Information Friction and the Labor Market for Public School Teachers
(Preliminary, please do not circulate)

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Abstract

We examine the equity-efficiency implication of information friction on teachers' labor market. In our equilibrium model, schools make job offers to teachers they want to hire and each teacher—market incumbent and potential entrant—chooses her most preferred option feasible. The market is subject to information asymmetry between a teacher's current employer and prospective employers, a friction that can be reduced by a transparent teacher evaluation system. We apply our model to data from Houston Independent School District, which launched a transparent teacher evaluation system in 2011. We estimate our model using the post-reform data and validate it using the pre-reform data. We use our estimated model to quantify the role of information friction on teacher-school sorting and how it affects the effectiveness of counterfactual bonus programs aimed at improving educational efficiency and equity.

1 Introduction

Extensive research has suggested that effective teachers play an instrumental role in students' success as measured by academic achievement and future labor market outcomes.[1] Therefore, it is crucial for economic growth and intergenerational mobility to staff every school with an effective workforce of teachers regardless of the student body it serves. One of the major obstacles to achieving this goal is information friction: Teacher effectiveness is not strongly correlated with observable characteristics (e.g., education and experience), making it hard to identify effective teachers upon hire. Moreover, to the extent that a school can learn about a teacher's effectiveness by daily observations, a teacher's employer has information advantages about her quality over other schools.[2]

It is well known that information friction, and in particular, information asymmetry between current and prospective employers, may obstruct optimal allocation on the labor market (e.g., Waldman 1984; Greenwald 1986; Chang and Wang 1996; Waldman and Zax 2016). In the case of the labor market for public school teachers, such information friction is accompanied with two distinct features of this market. First, in most public school districts, teacher salaries follow a rigid schedule imposed on all schools within a district, leaving little variation in compensation across schools for the same teacher. As a result, the relative attractiveness of a school largely lies in non-pecuniary factors, such as the body of students it serves. Second, in a typical labor market, optimality is largely equivalent to efficiency, i.e., labor allocation that maximizes the total output is optimal. However, in the case of teacher-school sorting, equity—providing students with equal access to effective teachers—is at least as important as efficiency in defining optimality.[3]

These features complicate the implication of information asymmetry on the teachers' labor market. On the one hand, as is the case in a typical labor market, breaking information asymmetry would make it easier for productive workers to move to more desirable jobs, and in this case, for effective teachers to move to schools with more attractive characteristics (given the lack of pay variation). If most teachers prefer teaching high-achieving students, the resulting teacher-school allocation can hurt schools serving more low-achieving students. On the other hand, the easier upward job mobility may pull effective teachers into the market, with whom schools can replace their ineffective incumbent teachers, thereby improving the overall quality of teachers in the market.[4] As a result, the equity-efficiency implication of breaking information asymmetry becomes an empirical question, which we answer in this paper.

[1] See, for example, Chetty, Friedman, and Rockoff (2014); Hanushek and Rivkin (2010); Hanushek (2011); and Jackson (2018).

[2] For studies on the difficulty in predicting teacher effectiveness, see, e.g., Staiger and Rockoff (2010) and Rivkin et al. (2005); for evidence that schools learn about the quality of their teachers, see, e.g., Jacob and Lefgren (2008), Chingos and West (2011) and Rockoff et al. (2012). Bates (2020) provides evidence on asymmetric information on the teachers' labor market.

[3] The issue related to the distribution of worker welfare exists in all labor markets, including teachers' labor market; the optimality mentioned here focuses on outputs.

[4] Kraft et al. (2020) find that teacher evaluation reforms increased the number of new teacher candidates who had attended more competitive undergraduate institutions but decreased the overall supply of teacher candidates.

Our empirical setting is Houston Independent School District (HISD), the 8th largest school district in the U.S. In the 2010-11 school year, HISD introduced the Effective Teachers Initiative (ETI), an initiative centered around a rigorous teacher evaluation system. By combining in-person observations with data on student test scores, ETI provided a multidimensional assessment of each teacher's quality and made this information accessible to all schools in the district. Noticeably, some aspects of a teacher's quality as measured by ETI (e.g., her in-classroom teaching practice), which could be learned by her employer through daily observations, would have been unobservable to other schools. Therefore, ETI largely broke the information asymmetry between a teacher's employer and other schools in the district.

Using HISD as a platform, we develop and estimate an equilibrium model of the labor market for public school teachers, accounting for the role of information friction. In the model, there is a distribution of teachers, including both market incumbents and potential entrants, characterized by observable attributes x and two quality measures q and v. A teacher cares about her salary and the characteristics of the school she teaches in, including the student composition. There are S schools on the market that value a teacher for her x, q, and v. Without a transparent teacher evaluation program (e.g., ETI), a teacher's employer is the only school fully-informed about her q and v. A school aims at filling its capacity with its most preferred teachers by extending job offers to teachers it wishes to hire, given its belief about the probabilities of acceptance by different teachers, and the expected quality of a teacher *conditional on her acceptance*. A teacher chooses her most preferred school among those offering her a job or the outside option, taking into account the cost of changing jobs. An equilibrium requires schools' beliefs be consistent with decisions by all schools and teachers.

The model highlights how a transparent teacher evaluation program can affect the equilibrium teacher-school sorting. When the incumbent employer is the only school fully-informed about its teachers' quality, schools may be apprehensive about hiring a teacher from another school in fear of the winner's curse: Given the cost involved in changing jobs, if a teacher originally working in another school nevertheless accepts an offer from school s, a possible explanation is that she has been found to be ineffective and fired by her original employer.[5] As a result, teachers may get few offers from other schools and therefore rarely switch jobs. Programs such as ETI evaluate the effectiveness of market incumbent teachers and give schools credible information about teachers working in other schools. This breaks the information asymmetry and affects both teacher-school sorting within the market and teachers' entry and exit.

We have obtained data covering both the pre-ETI and the post-ETI periods. We have estimated our model using the post-ETI data and will use the pre-ETI data to validate the estimated model. Our preliminary estimates suggest that all else being equal, teachers prefer schools with higher fractions of high-performing students, and more so among higher-quality teachers. Meanwhile, relative to experience and education, schools significantly value teachers' quality, and more so

[5]In our model, the market cannot observe whether a teacher is laid off or quits voluntarily. This is in contrast to the setup in, e.g., Gibbons and Katz (1991), where layoff is public information and serves as a signal of the worker's (low) ability.

among schools with larger fractions of high-performing students. That is, preferences on *both* sides of the market exhibit complementarity. Without frictions, these preferences would directly lead to assortative matching between teachers and schools, leaving lower-performing schools behind. The sorting can be less assortative with information friction, as schools are reluctant to hire teachers from other schools in fear of the winner's curse.

We first use the estimated model to quantify the role of information friction. We conduct a counterfactual simulation of the market equilibrium, where we *hold all the other initial conditions fixed* at the post-ETI level but revert to the pre-ETI information environment. We find that removing information asymmetry between current and prospective employers improves the overall quality of teachers on the market by encouraging higher-quality teachers to enter the market. However, it also exacerbates the inequality of teacher quality across schools, leaving schools with more low-performing students further behind.

Next, we use the model to study the effect of bonus programs that incentivize high-quality teachers to teach in low-performing schools. To explore the possibility for improvement at no additional monetary cost, we impose a budget-neutral condition for these bonus programs by reducing all teachers' base wages proportionally. To quantify how the effectiveness of such programs may differ by market information structures, we introduce this program to a market with and without information asymmetry between employers. We find that, qualitatively, the program has similar effects under both information structures: it increases overall teacher quality on the market and reduces the teacher-quality gap between high- and low-performing schools. However, quantitatively, the program is more effective when implemented in a market with symmetric information between employers.

1.1 Related Literature

Our paper contributes to the broad literature on the labor market of teachers, and in particular, the strand that studies this market via the lens of structural models. Among these studies, a large subset focuses on the supply side. For example, Stinebrickner (2001*a*,*b*); Wiswall (2007); Lang and Palacios (2018) model individuals' dynamic choices between teaching and non-teaching options. Using data from Chile, Behrman et. al. (2016) further breaks down the teaching option into teaching in one of three types of schools. Boyd et al. (2005) and Scafidi, Sjoquist, and Stinebrickner (2007) use competing risks models to study teachers' preferences for schools and find that teachers prefer schools with fewer low-achieving and minority students.[6]

A smaller subset of work considers both sides of the market. Tincani (2020) estimates an equilibrium model, where a representative private school sets teacher wages and tuition, workers choose among teaching in public schools (which are passive in the model), teaching in the private school, and non-teaching options, and households choose between public and private schools. Focusing on the market of public school teachers as we do, Boyd et al. (2013) estimate a two-sided matching model, assuming that the observed teacher-school matches are stable; Bobba et al. (2021) study

[6]Dolton and van der Klaauw (1999) use a competing risk model to study teachers' decision to leave the profession.

how wage bonuses affect teacher sorting in Peru's centralized teacher application-assignment system; Biasi, Fu and Stromme (2021) study how public school districts use wage and hiring strategies to compete for better teachers in a setting where districts have the control over teacher pay; Bates et al. (2022) study efficient teacher-school allocation within a district. Our paper well complements these studies: We account for the private information a school has about its teachers and examine how policies that reduce such informational asymmetry may affect equilibrium teacher-school matching, and teacher entry and exit.

There has been an extensive literature on the impact of incomplete information on labor market allocation, starting from Spence (1973). One strand of this literature focuses on asymmetric information between current and prospective employers, including both theory work (e.g., Waldman 1984; Greenwald 1986; Lazear 1986; Milgrom and Oster 1987; Riordan and Staiger 1993; Laing 1994) and empirical work (e.g., Gibbons and Katz 1991; Acemoglu and Pischke 1998; Schönberg 2007; Zhang 2007; Pinkston 2009; Hu and Taber 2011; DeVaro and Waldman 2012; Kahn 2013; Bognanno and Melero 2016; Cassidy, DeVaro, and Kauhanen 2016). Using a difference-in-differences approach, Bates (2020) examines the impact of two North Carolina school districts' adoption of value-added (VA) measures on teachers' within-district moves and exits; he finds direct evidence of asymmetric employer learning. His findings, based on quasi-experimental data variation from a different state, lend external support to our choice to include asymmetric information in our model of the teachers' labor market. Using a structural estimation approach, we aim at achieving a different research goal: to recover teacher and school preferences underlying the observed equilibrium outcomes, which we then use to conduct counterfactual policy evaluations. In addition, we are also interested in how information structure can affect teacher entry.

Our paper also contributes to the literature on teachers' mobility and educational inequality. Previous studies often find that better teachers tend to teach in schools with more advantaged students (e.g., Lankford, Loeb, and Wyckoff (2002); Ingersoll, Hoxby, and Scrupski (2004); Clotfelter, Ladd, and Vigdor (2005); Mansfield (2015)), and that teacher mobility is closely related to schools' student composition (e.g.,Hanushek, Kain, and Rivkin (2004)). However, there have been mixed findings about the effect of financial incentives on teacher behavior and student outcomes (see Jacob, 2007; Neal et al., 2011; Jackson, Rockoff, and Staiger, 2014, for reviews).[7] Specifically in the context of HISD, Brehm, Imberman, and Lovenheim (2017) and Imberman and Lovenheim (2015) study the effect of ASPIRE; Cullen, Koedel, and Parsons (2021) analyze the impact of ETI on teacher exit and student outcomes and find that ineffective teachers were more likely to exit the district after ETI.[8] Building on these papers, we study the interaction of ETI and ASPIRE via the lens of an equilibrium model, which we use to study counterfactual policy impacts on teacher-school sorting, teacher entry and exit.

[7]Some studies suggest that financial incentives can attract and retain teachers in disadvantaged schools (e.g., Clotfelter et al., 2008; Steele, Murnane, and Willett, 2010; Feng and Sass, 2018), while some other studies find little or no effect (e.g., Clotfelter et al., 2008; Clotfelter, Ladd, and Vigdor, 2011; Russell, 2020).

[8]Studies using data from other places in the U.S. have also found that more rigorous teacher evaluation systems increase turnover among lower-performing teachers (Loeb, Miller, and Wyckoff 2015; Steinberg and Sartain 2015; Rodriguez, Swain, and Springer 2020).

2 Background

The Houston Independent School District (HISD) serves as a community school district for most of the city of Houston and several nearby and insular municipalities in addition to some unincorporated areas. Like most districts in Texas, it is independent of the city of Houston and all other municipal and county jurisdictions. Unlike teachers in many other districts, teachers in HISD do not have tenure and most are on one-year contracts, leaving schools with significant latitude in terms which teachers to hire and which teachers to exit.

Over the past 15 years or so, HISD has implemented several policies aimed to improve teacher effectiveness and educational equality, including two major policies that affected the market in our sample period (2008-09 to 2014-15). The first policy is a performance pay scheme (ASPIRE), introduced in 2006-07, which rewards teachers and administrators for raising students' test scores. The second policy is the Effective Teachers Initiative (ETI), introduced in 2010-11. We describe these two policies briefly here, leaving more details in the Online Appendix.

ASPIRE: Like most other U.S. school districts, HISD teachers' salaries follow a rigid experience-education schedule. ASPIRE relaxes such pay rigidity by providing teachers with performance-based bonuses. Over the period we study, the generosity and detailed eligibility criteria of ASPIRE rewards changed, but its overall structure remained as follows. A teacher-level value-added measure known as the EVAAS score was calculated by the SAS Institute based on student growth over the course of the year on state-level standardized tests. At the *end* of an academic year, a teacher can receive up to two types of salary bonuses based on EVAAS scores: an individual reward and a campus reward. Individual rewards are given to teachers with own EVAAS scores above certain district-level thresholds.[9] Campus rewards are given to all eligible teachers employed at schools with high school-level EVAAS scores. A teacher's eligibility was mostly based on being a salaried teacher (not a substitute or associate teacher) and not exceeding a certain number of instructional days absent. Starting in 2010-11, teachers with very low EVAAS scores (roughly 15-20% of teachers) became ineligible for all ASPIRE awards.

In terms of teacher pay, ASPIRE leads to pay variation across teachers within an experience-education group and across schools for the same teacher. In terms of information, a teacher's EVAAS score is confidential but the list of ASPIRE winners and their reward amounts are widely disseminated information. This information, combined with the publicly-known ASPIRE formula, provides prospective employers with some limited information about a teacher's value-added. For example, for hiring decisions made between 2007 and 2010, prospective employers would know whether or not a teacher's EVAAS score was in top quartiles.[10]

ETI was designed to improve teacher quality through more effective recruitment at the front end, individualized professional development in the middle, and targeted retention and exit on the

[9]For example, in 2009-2010 school year, teachers received cash awards for any subjects in which their EVAAS scores placed them in the top two quartiles of teachers in the same grade and subject, up to a maximum award of $7,000. Awards for the top quartile were twice as much as awards for the second highest quartile.

[10]For hirings in 2011 and later years, prospective employers would also know, simply from previous-year's ASPIRE outcomes (even without ETI), that ineligible teachers working on eligible campuses had very low EVAAS scores.

back end. The cornerstone of ETI is a teacher evaluation system, which was designed by the district during the 2010-11 school year with inputs from stakeholders and formally approved by the school board in spring 2011. By 2012-13 school year, the ETI evaluation have fully developed to include three component scores : 1) instructional practice, concerning how well a teacher plans lessons and instructs students, 2) professional expectations, concerning how well a teacher interacts with colleagues, follows school policies, interacts with parents, and participates in professional development, and 3) student performance. The first two components are based on in-person observations in and out of class by at least one certified appraiser, who can be the teacher's supervisor or a person approved by the school board.[11] The last component—student performance—was measured by one or more student growth measures; for teachers in our sample, it was mainly measured by a teacher's EVAAS score.[12]

The ETI component scores are stored by the district in each teacher's personnel file and made accessible to prospective employers. In addition, each teacher is entitled to receive a written copy of the evaluation. Because ETI scores are recorded at the end of a school year, hiring decisions for 2011-12 and later years are made under the ETI information environment. In earlier years (including 2010-11), for a prospective employer, these quality measures were either unobservable (in-person evaluations) or partially observable (whether or not one's EVAAS score was in top quartiles). That is, ETI significantly changed the information structure in the HISD teachers' market. In this paper, we focus on this most salient aspect of ETI and how it interacted with (changes in) ASPIRE, while abstracting from other aspects of ETI (namely, providing teachers with regular feedback on their progress and opportunities for development).

3 First Glance at the Data

As detailed later in the data section, our data consist of three linked administrative data sets from HISD at the school, teacher, and student level between 2009 and 2015; our analysis focus on the market for Grades 3-5 math and reading teachers. In this section, we provide a first glance at this market before and after the introduction of ETI in 2010-11. For the rest of the paper, we refer the academic year using the calendar year of the spring semester (e.g. 2011 for 2010-11).

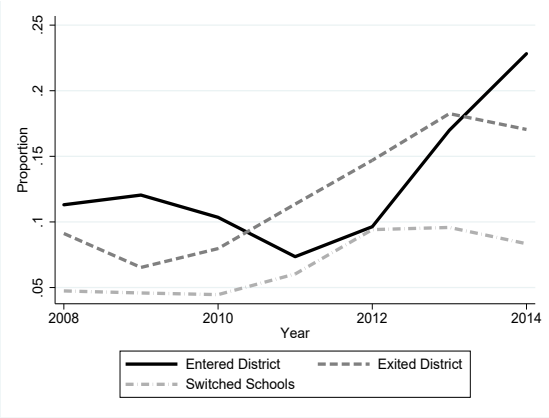
Teacher Job Mobility: Figure **??** shows, for each year $t = 2009, ..., 2015$, among district incumbent teachers, the fractions of district teachers who exited the district in $t + 1$ and who transferred to a different school in the district in $t + 1$, and the number of teachers who entered the district in t as a fraction of all teachers working in the district in that year. Job mobility became much more frequent after ETI. In particular, fewer than 5% of district teachers switched to a different school in the district in a given pre-ETI year, this fraction doubled in post-ETI years.

Teacher-School Sorting: To show teacher-school sorting patterns rather than individual teachers' development overtime, we use a time-invariant measure of teacher effectiveness, as mea-

[11] The appraisers also provided teachers with individualized feedback.

[12] The importance of the EVAAS score in the student performance component diminished over time. Starting in the 2015-2016 school year, the district excluded value-added scores from the student performance calculation.

Figure 1: Job Mobility

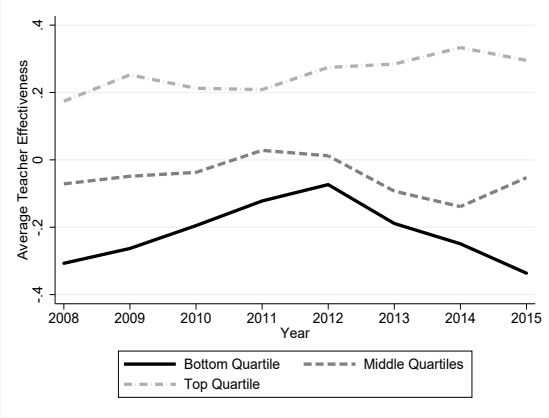


Note: "Exited District" is defined as the percentage of district teachers in the corresponding year who did not work in the district in the following year. "Transferred Schools" is defined as the percentage of district teachers in the corresponding year who worked at a different school in the district in the following year. "Stayed in Same School" is defined as the percentage of district teachers in the corresponding year who worked at the same school in the following year. "Entered District" is the percentage of district teachers in the corresponding year who did not work in the district in the previous year.

sured by one's average EVAAS score across all years observed during our sample period. Similarly, we use a time-invariant measure of school-level achievement that is not affected by ETI: the percentage of each school's Grades 3-5 students who met the state standards between 2009 and 2011. We rank schools by this measure from high to low and divide schools into three groups: the top 25%, the middle 50%, and the bottom 25% schools. We calculate the average teacher effectiveness within each school and each year. As teacher effectiveness is time-invariant, changes in these school-level measures reflect how the composition of teachers changed overtime. Figure 2 shows the evolution of these school-level effectiveness measures for the top school group (the solid line), the middle group (the dotted line), and the bottom group (the dashed line). Across all years, the average teacher effectiveness was higher in schools with higher (pre-ETI) achievement, suggesting positive assortative matching. Post ETI, the average teacher effectiveness increased in the top school group overtime, while it decreased in lower school groups, especially after 2013-14. As a result, teacher quality gap between the top and the lower school groups widened after ETI.

The data patterns show above provide some suggestive evidence that, under ETI, teachers' job mobility increased and teacher-school sorting became more assortative. However, these pre- versus post-ETI data patterns cannot be interpreted as the effect of reducing information friction, because market conditions differ in other aspects before and after ETI. To isolate the role of information in shaping the equilibrium allocation of teachers and, more importantly, to conduct counterfactual policy analysis, we build the following equilibrium model.

Figure 2: Average Teacher Effectiveness by Campus Performance



Note: Teacher effectiveness is measured as average EVAAS score over all years for a given teacher. The red line corresponds to the elementary schools with the most students who met standards before 2011, the green line corresponds to the elementary schools with the least students who met standards before 2011, and the blue line with the middle quartiles.

4 Model

We model the equilibrium in a labor market for public school teachers, where schools make job offers to teachers they want to hire and each teacher—incumbent and potential entrant—chooses her most preferred option feasible.[13] Without a transparent teacher evaluation system (e.g., ETI), the market is subject to information asymmetry between a teacher's current employer and prospective employers.

4.1 Primitives

There are S schools in a district/market ($s = 1, ..., S$). A school is endowed with κ_s teaching positions (capacity), and a vector of characteristics $z_s = \{z_{sk}\}_{k=1}^{K}$, including the composition of its student body (z_{s1}). There is a distribution of teachers $F(x, q, v, s_0)$, each characterized by a vector x (experience, education), the school she works in at the beginning of the model s_0 ($s_0 \in \{1, ..., S\}$ for district incumbents and $s_0 = 0$ for potential entrants), and two quality measures: q and v. In particular, q is $q$uantifiable by outputs, i.e., one's value-added to students' test scores (EVAAS), while v is reflected in one's daily teaching and professional practice.

The timing of the model is as follows:

1. Schools simultaneously make job offers.

2. Each teacher observes her contemporaneous preference shocks for the outside option and for each school $\epsilon = \{\epsilon_s\}_0^S$ and chooses her most preferred option within her offer set, which always includes

[13] As is true in most public school districts, HISD follows a rigid schedule of teacher salaries based on experience and education. Accordingly, schools in our model can only choose whom to hire but not how they are paid.

the outside option.

4.1.1 Information Structure

School characteristics (z, κ) and teacher characteristics (x, s_0) are public information. The structure of information about a district incumbent teacher's (q, v) varies across policy eras. Before ETI, a teacher and her employer s_0 have full information about (q, v); other schools have no information about v and limited information about q. In particular, all schools observe a teacher's ASPIRE award outcome, governed by formula $A(q)$.[14] After ETI, q and v are observable to all schools. The structure of information about a potential entrant is the same before and after ETI and common across schools: A potential entrant's (q, v) are unobservable to all schools. After a teacher enters the market and teaches for one period, she becomes an incumbent and therefore the structure of information about an incumbent teacher applies.

Letting $\Gamma_s(x, q, v, s_0)$ be the set of information available to school s about teacher (x, q, v, s_0), Table 1 summarizes a school's set of information about a district incumbent teacher for her current employer (Column 1) and other schools (Column 2) and all schools' (common) information set about a potential entrant (Column 3).

Table 1: School's Information Set $\Gamma_s(x, q, v, s_0)$

	District Incumbent Teacher		Potential Entrant
	Current school ($s = s_0$)	Other schools ($s \neq s_0$)	All schools
Pre-ETI	x,q,v, s_0	x,$A(q)$, s_0	x, s_0
ETI	x,q,v, s_0	x,q,v, s_0	x, s_0

A teacher has full information about her characteristics (x, q, v, s_0) and observes her contemporaneous preference shocks ϵ right before making her decisions. The researcher has information on school characteristics (z, κ), teacher characteristics (x, q, v, s_0) for all incumbents and entrants, and the distribution of (x, q, v) for potential entrants.

4.1.2 Preferences

Schools Schools' preferences over teacher characteristics are allowed to differ by school characteristics z_s, given by

$$B(x, q, v, z_s), \tag{1}$$

where $B(\cdot)$ is weakly increasing in x, q, and v.[15]

[14] Here $A(q)$ is the formula for individual award: As described in Section 2, before 2011-2012, only individual award contained information about q, while campus award did not.

[15] We assume that *conditional on* (x, q, v), schools do not care about a teacher's origin s_0. Given that we only observe accepted offers, it is hard to distinguish between teachers' moving costs and schools' direct preference for its current employees. We therefore assume the latter away.

Teachers For a teacher with (x, v, q, s_0), the utility of teaching in school s, net of moving costs, is given by

$$U_s(x, q, v, s_0) = W(x, q, v, z_s) + z_s\alpha_0 + z_{s1}(\alpha_1 q + \alpha_2 v) - I(s \neq s_0)(d_1 + d_2 x_1), \tag{2}$$

where $W(\cdot)$ is the pay function set by the district (base salary plus bonuses).[16] The vector α_0 measures teachers' preferences for school characteristics; α_1 and α_2 capture potentially different preferences for student composition (z_{s1}) among teachers with different q and v, respectively; d_1 and d_2 capture the cost of moving and how it may vary by experience.

The value of the outside option, net of moving costs, is given by

$$U_0(x, q, v, s_0) = u_0(x, q, v, s_0) - I(0 \neq s_0)(d_1 + d_2 x_1). \tag{3}$$

We allow $u_0(\cdot)$ to depend on whether the teacher is a district incumbent or a potential entrant in order to better capture what the outside option, as defined in our model, may be. For potential entrants, most of whom are teachers working in other districts, the outside option most likely means staying in their current teaching job. For district incumbent teachers, the outside option may include teaching in other districts, teaching in private schools, non-teaching jobs, and non-employment.

Remark 1 *The ASPIRE component of $W(\cdot)$ includes both individual and campus awards. We need to make an assumption as to how teachers predict which campuses are eligible for campus awards. If we assumed that teachers are fully rational, we would have to deal with a potential multiple equilibrium problem because a teacher's pay in school s depends on which other teachers also accept offers from s. To avoid this complication, we assume that a teacher uses schools' previous years' campus award eligibility (a component of z_s) in forming her belief about how much she will be paid in each school. Empirically, past eligibility predicts future eligibility very well because the set of eligible campuses was quite stable in our sample period.*

4.2 Teachers' Problem

4.2.1 District Incumbents

Observing her preference shocks $\epsilon = \{\epsilon_s\}_{s=0}^{S}$ and job offers, a district incumbent teacher (x, q, v, s_0) solves the following problem

$$V_1(x, q, v, s_0, \epsilon) = \max_{s: o_s(x,q,v,s_0)=1} \{U_s(x, q, v, s_0) + \epsilon_s\}, \tag{4}$$

where $o_s(x, q, v, s_0)$ is the indicator of whether or not teacher (x, q, v, s_0) has an offer from school $s = 1, ..., S$; $o_0(\cdot) = 1$, i.e., the outside option is always available.

[16] In the baseline, we calculate $W(\cdot)$ following the district's salary schedule (a rigid function of x) and the ASPIRE formula, where pay varies by q and z_s but not by v. In our counterfactual policy analysis, we will explore alternative bonus formulae.

4.2.2 Potential Entrants

A potential entrant's quality (q, v) is not observable to district schools. After a teacher has taught in the district, her quality will be fully revealed to her employer and fully (partly) revealed to other schools if ETI is (not) in place. As clearly reflected in (4), once becoming an incumbent, a teacher's job prospective will depend on (q, v) and the identity of her employer. To incorporate these considerations, we model the payoff of working in school s for an entrant $(x, q, v, s_0 = 0)$ as the sum of her current payoff and her expected future payoff, given by

$$U_s(x, q, v, 0) + \beta E\left[V_1\left(x, q, v, s_0 = s, \epsilon'\right)\right]. \tag{5}$$

In (5), $U_s(\cdot)$ is the utility of working in school s defined in (2); $\beta E\left[V_1\left(x, q, v, s_0 = s, \epsilon'\right)\right]$ is the discounted (at rate β) expected value of being an incumbent in s, where $V_1(\cdot)$ is defined in (4) and the expectation is taken over next-period's preference shocks.

With this payoff structure, we define a potential entrant's problem as

$$V_0(x, q, v, 0, \epsilon) = \max\left\{\begin{array}{c} \max_{s:o_s(x,q,v,0)=1}\left\{U_s(x, q, v, 0) + \beta E\left[V_1\left(x, q, v, s_0 = s, \epsilon'\right)\right] + \epsilon_s\right\}, \\ U_0(x, v, q_0, 0) + \epsilon_0 \end{array}\right\}, \tag{6}$$

where ϵ is one's current preference shocks. We assume that preference shocks are i.i.d. across individuals, options, and periods, drawn from a Type-1 extreme value distribution with mean 0 and scale parameter σ_ϵ.

Discussion: We model teachers' problem differently for incumbents and potential entrants in order to balance between the following considerations.[17] On the one hand, it would be intractable to embed a fully dynamic (e.g., life-cycle) individual decision model within our *equilibrium* framework. On the other hand, to evaluate the importance of information structure for teachers' labor market, we need to allow teachers' self selection into the market to depend on the information structure. This dependence arises from the forward-looking behavior of potential entrants, as captured in our model.

4.3 Schools' Problem

A school aims at filling its capacity with its most preferred teachers it can attract. Letting $O_s(\Gamma_s(\cdot)) \in [0, 1]$ be the offer decision rule of school s given its information $\{\Gamma_s(x, q, v, s_0)\}_{(x,q,v,s_0)}$ specified in Table 1, $O_s(\Gamma_s(\cdot))$ solves the following problem

$$\max_{O_s(\Gamma_s(\cdot))\in[0,1]}\left\{\int O_s(\Gamma_s(x, q, v, s_0))\, h_s(\Gamma_s(x, q, v, s_0))\, \overline{B}_s(\Gamma_s(x, q, v, s_0))\, dF(x, q, v, s_0)\right\} \tag{7}$$
$$s.t. \int O_s(\Gamma_s(x, q, v, s_0))\, h_s(\Gamma_s(x, q, v, s_0))\, dF(x, q, v, s_0) \leq \kappa_s.$$

[17] As is the case in any discrete choice model, welfare/value *levels* are not comparable across individuals, and in particular, between incumbents and potential entrants.

From the perspective of school s, given a teacher about whom s observes $\Gamma_s(x,q,v,s_0)$, $h_s(\Gamma_s(x,q,v,s_0))$ is the probability that she will accept an offer from s, and $\overline{B}_s(\Gamma_s(x,q,v,s_0))$ is the expected value of $B(x,q,v,z_s)$ *conditional on* the teacher accepting the offer. That is, subject to its capacity constraint, a school's offer decision rule $O_s(\Gamma_s(\cdot))$ maximizes the total expected value of teachers it hires, where the expectation is based on its information set $\Gamma_s(\cdot)$. This decision rule governs $\{o_s(x,q,v,s_0)\}_{(x,q,v,s_0)}$, i.e., whether or not each teacher receives an offer from s. All teachers that look identical to school s will be treated equally.

As detailed in Appendix A1, both $h_s(\cdot)$ and $\overline{B}_s(\cdot)$ are derived from the teachers' acceptance probabilities. We denote $P_s(x,q,v,s_0)$ as the probability that a teacher with (x,q,v,s_0) will accept an offer from s. From equations (4) and (6), it is clear that $P_s(\cdot)$ depends not only on teachers' preferences but also on other schools' offer decisions $\{O_{s'}(\cdot)\}_{s'\neq s}$: All else being equal, a teacher is more likely to accept an offer from s if she has fewer options, and in particular, if she is fired by her employer. When a teacher's employer is the only school fully informed of her quality, schools may be apprehensive about hiring teachers from other schools in fear of the "winner's curse." This could leave teachers with very limited offers from other schools and hence very limited job mobility. Relaxing information friction will make it easier for high-quality teachers to get more job offers and move to more desirable schools. On the one hand, this can exacerbate the inequality between advantaged schools and disadvantaged schools, if most teachers prefer the former. On the other hand, given the easier upward job mobility under information transparency, high-quality teachers may be induced to enter the market and willing to work in less desirable schools upon entry. Schools can replace their ineffective incumbent teachers with these entrants. As a result, teacher effectiveness in the market as a whole and in disadvantaged schools can potentially improve. With these two offsetting forces, the ultimate equity-efficiency implication of information intervention becomes an empirical question.

4.4 Equilibrium

Definition 2 *A market equilibrium is given by* $\{s^*(\cdot), O_s^*(\Gamma_s(\cdot)), P_s(\cdot)\}$ *such that*
1) Given $\{o_s(x,q,v,s_0)\}_s$ *implied by* $\{O_s^*(\Gamma_s(x,q,v,s_0))\}_s$, $s^*(x,q,v,s_0,\epsilon)$ *solves the teacher's problem, for all* (x,q,v,s_0,ϵ).
2) Given its belief about $\{P_s(x,q,v,s_0)\}_{(x,q,v,s_0)}$, $\{O_s^*(\Gamma_s(x,q,v,s_0))\}_{(x,q,v,s_0)}$ *solves school's problem for all* s.
3) $\{P_s(\cdot)\}_s$ *is consistent with teacher and school decisions* $\{s^*(\cdot), O_s^*(\Gamma_s(\cdot))\}$.

4.4.1 Simplification

Teachers' acceptance probabilities $P_s(\cdot)$ are the sufficient information for school s to solve its problem. Therefore, an equilibrium boils down to a fixed point of $\{P_s(\cdot)\}_s$. However, forming exact beliefs about the high dimensional (non-parametric) objects $\{P_s(\cdot)\}$ is a daunting task for

any decision maker.[18] As a feasible alternative, we assume that schools make decisions based on a simplified parametric belief function $\widetilde{P}_s(\cdot;\zeta)$:

$$\widetilde{P}_s(x,q,v,s_0;\zeta) = \frac{\exp\left(g\left(x,q,v,s_0,s;\zeta\right)\right)}{1+\exp\left(g\left(x,q,v,s_0,s;\zeta\right)\right)}, \tag{8}$$

where

$$\begin{aligned} g(\cdot) = {} & \zeta_0 \frac{W(x,q,v,z_s) - \overline{w}(x,q,v)}{\sigma_{w(x,q,v)}} + x\zeta_1 + q\zeta_2 + v\zeta_3 \\ & + z_s\zeta_4 + z_{s1}\left(\zeta_5 q + \zeta_6 v\right) + I(s=s_0)\left(\zeta_7 + \zeta_8 x_1\right) + I(s_0=0)\,\zeta_9 \\ & + I(s_0>0, s\neq s_0)\left(\zeta_{10} q + \zeta_{11} v\right) + I(s_0=0)\left(\zeta_{12} q + \zeta_{13} v\right). \end{aligned} \tag{9}$$

This simplified belief function captures all the factors governing its counterpart $\{P_s(\cdot)\}$ implied by teachers' optimal decisions. The first term in (9) relates to how acceptance probabilities vary with the relative pay attractiveness in school s. In particular, $\overline{w}(x,q,v)$ and $\sigma_{w(x,q,v)}$ are the cross-school average and standard deviation (std) of pay for a teacher with attributes (x,q,v) according to the district's pay function $W(\cdot)$; we measure relative pay attractiveness by the standard deviation of pay at school s relative to the teacher's average pay in the district.[19] The other terms in the first row relate to the overall quality of the teacher: A school should expect more competitors for a better teacher. The second row of (9) mirrors teachers' preferences for schools as in (2). The third row captures the effect of information. For district incumbent teachers ($s_0>0$), ζ_{10} and ζ_{11} capture a prospective employer's belief about the quality of teachers coming from other schools. With information asymmetry, a school s may expect it to be harder to hire a teacher with high q and/or high v from another school, because the informed school (s_0) is very likely to have made an offer to the teacher. In that case, ζ_{10} and ζ_{11} are expected to be negative. Finally, ζ_{12} and ζ_{13} capture schools' belief about how potential entrants self-select into the district in terms of q and v.

For the rest of this paper, we will study the equilibrium with the simplified belief $\widetilde{P}_s(\cdot;\zeta)$. Solving for the equilibrium with the simplified belief boils down to finding the vector ζ that make $\widetilde{P}_s(\cdot;\zeta)$ defined in (8) consistent with acceptance probabilities $P_s(\cdot)$ derived from teachers' optimal decisions. Notice that ζ is *equilibrium-specific and policy variant.* In our counterfactual policy simulations, we will search for the equilibirum-consistent vector ζ for each given policy, using the equilibrium algorithm described in Online Appendix B1.

4.5 Model Discussion

For tractability, we abstract from several important aspects. First, we take a school's characteristics z_s as given. In particular, we assume away systematic household re-sorting in response to our policy

[18] Alternatively, a school can derive $\{P_s(\cdot)\}$ based on its belief about other schools' strategies, which is also a rather high-dimensional object.

[19] After 2011-2012, teachers with q in the bottom quartile of the distribution are not eligible for campus-wide award, therefore their pay does not differ across schools. In these cases, we set the first term in (9) to zero.

interventions that would change school-level student characteristics. In our sample period, school-level student demographics and achievement were quite stable and seemingly unaffected by ETI. Although we do not expect our counterfactual policies to significantly affect schools' student bodies, readers should be aware of this limitation when interpreting our results.

Second, we abstract from the effect of financial incentives and information on individual teachers' effort and effectiveness. A large literature has focused on the effect of financial incentives on students' test scores; the findings are mixed.[20] We complement this literature by focusing on a different channel through which information and financial incentives may affect education, i.e., information and incentives may affect teacher-school sorting and teacher exit and entry. To the extent that teachers may improve their effectiveness in response to financial incentives and information, our counterfactual policy results could understate the total policy effects.

Third, we model the outside option value as a function of teachers' characteristics. A more comprehensive approach would explicitly model outside employers' reactions. This exercise is very challenging and data-demanding, which we leave for future work.

5 Estimation

As we describe in detail in the next section, we have obtained data from both the pre- and the post-ETI periods. To the extent that ETI introduced non-trivial changes to the information structure, if our model, estimated under one regime, can fit the data under the other regime, it will increase our confidence in the model's ability to make credible counterfactual policy predictions. Both model validation and counterfactual policy simulations are based on the premise that model parameters are fixed across different scenarios. However, our pre-ETI data are from the 2010-11 (a great recession year), while our post-ETI data are from 2013-14. It is unlikely that the value of the outside option (e.g., non-teaching jobs) would be the same between these two years. As such, we allow (only) the outside option value parameters to differ between the pre- and post-ETI sample periods. We estimate our model in two stages, leaving enough information out of the estimation to conduct model validation.

Stage 1 We estimate all model parameters Θ using only the post-ETI data via indirect inference, which involves 1) computing from the data a set of "auxiliary models" that summarize the patterns in the data, and 2) repeatedly simulating data with the structural model, computing corresponding auxiliary models with the simulated data, and searching for model parameters such that the auxiliary models from the simulated data match those from 1). In particular, letting $\overline{\beta}$ denote our chosen set of auxiliary model parameters computed from data and $\widehat{\beta}(\Theta)$ be the corresponding auxiliary

[20] Studies using data from outside of the US have found evidence that financial incentives for teachers affect student achievement (Muralidharan and Sundararaman, 2011; Duflo, Hanna, and Rya, 2012; Lavy, 2002; Atkinson et al., 2009; Glewwe, Ilias, and Kremer, 2010). However, incentive programs implemented in the US have yielded mixed results, e.g., Fryer (2013); Imberman and Lovenheim (2015); Dee and Wyckoff (2015); Brehm, Imberman, and Lovenheim (2017).

model parameters obtained from simulating a large dataset from the model (parameterized by Θ) and computing the same estimators, the estimated vector of structural parameters is the solution

$$\widehat{\Theta} = \text{argmin}_{\Theta} \left\{ [\widehat{\beta}(\Theta) - \overline{\beta}]' W [\widehat{\beta}(\Theta) - \overline{\beta}] \right\},$$

where W is a weighting matrix. In this stage, we target auxiliary models designed to extract all identifying information from the post-ETI data. The vector of parameter estimates $\widehat{\Theta}$ is used to conduct our counterfactual policy analysis in Section 8.

Stage 2 We allow parameters related to teachers' outside options to differ in the pre-ETI year. Denoting Θ^{sub} as the subvector of model parameters excluding outside value parameters, we fix $\widehat{\Theta}^{sub}$ estimated from Stage 1 and estimate the outside-value parameters in the pre-ETI period by matching exit-and-entry related moments *only* from the pre-ETI data. With these estimated pre-ETI outside value parameters and $\widehat{\Theta}^{sub}$ from Stage 1, we use all the other auxiliary models computed from the pre-ETI data to validate our model.

5.1 Identification

A challenge involved in identification is the fact that the researcher observes only the accepted offers, rather than all offers made. To separately identify teacher preferences and school preferences in our Stage 1 estimation, we fully exploit the school's optimization problem. Below, we first provide the main argument and then provide further discussions.

The expected marginal benefit of hiring a teacher for school s given its information set $\Gamma_s(\cdot)$ is given by $\overline{B}_s(\Gamma_s(x, q, v, s_0))$. Under ETI, $\Gamma_s(x, q, v, s_0) = (x, q, v, z_s)$ for district incumbent teachers and therefore the expected marginal benefit of hiring a district incumbent is simply $B(x, q, v, z_s)$, which is weakly increasing in each of the three observed traits—x, q, and v. The marginal cost is the shadow price of a slot, which is common for all teachers. If school s hired district incumbent teacher i, then district incumbent teacher j, who has weakly higher x, q and v than i, must also have had an offer from s under ETI. From the observed "seed pair" ((s, i) in this example), we can infer offers for other incumbent teachers (j in this example). Together with the observed offers, these inferred offers allow us to construct, for each district incumbent teacher, a subset $\widetilde{O}_i$ of all offers O_i she received (which always include the outside option). When $\widetilde{O}_i$ is not a singleton, teachers' choices within $\widetilde{O}_i$ inform us of their preferences.[21]

We can also leverage observed offers in a different way to learn about schools' preferences. For each teacher i, the entire set of schools S is the union of i's full offer set O_i, of which $\widetilde{O}_i$ is a subset, and non-offer set $S \backslash O_i$.[22] If one were to infer teacher preferences under the (false) assumption

[21] Multinomial discrete-choice models can be point-identified using a subset of choices, parametrically (e.g., McFadden, 1978) and semiparametrically (e.g., Fox, 2007). In a framework much more flexible than ours, Barseghyan et al. (2021) allow for *unrestricted correlation* between choice sets and preferences and characterize the sharp identification region of model parameters. We build on insights from these studies to design our auxiliary model Aux 1a (Section 5.2), which is used to extract information useful for identification.

[22] The inference procedure above identifies $\widetilde{O}_i$ but not O_i or $S \backslash O_i$.

that every teacher had offers from *all* schools, the inferred "preferences" would be contaminated by the existence of infeasible choices ($S \backslash O_i$) in a teacher's "choice set" and thus would be different from preferences inferred from choices within $\widetilde{O}_i$. The discrepancy between the two sets of inferred teacher preferences depends on the composition of the non-offer set $S \backslash O_i$ for each district incumbent teacher i. The non-offer set $S \backslash O_i$ in turn is governed by schools' preferences over teacher traits (x, q, v). Therefore, we can learn about schools' preferences from the aforementioned discrepancy: Schools' preference parameters have to generate not only the observed offers, but also the lack of offers from certain schools to certain teachers ($S \backslash O_i$ for each i) that would reconcile this discrepancy.

Discussion Several aspects of the identification strategy deserves further discussion. First, the argument used to construct $\widetilde{O}_i$ is tied to a school's optimal decisions given its information set. Under ETI, a school has full information about teachers' attributes (x, q, v), given which, we can rank teachers and construct $\widetilde{O}_i$ based on (x, q, v). We cannot use the same argument to construct $\widetilde{O}_i$ pre ETI because the information about (q, v) is asymmetric between a teacher's employer and other schools. Therefore, we use the post-ETI sample rather than the pre-ETI sample for Stage-1 estimation. Similarly, because schools only observe potential entrants' x but not their (q, v), we use only district incumbents to find seed pairs and to construct $\widetilde{O}_i$. District incumbents' choices within $\widetilde{O}_i$ reveal teachers' evaluation of school characteristics relative to wages, governed by preference parameters that are common among all teachers. In addition, these choices also inform us of how much district incumbents value the outside option. The entry rates of potential entrants with different characteristics in turn inform us of how much they value the outside option.

Second, we assume that schools cannot discriminate teachers by factors other than (x, q, v). If some job offers were made based on factors we cannot observe, then the inferred $\widetilde{O}_i$ might include infeasible options for some teachers, and thus introducing biases in the inferred teacher preferences based on $\widetilde{O}_i$. However, as long as most job offers are based on (x, q, v), such biases would be small and teacher preferences inferred from $\widetilde{O}_i$ would still be much closer to their true preferences than those inferred assuming that all teachers had offers from all districts. Therefore, the essence of our identification argument still holds. As a robustness check, we re-estimate our key auxiliary models but do not use teacher-school (i, s) matches to infer offers for other teachers if i's q or v is below the 10th percentile among all teachers, since these ineffective teachers may indeed have been hired for other reasons. Doing so significantly affects the number of inferred offers for other teachers; yet our auxiliary models remain robust.

Third, we assume that there is no job posting costs. This assumption is plausible because in reality vacancies in HISD are posted publicly online.[23] We also assume that teachers get offers without having to apply. This assumption does not affect our inference of teacher preferences because the following two cases would both imply that school s was not attractive enough to teacher i : 1) s made an offer to i but i did not accept; 2) i was eligible for a job in s but did not apply.[24]

[23] https://www.applitrack.com/houstonisd/onlineapp/

[24] If it is costly for teachers to apply for jobs (more so for jobs in schools other than one's current school), then

5.2 Auxiliary Models

We design our auxiliary models to closely reflect our identification argument above. We target the following post-ETI auxiliary models in our Stage-1 estimation.

1. Coefficients from two regressions of the following form

$$\begin{aligned} y_{is} = {} & \beta_1 W(x_i, q_i, v_i, z_s) + z_s' \beta_2 + z_{s1}(\beta_3 q_i + \beta_4 v_i) + I(s = s_{0i})(\beta_5 + \beta_6 x_{i1}) \\ & + I(s = 0)\left[\beta_7 + x_i' \beta_8 + \beta_9 q_i + \beta_{10} v_i\right] + \psi_i + \varepsilon_{is}, \end{aligned} \tag{10}$$

   where $y_{is} = 1$ if teacher i is matched with school s, 0 otherwise. The right-hand-side variables are the same as those enter teacher's preferences, including wage $W(\cdot)$, the vector of school characteristics z_s (including z_{s1}), z_{s1} interacted with q_i and v_i, whether or not s is one's current school $I(s = s_{0i})$ (in itself and interacted with experience), whether or not s is the outside option $I(s = 0)$ (in itself and interacted with teacher characteristics). In addition, we include a teacher dummy ψ_i to relate all (i, s) observations associated with teacher i.[25] The two regressions differ in the number of observations, reflecting the identification argument in Section 5.1.

   (a) In the first regression, i's are all district incumbent teachers whose inferred subsets of offers $\widetilde{O}_i$ contain more than one option, and an observation (i, s) is a teacher-district pair in these inferred subsets.

   (b) In the second regression, an observation is any incumbent teacher-destination pair, with #incumbents$\times (S + 1)$ total observations.

2. Average school-level teacher characteristics within each group of schools by quartiles of z_{s1}.

3. Moments capturing entry and exit, including

   (a) Average entrants' characteristics and the average school z_{s1} weighted by the number of entrants.

   (b) Cross moments of entrants' characteristics and z_{s1} of their employers: $E(xz_1|entrants)$, $E(qz_1|entrants)$, $E(vz_1|entrants)$;

   (c) The exit rate among incumbents; the ratio between the number of entrants and the number of incumbents who stayed.

these costs would be absorbed in teachers' moving costs in our model.

[25] To summarize discrete choices, conditional logit regressions may seem more intuitive, which are, however, computationally too costly to run within each iteration of the estimation. We use a linear regression specification with teacher dummies, which capture the idea that the same teacher is choosing one school out of a given choice set.

6 Data

Our data consist of three linked data sets from HISD at the teacher, student and school levels respectively for years 2009 to 2015. Data are reported by academic year, and referenced using the calendar year of the fall semester (e.g. 2013 for 2012-13). Here, we provide a brief summary of our data and how we construct data counterparts of our model components; in the Online Appendix, we provide further details.

Teacher Data Our data on district incumbent teachers come from a variety administrative data files from HISD, covering all individuals employed by HISD between 2009 and 2015. This panel contains information about teachers' education, years of teaching experience, EVAAS scores, school and class identifiers, grades and subjects taught. For post-ETI years, we also observe each teacher's yearly ETI component scores. For information on potential entrants to the district, we use data from the Texas Academic Performance Reports, which provide campus-level data on public schools across the state of Texas. From these reports, we use information on the distribution of teachers' experience and education (x) in all the 64 non-HISD districts located in the Houston metropolitan statistical area (MSA).[26]

Student Data include demographics and state standardized test scores for all public school students in Grades 3 to 5 between 2009 and 2015.

School Data come from the Common Core and the Texas Education Agency, containing information on school characteristics including funds received.

6.1 Empirical Definitions

To map our equilibrium model to the data, we need to introduce some empirical definitions.

The Market Our model is in a static equilibrium setting. For estimation and counterfactual policy analyses, we use data from 2013-14. Teachers started to get all three ETI component scores in 2012-13, and therefore 2013-14 was the first hiring year when prospective employers had information on all three ETI component scores. To validate the estimated model, we simulate the market equilibrium under initial conditions in 2010-11. In 2010-11 academic year, teachers began to receive ETI scores and hence we observe these scores. However, evaluations were conducted during and scores recorded at the end of the academic year, therefore, hiring in 2010-11 was made in the pre-ETI information environment.

In both 2010-11 and 2013-14, we focus on the market for non-substitute full-time public-school math and reading teachers in Grades 3-5 for the following reasons. First, we exclude substitute and part-time teachers, as these workers typically face different types of contracts than regular, full-time teachers. Second, we follow the literature and exclude secondary school teachers because, unlike elementary school teachers, secondary school teachers often teach multiple grades, making

[26] Both incumbents and potential entrants include new teachers with 0 experience.

it hard to identify individual teacher contribution (Kane and Staiger, 2008; Chetty, Friedman, and Rockoff, 2014). Among elementary school teachers, effectiveness measures are obtainable for those who teach math or language in Grades 3-5. The cost of this focus is the implicit assumption that a school's capacity constraint for these teachers does not interact with that for other teachers. Within HISD, the estimation sample contains 169 schools and 2,033 teachers (incumbents and entrants); and the validation sample contains 171 schools and 1,970 teachers.

For potential entrants, we use information on teachers who have lower than 30 years of experience and work in other districts within the Houston MSA to construct the distribution of x among potential entrants.[27]

Schools *School Characteristics* z_s include three variables. z_{s1} is the fraction of the school's students who passed the state's standards on standardized math tests; z_{s2} is the school's total funding per teacher net of teacher salaries (henceforth funding per teacher);[28] z_{s3} is the school's previous-year campus award eligibility as discussed in Remark 1.
School Capacity is binding in the equilibrium. Assuming that the data are generated from an equilibrium, κ_s is the number of teachers in our sample working in s in year t, where $t = 2014$ (2011) for the estimation (validation) sample.

Teachers *Teacher Characteristics* x include experience (x_1) and an indicator of whether or not one has a graduate degree (x_2). Experience falls into one of 7 groups: 0, 1-2, 3-4, 5-8, 9-13, 14-29, and 30 or more years. We refer the last experience group as retirement-age teachers. We group experience for data confidentiality reasons; the specific grouping is made both to respect the experience-education wage schedule in HISD and to be comparable with previous literature.[29]
Teacher Quality (q, v) : For q, we use the average of a teacher's reading and math EVAAS scores prior to the hiring year in question. We standardize q such that it mean 0 with and standard deviation of 1 within each year. To construct v, we utilize data on the teacher's instructional practice and professional expectations. We describe this procedure, and how we calculate v for teachers' in pre-ETI years, in the Online Appendix. This procedure gives us individual-level (q, v) for all HISD incumbents and entrants.

For other potential entrants, we only observe the distribution of x. We assume that the conditional distribution $F(q, v|x)$ among all *potential* entrants is the same as that among teachers in HISD; we obtain the joint distribution of $F(q, v, x)$ using the information about the x distribution among potential entrants. Notice that the distribution of $(q, v|x)$ among entrants, i.e., who chose to enter HISD, is endogeneous and therefore would be different from the distribution of $(q, v|x)$

[27] The exclusion of teachers with over 30 years of experience from potential entrants is consistent with the data.

[28] Since salaries directly enter a teacher's utility function, we use non-teacher salary funding to capture a school's other expenditure that a teacher may care about.

[29] To simulate the model, we need the initial joint distribution of teachers' characteristics (x, q, v) across schools; we are not allowed to export this information at finer experience levels. To save on the number of parameters, we use the median within each experience groups as x_1 in teachers' moving cost function and in deriving our summary statistics and auxiliary models.

among all *potential* entrants. We assume the latter is common in Houston MSA and use our model to explain the endogenous distribution of (x, q, v) among entrants.

Teacher's Origin School (s_0) : For most district incumbent teachers, s_0 is the school a teacher worked at before the year in question. If a teacher was out of the district temporarily, we count these teachers as incumbents and use their most recent school as s_0. District entrants are defined as teachers who entered HISD but had never worked in HISD before the year in question (since 2008). Entrants and other potential entrants have $s_0 = 0$.

6.2 Summary Statistics

Table 2 summarizes our post-ETI sample; Online Appendix Table 1 summarizes our pre-ETI sample. Panel A shows teachers' characteristics (standard deviations are in parentheses) for all HISD teachers, HISD incumbents, and entrants. Compared to incumbent teachers, entrants have lower experience, education, and quality as measured by q and v.

Table 2: Summary Statistics (Post-ETI)

A. Teacher Characteristics	All		Incumbents		Entrants	
Experience (x_1)	9.74	(8.90)	11.07	(8.89)	4.51	(6.72)
Graduate Degree (x_2)	0.28		0.29		0.23	
q	-0.06	(1.02)	0.01	(1.00)	-0.34	(1.06)
v	-0.09	(0.85)	0.02	(0.81)	-0.53	(0.86)
# Teachers	2,033		1,620		413	
B. School Characteristics	**All**		**Bottom Quartile z_1**		**Top Quartile z_1**	
z_1(Frac. students meeting std.)	0.73	(0.15)	0.52	(0.07)	0.90	(0.04)
Funding per teacher ($1,000)	21.35	(6.51)	25.48	(9.76)	20.74	(4.82)
Capacity (#teaching slots)	10.23	(3.86)	7.67	(3.15)	12.10	(4.29)
Initial School-level Incumbent Teacher Characteristics $(s_0 = s)$						
Average Experience	10.55	(4.00)	9.18	(4.29)	11.97	(4.10)
Fraction w/ Grad Degree	0.27	(0.17)	0.27	(0.18)	0.30	(0.17)
Average q	-0.03	(0.45)	-0.32	(0.44)	0.27	(0.28)
Average v	0.00	(0.34)	-0.10	(0.38)	0.13	(0.25)
# Schools	169		42		42	

Panel B of Table 2 summarizes schools' characteristics and the *initial* composition of a school's incumbent teachers $(s_0 = s)$, with cross-school standard deviations shown in parentheses. We present statistics for all schools in our estimation sample and separately for schools ranked in the bottom and the top quartiles in the distribution of z_1, i.e., the fraction of a school's students who met the state standard. Schools with fewer standard-meeting students tend to have fewer slots but larger funding per teacher. The latter is largely because of the additional funding for economically-disadvantaged students from the district. The last four rows show that teachers initially working in lower-performing schools tend to have lower experience, education, q, and v.

Table 3 shows the equilibrium *outcome* teacher-school sorting, entry, and exit realized at the end of the model. Panel A shows the average school-level characteristics of teachers hired by schools in different quartiles of the z_1 distribution (cross-school std. dev. shown in parentheses). Teacher-school matching exhibits a strong assortative pattern. Panel B shows that in 2014, 19% of district incumbent teachers exited HISD and 8% of them switched schools within HISD. Among teachers who ended up working in HISD, the ratio between entrants and staying incumbents is 0.24.

Table 3: Outcome Sorting, Entry, and Exit (post-ETI)

A. Average School Employee Characteristics			
School Group by z_1	Experience	q	v
Quartile 1	8.00	-0.46	-0.24
Quartile 2	8.85	-0.18	-0.15
Quartile 3	9.99	0.01	-0.08
Quartile 4	10.49	0.24	0.03
B. Job Mobility			
Incumbents		Entrants	
Exit HISD	0.19	$\frac{\#Entrants}{\#Stayers}$	0.24
Within-HISD Job Switch	0.08		

7 Estimation Results (preliminary)

7.1 Parameter Estimates

Table 4 shows estimated model parameters. Panel A shows estimated parameters governing teachers' preferences. On the left, we see that schools with higher fractions of students meeting the state standard (z_1) are more desirable. Moreover, the interaction between q and z_1 and the interaction between v and z_1 are both estimated to be positive. That is, higher-quality teachers, as measured by q (value-added) and/or v (teaching and professional practice), have stronger preferences for schools with academically stronger student bodies.[30] For example, a teacher with $(q, v) = (0, 0)$ would put a premium of \$4,576 on a school with $z_1 = 0.9$ over an otherwise identical school with $z_1 = 0.5$. We also find that beyond their own wages, teachers prefer schools with larger funding per teacher. On average, teachers face high moving costs and these costs are larger for more experienced teachers. However, individuals compare the total value of each option when making their choices, including their preference shocks (governed by the scale parameter σ_ϵ). High average moving costs help explain the lack of teacher mobility in general, while preference shocks absorb idiosyncratic reasons for mobility. Our findings of large average moving cost and dispersion of preference shocks are consistent with those in previous studies on worker mobility (e.g., Kennan

[30]Notice that academic performance is correlated with other student characteristics that teachers may (also) care about. Teachers' preferences over z_1 in our model is better interpretted as their preferences for teaching the type of students that have higher performance.

and Walker, 2011).[31] On the right, we show estimates related to the value of the outside option. For both incumbents and potential entrants, their outside option values increase with all measures of teacher traits (x, q, v). Not surprisingly, for those reaching retirement age, the outside option, which includes non-employment, becomes particularly attractive.

Panel B shows school-side parameter estimates. These parameters govern how much relative weights schools put on teachers' traits: x (experience, education), q, and v. We find that schools significantly value teachers' quality as measured by q and v. Conditional on (q, v), schools directly value whether or not a teacher has ever taught, beyond which, however, schools do not significantly value teachers' years of experience or education per se. Although we do not put any restriction as to how schools with different student bodies may value (x, q, v) differently, we find that q (v) is more valued by schools with more (fewer) well-performing students and that all schools value q more than v.

Our estimates have major implications for educational equity and how it may be affected by the information structure. We find that preferences on *both* sides of the market exhibit complementarity: Higher-quality teachers have stronger preferences for higher-performing schools and higher-preforming schools put more weights on teachers' quality relative to their experience and education. Without frictions, these preferences would directly lead to assortative matching between teachers and schools, leaving lower-performing schools behind. The sorting can be less assortative with information friction, as schools are reluctant to hire teachers from other schools in fear of the winner's curse.

[31] One possible explanation, which we abstract from, is the family joint location problem: The tied stayer (mover) would appear to have very high (low or negative) moving costs (e.g., Gemici, 2007).

Table 4: Parameter Estimates (preliminary)

A. Teacher Preferences				
wage ($1,000)	1	normalized	Outside option for incumbents	
z_1(Frac. students meeting standard)	11.44		constant	108.16
$z_1 \times q$	14.87		experience	1.81
$z_1 \times v$	7.12		retirement age	7.99
funding ($1,000 per teacher)	0.10		graduate degree	5.43
$I(s \neq s_0)$ (moving)	-68.60		q	17.62
$I(s \neq s_0) \times$experience	-1.12		v	3.92
σ_ϵ	10.02		Outside option for potential entrants	
			constant	53.95
			experience	0.92
			graduate degree	2.30
			q	16.76
			v	9.57
B. School Preferences $B(x,q,v,z_s) = xb_0 + \exp(b_1 z_{s1}) \ln(q - \underline{q}) + \exp(b_2 + b_3 z_{s1}) \ln(v - \underline{v})$				
q :			Yrs of experience:	
	b_1	1.04	1-2	1.15
v :			3-4	1.45
	b_2	-0.58	5-8	1.45
	b_3	-0.45	9-13	1.66
Graduate degree		0.09	≥ 14	1.66

7.2 Within-Sample Model Fit

Table 5 shows within-sample model fits of the coefficients from the two regressions specified in Section 5.2 (Aux 1a on the left and Aux 1b on the right), which characterize the allocation of incumbent teachers across schools within HISD and the outside option. Table 6 shows model fits for the moments of school-level teacher characteristics (Panel A) and job mobility (Panel B). The model well replicates data patterns in both tables.

Table 5: Model Fit: OLS of Teacher-School Match (post-ETI)

Teacher's Choice Set	Inferred Offer Set[a]		All Schools[b]	
	Data	Model	Data	Model
wage	0.001	0.001	0.0004	0.0002
funding	0.00004	0.00004	0.00001	-0.00001
$I(s = s_0)$	0.839	0.881	0.708	0.657
$I(s = s_0)$ ×experience	0.0002	-0.001	0.003	0.006
z_1	0.004	0.004	0.002	0.001
$z_1 \times q$	-0.001	-0.001	0.001	0.002
$z_1 \times v$	-0.002	-0.003	-0.00008	0.0006
$I(s = 0)$	0.264	0.241	0.236	0.216
$I(s = 0)$ ×experience	-0.003	-0.001	-0.003	-0.002
$I(s = 0)$ ×retirement age	0.104	0.103	0.088	0.115
$I(s = 0)$ ×grad degree	0.034	0.041	0.034	0.037
$I(s = 0) \times q$	-0.002	0.009	-0.010	-0.006
$I(s = 0) \times v$	-0.03	-0.03	-0.048	-0.038

$a(b)$: OLS specified in Aux 1a (1b), teacher fixed effects included: data vs model, post-ETI.

Table 6: Model Fit: Outcome Sorting, Entry, Exit

A. Average Employee Characteristics post-ETI (Aux 2)

	Experience		q		v	
School Group by z_1	Data	Model	Data	Model	Data	Model
Quartile 1	8.00	7.98	-0.46	-0.45	-0.24	-0.25
Quartile 2	8.85	8.92	-0.18	-0.18	-0.15	-0.15
Quartile 3	9.99	9.72	0.01	0.06	-0.08	-0.03
Quartile 4	10.49	10.61	0.24	0.25	0.03	0.06

B. Entry and Exit post-ETI (Aux 3)

Entrant (x, q, v)			Entrant $(x, q, v) \times z_1$				
	Data	Model	Data	Model		Data	Model
Experience	4.54	4.52	3.13	3.23	$E(z_1 \vert entrants)$	0.70	0.72
Grad Deg.	0.23	0.20	0.15	0.14	$\frac{\#Entrants}{\#Stayers}$	0.24	0.22
q	-0.34	-0.38	-0.20	-0.24	Exit rate	0.19	0.20
v	-0.53	-0.54	-0.38	-0.38	Job Switch	0.08	0.07

7.3 Model Validation (TBD)

8 Counterfactual Policy Simulations

Using our estimated model, we evaluate the role of information asymmetry on the market and how it affects the effectiveness of policies that incentivize teachers to teach in lower-performing schools.

8.1 The Role of Information

In our first counterfactual simulation, we compare the baseline equilibrium under the symmetric-information environment with a counterfactual equilibrium where prospective employers have no information on a teacher's (q, v). The information structure in these two cases are displayed in Table 7.

Table 7: Schools' Information Set $\Gamma_s(x, q, v, s_0)$for Counterfactual Simulations

	District Incumbent Teacher		Potential Entrant
	Current school	Other schools	All schools
Symmetric (baseline)	x,q,v, s_0	x,q,v, s_0	x, s_0
Asymmetric (counterfactual)	x,q,v, s_0	x, s_0	x, s_0

Panel A of Table 8 shows that with symmetric information across employers, teachers are more mobile, relative to they are in the asymmetric-info equilibrium. Most noticeably, within-district job switching rate is 6.4% in the symmetric-info case while this rate is only 4.1% in the asymmetric-info case. Panel B shows that the overall teacher quality, as measured by both q and v, is higher on the market when information is symmetric, however, teacher quality gap is also larger between schools with higher and lower fraction of well-performing students (z_1).

Table 8: Symmetric vs Asymmetric Information Equilibrium

	Symmetric		Asymmetric	
A. Job Mobility (%)				
Exit Rate	20.7		19.8	
Job Switch Rate	6.4		4.2	
$\frac{\#Entrants}{\#Stayers}$	22.8		22.3	
B. Teacher Quality	q		v	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Overall	-0.057	-0.067	-0.080	-0.089
By school z_1 : Quar 1	-0.50	-0.48	-0.25	-0.25
Quar 4	0.25	0.23	0.06	0.04
Gap (Q4-Q1)	0.75	0.71	0.31	0.29

8.2 Teacher Bonus Programs and Information

With the goal of providing students with equal access to high-quality teachers, many school districts have implemented various policies that favor low-performing schools. One type of policy is to provide bonuses to high-quality teachers if they choose to work in low-performing schools. In the following, we design counterfactual teachers' bonus programs in the same spirit and examine how program effectiveness may differ by market information structures as shown in Table 7. Our program incentivizes higher-q (value added) teachers to teach in schools ranked in the bottom 20% of the z_1 distribution. Specifically, the amount of bonus a teacher receives for working in a given school is shown Table 9.[32] Furthermore, to explore the possibility of improving efficiency and equity on the teachers' market at no additional monetary cost, we impose a budget-neutral condition for our bonus programs. We do so by reducing teachers' base wages $W(\cdot)$ proportionally by a fraction τ when teacher bonus programs are in place; τ is calibrated for each counterfactual simulation such that the total per-teacher compensation is the same with and without the bonus program.[33]

Table 9: Teacher Bonus ($/year)

$Bonus(q, z_1)$	School z_1		
Teacher q	1st decile	2nd decile	other schools
4th quartile	10,000	5,000	0
3rd quartile	8,000	4,000	0
below median	0	0	0

The effect of these bonus programs are shown in Table 10. The first two columns show that on a market with symmetric information, if we introduce the bonus program, teachers' overall q (v) increases by 0.06 (0.007), thus improving efficiency. In addition, the average q (v) of teachers increases by 0.23 (0.05) in the bottom quartile z_1 schools, while the top quartile schools experience little change in the quality of teachers they hire, thus reducing the teacher-quality gap between the top and the bottom schools. The last two columns show the impact of this bonus program on the market with asymmetric information. Qualitatively, the bonus program has similar effects; however, quantitatively, its effects are larger on a market with symmetric information.

[32] Online Appendix shows results for programs that give bonuses based on $(q + v)$.

[33] To the extent that the district may face resistance for reducing teachers' base wages, we also conduct counterfactual bonus experiments without changing base wages, which require additional costs for the district. Unsurprisingly, the overall effect is larger with additional costs.

Table 10: Effects of Bonuses (Symmetric vs. Asymmetric Info)

Change in Teacher Quality	Sym. Info		Asy. Info	
	Δq	Δv	Δq	Δv
All	0.06	0.007	0.05	0.008
Bottom quartile z_1 schools	0.23	0.05	0.19	0.03
Top quartile z_1 schools	0.003	-0.01	0.02	0.0004

9 Conclusion (TBD)

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Reference (To be updated)

Appendix

A1. Optimal Job Offer Decisions

The school's problem is given by

$$\max_{O_s(\Gamma_s(\cdot))} \left\{ \int O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) h_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) \overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) dF\left(x,q,v,s_0\right) \right\} \tag{11}$$
$$s.t. \int O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) h_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) dF\left(x,q,v,s_0\right) \leq \kappa_s,$$

The first order condition is

$$\overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) - \nu_\kappa = 0,$$

where ν_κ is the non-negative multiplier associated with the capacity constraint. If school s makes an offer to a teacher, of whom it observes $\Gamma_s\left(x,q,v,s_0\right)$, and if it is accepted, the school must surrender a slot from its limited capacity, thus inducing the marginal cost ν. Balancing between the marginal benefit and the marginal cost, the solution is characterized by:

$$O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) \begin{cases} = 1 & \text{if } \overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) - \nu_\kappa > 0 \\ = 0 & \text{if } \overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) - \nu_\kappa < 0 \\ \in [0,1] & \text{if } \overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) - \nu_\kappa = 0 \end{cases}, \tag{12}$$

and

$$\int O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) h_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) dF\left(x,q,v,s_0\right) \leq \kappa_s. \tag{13}$$

That is, for most cases, $O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) \in \{0,1\}$, $O_s\left(\Gamma_s\left(x,q,v,s_0\right)\right) \in [0,1]$ only for the marginal teacher(s) with $\overline{B}_s\left(\cdot\right) = \nu_\kappa$. When potential entrants with $\Gamma_s\left(x,q,v,s_0\right) = \{x, s_0\}$ are ranked as the marginal group, we assume that each of them would get an offer from s with the same probability.

A1.1 $P_s\left(x,q,v,s_0\right)$, $h_s\left(\Gamma_s\left(x,q,v,s_0\right)\right)$ **and** $\overline{B}_s\left(\Gamma_s\left(x,q,v,s_0\right)\right)$

It follows from teacher's optimization that *if receiving an offer from school* s, a teacher with (x,q,v,s_0) would accept this offer with probability

$P_s\left(x,q,v,s_0\right) =$

$$\begin{cases} \frac{\exp\left(\frac{U_s(x,q,v,s_0)}{\sigma_\epsilon}\right)}{\exp\left(\frac{U_s(x,q,v,s_0)}{\sigma_\epsilon}\right) + \sum_{s' \in \{0,\ldots S\} \setminus s} O_{s'}\left(\Gamma_{s'}\left(x,q,v,s_0\right)\right) \exp\left(\frac{U_{s'}(x,q,v,s_0)}{\sigma_\epsilon}\right)} & \text{for } s_0 > 0, \\ \frac{\exp\left(\frac{U_s(x,q,v,0) + \beta EV_1\left(x,q,v,s_0 = s,\epsilon'\right)}{\sigma_\epsilon}\right)}{\exp\left(\frac{U_s(x,q,v,0) + \beta EV_1\left(x,q,v,s_0 = s,\epsilon'\right)}{\sigma_\epsilon}\right) + \sum_{s' \in \{0,\ldots S\} \setminus s} O_{s'}\left(\Gamma_{s'}\left(x,q,v,0\right)\right) \exp\left(\frac{U_{s'}(x,q,v,0) + \beta EV_1\left(x,q,v,s_0 = s',\epsilon'\right)}{\sigma_\epsilon}\right)} & \text{for } s_0 = 0. \end{cases} \tag{14}$$

From a school's perspective, the acceptance probability based on its information $\Gamma_s\left(x,q,v,s_0\right)$ is given by

$h_s(\Gamma_s(x,q,v,s_0)) = E[P_s(x,q,v,s_0)|\Gamma_s(x,q,v,s_0)] =$

$$\begin{cases} P_s(x,q,v,s_0) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,q,v,s_0\}, \\ \int P_s(x,q',v',s_0)\, dF(q',v'|x,A(q),s_0) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,A(q),s_0\}, \\ \int P_s(x,q',v',s_0)\, dF(q',v'|x,s_0) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,s_0\}, \end{cases} \tag{15}$$

where we use a prime to highlight a variable that needs to be integrated out. Given the information structure in Table 1, the first two rows of (15) are about district incumbent teachers $s_0 > 0$: Before ETI, the first row applies to a teacher's employer and the second row applies to other schools. After ETI, the first row applies to all schools. The third row of (15) is about potential entrant teachers ($s_0 = 0$), applicable to all schools both before and after ETI.

Similarly, the inferred value of the teacher conditional on her acceptance is given by
$\overline{B}_s(\Gamma_s(x,q,v,s_0)) = E[B(x,q,v,z_s)|\Gamma_s(x,q,v,s_0), accept] =$

$$\begin{cases} B(x,q,v,z_s) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,q,v,s_0\} \\ \frac{1}{h_s(\Gamma_s(x,q,v,s_0))} \int B(x,q,v',z_s) P_s(x,q',v',s_0)\, dF(q',v'|x,q,s_0) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,A(q),s_0\} \\ \frac{1}{h_s(\Gamma_s(x,q,v,0))} \int B(x,q',v',z_s) P_s(x,q',v',s_0)\, dF(q',v'|x,s_0) \text{ if } \Gamma_s(x,q,v,s_0) = \{x,s_0\}. \end{cases} \tag{16}$$

A2. Detailed Functional Forms

A2.1 Teachers' Payoff from the Outside Option is allowed to be different for districts incumbents and potential entrants, given by

$$u_0(x,q,v,s_0) = I(s_0 = 0)(\varphi_{10} + \varphi_{20}x_1 + \varphi_{30}q + \varphi_{40}v) + I(s_0 > 0)(\varphi_{11} + \varphi_{21}x_1 + \varphi_{31}q + \varphi_{41}v)$$

A2.2 Schools' Preferences for teachers are given by

$$B(x,q,v,z_s) = xb_0 + \exp(b_1 z_{s1}) \ln\left(q - \underline{q}\right) + \exp(b_2 + b_3 z_{s1}) \ln(v - \underline{v}).$$

Schools' direct preferences for x (education and experience) are captured by $b_0 \geq 0$; their preferences for q and v are assumed to be concave (in logs) with coefficients given by $\exp(b_1 z_{s1})$ and $\exp(b_2 + b_3 z_{s1})$, respectively.[34] We assume that all teachers yield non-negative values for schools, which implies that schools do not prefer to be under-staffed and their capacities are binding in the equilibrium. Because q and v are standardized to have mean zero, they can take negative values. We subtract q by $\underline{q}$ to ensure that $\ln\left(q - \underline{q}\right) > 0$; we treat v in the same way.[35] This re-scaling does not affect the relative ranking of q (v) among teachers. The coefficients in front of these two terms—$\exp(b_1 z_{s1})$ and $\exp(b_2 + b_3 z_{s1})$—are allowed to differ by a school's student composition (z_{s1}). We use exponential functions to parameterize these coefficients to guarantee that $B(\cdot)$ is weakly increasing in q and v for all schools.

[34] As a normalization, the constant term is zero in $\exp(b_1 z_s)$, so that a teacher's value is measured in units of (log) q.

[35] $\underline{q}$ and $\underline{v}$ are set at 0.5 standard deviations below the sample min of q and v, respectively.