American Educational Research Journal
February 2021, Vol. 58, No. 1, pp. 201–233
DOI: 10.3102/0002831220930199
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What Teachers Want: School Factors Predicting Teachers' Decisions to Work in Low-Performing Schools

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Attracting and retaining teachers can be an important ingredient in improving low-performing schools. In this study, we estimate the expressed preferences for teachers who have worked in low-performing schools in Tennessee. Using adaptive conjoint analysis survey design, we examine three types of school attributes that may influence teachers' employment decisions: fixed school characteristics, structural features of employment, and malleable school processes. We find that teachers express a strong preference for two malleable school processes, administrative support and discipline enforcement, along with a higher salary, a structural feature. Estimates indicate these attributes are 2 to 3 times more important to teachers than fixed school characteristics like prior achievement. We validate our results using administrative data on teachers' revealed preferences.

KEYWORDS: low-performing schools, survey methods, teacher preferences, turnaround schools, working conditions

Along with compelling research that finds teachers influence student achievement gains more than any other school-based factor (Chetty et al., 2014; Jackson, 2012; Koedel & Betts, 2007; Rivkin et al., 2005; Rockoff, 2004; Jackson et al., 2014), recent research suggests that recruiting and retaining effective teachers to serve in the lowest performing schools is integral to the success of reforming those schools (Dee, 2012; Henry et al., 2020; Papay & Hannon, 2018; Strunk et al., 2016; Sun et al., 2017). After the disappointing results from initial federal investments in comprehensive school reform, studies in California, Tennessee, Massachusetts, and Ohio found positive effects of school turnaround reforms that required substantial teacher replacements (Carlson & Lavertu, 2018; Dee, 2012; Johnson & Heal, 2017; Papay & Hannon, 2018; Player & Katz, 2016; Strunk et al., 2016; Sun et al., 2017; Zimmer et al., 2017). Moreover, several studies suggest that schools replacing more staff also produced larger positive effects than schools replacing fewer staff (Dee, 2012; Strunk et al., 2016; Sun et al., 2017). In addition, a study of Tennessee's district turnaround networks, known as Innovation Zones, found that nearly 40% of their initial positive effect can be explained by hiring more effective teachers (Henry et al., 2020). The same study found that after initially hiring effective teachers, high rates of teacher turnover suppressed potential positive effects in schools taken over by Tennessee's statewide turnaround model, called the Achievement School District (ASD).

These studies highlight the importance of teacher recruitment and retention in turnaround schools; however, prior studies have also shown that low-

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performing schools are hard to staff. Several studies, many of which rely on administrative data, show that teachers leave high-poverty, high-minority, and low-performing schools at much higher rates than other schools (Guarino et al., 2006; Hanushek et al., 2004; Hughes, 2012; Redding & Henry, 2018). In addition, teacher turnover itself has been shown to have overall negative effects on student achievement (Hanushek et al., 2016; Ronfeldt et al., 2013), effects that are larger and more consistent for within-year turnover (Henry & Redding, 2020). However, the effects of overall teacher turnover should be considered in light of studies that find that positive effects can be produced by intentional efforts to replace existing staff with more effective teachers (Dee, 2012; Strunk et al., 2016; Sun et al., 2017).

In the current study, we use an innovative survey design known as adaptive conjoint analysis to provide insights into school attributes that can affect teachers' labor market decisions focusing on the expressed preferences of a sample of teachers who have chosen to work in low-performing schools targeted for a school turnaround effort in Tennessee known as the ASD. More specifically, we examine expressed school attribute preferences using a sample of three different groups of teachers—(1) teachers who, during the year of our survey, worked at an ASD school, (2) teachers who previously worked at an ASD school prior to our survey year, and (3) teachers who worked in a school that was eventually taken over by the ASD, but left the school before takeover. Since only the first two groups of teachers have experience working in a school operated by the ASD, we refer to these three groups in our sample as ASD-affiliated teachers.

We argue that research utilizing our sample of ASD-affiliated teachers has implications for the preferences of teachers in other states' low-performing and turnaround schools because Tennessee's turnaround efforts have significant overlap with a number of other states' reforms—both in the types of schools targeted for reform and the turnaround interventions.[1] For instance, like most other states' turnaround efforts, Tennessee identifies the 5% of its lowest performing schools (Aragon & Workman, 2015). As of 2016, Tennessee and 28 other states employed a turnaround strategy where schools can be removed from the local district and placed in a state-run district (Jochim, 2016).[2] Similar to reforms in Florida, Illinois, Louisiana, Massachusetts, Michigan, and North Carolina, these schools are then managed outside of the local district, either through an entity like the ASD or authorized external operators, which in Tennessee are authorized charter management organizations or CMOs (Henry et al., 2014; U.S. Department of Education, 2012). The ASD model combines these two management structures by selecting some schools to be directly managed by the ASD and others to be managed by a CMO.

In addition, Tennessee's approach aligns with multiple states that have implemented reforms under the School Improvement Grant (SIG) program.

The SIG program, a signature initiative under the Obama administration, is one of the largest federal investments in educational grants in U.S. history (Dragoset et al., 2017). The SIG program awards grants to states to implement one of four reform models (transformation, turnaround, restart, or closure) in their lowest performing schools. Consistent with SIG requirements, Tennessee's approach utilizes strategic staffing practices, which includes replacing the school leader and teachers (U.S. Department of Education, 2018). Moreover, like Tennessee, many other states implementing SIGs emphasize hiring and retaining high-quality teachers and principals, due to the compelling evidence supporting their influence on student achievement (Chetty et al., 2014; Jackson, 2012; Koedel & Betts, 2007; Rivkin et al., 2005; Rockoff, 2004; Jackson et al., 2014).[3] Since our results are drawn from a sample of teachers who have worked in low-performing schools, both before and after the ASD turnaround interventions began, they are most relevant to the ASD context. However, given the meaningful parallels we have described between Tennessee's ASD and turnaround efforts in other states, we believe our results also have implications for other low-performing schools that will or have already undergone similar turnaround reforms. Henceforth, we refer to our results as relevant to low-performing school settings targeted for turnaround, but note that they are most applicable to turnaround models similar to the ASD (described in more detail below).

While a robust literature has examined teacher preferences more generally (e.g., Horng, 2009; Ladd, 2011), few studies have explicitly examined teachers with experience in low-performing school settings. Teachers who have shown they are willing to work in these schools may have distinctly different concerns from those who do not have experience in these environments. We contribute to this sparse literature with more information on the specific population of teachers who are willing to work in low-performing and turnaround schools. To do so, we use adaptive conjoint analysis, an innovative survey method that has not previously been utilized to examine expressed preferences of teachers in low-performing schools. Our method helps to overcome the limitation of other survey methodologies in that it requires the respondent to rank order their preferences. A rank order of preferences is useful for teacher recruitment and retention because it not only shows which attributes matter but also clearly distinguishes which attributes matter more than others. Therefore, we are able to identify which school attributes could be most useful in recruiting ASD-affiliated teachers to a new school or in retaining ASD-affiliated teachers in their current school.

Tennessee's Achievement School District

Supported by SIGs and Race to the Top funding, and authorized through an NCLB (No Child Left Behind) waiver, Tennessee began in 2012 to place some of the state's chronically lowest performing 5% of schools into a statewide district called the ASD (Henry et al., 2014; Glazer et al., 2019). Under the ASD model, these turnaround schools were removed from their local districts and placed under the management of either the ASD itself or authorized CMOs that were granted autonomy over school operations and given significant additional resources from federal and philanthropic sources. ASD schools also replaced the principal and most of the existing staff (Henry et al., 2014). We note that during the time period of this study, all but one ASD school was located in Memphis with the remaining school in Nashville.

Since teacher replacement is integral to the ASD intervention model, it is important to clarify teacher recruitment and retention in this context. Our sample is composed of teachers who have experience working in a school that would be part of the ASD either before or after ASD interventions began. Inferences made from our results apply only to turnover among teachers in low-performing schools targeted for turnaround. Using this sample of teachers, we refer to turnover as teachers leaving their current school and retention as these same teachers staying in their current school. Teacher recruitment refers to attracting teachers with experience in low-performing and/or turnaround school settings and not the process of bringing new teachers into the profession or the recruitment of teachers from non-low-performing schools. That is, our analysis examines school attributes that may be useful for recruiting or retaining teachers who are in a similar setting/context as ASD-affiliated teachers.

Conceptual Framework: A Typology for Understanding Teacher Preferences

We propose a conceptual framework that defines three types of school factors that may attract or repel teachers from certain schools or teaching positions: (1) fixed school characteristics, (2) structural features of teachers' employment, and (3) malleable school processes. Fixed school characteristics (e.g., student composition or commute times)[4] include less readily-altered features that can only be changed over a longer time frame by changing attendance zones or altering student and parent choice mechanisms, including converting a school into a magnet or charter. Structural features include salary, tenure, and performance-based pay and are generally set for longer periods. These are often subject to regulations and are likely applied to all schools managed by the same organization (e.g., all schools in the same school district). Malleable school processes are those for which the locus of control is expected to be within the school and under the control of school administrators. Malleable factors can be changed by school administrators in the short term (e.g., consistent enforcement of student discipline policies). Prior research has also shown that personal factors are highly predictive of teacher mobility, in particular age, gender, and family characteristics (Grissom et al., 2016), but this study seeks to address school conditions that influence teachers' mobility decisions.

Prior studies of factors correlated with teacher mobility heavily influenced our typology. Multiple studies agree that certain fixed school characteristics like neighborhood characteristics, student race, socioeconomic status, and achievement predict teacher mobility patterns (Borman & Dowling, 2008; Boyd, Lankford, et al., 2011; Grissom, 2011; Guarino et al., 2006; Hughes, 2012; Johnson et al., 2012). These studies found that schools with larger populations of minority and/or lower socioeconomic students with lower average student achievement experience higher rates of teacher turnover or teachers were less likely to transfer to these schools. Research in current and former turnaround schools in Massachusetts found that teacher recruitment materials described the students as having "significant challenges," in order to target teachers committed to working in this type of school context (Simon et al., 2015; Simon et al., 2019). Another characteristic, which we categorize as a fixed school factor, that is correlated with teacher preferences for a school placement is commute time. While many studies lacked data to correlate teacher turnover with commute time, studies of job applications in Chicago and job preferences among California teachers both found that teachers prefer shorter commutes (Engel et al., 2014; Horng, 2009).

Among structural features, salary has garnered the most attention. Correspondingly, many studies have found that higher salaries are associated with lower probabilities of teacher turnover (Clotfelter et al., 2008; Hanushek et al., 2004; Hendricks, 2014; Podgursky et al., 2004). Relatedly, some studies have also linked performance-based pay with improved retention (Springer et al., 2016; Swain et al., 2019) but others report mixed effects (Dee & Wyckoff, 2013). Tenure is another contested structural feature of employment that many researchers hypothesize can be used to attract and retain teachers (Rothstein, 2014; *Vergara v. State of California*, 2015). A recent study on the effect of tenure reform in Louisiana found that the removal of tenure protection is associated with increased teacher turnover, especially concentrated among teachers in the lowest-performing schools (Strunk et al., 2017).

Research on malleable school processes has shown that teachers' turnover decisions are highly responsive to the day-to-day working conditions in a school. For example, prior research found that teacher collaboration and collegiality, student disciplinary policies, professional development (PD) quality, expectations for working outside of the school day, and support from school administrators were correlated with teachers' employment decisions and job satisfaction (Johnson & Birkeland, 2003; Johnson et al., 2012; Johnson et al., 2016; Simon et al., 2019). The positive association between higher levels of administrator support and lower rates of teacher turnover has been examined in a number of studies including a meta-analysis of 34 teacher mobility studies (Borman & Dowling, 2008). Administrator support might also be particularly salient in the ASD context, which included principal replacement. Other studies have also confirmed that expectations for working outside of the school day are correlated with both intended and actual teacher turnover decisions (Ladd, 2011). One study in particular noted that school administrators clearly communicated long work hours to job candidates in order to find teachers who were prepared to work under those expectations (Simon et al., 2019). Another malleable school process that has been shown to be correlated with lower teacher turnover is classroom autonomy, including autonomy to choose instructional materials, methods, and assessments (Achinstein et al., 2010; Guarino et al., 2006; Johnson, 2006). Previous research also suggests that class size and school safety are malleable factors that are either important to teachers or correlated with teacher turnover (Horng, 2009; Loeb et al., 2005). These kinds of malleable school processes might be even more influential in low-performing schools. Prior research from Massachusetts suggests that higher teacher turnover rates in schools serving high proportions of low-income and minority students could be explained by lower levels of administrative support, poorer teacher relationships, and weaker school cultures (Johnson et al., 2012).

In the current study, we extract 16 attributes of schools from the research cited above[5] and examine preferences among teachers who have shown a willingness to work in low-performing and turnaround schools, a subset of teachers for which only a nascent literature base examines preferences (e.g., Springer et al., 2016; Swain et al., 2019). Focusing on this understudied sample of teachers, we specifically address the following research questions:

Research Question 1: What are the preferred school attributes expressed by teachers who have experience in low-performing or turnaround schools affiliated with the ASD?

Research Question 2: To what extent do teachers with experience in low-performing or turnaround schools affiliated with the ASD say that they prioritize fixed school characteristics, structural conditions, and malleable school processes?

Method

Adaptive Conjoint Analysis Survey

The factors that predict teacher mobility decisions are traditionally studied using either qualitative methods or surveys asking teachers to rate their preferences. These traditional survey methods can result in less distinct differences between factors if teachers can rate multiple, if not all, factors as highly important. Adaptive conjoint analysis (henceforth ACA) is a survey design that addresses this concern. Originally developed for marketing research, several recent studies of teacher mobility decision-making utilized ACA because of multiple distinct advantages (Horng, 2009; Robinson, 2012). First, the ACA format asks respondents to choose between different attributes of a school profile such that they must express relative preferences. This process clarifies how teachers weigh different trade-offs between teaching positions and shows which factors appear to be more important than others. Second, ACA has been frequently tested by researchers within the marketing community, showing that this method can reliably differentiate between respondents' preferences (Green et al., 1991; Tumbusch, 1991). Third, this analysis quantifies the likelihood that teachers will choose schools with particular attributes or sets of attributes by calculating likelihood measures that are easily interpretable, making them attractive metrics to researchers and practitioners interested in more refined data on the choices teachers make between different schools.

Before outlining the study methods, we note that this study does not aim to advance the ACA methodology, generally, or to explicitly show how our version of the ACA survey increases validity or reliability over prior uses of ACA to assess teacher preferences. Rather, since prior studies have utilized samples of traditional public school teachers in nonturnaround settings (Horng, 2009) and preservice music teachers (Robinson, 2012), our study extends these prior works to a novel sample: teachers working in low-performing schools prior to and during turnaround reforms.

Below, we describe our process for designing and implementing our survey along with the procedures for data analysis. For brevity, we describe the most important information on design, analysis, and methodological decisions in the article. We include greater detail and illustrative examples of the survey analysis and measures in Supplemental Appendix A in the online version of the journal.

Survey Design

We utilized Sawtooth software (https://www.sawtoothsoftware.com/) to construct an online ACA survey that comprises 16 school *attributes*, or school characteristics that may affect teachers' decision to work there. For each attribute, we included two or three attribute *levels*. For example, the PD attribute has two levels: either the school has opportunities or does not have opportunities for high quality PD.[6] Table 1 displays each attribute, attribute type, attribute levels, and the research base that supports its inclusion in the survey. We chose these attributes using an iterative process that included reviewing the literature on predictors of teacher mobility (see Table 1); considering school attributes that are relevant to teachers in

Table 1
Attributes and Levels of the ACA Survey

Attribute	Category	Levels	Reason for inclusion
Student race	Fixed	More than 50% White 10% or less White	Borman and Dowling (2008); Grissom (2011); **Horng (2009)**; Johnson et al. (2012); Ladd (2011); Loeb et al. (2005); Simon et al. (2015); Simon et al. (2019)
Student income	Fixed	Most students from low-income families Most students from middle-income families Most students from high-income families	Borman and Dowling (2008); Guarino et al. (2006); Hanushek et al. (2004); **Horng (2009)**; Hughes (2012); Ladd (2011); Loeb et al. (2005); Simon et al. (2015); Simon et al. (2019)
Prior achievement	Fixed	Less than 20% of students scored proficient last year More than 50% of students scored proficient last year	Borman and Dowling (2008); Hanushek et al. (2004); **Horng (2009)**; Simon et al. (2015); Simon et al. (2019)
Commute	Fixed	15 minutes or less More than 30 minutes	Engel et al. (2014); **Horng (2009)**
Involvement in establishing school	Fixed	Teachers play a key role in establishing culture and structure Structure and culture already well-established	(a key characteristic of ASD schools)
Salary	Structural	$0 additional salary $4,000 additional salary $8,000 additional salary	Borman and Dowling (2008); Clotfelter et al. (2008); Hanushek et al. (2004); Hendricks (2014); **Horng (2009)**; Johnson and Birkeland (2003); Loeb et al. (2005); Podgursky et al. (2004)
Tenure	Structural	No guarantee of future employment Future employment guaranteed based on performance	Rothstein (2014); Strunk et al. (2017); Vergara v. State of California (2015)

(continued)

Table 1 **(continued)**

Attribute	Category	Levels	Reason for inclusion
Performance-based pay	Structural	No performance-based pay Eligible for bonuses of $1,000 or less Eligible for bonuses of $5,000 or more	Springer et al. (2016); Swain et al. (2019)
School safety	Malleable	Safety is a minor problem Safety is a serious problem	**Horng (2009)**
Class size	Malleable	Less than 20 students More than 25 students	**Horng (2009)**; Loeb et al. (2005)
Classroom autonomy	Malleable	Use provided materials Access to materials but flexibility on use I find or develop my own materials	Achinstein et al., 2010; Guarino et al. (2006); Johnson and Project on Next Generation of Teachers (2006) (a key characteristic of ASD schools)
Administrator support	Malleable	Not consistent in supporting faculty Consistent in supporting faculty	Borman and Dowling (2008); **Horng (2009);** Johnson and Birkeland (2003); Johnson et al. (2012)
Student discipline policy	Malleable	Administrators and teachers do not consistently enforce discipline Administrators and teachers do consistently enforce discipline	Johnson and Birkeland (2003)
Professional development (PD)	Malleable	No opportunities for high-quality PD Opportunities for high-quality PD	Johnson and Birkeland (2003)
Time	Malleable	Culture of teachers doing some work after school and on weekends Teachers work regularly almost every evening/ weekend	Johnson and Birkeland (2003); Ladd (2011); Simon et al. (2019)

(continued)

Table 1 **(continued)**

Attribute	Category	Levels	Reason for inclusion
Teacher relationships	Malleable	Teachers are respectful but rarely interact Community of teachers that support one another	Borman and Dowling (2008); Johnson and Birkeland (2003); Johnson et al. (2016); Simon et al. (2019)

Note. Citations from Horng (2009) are in boldface because this study uses the same survey design as the current study. ACA = adaptive conjoint analysis; ASD = Achievement School District.

a low-performing school context; accounting for the reasons provided by ASD leadership regarding why teachers seek employment in ASD schools (e.g., classroom autonomy, involvement in establishing a school); and conducting cognitive interviews with teachers who have worked in low-performing schools similar to the ASD schools in our sample (details on the cognitive interviews are available in Supplemental Appendix A in the online version of the journal). While our review of the literature suggests that more than 16 attributes are needed to comprehensively assess teacher preferences, we had to limit the number of attributes to make the survey short enough for us to obtain an acceptable response rate. The study by Horng (2009) heavily influenced our ACA survey design. We included eight of the 10 attributes that were part of the Horng (2009) study. Enhanced software allowed us to include more attributes than the prior study, allowing for more nuance and complexity in the ACA survey than was present in the Horng study.

Following the advice of Horng (2009) and Sawtooth, we limited each attribute to two or three levels. While we would have preferred greater nuance between the attribute levels, we simplified the levels to maintain a reasonable survey length. Similar to our process for selecting the 16 attributes, we chose the attribute levels based on prior literature, contextual relevance, and advice from teachers in our cognitive interviews. For many attributes, we chose levels that represent direct contrasts between two logical extremes. For example, the administrator support attribute was separated into two levels: consistent and inconsistent support. Other attributes with directly contrasting levels include family income, involvement in establishing a school, tenure, school safety, classroom autonomy, student discipline policy, PD opportunities, time, and teacher relationships. For a few attributes, we chose levels that were not necessarily direct contrasts to help shorten the survey and present realistic options available to teachers in Memphis. For example, most Memphis schools tend to be either very low or very high performing.

Thus, for the student achievement attribute, we chose two levels: less than 20% or greater than 50% of students scoring proficient. We excluded the level for 20% to 50% proficient because these schools are rare in Memphis, and when directly asked, none of the teachers in our cognitive interviews suggested the middle level was necessary to accurately capture their preferences. Likewise, racial segregation in Memphis schools led us to choose the attribute levels of less than 10% or more than 50% White students. Finally, we chose the numerical values of the attribute levels for commute time, salary, and performance-based pay to reflect realistic expectations for teachers in our sample (often in consultation with teachers during the cognitive interviews).[7] For example, $5,000 performance pay bonuses are potentially available for teachers moving into ASD schools (Springer et al., 2016; Swain et al., 2019).

Survey Administration

Using a unique link to the survey on Sawtooth software, respondents filled out the ACA survey in four stages: (1) rank the attribute levels in order of desirability; (2) indicate the importance of one attribute level over another; (3) select along a continuum between two different school profiles; (4) enter a number between 0 and 100, indicating their likelihood of choosing to work at a school with given attributes.

In the first stage, respondents answered the prompt "Please rate the following in terms of their desirability," for each attribute level on a 7-point scale from *Not Desirable* to *Extremely Desirable*. See Figure 1 for an example of what an item on the first section of the survey looks like for the two levels of the teacher relationships attribute. This first section established which level of each attribute respondents preferred (e.g., whether they preferred to work in a high-performing school or a low-performing school). The respondent was only asked to rate the desirability of the attribute levels where the preference for each level cannot be assumed. We assumed that, all else equal, the vast majority of teachers would prefer a shorter commute, higher salary, a safer school, consistent discipline enforcement, smaller class size, consistent administrative support, and high-quality PD. Therefore, we did not include these attributes in the first section. Making these assumptions and not including these attributes in the first section greatly reduced the length of the survey without compromising the validity of the results because the second section of the survey asked respondents about all attributes.

In the second section, the respondent answered the prompt "If two teaching jobs were identical in *all other ways*, how important would *this difference* be to you?" using a 7-point scale ranging from *Not Important* to *Extremely Important*. See Figure 1 for an example of an item from the second section of the survey on school safety. By comparing the attribute levels

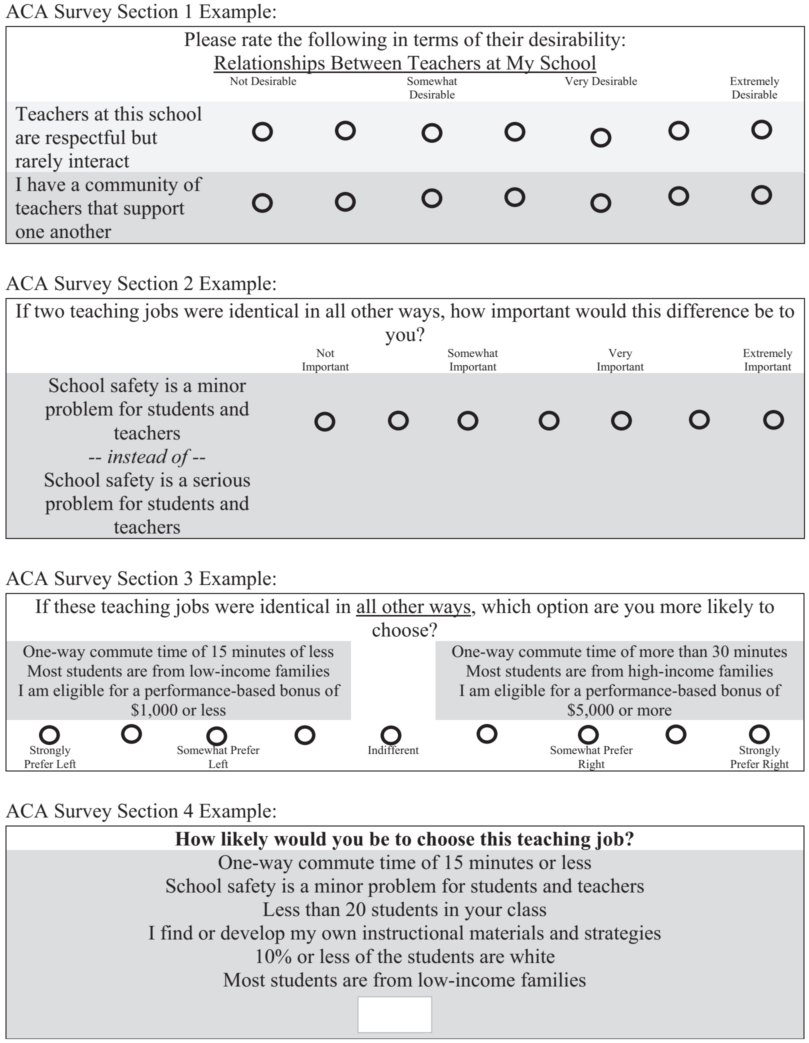

Figure 1. **Example items from the adaptive conjoint analysis (ACA) survey by survey stage.**

relative to each other for all 16 attributes, the respondent provided information on which attributes are important to her decision-making process. Using this information, the software was more likely to present attributes in the third and fourth stages that respondents identified as more important in the second stage.

In the third stage, the paired trade-off section, respondents were asked to choose between two job profiles. Two job profiles were placed on the page such that one job profile was listed on the left while the other was on the right side of the page. These two job profiles were designed by the software to include both desirable and undesirable attribute levels based on the respondents' answers in the first two sections. Respondents answered the prompt, "If these teaching jobs were identical in *all other ways*, which option are you more likely to choose?" using a 9-point scale ranging from *Strongly Prefer Left* to *Strongly Prefer Right* with *Indifferent* in the middle of the scale. For an example of what the two job profiles might include, see Figure 1.

By asking respondents to choose between two profiles with both desirable and undesirable attribute levels, the software obtained more refined information on the trade-offs that the respondent was willing to make. The software continuously updated the estimated relative preference of each attribute and attribute level after each paired trade-off item, choosing the next job profile based on the prior answers. Respondents were asked 18 items in this section of the survey: 10 items with two attributes on each school profile and eight items with three attributes on the school profiles. This stage allowed the software to obtain a more refined measure of the respondent's relative preferences for each attribute and attribute level.

In the last section of the survey, respondents were given a job profile (created by the software) with six attribute levels listed and given the prompt, "How likely would you be to choose this teaching job?" To answer the question, the respondent is instructed to "Please type a number between 0 and 100 where 0 means *Definitely would NOT choose* and 100 means *Definitely WOULD choose*." They were asked five of this type of item to calibrate the likelihood the respondent would choose a particular job profile (Orme, 2014). See Figure 1 for an example of a job profile that a respondent might have be given. The calibration information was combined with the rank order preferences from the first three sections to produce a measure called the respondent's utilities. Below, we define utilities and describe how the utilities produced by Sawtooth are used in our analysis.

Data Analysis

We use the ACA results to obtain three measures we will discuss in the results and validation sections: *importance scores, first choice preferences*, and *shares of preference*. We include a broad overview of each of the measures below including how they are calculated and interpreted. We have provided a simplified example of how each of these measures is calculated in the Supplemental Appendix A in the online version of the journal.

First, the Sawtooth software used survey responses to output *part-worth utilities* for each respondent. Part-worth utilities are interval measures that rank the attribute levels within each attribute. Within each attribute, a higher part-worth utility is more preferred. Part-worth utility values were calculated by proprietary Sawtooth software using a hierarchical Bayesian model (see Supplemental Appendix A in the online version of the journal for more information) and while not easily interpretable, they are used to calculate the three measures we discuss in this study.

The first measure we present in this study's findings are *importance scores*. Importance scores are calculated using the following formula:

$$\text{Importance} = \frac{\text{range of part-worth utilities of an attribute}}{\text{total of all ranges of all attributes' part-worth utilities}} \times 100. \quad (1)$$

Range refers to the typical calculation of the distance between the highest and lowest values. The numerator represents the range of part-worth utilities across the attribute levels within one attribute. The denominator is the sum of the ranges of all 16 attributes. The intuition behind importance scores is that attributes with a larger range of part-worth utilities are more important to the respondent than attributes with a smaller range of part-worth utilities (see the example in Supplemental Appendix A, for more information about why the range would be related to relative importance).

The importance scores are interpreted as the difference that each attribute could make in the total utility of a job. That is, importance values can be used to directly rank and statistically compare different attributes in the study. To obtain aggregate importance scores for each attribute, we average the importance scores across all respondents. To include information about uncertainty of importance scores, we report 95% confidence intervals of each importance score. The 95% confidence intervals are calculated using the full distribution of importance scores for each individual to calculate standard errors robust to nonconstant residual variance. We compare importance scores and 95% confidence intervals graphically to examine the relative rank of importance scores compared to each other.

The average importance scores can be used to compare attributes (e.g., salary vs. commute time), but they do not describe the preference for the levels within an attribute (e.g., the student race attribute will receive an importance score, but this number does not indicate whether the preference is for a school that is 10% or less White vs. a school that is more than 50% White). In order to quantify and compare teacher preferences for each attribute level, we use first choice market simulations (FCMS) to ascertain teachers' *first choice preference*. Market simulations are designed to predict respondents' choices when they are in real-world conditions. In a market simulation, we set each attribute to a specific attribute level. After creating at least two complete job profiles, FCMS predicts the percentage of respondents who would select each job profile. In this study, we utilize FCMS by setting 15 of the attributes at the same level with the variation between job profiles focusing on the difference in levels in one attribute.

The FCMS are conducted for each attribute separately. For example, to estimate the first choice preference of a school that is 10% or less White versus a school that is more than 50% White, we create a FCMS with two job profiles that have exactly the same levels set for 15 of the attributes, so the two job profiles only differ on the student race attribute. The two job profiles are then compared by summing the part-worth utilities for each of the 16 attribute levels separately for the two job profiles. The respondent is predicted to select as the first choice the job profile with the larger sum of part-worth utilities (i.e., the job profile that maximizes the respondent's utility). After obtaining first choice preferences for each respondent from the FCMS, we calculated the percentage of respondents who would choose a particular attribute level as their first choice. For example, we would report an aggregated first choice preference value of 70% for a school with less than 10% White students if seven out of 10 respondents are predicted to have this school as their first choice. We also utilize the FCMS to compare job profiles with differences in multiple attributes, predicting what percentage of respondents would select one job profile over another. For this type of market simulation, we utilized data gathered from school performance reviews (SPRs) conducted at all ASD schools during the 2014–2015 school year to construct the relevant job profiles (more information in the Results section below).

As part of our validation analysis conducted after reviewing the main results, we utilize results from another type of market simulation: share of preference (SOP). Unlike FCMS, which assumes the respondent would choose the job profile that maximizes their utility, SOP indicates which job profile is preferred over the others and the relative desirability of the other job profiles. SOP is calculated using the sum of the part-worth utilities, just like with the FCMS. For SOP, the summed part-worth utilities for each job profile are exponentiated (the part-worth utilities are created using the logit rule as part of the hierarchical Bayesian analysis). The SOP is then calculated for each job profile just like a proportion. For instance, when comparing two job profiles, A and B, we calculate the SOP using the following formula:

$$SOP_A = \frac{e^{\sum_{i=1}^{16} \alpha_{Ai}}}{e^{\sum_{i=1}^{16} \alpha_{Ai}} + e^{\sum_{i=1}^{16} \alpha_{Bi}}}. \tag{2}$$

In this formula, α represents the part-worth utility for each attribute level of job profile A. All 16 selected levels' part-worth utilities are summed and exponentiated. The SOP compares the value for job profile A versus the total of values for job profiles A and B. Respondents that show a very high preference of a certain attribute will have SOP that are close to 1, showing that the alternate job profiles have little utility to that respondent.

Sample

Our target population for the survey includes current teachers who can be categorized into one of three groups: (1) teachers at an ASD school in the 2014–2015 school year (the time of survey administration), (2) teachers who previously worked at an ASD school prior to the 2014–2015 school year, and (3) teachers who worked in a school that was eventually taken over by the ASD but left the school before takeover. Therefore, each set of teachers has intimate knowledge of teaching in a low-performing school. We identified our target population of teachers using a combination of personnel data provided directly by the ASD and statewide longitudinal data compiled by the Tennessee Education Research Alliance. The final sample included 811 teachers: all 2014–2015 ASD teachers (N = 565) and a random sample of the other two groups of teachers (N = 246; comparisons between those randomly selected and not selected indicate the randomization process produced balanced samples as shown in Supplemental Appendix Table B1 in the online version of the journal). To reflect the sampling strategy, all estimates in this paper include a probability selection weight where the responses from the 2014–2015 ASD teachers are given a weight of one, because they were all included in the sample. The other two groups of teachers' responses are given a probability weight of approximately 1.62 in order to weight the sample to be representative of the target population.

Teachers were given approximately 6 weeks to take the online survey in the spring of 2015, and teachers who completed the survey were sent a gift card. Survey reminders were emailed on a weekly basis to nonresponders. The final response rate was 63.5% or 515 teachers, with current ASD teachers having a higher response rate (68.8%) than the response rate of teachers who no longer worked at ASD schools (52.5%). When comparing respondents and nonrespondents, we noted that teachers with more years of experience (6 or more years) were less likely to respond to the survey than teachers with fewer years of experience (1 or 2 years). To address this pattern of nonresponse, we created a nonresponse weight to down-weight respondents with 1 to 2 years of experience and up-weight respondents with 6 or more years of experience such that the weight creates proportions that are representative of the original sample. The weights are approximately 0.86 for 1 to 2 years of experience, 1 for 3 to 5 years of experience, and 1.15 for 6 or more years of experience. We found no other significant differences between other observable characteristics of the sample (see Supplemental Appendix Table B2 in the online version of the journal). The probabilities of selection weight and nonresponse weight were multiplied to create the final weight.

Results

Attribute Importance Scores

The overall attribute importance scores are shown in Figure 2. The vertical black line indicates what the attribute importance score would be if all attributes were equally important to the respondents (100/16 = 6.25). Among teachers who were surveyed, the most important attribute out of the 16 we tested is enforcement of the student discipline policy followed by salary, administrator support, and school safety, as shown on Figure 2. The high relative importance of administrative support and school safety is consistent with Horng (2009) who found clean and safe school facilities, administrator support, and class size to be the most important attributes.[8] The least important attribute in our study is student race followed by student income, involvement in establishing a school, student achievement, time spent working outside of the school day, and commute time. Since importance percentages are ratio measures, we can observe that the most important attributes in this study are two to three times more important to our sample of teachers than the least important attributes. For instance, the importance percentage for commute time is 4.76, and the importance percentage for discipline is 9.47. Therefore, discipline is almost two times (9.47/4.76 = 1.99) as important as commute time. Generally, attributes categorized as fixed school characteristics are clustered at the lower end of importance percentages while attributes categorized as structural and malleable characteristics are dispersed throughout the ranking of important characteristics.

First Choice Market Simulations

Next, we conducted FCMS for all 16 attributes separately. We conducted 16 FCMS with two to three school profiles in each simulation (the number of school profiles matches the number of attribute levels within each attribute) where the school profiles are identical on 15 of the attributes, only differing on the level of one attribute. The results reflect the percentage of respondents who are predicted to select each school profile. The results are displayed in Figure 3 with each bar (i.e., attribute) representing the results from one simulation. For six of the malleable attributes, the respondents are highly sensitive to the difference between levels such that 95% to 100% of respondents would select a school with consistent administrator support, consistently enforced student discipline, safety as a minor concern, small class size, supportive teacher relationships, and available high-quality PD over a school with the alternative for each attribute. For the structural conditions attributes, the only one that had over 95% of the first choices was the ability to make $8,000 more per year (which had 100% of first choices). The first choice percentages are less stark for fixed school characteristics, with commute time as the exception. The vast majority, 94%, of respondents were predicted to select a school

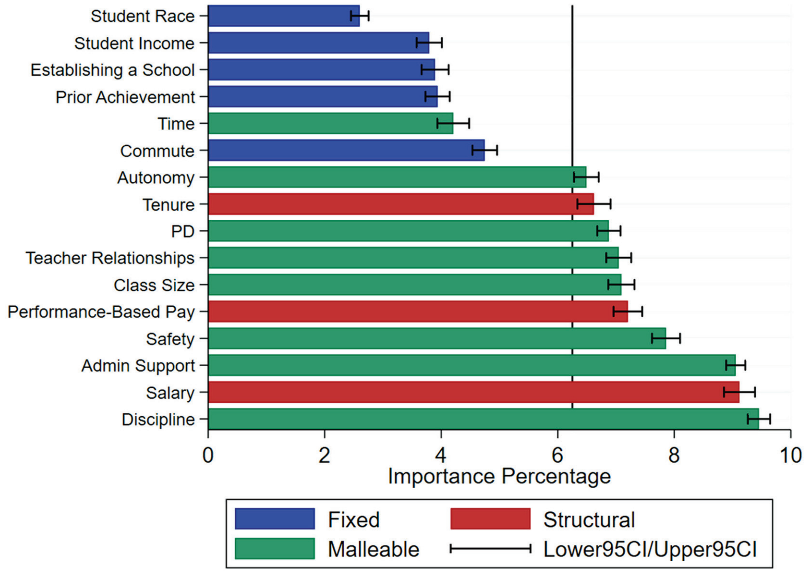

Figure 2. **Attribute importance scores. All estimates calculated using probability weights and nonresponse weights. The vertical line represents what the attribute importance percentage would be if all attributes were equally valued by the respondents (6.25%).**

with tenure available. Moreover, 92% of respondents were predicted to select a school with some sort of performance-based pay (combining those preferring small incentives of $1,000 or less to larger incentives of $5,000 or more). Respondents are less resolute on which level of the other fixed school characteristics attributes (student race, student income, establishing a school, and prior achievement) they would prefer when deciding to work at a certain school.

Market Simulation Based on Conditions in ASD Schools

We were interested in how ASD schools would fare if teachers were hypothetically choosing between existing ASD schools to mirror labor market conditions. In the fall of 2014, the ASD and CMO staff conducted a SPR at each ASD school, and the summaries were made available to the research team. The SPR summaries were created using the same template, each addressing five of the attributes included in our ACA survey. In particular, each SPR summary allowed us to ascertain if (1) high-quality PD was available, (2) teacher relationships were supportive, (3) the discipline policy was consistently enforced, (4) safety was a minor or serious concern, and (5)

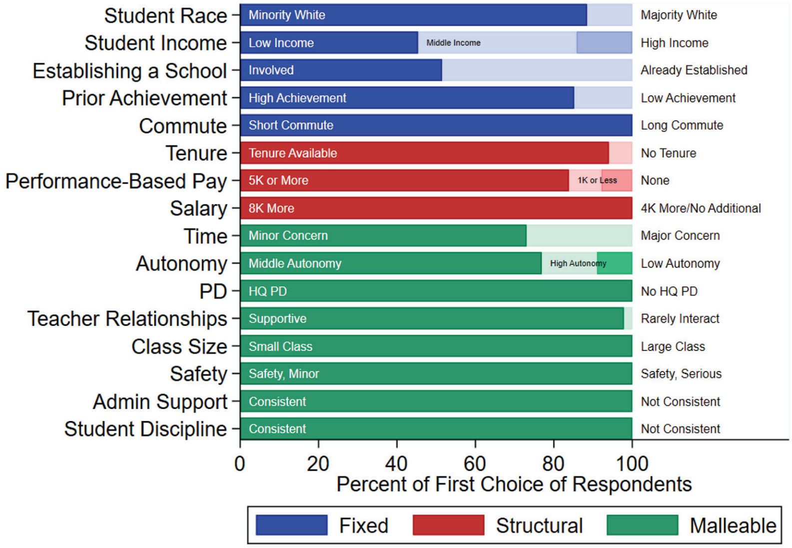

Figure 3. **Results from first choice market simulation for each attribute holding the other 15 attributes constant. All estimates calculated using probability weights and nonresponse weights. All differences between attribute levels within attribute are statistically significant except for the following: Performance-based pay of 1,000 or less versus no performance-based pay; involved in establishing a school versus already established school.**

administrators were consistently supportive of teachers. Given the nature of the SPR, it only included malleable attributes that school administrators can directly influence.

We coded each SPR to determine the levels of these five attributes for each school. In particular, we found that many schools had the preferable level (according to the FCMS) on all of the attributes except for one.[9] To see how teachers would pick between four schools that had the more-preferred level on four of the five attributes and the least-preferred level on the fifth attribute, we conducted a market simulation. Among these four malleable factors, 58% of teachers are predicted to select a school that did not have high-quality PD but had consistent discipline, safety is a minor concern, and supportive administration. The attribute that was strongest in deterring teachers from choosing a school as their first choice was inconsistent administrative support with only 5% choosing these schools, followed by inconsistently enforced discipline (7%) and safety as a serious concern (30%). These results help order the attributes in terms of their impact on the expressed preferences of ASD-affiliated teachers and allow more precise distinctions to be made among these malleable attributes than the original importance percentages from Figure 2.

Validation Checks

While the ACA design theoretically offers a substantial improvement over traditional survey designs when assessing teacher preferences for school conditions, it is possible that teachers' expressed preferences do not match the attributes of schools where they will choose to work. The ACA survey results are most useful if they predict the actual behavior of teachers in the labor market, but there are potential reasons why teachers' expressed preferences could differ from their revealed preferences. For example, teachers who express a desire to teach in schools with a large proportion of non-White students may be influenced by social desirability, and they may choose an assignment with fewer underserved minorities when given the opportunity. Therefore, it is useful to examine the extent to which teachers' expressed preferences match their revealed choices.[10]

To this end, we perform a series of validity checks using administrative data to assess if the expressed preferences from the survey are indicative of the teachers' revealed preferences when they choose to either transfer or stay in their schools between 2014–2015 (when the ACA survey was administered) and 2015–2016. Note, we are somewhat limited in our ability to do a comprehensive set of validity checks for several reasons. First, out of our 16 attributes, we are only able to find 11 approximate matches using administrative data. The five attributes which we did not have administrative measures to use for validation include commute time, involvement in establishing a school, opportunities for tenure, performance-based pay, and expectations to work outside of school hours. Although the lack of administrative measures for these five attributes are a limitation for our validity checks, they also highlight why our survey provides insight into teacher preferences with measures that are typically unavailable in administrative data. Another limitation is that the school characteristics we obtain from administrative data do not always directly correspond to the ACA survey measures, because the administrative data is not structured in the same manner as the survey. Moreover, we cannot assess revealed preferences of teachers who decide to teach in another state or a private school because our administrative data only includes teachers in Tennessee's public schools, and we only were able to match 364 of the 515 respondents to a school in both the 2014–2015 and 2015–2016 school years.

In order to assess whether the sample used to validate expressed preferences is representative of the full sample of respondents, we used *t* tests to compare importance values for each attribute between the 364 respondents matched to administrative data and the 151 respondents not matched (see Supplemental Appendix Table B4 in the online version of the journal).

We compare importance values instead of demographic characteristics, because these demographic variables are not available for respondents who were not matched to the administrative data. Overall, the *t* tests show that matched and nonmatched respondents reported similar importance values, with only one attribute that is significantly different: class size. Even though the importance values for class size were statistically different, the values are substantively similar (6.7 for matched respondents vs. 7.2 for nonmatched respondents). This analysis provides some evidence that the 364 respondents used to validate expressed preferences provided similar survey responses to the respondents that could be not matched with the administrative data.

We created 11 measures of school characteristics based on information on school demographics, class size, teacher salary, student discipline, and student achievement. We also have results from the Tennessee Educator Survey,[11] which contains several scales and items on classroom autonomy, administrative support, discipline policy, PD, and teacher collegiality. More information on these data sources are included in Supplemental Appendix C in the online version of the journal. When possible, we calculated the attribute levels for each school using the same values stated on the ACA survey (i.e., for demographics, salary, test scores, and class size). For example, since the attribute levels for student race on our survey is either schools with less than 10% or more than 50% White students, we directly aligned the survey and administrative data and identified whether teachers' schools had less than 10% or more than 50% White students. When no exact values were stated on the ACA survey, we use the administrative data to identify whether a school is above or below the mean value of that attribute relative to the rest of the state. For example, the ACA survey attribute levels for administrator support is either consistent or inconsistent support. Since this dichotomy is not on the Tennessee Educator Survey, we identify a school as having more or less consistent support if average teacher ratings of administrative support in that school are above or below the state mean, respectively.

We have several options for categorizing expressed preferences from the ACA survey including importance values and results from the market simulations. Our preferred strategy is to use results from the market simulations that indicate the respondents' SOP for one attribute level over the other. This value represents the probability a respondent will choose a school with one attribute level over the other attribute level. In the spirit of only including respondents who show a strong expressed preference (i.e., excluding respondents with only a slight preference who might not actually make decisions based on that attribute), we include respondents who express a SOP of at least 90%. We also include other tests using importance values (in their top five or their number one attribute according to the importance values) and looking only at higher versus lower SOP. The detailed results are in

Supplemental Appendix C in the online version of the journal and are generally consistent with the results discussed here.[12]

A summary of the results of this exercise exploring revealed and expressed preferences are listed in Table 2. The first column lists the 11 attributes we were able to test. The second column indicates the number (and percent) of respondents where the actual conditions of the teachers' schools in the 2015–2016 school year matched the preferences they expressed on the ACA survey. The third column is the number (and percent) of respondents whose revealed preferences (the conditions at their school in the 2015–2016 school year) did not match their expressed preferences on the survey. For eight of the 11 attributes, the majority of teachers were at schools with attributes that matched their expressed preferences. A particularly high rate of match between expressed and revealed preference occurs for schools with less than 10% White students. 95% of the sample expressing a strong preference for majority non-White schools worked in a school that matched that description. A skeptic may have assumed that respondents' expressed preferences for minority White schools was driven by social desirability, but the validity check would suggest otherwise, at least for the teachers in our sample.

For three attributes, teacher revealed preferences do not match their expressed preferences: salary, safety, and flexible autonomy. Of these, we might expect that teachers have less flexibility on salary when they are moving within the same state's public school system. Moreover, teachers in the sample tended to be paid more between 2014–2015 and 2015–2016 (see Supplemental Appendix Table C4 in the online version of the journal). However, the values in Table 2 only counts matches as cases where teachers receive a pay increase of $8,000 or more and not cases where the salary increase is less than $8,000. Since the average salary difference between 2014–2015 and 2015–2016 in our sample is $1,611, an $8,000 pay increase is relatively large and less often observed. If we match teachers who express a preference for higher salary (regardless of amount) with teachers who do receive a higher salary between the 2 years, the match between expressed and revealed preferences is much higher. For example, Supplemental Appendix Table C4 in the online version of the journal shows that among those who were working in a new school in the 2015–2016 school year who had a strong expressed preference for $8,000 of additional salary, two thirds received a higher salary in their new school.

Moreover, our measure of the safety attribute might not be an accurate representation of the actual safety of the school because we use reports of safety-related disciplinary incidents. Having a higher number of disciplinary incidents does not necessarily mean the school is less safe, because schools may not accurately report these numbers or may not discipline these behaviors (e.g., teacher harassment).[13] Finally, our results on classroom autonomy might be reflective of utilizing a measure from the Tennessee Educator

Table 2
Validation Tests Exploring Revealed Versus Expressed Preferences

	Revealed preferences matches expressed	Revealed preferences do not match expressed
Schools with <10% White students	19 (95.00)	1 (5.00)
Schools with mostly low-income students	10 (90.90)	1 (9.09)
Schools with at least 50% of students scoring proficient to advanced	10 (71.43)	4 (28.57)
$8,000 additional salary	6 (16.22)	31 (83.78)
Safety is a minor concern	18 (12.86)	122 (87.14)
Class size is less than 20	117 (81.82)	26 (18.18)
Classroom autonomy is flexible	2 (16.67)	10 (83.33)
Administrator support is consistent	57 (56.44)	44 (43.56)
Discipline policy is consistently enforced	82 (82.00)	18 (18.00)
Opportunities for high-quality professional development	73 (90.12)	8 (9.88)
Teachers are supportive of each other	51 (62.20)	31 (37.80)

Note. Sample for each row represents the teachers whose personal share of preference for that attribute level is above 90% according to first choice market simulations. Row percentage is listed next to each count in parentheses.

Survey that is not equivalent to how we measure classroom autonomy in the ACA survey. The wording of the items is relatively similar, but the Tennessee Educator Survey asked about classroom autonomy on a Likert-type scale (the item was worded, "Teachers have autonomy to make decisions about instruction, e.g., pacing, materials, and pedagogy.") while we asked about classroom autonomy with more specific examples of three different levels of autonomy (see Table 1). We define schools with "flexible" autonomy as those with responses on the Likert-type scale that were in the middle third of the distribution of all schools. This middle tier could be teachers who have what we call "flexible" autonomy, or they could be teachers with very little autonomy.

Across the board, teachers' ability to work in a school with the attributes they prefer will depend on whether their desirable characteristics are available within the geographic area in which they consider working and inconsistencies in matches may be related to differences in how school characteristics are measured on the ACA survey versus the administrative data. Given these limitations, a conservative approach would be to examine only cases where there is a nearly perfect match rate between expressed and revealed preferences (i.e., nearly 100%). Attributes with the highest match rates are on student race, student income, consistent discipline enforcement, class size, and high-quality PD opportunities. Many of these attributes with the highest match rates are relatively important to teachers (e.g., consistent discipline, class size, and opportunities for high-quality PD). Given high match rates for a number of the more important attributes, we can be more confident in the expressed preferences in our survey indicating revealed preferences. Though there is still potential for bias between expressed and revealed preferences, overall, we find that the revealed preferences of teachers are consistent with their expressed preferences from the ACA survey, evidence that the survey results are showing actual preferences for school working conditions.

Conclusions

Our findings suggest that five malleable school processes are likely to have the greatest influence on teachers' employment decisions, at least for those with experience in pre- and posttakeover of ASD schools. These five malleable processes include consistent enforcement of discipline, consistent administrative support, school safety, small class sizes, and availability of high-quality PD. These results are encouraging because the attributes most important to teachers in the sample may be more directly influenced by school administrators. Therefore, these findings could be used to recruit and retain teachers who have shown a willingness to teach in lower performing and turnaround schools. In light of recent research finding that overall teacher turnover harms student achievement (Hanushek et al., 2016; Henry & Redding, 2020; Ronfeldt et al., 2013), these five malleable processes should be considered important for the management, and ultimately, reduction of teacher turnover in low-performing and turnaround schools. Teachers in our study sample, who have had experience teaching in high-poverty, low-performing schools, are unlikely to choose moving into or staying in schools without all of these attributes in place. The validity check shows that these teachers are indeed able to realize their preferences for most of these attributes.

Districts and states might want to consider how to use accountability and measurement systems already in place to encourage the types of behaviors associated with desirable attributes. Many states have administrator evaluation systems and/or surveys that measure many of these attributes. These systems can be used to monitor schools and see which schools need more support on important attributes like consistent discipline and administrative support.

At the same time, low-performing schools often struggle to consistently have the desired level of these types of attributes because of their high turnover rates. While a school might have a strong discipline system in one year with small class sizes and a strong safety record, leadership turnover could undermine the attainment of these attributes. School districts might be especially interested in helping to protect schools from the deleterious effects of teacher and leader turnover on these areas of importance to teacher preferences.

Perhaps surprising in this analysis is the relatively low importance of structural features or even fixed school characteristics with the notable exception of salary. The responses of individuals when asked about preferred fixed school characteristics might be biased by social desirability, but we are less concerned about this threat with this sample and the ACA survey design. This is especially the case for those preferences that passed the validity check such as racial composition of the schools. Teachers who work at high-poverty, low-achieving, or turnaround schools might feel pressure to express a preference for those school attributes, but the results indicate that these teachers, on average, do not place a high importance on these kinds of school attributes. The survey design forces teachers to go beyond their initial responses on the desirability of working in certain settings to ascertain a rank order of the relative importance of many factors when selecting a school. At the same time, all teachers in this sample have experience in very similar school settings which might indicate that they are more flexible in where they are willing to work than the broader population of teachers, leading to fixed school characteristics taking on less importance.

Teachers in our sample seem to value malleable school factors more highly when deciding where to work. This finding cautions against reliance on administrative data alone to investigate how fixed school characteristics affect teacher mobility, because administrative data often contain the correlates rather than actual measures of the characteristics that seem to be most important to teachers willing to work in the lowest performing schools. For instance, relying on suspension rates to explain teacher turnover patterns could be misleading if higher suspension rates are indicative of consistent discipline enforcement. Teachers might be more likely to stay in a school with higher suspension rates because of the consistent discipline enforcement, not because of the suspension rate itself.

How This Study Advances the Literature on Teacher Preferences

Understanding teacher preferences for their school and position is a commonly explored topic within the education research literature. We advance the research in this area by continuing the use of an innovative survey technique, ACA, with a policy-relevant group of teachers who have taught in some of the lowest performing schools in the nation. That is, our study contributes novel information on the preferences of teachers who have experience working in low-performing and turnaround school settings.

Using this sample, we confirm several findings from the work of Horng (2009) who was the pioneer in using ACA with teachers to gauge their preferences. Like Horng, we found teachers place little importance on school demographics and performance, a finding we were able to validate using administrative data on teacher labor market decisions. We also confirmed the importance of administrative support, school safety, and class size, attributes Horng found to be important in her sample. We were able to extend the work of Horng and advance the ACA methodology for use with teachers by incorporating other attributes which we found to be very important to teachers: student discipline enforcement, performance-based pay, relationships among teachers, and high-quality PD.

This study provides motivation for the continued use of ACA to gauge teacher preferences. Unlike the output of a traditional survey, using ACA allowed us to rank school attributes by importance on a ratio scale. For instance, we found discipline enforcement and salary were almost two times more important than commute time. ACA also allowed us to conduct market simulations, predicting the likelihood of a teacher preferring specific schools over others. We offer evidence on the validity of ACA to measure revealed preferences on many of the attributes we include in this study. We also have developed a list of attributes and levels that could be useful for future ACA surveys of teachers. For those who are interested in learning more about teacher preferences for their school and position, utilizing an ACA survey could be a particularly useful method to do so.

Limitations and Future Research

Schools and districts might be particularly interested in attracting and retaining certain subpopulations of teachers like teachers with more experience, high evaluation scores, high value-added scores, or teachers of color. As was noted earlier, some evidence indicates a successful school improvement strategy involves replacing staff with more effective teachers (e.g., Dee, 2012; Strunk et al., 2016; Sun et al., 2017). We conducted these subgroup analyses based on race, teaching experience, and teaching effectiveness to see if certain groups showed a stronger preference for certain attributes than others (full results in Supplemental Appendix Table B3 in the online version of the journal), but our samples sizes were too small to have adequate precision. In these exploratory, descriptive analyses, we appear to see that Black and more experienced teachers show a stronger expressed preference for tenure and longer work hours than White and less experienced teachers, but these results were no longer significant after correcting for multiple comparisons. Future research could explore if schools and districts can leverage certain aspects of the position and school to attract specific subgroups of teachers.

Our results may not generalize to all teachers, including those who do not have experience in the lowest performing schools or teachers unaffiliated with ASD schools. We also note that the preferences of teachers who have not shown a willingness to work in low-performing schools could also be important to schools as they seek to recruit high-quality teachers. While it might be theoretically easier for low-performing schools to recruit teachers who have shown a willingness to work in that setting, administrators might seek candidates with experience in higher performing schools. Our results do not necessarily generalize to teachers with the potential to work in low-performing schools who have not yet been recruited to do so, and this is a potentially fruitful route for future research.

Our results also might not generalize to teachers choosing their first school who may not be aware of these variations. Structural elements such as salaries, tenure, and bonuses could be more important than the malleable school processes earlier in teachers' careers, especially when they choose to enter the teaching profession. Future work should examine how structural features and fixed school characteristics influence decisions to entertain and/or accept an offer to teach with a sample of eligible individuals, perhaps among teacher preparation program graduates, since many of them do not enter teaching (UNC Educator Quality Dashboard, n.d.). Our findings suggest that preferences may change with experience or, alternatively, as a function of selection into higher levels of experience (i.e., for teachers who choose to continue teaching for more years). Exploring this issue further may have serious implications for the retention of more experienced teachers in the lowest-performing schools and provide solutions for stabilizing the teaching workforce.

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Notes

Funding for this research was provided by the state of Tennessee's Race to the Top grant from the U.S. Department of Education and the Walton Family Foundation.

[1]While many highlight the overlap between Tennessee's and New Orleans' reform efforts (Mason & Reckhow, 2016), Tennessee has overlap with reform efforts across a number of states.

[2]Many other states, including Massachusetts, also have state takeover of districts either exclusively or in addition to state takeover of schools (e.g., Massachusetts has both options). See Schueler et al. (2017) for an evaluation of the state's takeover of the Lawrence, Massachusetts, district.

[3]Teachers have also been important in district-led turnaround efforts, which have also used the approach of hiring high-quality teachers. See the example of Springfield, Massachusetts (Jochim & Opalka, 2017).

[4]Within this framework, commute time does not fit as neatly within a category since teachers can exercise control over commute time by moving. We include commute times as a fixed school characteristic, since it is not directly manipulable by the school administration (i.e., a malleable school process) and is tied to the location of the school, but recognize that it is under the control of individual teachers and, as such, is subject to change with or without teachers transferring to another school.

[5]While we would ideally consider more than 16 attributes since the relationship between school attributes and teacher preferences is quite complex, our method prohibits us from including a longer list of attributes. In cognitive interviews with teachers (described in Supplemental Appendix A in the online version of the journal), we asked if we were missing attributes that would be extremely important to include and revised our list based on their feedback.

[6,7]The levels were originally chosen by the research team based on their knowledge of the typical conditions in ASD schools as well as thorough review of the Horng (2009) study. During the cognitive interviews (described in Supplemental Appendix A in the online version of the journal), we validated the levels and made updates accordingly based on teacher feedback on the plausibility of these differences.

[8]Findings from different ACA surveys should be interpreted carefully since all comparisons are between attributes included on the survey.

[9]There were no schools that had the preferable level on all the attributes except teacher relationships, so this profile was not included in this market simulation.

[10]While examining the revealed preferences for all teachers in the state could also provide important insights, doing so is beyond the scope of our analysis. Instead, we focus on our survey respondents in order to compare expressed and revealed preferences.

[11]The Tennessee Educator Survey is an online survey that is distributed on an annual basis to all teachers in Tennessee public schools. We utilize the 2016 and 2017 surveys for this analysis. More information is available here https://www.tn.gov/education/data/educator-survey.html.

[12]In Supplemental Appendix C in the online version of the journal, we separate the results between those who changed schools between the 2014–2015 and 2015–2016 school years and those who remained in the same school. Theoretically, the revealed preferences of teachers could be more accurately measured by teachers who change schools since teachers might have a variety of reasons beyond preferences for working conditions to remain in the same school. The results are very similar between mover and stayer teachers, so we combine the groups in the main paper.

[13]It is even possible to interpret these schools as safer, because the larger number of disciplinary infractions may signal a more active approach to maintaining school safety.

Supplemental Material

Supplemental material for this article is available online.

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Manuscript received October 14, 2018
Final revision received April 24, 2020
Accepted April 29, 2020