (1,118)	3,455

Note. Parentheses include standard errors derived using the delta method. SPED = special education. WTP estimates calculated by dividing the AMCE for each attribute by the AMCE for a 10% salary increase. Column 1 contains WTP estimates in terms of a percentage increase in salary. Column 2 provides WTP estimates in dollar terms, assuming an average teacher salary of \$60,000. Column 3 contains the unit cost of each attribute per teacher. For school-level investments such as nurses as counselors, we estimated cost per teacher using the national average number of full-time teachers per school (n=33).

Table 5*Heterogeneity in Preferences for Childcare Subsidies, by Dependent Status*

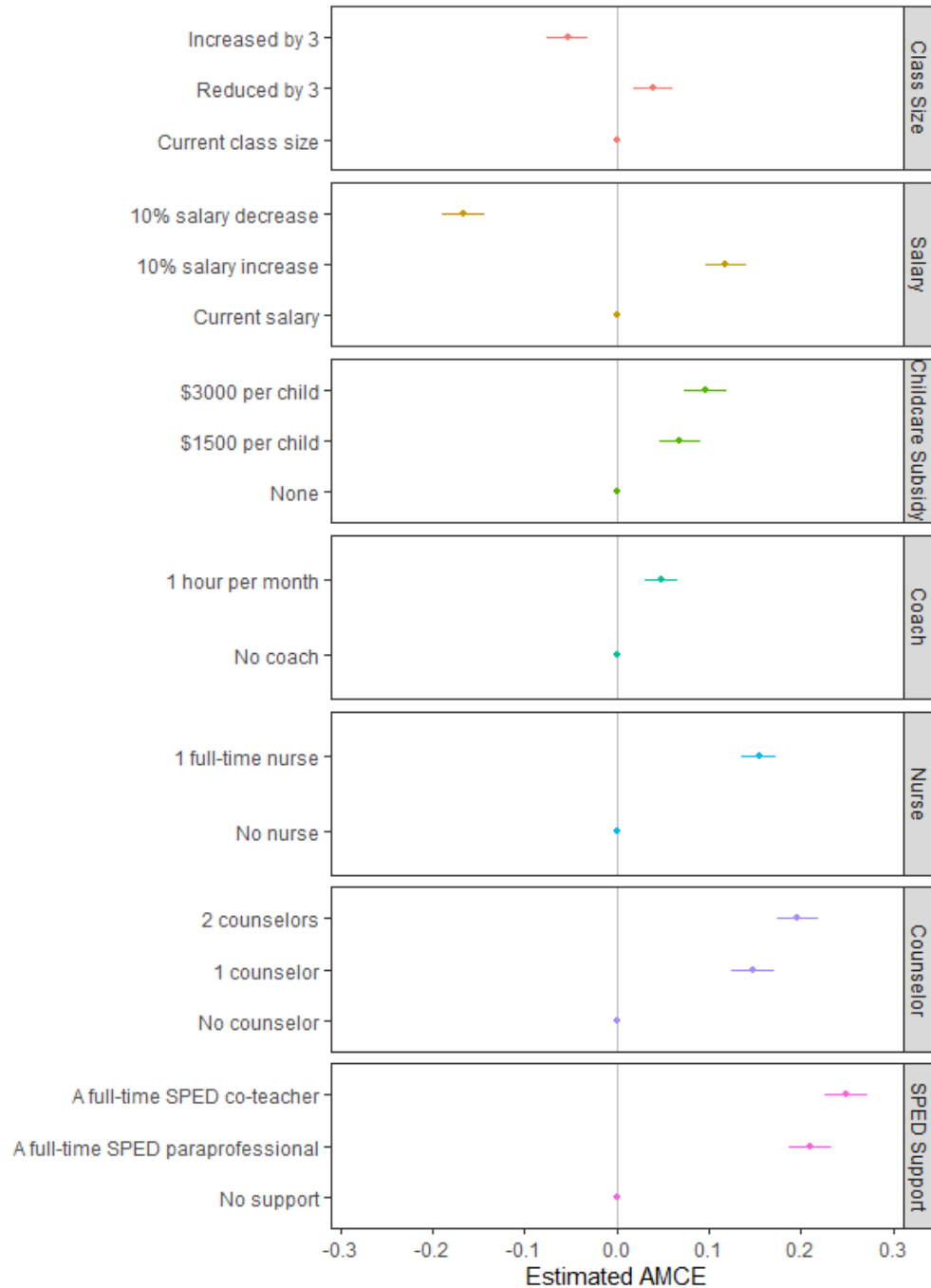
	All teachers	Teachers with no dependents under 12	Teachers with dependents under 12
\$1,500 childcare subsidy	5.78*** (1.11) [\$3,468]	5.85*** (1.51) [\$3,510]	5.83*** (1.67) [\$3,498]
\$3,000 childcare subsidy	8.17*** (1.26) [\$4,902]	6.01*** (1.51) [\$3,606]	10.97*** (2.16) [\$6,582]
Observations	10,300	5,840	4,460

Note. The table reports the WTP for each value of the childcare subsidy attribute. WTP estimates calculated by dividing the AMCE for each attribute by the AMCE for a 10% salary increase. Parentheses include standard errors derived using the delta method. Brackets include the WTP estimate in dollar terms, assuming an average teacher's salary of \$60,000. The estimates in Columns 2 and 3 are from a regression that interacts a parent indicator variable with each of the attribute indicator variables.

* $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 1

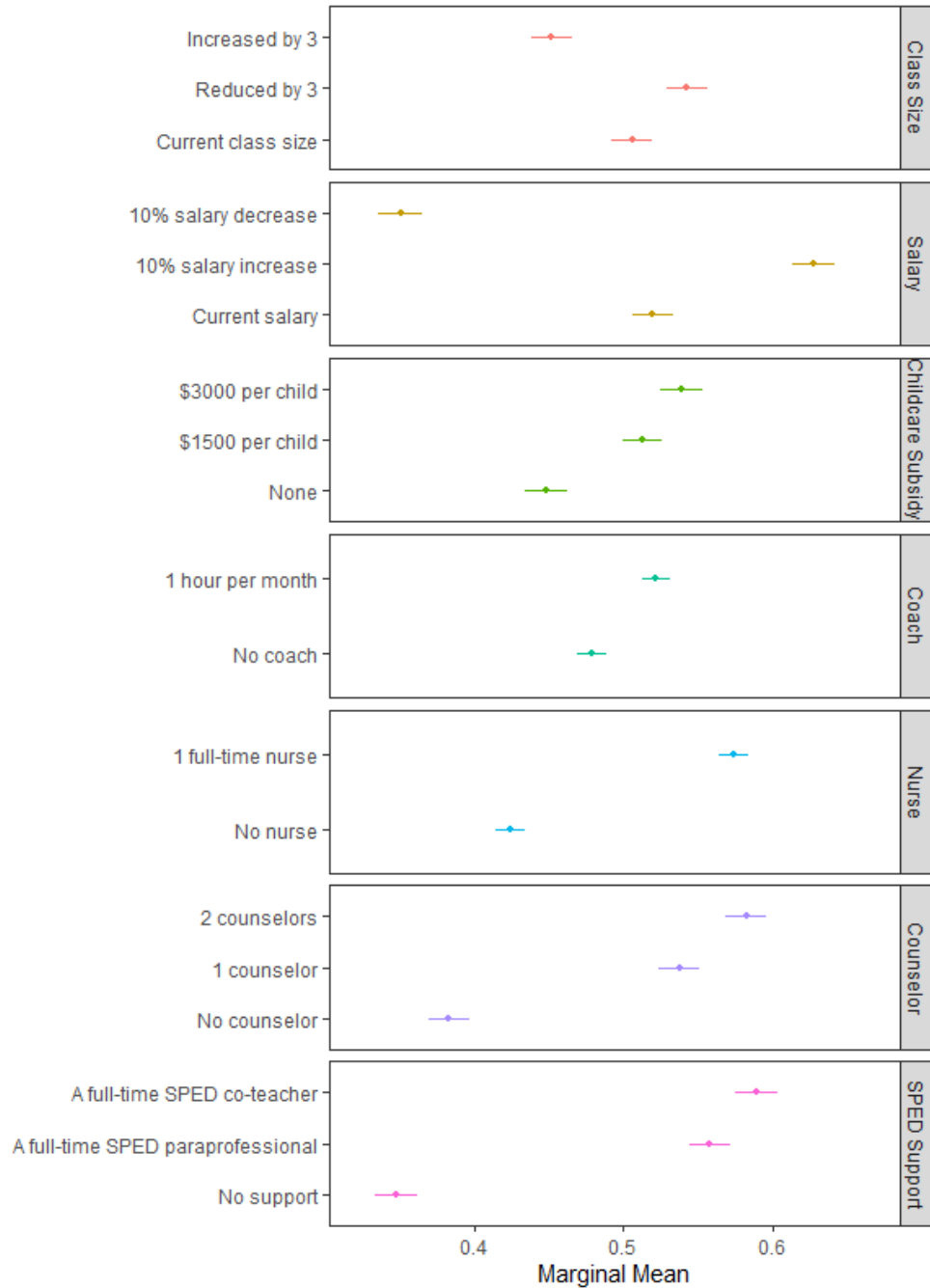
Effects of School Attributes on Teachers' Employment Preferences



Note. This figure presents estimates of the effects of each school attribute on the probability a teacher preferred a given school. The point estimates result from a regression of a binary indicator for whether or not a specific school profile was preferred on a full set of indicator variables for each school attribute. Standard errors are clustered at the teacher level. The error bars surrounding each estimate depict 95% confidence intervals.

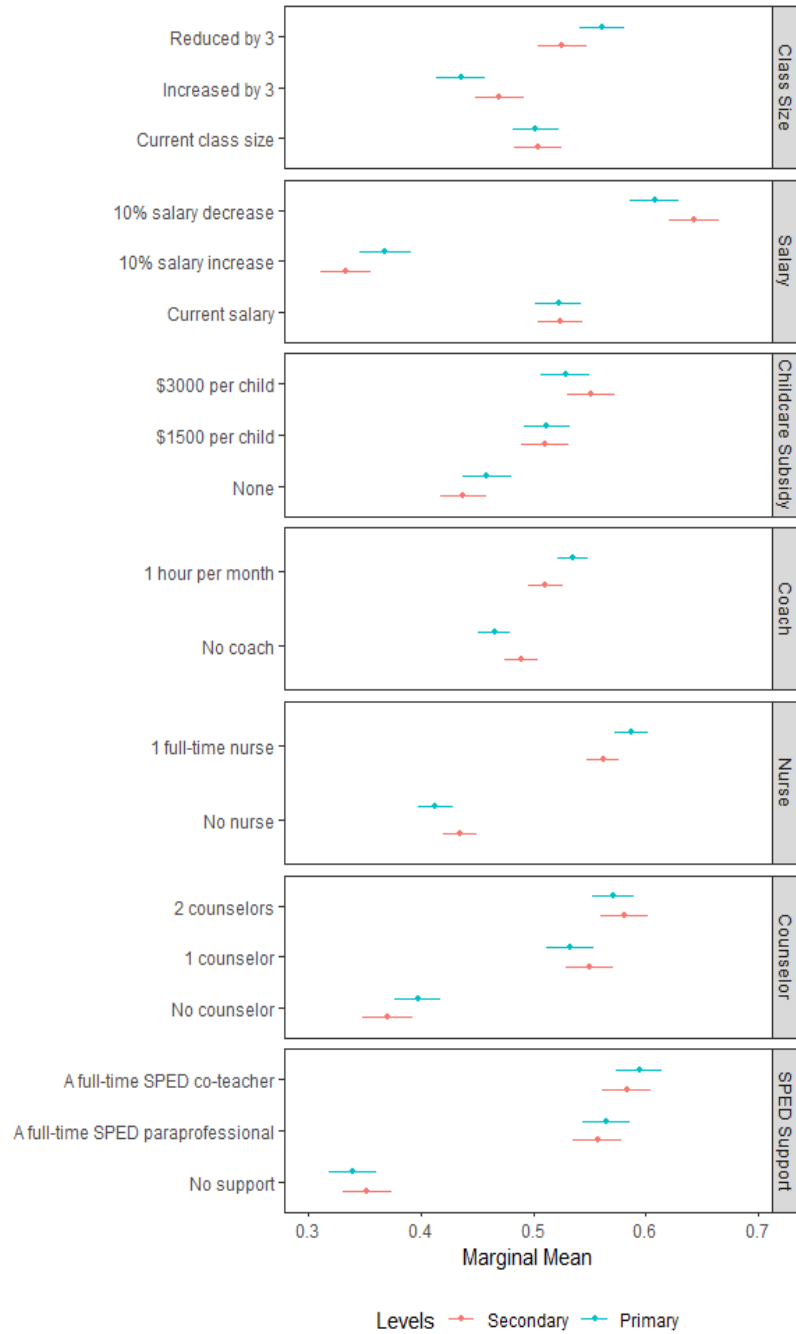
Figure 2

Probability a Teacher Preferred a School Conditional on Each Attribute



Note. This plot presents the simple probability that a teacher preferred a school when it contained each of the listed attributes.

Figure 3
Teacher Preferences by Grade Level (Primary or Secondary)



Note. The figure reports preferences for each attribute, separately for primary teachers (Grades K–6) and secondary teachers (Grades 7–12). Each estimate is shown alongside a 95% confidence interval. The marginal means represent the simple probability a teacher prefers a profile when it contains a given feature, ignoring all other features. We present marginal means as descriptive statistics when drawing comparisons across two groups (rather than presenting average marginal component effects) to examine possible differences across teachers in preferences for the baseline category.

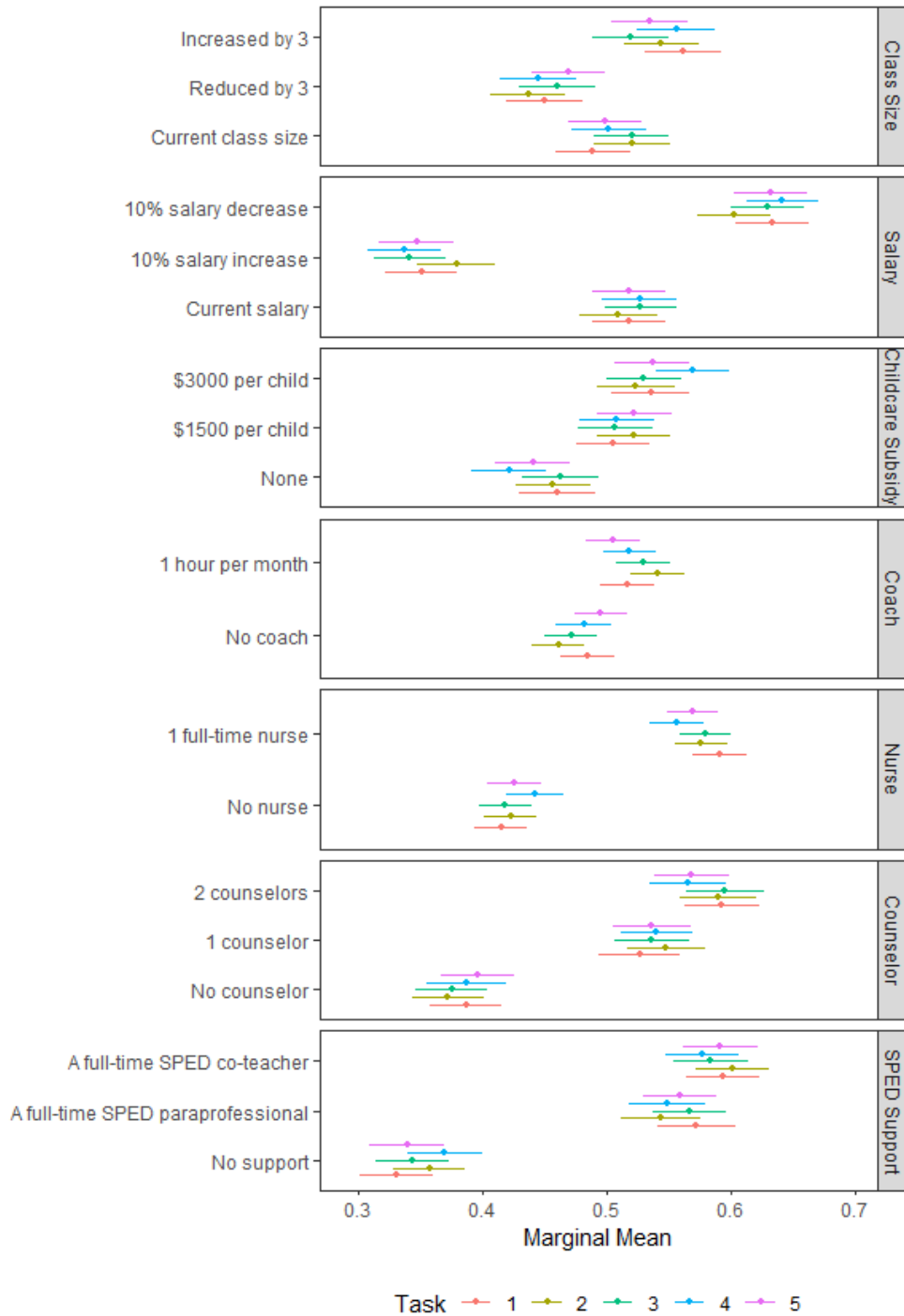
Notes.

1. A detailed discussion of why we selected these seven features is provided in the “Context” section below. Elaboration on why we restricted the number of features to seven can be found in our description of the choice experiment in the “Data” section below.
2. Data from the National Teacher and Principal Survey combines coaches, who work with teachers, and specialists, who work with students. Thus, the estimate of one-third of schools with no coach should be interpreted as a lower bound.
3. The average coach makes \$66,000 per year, or approximately \$41 per hour for a coach working 8 hours per day for 200 days per year (180 school days plus 20 additional spread across the beginning and end of the school year). If it takes a coach about three hours of total time to provide one hour of coaching, including preparation, delivery, debriefing, and any administrative paperwork, then the per teacher cost of a coach would be \$41 per hour X 3 hours per month X 9 months per year = \$1,107.
4. A comparison of the class size results of this study alongside those of Johnston (2020) suggest that unlike preferences for other school features, teacher preferences regarding changes in class size are fairly linear.
5. Johnston’s (2020) discrete choice study examined teachers’ preferences for salary structure, retirement benefits, and performance pay.

Online Supplementary Materials

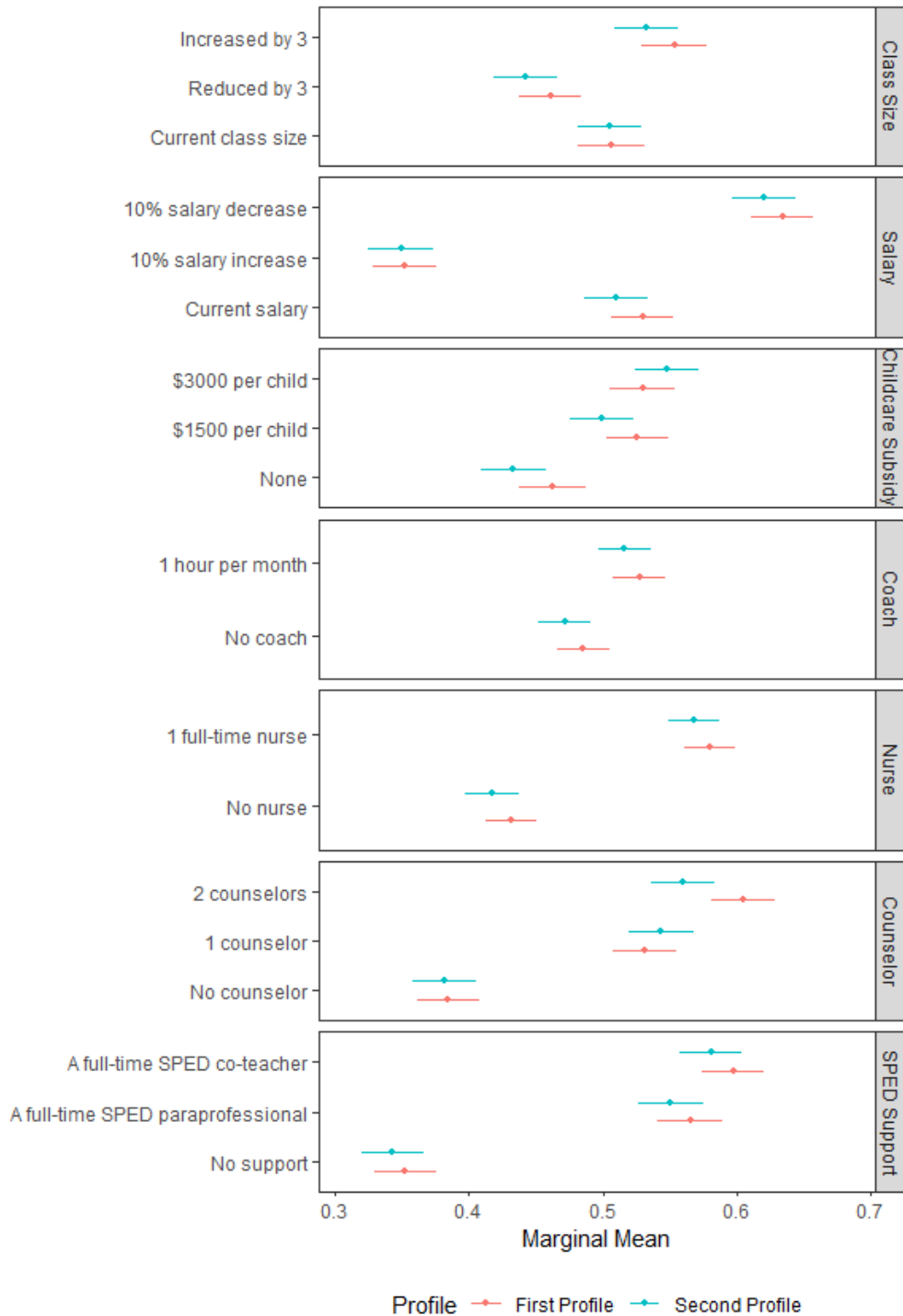
Appendix A: Additional Tables and Figures

Figure A1
Task Order Effects



Note. The figure presents within-teacher variation in preferences for each attribute across the five choice tasks. Each estimate is shown alongside a 95% confidence interval.

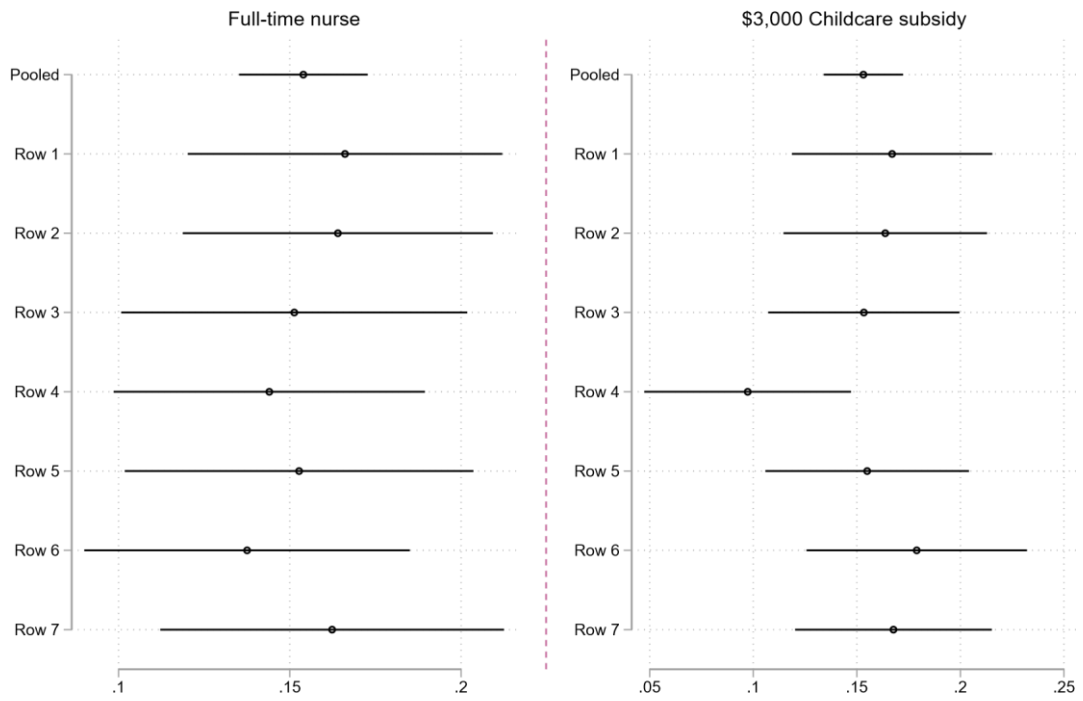
Figure A2
Profile Order Effects



Note. The figure reports the marginal mean for each attribute separately by profile order (first or second). Each estimate is shown alongside a 95% confidence interval.

Figure A3

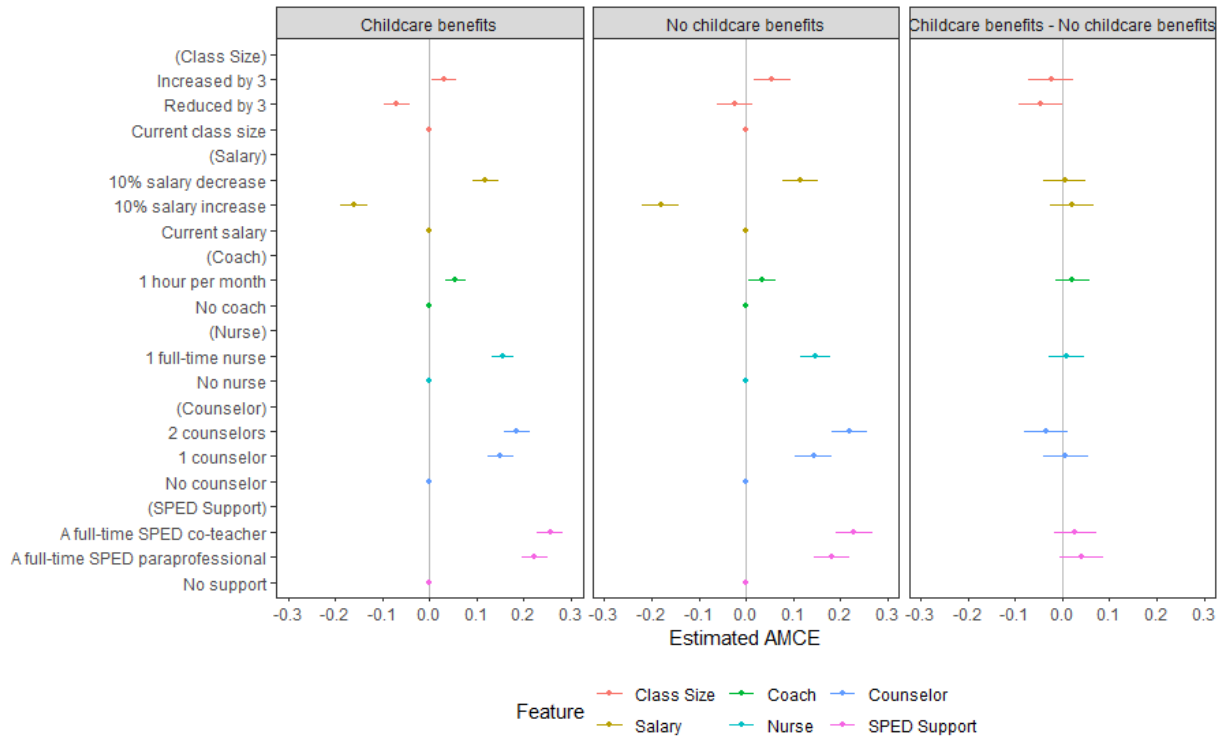
Attribute Order Effects



Note. The figure reports the average effect of two attributes (full-time nurse and \$3,000 childcare subsidy) on the probability a teacher preferred a school profile, separately by row. Each estimate is shown alongside a 95% confidence interval. Each row represents a unique regression.

Figure A4

Difference in Treatment Effects Between School Profiles With and Without Childcare Benefits



Note. The figure reports the effect of each attribute on the probability a teacher preferred a school, separately for schools profiles that (randomly) contained an offer of a childcare benefit and profiles that did not. 95% confidence intervals are depicted. The first panel includes the 6,890 schools profiles that were described as offering either a \$1500 or \$3000 per child benefit. The second panel includes the 3,410 schools that were described as offering no childcare benefits. The third panel presents the difference in treatment effects across the two samples.

Table A1*Teachers' Beliefs on Benefits of School Staff Members*

	Not beneficial at all	Not too beneficial	Somewhat beneficial	Beneficial	Very Beneficial
How beneficial do you believe school nurses are for students?	0	2	10	27	61
How beneficial do you believe school counselors are for students?	0	3	9	26	63
How beneficial do you believe instructional coaches are for teachers?	2	10	27	34	27
How beneficial do you believe it is for teachers assigned students with disabilities to have a co-teacher for support?	0	1	6	22	71
How beneficial do you believe it is for teachers assigned students with disabilities to have a paraprofessional for support?	0	1	7	22	70

Note. $N = 1,030$. Estimates in the table indicate the percentage of teachers who selected each response for that survey item. Due to rounding, not all rows sum to 100%.

Table A2

Top 10 Most Favored School Profiles

Rank	Predicted value	Salary	Childcare Subsidy	Counselor	Nurse	SPED Support	Coach	Class Size
1	0.74	10% increase	None	2 counselors	Nurse	None	Yes	Reduced by 3
2	0.73	Current salary	\$3,000	1 counselor	No nurse	Co-teacher	Yes	Increased by 3
3	0.73	Current Salary	\$3,000	1 counselor	No nurse	Co-teacher	Yes	Current size
4	0.72	10% increase	\$3,000	1 counselor	Nurse	Paraprofessional	No	Reduced by 3
5	0.72	10% increase	\$3,000	1 counselor	Nurse	Paraprofessional	Yes	Reduced by 3
6	0.71	10% increase	\$3,000	1 counselor	Nurse	Paraprofessional	Yes	Current size
7	0.71	Current salary	\$3,000	1 counselor	No nurse	Paraprofessional	Yes	Increased by 3
8	0.71	Current salary	None	2 counselors	Nurse	None	Yes	Reduced by 3
9	0.71	10% increase	None	2 counselors	Nurse	None	Yes	Reduced by 3
10	0.70	10% increase	\$3,000	1 counselor	No nurse	Co-teacher	Yes	Current size

Note. Tables A3 report the probability a teacher selected a profile as preferred when it contained the attributes specified in the corresponding table row.

Table A3

Bottom 10 Least Favored Profiles

Rank	Predicted value	Salary	Childcare Subsidy	Counselor	Nurse	SPED Support	Coach	Class Size
1	0.00	10% decrease	\$1,500	No counselor	No nurse	Co-teacher	Yes	Increased by 3
2	0.00	10% decrease	\$1,500	No counselor	No nurse	Co-teacher	No	Increased by 3
3	0.02	10% decrease	\$1,500	No counselor	Nurse	Co-teacher	Yes	Increased by 3
4	0.03	10% decrease	\$1,500	No counselor	Nurse	None	No	Current size
5	0.03	10% decrease	\$1,500	No counselor	No nurse	Paraprofessional	No	Increased by 3
6	0.03	10% decrease	\$1,500	No counselor	No nurse	Co-teacher	No	Current size
7	0.04	10% decrease	\$1,500	No counselor	No nurse	None	Yes	Increased by 3
8	0.04	10% decrease	\$1,500	No counselor	No nurse	Paraprofessional	No	Reduced by 3
9	0.05	10% decrease	\$1,500	No counselor	No nurse	Co-teacher	No	Increased by 3
10	0.06	10% decrease	\$1,500	No counselor	Nurse	Co-teacher	No	Reduced by 3

Note. Tables A3 reports the probability a teacher selected a profile as preferred when it contained the attributes specified in the corresponding table row.

Table A4

Ranges of Estimated Average Marginal Component Effects (AMCEs) and Average Marginal Interaction Effects (AMIEs)

	Range
AMCE	
Salary	0.27
Special education support	0.23
Counselor	0.20
Nurse	0.17
Childcare subsidy	0.10
Class size	0.09
Instructional coach	0.04
AMIE	
Nurse x Counselor	0.033
Nurse x Salary	0.017

Note. We follow a method proposed by Igami & Imai (2018) to estimate treatment effects and interaction effects in the context of factorial experiments. These estimates are invariant to the specified baseline condition and use a data-driven approach to reduce the false discovery rate. The interaction Nurse X Counselor has a range of 3.3 percentage points and the interaction Salary X Nurse has a range of 1.7 percentage points. Relative to the AMCEs reported here and elsewhere, these interactive effects are quite small. Non-significant interactions are not noted.

Table A5*Self-Reported Teacher Measures (%)*

Panel A: Teachers' feelings of burnout					
	To a very low degree	To a low degree	Somewhat	To a high degree	To a very high degree
Is your work emotionally exhausting?	3	12	31	26	28
Do you feel burnt out because of your work?	9	22	31	18	20
Does your work frustrate you?	12	22	34	17	15
Do you have enough energy for family and friends during leisure time?	3	17	41	29	9
Do you have the support you need at your school to improve your instruction?	7	27	37	20	9
Panel B: Teachers' beliefs on benefits of school staff members					
	Not beneficial at all	Not too beneficial	Somewhat beneficial	Beneficial	Very Beneficial
How beneficial do you believe school nurses are for students?	0	2	10	27	61
How beneficial do you believe school counselors are for students?	0	3	9	26	63
How beneficial do you believe instructional coaches are for teachers?	2	10	27	34	27
How beneficial do you believe it is for teachers assigned students with disabilities to have a co-teacher for support?	0	1	6	22	71
How beneficial do you believe it is for teachers assigned students with disabilities to have a paraprofessional for support?	0	1	7	22	70
Panel C: Teachers' values when considering a job					
	Not important at all	Not too important	Somewhat important	Important	Very Important
How important to you is work–life balance?	0	1	5	31	63
How important to you is salary?	0	1	9	41	49
How important to you is expected stress level?	0	3	14	42	42
How important to you is service to society?	0	3	20	43	34

Note. $N = 1,030$. Estimates in the table indicate the percentage of teachers who selected each response for that survey item. Due to rounding, not all rows sum to 100%.

Appendix B: Survey Items

Staff values questions

Questions pertaining to staff values had the following response choices: *Very Beneficial, Beneficial, Somewhat Beneficial, Not Too Beneficial, Not Beneficial At All*

How beneficial do you believe it is for teachers assigned students with special needs to have a **paraprofessional** for support?

How beneficial do you believe it is for teachers assigned students with special needs to have a **special education co-teacher** for support?

How beneficial do you believe **instructional coaches** are for teachers?

How beneficial do you believe **school counselors** are for students?

How beneficial do you believe **school nurses** are for students?

Career values questions

Questions pertaining to career values had the following response choices: *Very Important, Important, Somewhat Important, Not Too Important, Not Important At All*

When considering a job, how important to you is service to society?

When considering a job, how important to you is the expected stress level?

When considering a job, how important to you is salary?

When considering a job, how important to you are **childcare benefits**?

When considering a job, how important to you is **work–life balance**?

Teaching circumstances questions

Which best describes the school where you work? (*Traditional Public School, Public Charter School, Private School, Other*)

Which best describes your school locale? (*City, Suburban, Town, Rural*)

How many years have you been working as a teacher? (*This Is My First Year, 1–2 Years, 3–5 Years, 6–10 Years, More Than 10 Years*)

On average, how many students do you teacher per class? (*Fewer Than 15, 15–19 Students, 20–24 Students, 25–29 Students, 30 Students or More*)

What grade levels do you teach? Check all that apply. (*Pre-K, K, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12*)

What subjects do you teach? Check all that apply. (*ELL/Bilingual Education, English/Language Arts, Foreign Language, History/Social Studies, Math, Science, Special Education, Other [Please Specify]*)

Which best characterizes your school’s instructional model for the fall of 2020? (*Online Instruction, In-Person Instruction, Hybrid Instruction*)

How effective do you feel at your job right now? [Source: Panorama] (*Not At All Effective, Slightly Effective, Somewhat Effective, Quite Effective, Extremely Effective*)

Overall, how satisfied are you with your job right now? [Source: Panorama] (*Not At All Satisfied, Slightly Satisfied, Somewhat Satisfied, Quite Satisfied, Extremely Satisfied*)

How likely are you to leave teaching in the next 2 to 3 years? (*Very Likely, Likely, Unsure, Not Likely, Very Unlikely*)

Teacher burnout questions

Questions pertaining to teacher burnout had the following response choices: *To a Very High Degree, To a High Degree, Somewhat, To a Low Degree, To a Very Low Degree*

- Is your work emotionally exhausting? [Source: Copenhagen Burnout Inventory]
- Do you feel burnt out because of your work? [Source: Copenhagen Burnout Inventory]
- Does your work frustrate you? [Source: Copenhagen Burnout Inventory]
- Is your work emotionally exhausting? [Source: Copenhagen Burnout Inventory]
- Do you feel you have the support you need at your school to improve your instruction?
- Do you have enough energy for family and friends during leisure time?

Personal characteristics questions

- What is your marital status? (*Married, Civil Union, Living With A Partner, Widowed, Separated, Divorced, Single*)
 - How many children do you have under the age of 13? (*0, 1 or 2, 3 or More*)
 - When you were growing up, would you describe your family as belonging to the..? (*Upper Class, Upper Middle Class, Lower Middle Class, Upper Lower Class, Lower Class*)
 - (Additional embedded demographic data on gender, age, household income, ethnicity, education level, political party, region, zip code)
-

Appendix C: Sample Choice Task

If two schools were otherwise identical in every way—same building, same principal, same teaching assignment, same students—which school would you prefer?

	School A	School B
School nurse	One full-time nurse	One full-time nurse
Salary	10% more than your current position	10% more than your current position
In-class support for students with special needs	Full-time support from special education co-teacher	Full-time support from paraprofessional
School counselor	One full-time counselor	No counselor
Average class size	Same as your current position	3 students fewer than your current position
One-on-one instructional coaching	1 hour of coaching per month	No coaching
Childcare subsidies ^a	No childcare subsidies	\$3,000 per child

^a Eligible expenses for reimbursement include cost of attendance at a licensed program (e.g., daycare, before/after school care, summer camp) for children ages 0–12. Maximum benefit is \$6,000 per family per year.

