Information Frictions and the Labor Market for Public School Teachers*

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Abstract

Information frictions —- that a worker and her current employer know more about the worker's productivity than prospective employers —- have complex equity-efficiency implications in the teachers' labor market. Reducing information frictions may make it easier for effective teachers to move to their preferred schools and increase cross-school inequality, but it may also attract high-quality entrants and improve market-level teacher quality. Taking these factors into account, we develop an equilibrium model of the teachers' labor market and estimate it using data from the Houston Independent School District, which launched a transparent teacher evaluation system in 2011. Counterfactual simulations reveal that (1) making district teachers' quality observable to all district schools improves average teacher quality at the district level and in the top and bottom 25% of schools ranked by student performance, while decreasing it in other schools; (2) budget-neutral bonus programs that incentivize high-quality teachers to teach in low-performing schools can increase overall teacher quality and reduce cross-school inequalities; and (3) these programs are more effective in markets with cross-employer information symmetry.

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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 effective teachers regardless of the student body it serves. A major obstacle to achieving this goal is information frictions: 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 its teachers' effectiveness through daily observations, a teacher's employer has an information advantage about her quality over other schools.[2]

It is well known that information frictions, and in particular, information asymmetry between current and prospective employers, can obstruct efficient labor allocation (e.g., Waldman, 1984; Bruce, 1986; Chang and Wang, 1996; Waldman and Zax, 2016). In the case of the labor market for public school teachers, such information frictions are accompanied by 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, the gold standard for optimal worker-firm allocation is total output maximization; how total output is distributed across firms is second order. However, in the teachers' labor market, both student achievement overall and its distribution across schools are fundamental issues. As such, teacher-school allocations involve a more salient and complex equity-efficiency trade-off than typical worker-firm allocations.[3]

These features complicate the implications 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.

[1] See, for example, Chetty et al. (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 worker welfare exists in all labor markets and is not the focus of our paper. Throughout the paper, we focus on the quality of teachers in the market overall (efficiency) and across schools (equity).

On the other hand, with easier upward job mobility, a market with symmetric information can attract more effective teachers to enter, thus improving the overall quality of teachers in the market. Taking these factors into account, this paper examines the equity-efficiency implication of information frictions on the teachers' labor market.

Our empirical setting is the Houston Independent School District (HISD), the eighth-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 (e.g., how a teacher interacts with students, colleagues, and parents) with estimates of teachers' value-added (VA) to test scores, ETI provided a multidimensional assessment of each teacher's quality and made this information accessible to all schools in the district. Notably, some aspects of a teacher's quality as measured by ETI (e.g., quality revealed via in-person observations) could be learned by her employer through daily observations but were likely unobservable to other schools before ETI. 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 an equilibrium model of the labor market for public school teachers, accounting for the role of information frictions. In the model, there is a distribution of teachers, including market incumbents and potential entrants, characterized by publicly observable attributes and by quality measures that are fully observed by the teacher and her current employer but (partly) unknown to prospective employers. A teacher cares about her salary and a school's characteristics and chooses her most-preferred school among those offering her a job or the outside option, subject to moving costs. Each school aims to fill its capacity with its most preferred teachers by extending job offers to teachers it wishes to hire, given its belief about (1) the probabilities of acceptance by different teachers and (2) the expected quality of a teacher *conditional on her acceptance* — two equilibrium objects resulting from 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 school s accepts an offer from another school, one possible explanation is that she has been found to be ineffective and dismissed by s.[4] As a result, teachers may get few offers from other schools and therefore rarely switch jobs. Programs such as ETI

[4]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.

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 estimate our model using the post-ETI data and use the pre-ETI data to validate the estimated model. The model replicates the data patterns well in both periods. Our estimates suggest that all else equal, teachers prefer schools with higher fractions of high-performing students and that such a preference is stronger among higher-quality teachers. Meanwhile, relative to experience and education, schools significantly value teachers' quality, especially teachers' VA. Moreover, preferences for higher-VA teachers are stronger among schools serving higher 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.[5] The sorting can be less assortative with information frictions, as schools are reluctant to hire teachers from other schools in fear of the winner's curse.

We use the estimated model to quantify the role of information frictions. Holding *all the other initial conditions fixed* at the post-ETI level, we simulate the equilibrium under a counterfactual asymmetric information environment in which prospective employers do not observe teachers' quality. Contrasting this equilibrium with the (baseline) post-ETI equilibrium, we find that removing information asymmetry between current and prospective employers improves the overall teacher quality in the district. Moreover, breaking schools into four groups by a school's fraction of high-achieving students, we find that average teacher quality improves in the top and the bottom 25% of schools, while decreasing that in other schools. These changes result from the interplay of information's intensive- and extensive-margin impacts on the market. At the intensive margin, symmetric information benefits top schools because it makes it easier for these schools—preferred by most teachers—to recruit effective teachers from other schools. At the extensive margin, symmetric information induces higher-quality teachers to enter the market. These entrants, although less effective than incumbent teachers on average, are more effective than many teachers working in low-performing schools; therefore, these schools benefit most from this extensive-margin effect.

With the goal of providing students with equal access to high-quality teachers, many school districts have implemented programs, such as teacher bonuses, aimed at improving teacher quality in low-performing schools. Given the role of information frictions in shaping equilibrium allocations, it is natural to hypothesize that the impacts of such programs may vary with the market's information environment, although it is not clear how. To shed light

[5]Throughout the paper, we use "low-performing schools" and "schools with more low-performing students" interchangeably.

on this, we introduce counterfactual teachers' bonus programs to incentivize high-quality teachers to teach in low-performing schools. We evaluate these programs in a market with information asymmetry between employers and an otherwise-identical market without such information asymmetry. We find that these bonus programs can both increase overall teacher quality on the market and reduce the teacher-quality gap between high- and low-performing schools, even though we hold the total per-teacher compensation fixed for the district by reducing teachers' base salaries. More importantly, these programs are more effective when implemented in a market with symmetric information between employers. Our findings point to fruitful interactions between policies that reduce information frictions and policies that aim at improving educational equity.

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, Dolton and Klaauw (1999) study teachers' decision to leave the profession; Stinebrickner (2001a), Stinebrickner (2001b), Wiswall (2007), and Lang and Palacios (2018) model individuals' dynamic choices between teaching and non-teaching options; 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 et al. (2007) find that teachers prefer schools with fewer low-achieving and minority students.

A smaller subset of work considers both sides of the market. Tincani (2021) 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; using data from Peru, Bobba et al. (2024) and Ederer (2023) study teacher-school sorting in a centralized application-assignment environment; Biasi et al. (2024) 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. (2024) study efficient teacher-school allocation within a district. Our paper complements these studies: We account for information frictions about a teachers' quality and examine how policies that reduce informational asymmetry may affect equilibrium teacher-school matching, and teacher entry and exit.

There is an extensive literature, both theoretical and empirical, on the impact of incomplete information on labor market allocation, with one strand focusing on the impact

of asymmetric information between current and prospective employers.[6] In the context of the teachers' labor market, Bates (2020) develops novel tests of cross-school information asymmetry. Using a difference-in-differences approach, he examines how teachers' within-district movement and exits were affected by the adoption of value-added (VA) measures by two North Carolina school districts. He finds direct evidence of asymmetric information between employers. His findings, based on quasi-experimental data variation from a different state, lend external support to our finding that asymmetric information plays a key role in the teachers' labor market. Complementary to his work, we use a structural estimation approach 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 (see Jacob, 2007; Neal, 2011; Jackson et al., 2014, for reviews). Previous studies have found that better teachers tend to teach in schools with more advantaged students (e.g., Lankford et al., 2002; Ingersoll et al., 2004; Clotfelter et al., 2005; Mansfield, 2015)), and that teacher mobility is closely related to schools' student composition (e.g., Hanushek et al., 2004). Kraft et al. (2020) find that teacher evaluation reforms increased the number of new teachers from more competitive colleges but decreased the overall supply of teachers. Specifically in the context of HISD, Brehm et al. (2017) and Imberman and Lovenheim (2015) study the effect of ASPIRE; Cullen et al. (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.[7] Building on these papers, we study the interaction of ETI and ASPIRE via the lens of an equilibrium model.

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, HISD has two features that distinguish it from many districts in the rest of the country: (1) HISD is independent of the city and all

[6]Examples of theoretical papers include Waldman (1984); Bruce (1986); Lazear (1986); Milgrom and Oster (1987); Riordan and Staiger (1993); and Laing (1994). Examples of empirical papers include Gibbons and Katz (1991); Chang and Wang (1996); 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 et al. (2016); andWaldman and Zax (2016).

[7]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 et al., 2015; Steinberg and Sartain, 2015; Rodriguez et al., 2020).

other municipal and county jurisdictions;[8] (2) teachers do not have tenure and most of them are on one-year contracts, leaving schools with significant latitude in hiring and dismissal decisions.

Over the past 20 years, 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 (2006-07 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 and in detail in Online Appendix C.

ASPIRE Like most other U.S. school districts, HISD uses a rigid experience-education schedule to pay its teachers. ASPIRE relaxes this pay rigidity by providing teachers with performance-based bonuses. Over the period we study, the generosity and detailed eligibility criteria of ASPIRE rewards varied across years, but its structure is as follows. A teacher-level value-added measure known as the EVAAS score is calculated by the SAS Institute based on student growth over 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 whose EVAAS scores exceed certain thresholds.[9] Campus rewards are given to all eligible teachers employed at schools with school-level EVAAS scores above a specific percentile. In this case, a teacher's eligibility was mostly based on being a salaried (not 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 both across teachers within an experience-education group and across schools for the same teacher, the latter of which is key to identifying teachers' preferences for pay. In terms of information, a teacher's EVAAS score is confidential but the list of ASPIRE winners and their reward amounts are publicly announced. This information, combined with the publicly-known ASPIRE formula, could provide prospective employers with some information about a teacher's VA.

ETI 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 back end. The cornerstone of ETI is a teacher evaluation system, which

[8] In 2023, after our sample period, the Texas Education Agency assumed direct control of the HISD.

[9] For example, during the 2012-2013 school year, teachers received $5,000 if their overall EVAAS score was above 1.0 but below 2.0, and $10,000 if their EVAAS score exceeded 2.0.

was designed by the district during the 2010-11 school year with inputs from stakeholders and formally approved by the school board in spring of 2011. By 2012-13 school year, the ETI evaluation had 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 and parents, follows school policies, and participates in professional development, and 3) student performance, measured primarily by EVAAS scores for teachers in our sample. The first two components are based on in-person observations of the teacher in class (e.g., communicates concepts with students) and out of class (e.g., collaborates with colleagues) by at least one certified appraiser. The appraiser, who also provides teachers with individualized feedback, can be the teacher's supervisor or a person approved by the school board.

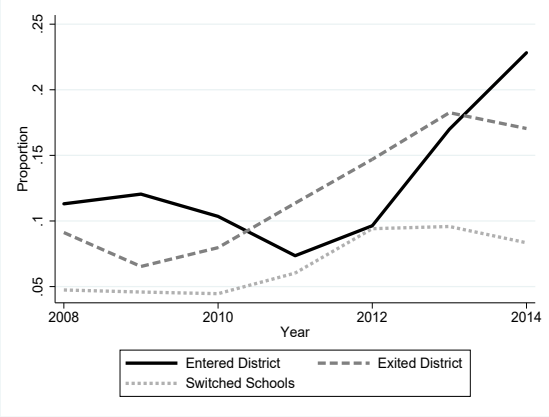
The ETI component scores are stored by the district in each teacher's personnel file and made accessible to all district schools. In addition, each teacher is entitled to receive a copy of the evaluation. Because ETI scores are recorded at the end of a school year, hiring decisions for 2011-12 and later years are made under the ETI information environment. In earlier years (including 2010-11), a prospective employer's information was much more limited: For example, they had no information about teacher's quality reflected by in-person evaluations. 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, while abstracting from its other components (namely, providing teachers with regular feedback on their progress and opportunities for development).

3 A First Glance at the Data

As detailed later in the data section, our data consist of linked administrative data sets from HISD at the school and teacher level between 2007 and 2015; we 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 1 shows, for each year $t = 2008, ..., 2014$, three measures of job mobility: (1) the exit rate, i.e., the fraction of district teachers who exited the district in $t+1$ (the dotted line), (2) the job-switching rate, i.e., the fraction of district teachers who transferred to a different school in the district in $t+1$ (the dashed line), and (3) the number of period-t entrants—those who entered in t—as a fraction of all teachers working in this market in t (the solid line). All three types of job mobility became much more frequent after ETI. For example, fewer than 5% of district teachers switched to a different school in the

Figure 1: Job Mobility



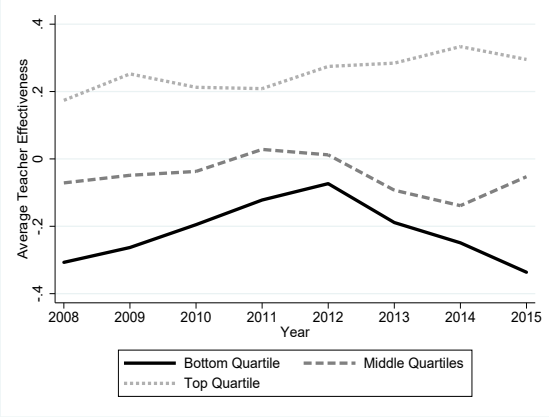
Note: "Exited District" is defined as the fraction of district teachers in the corresponding year who did not work in the district in the following year. "Switched Schools" is defined as the fraction of district teachers in the corresponding year who worked at a different school in the district in the following year. "Entered District" is the number of teachers who entered the district divided by the number of all teachers working in the district in the corresponding year .

district in a given pre-ETI year; this fraction doubled in post-ETI years. In addition, the fraction of entrants in the market (the solid line) dipped between 2010 and 2012 (concurrent with the great recession), but by 2014 this fraction was twice as high as that in 2008.

Teacher-School Sorting: Figure 2 shows a school's average teacher effectiveness over time for three groups of schools: the top 25% (the solid line), the middle 50% (the dotted line), and the bottom 25% (the dashed line), ranked by the percentage of each school's Grades 3-5 students who met the state testing standards between 2008 and 2011. Figure 2 uses a time-invariant measure of teacher effectiveness (one's average EVAAS score across all years observed during our sample period) and 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 testing standards between 2008 and 2011). As such, changes in a school's average teacher effectiveness reflect changes in its teacher composition.[10] 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, while it decreased in the other school groups. As a result, the teacher quality gap between the top and the lower school groups widened after ETI. We find similar patterns if we divide schools by the fraction of minority students or the fraction of

[10]In Online Appendix Figure 3, we use each teacher's EVAAS score in the year in question and repeat the exercise. That figure shows patterns very similar to but noisier than those in Figure 2.

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 dotted line corresponds to the elementary schools with the most students who met standards before 2011, the dashed corresponds to the elementary schools with the least students who met standards before 2011, and the solid line with the middle quartiles.

economically disadvantaged students (Online Appendix Figures 4 and 5): Post-ETI, average teacher quality increased (decreased) in schools with fewer (more) minority or economically disadvantaged students.

Figures 1 and 2 provide some suggestive evidence that, under ETI, teachers' job mobility increased and teacher-school sorting became more assortative. However, these pre- and post-ETI data patterns cannot be interpreted as the effect of reducing information frictions, as other market conditions also changed over time. To assess 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.

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 feasible option.[11] 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.

[11]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.

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, as measured by one's value-added (EVAAS) to students' achievement; v is reflected in one's daily teaching and professional activities, as measured by ETI in-person evaluations.

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 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 some information about q, the latter being governed by a function $A(q)$. Rather than taking a firm stand on the informational contents of $A(q)$, we hypothesize alternative forms of $A(q)$ based on policy background and our conversations with HISD; we will use the pre-reform data to infer which information environment is closer to the truth in Section 5. 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). 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

Table 1: Schools' 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

Column 1 gives the current employer school's information set about a teacher. Column 2 gives other schools' information set about a district incumbent teacher. Column 3 gives all schools' (common) information set about a potential entrant.

(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.[12]

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.[13] 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

[12] 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.

[13] In the status quo, $W(\cdot)$ includes the teacher salary (a rigid function of x) and the ASPIRE awards, the latter vary by q and z_s but not by v. In our counterfactual policy analysis, we will explore alternative bonus formulae.

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. The campus award structure provides pay variation across schools for the same teacher, which is critical for identifying teachers' preferences with respect to pay. However, 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.*[14] *Similarly, when calculating a teacher's individual-level ASPIRE award, we assume that the EVAAS score cutoffs for awards are fixed.*

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. We assume that preference shock ϵ's are i.i.d., drawn from a Type-1 extreme value distribution with mean 0 and scale parameter σ_ϵ.

[14] Specifically, we assume teachers predict a school will receive a campus award if campus-level VA was in the top 30 percentile in the previous year or in the top 20 percentile two years prior (which is treated as a school's characteristics in our model). Across our sample period, the correlation of between current year's campus-level value added percentile with the previous year's is 0.86.

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 may also be revealed to other schools depending on the market informational environment. As clearly reflected in (4), once becoming an incumbent, a teacher's job prospects will depend on the identity of her employer and her quality (q, v). 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:

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

In (5), $U_s(\cdot)$ is the utility of working in school s defined in (2); $\beta E\left[V_1(x, q, v, s_0 = s, \epsilon')\right]$ is the discounted (at the 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

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

where ϵ is one's current preference shocks.

Notice that the degree of the dependence of an incumbent's value $V_1(\cdot)$ on (q, v) varies with the market's informational environment. As such, (6) implies that the pool of teachers who self-select to enter the market will depend on the information structure.

Discussion: We model teachers' problems differently for incumbents and potential entrants due to the following consideration.[15] To assess the role of information structure for teachers' labor market, we need to allow teachers' self-selection into the market to depend on the information structure. Our specification of a potential entrant's problem allows us to capture this dependence.[16]

4.3 Schools' Problem

A school seeks to fill 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 $\{\Gamma_s(x, q, v, s_0)\}_{(x,q,v,s_0)}$

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

[16] Ideally, one would capture this dependence with a fully dynamic (life-cycle) individual decision model. Unfortunately, embedding such individual dynamics within our *equilibrium* framework would make the exercise intractable.

specified in Table 1, $O_s(\Gamma_s(\cdot))$ solves the following problem

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

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, while $\overline{B}_s(\Gamma_s(x,q,v,s_0))$ is the expected value of $B(x,q,v,z_s)$ *conditional on* the teacher accepting the offer. 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 are treated equally.

As detailed in Appendix A.1, both $h_s(\cdot)$ and $\overline{B}_s(\cdot)$ are derived from teachers' acceptance probabilities; we denote by $P_s(x,q,v,s_0)$ the probability that a teacher characterized by (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," potentially limiting her job prospects and restricting overall mobility.

Relaxing information frictions can ease job transitions for high-quality teachers, allowing them to receive more 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 accept positions in less desirable schools upon entry. Schools can replace their ineffective incumbent teachers with these entrants. As a result, teacher effectiveness may improve both market-wide and in disadvantaged schools. Given these two offsetting forces, the ultimate equity-efficiency implications of information interventions become 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.[17] As a feasible alternative, we assume that schools make decisions based on a simplified parametric belief function $\widetilde{P}_s(\cdot;\zeta)$:

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

where

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

This simplified belief function captures all the factors governing its counterpart $\{P_s(\cdot)\}$ implied by offers made by other schools and 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.[18] 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

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

[18] 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.

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 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.[19] 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

[19] Of schools that remain in our sample from 2007-2015, 82% in the bottom quartile of student achievement (percms) before 2011 remain in the bottom quartile post 2011 (inclusive). 93% percent of schools in the top quartile remain in the top quartile. 95% of schools in the lowest quartile of percent minority students remain in the lowest quartile while 85% in the top quartile remain in the top.

[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 et al., 2012; Lavy, 2002; Atkinson et al., 2009; Glewwe et al., 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 et al. (2017).

exercise is very challenging and data-demanding, which we leave for future work.[21]

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 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

[21] We did not find any evidence of other districts introducing pay schemes in response to HISD's introduction of the ASPIRE program or the ETI.

($\widehat{\Theta}^{out}$) in the pre-ETI period, for a given information structure $A(q)$ (Table 1), by matching exit-and-entry related moments *only* from the pre-ETI data. Specifically, we hypothesize two cases about $A(q)$, i.e., how much prospective employers know about the q of a teacher working in another district school.

Case 1) $A(q) = q$, i.e., prospective employers know q, since a teacher can present her EVAAS scores to schools;

Case 2) $A(q)$ is such that prospective employers know about q up to the information revealed by the ASPIRE award outcomes (whether or not the teacher's q is above certain thresholds).

In both cases, a prospective employer will use $(A(q), x, s_0)$ to infer a teacher's expected value conditional on acceptance as stated in the school's problem (7).

For a given $A(q)$ case, we estimate the $\widehat{\Theta}^{out}$ associated with it, together with Stage-1 estimates $\widehat{\Theta}^{sub}$, we simulate the model and use all the other auxiliary models computed from the pre-ETI data to gauge the fit. Out of the two $A(q)$ cases, the one that fits the pre-ETI data the best is the information environment that is closest to the truth. Moreover, how well this best case fits the pre-ETI data serves 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 (for 1605 out of 1620 incumbent teachers, $\widetilde{O}_i$ contains 2 or more schools), teachers' choices within $\widetilde{O}_i$ inform us of their preferences.[22]

[22]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

We can also leverage observed offers in a different way to learn about schools' preferences. First, given that teachers are subject to preference shocks with an unbounded support, as the number of teachers per school grows large, the lowest (x, q, v) among district incumbents working in s is the lowest (x, q, v) that school s is willing to hire (since an offer would be accepted by some teacher). This identifies schools' preferences over teachers.[23] However, in practice, many schools are small, therefore, our identification also relies on the next observation.

Second, given that the distribution of teachers' preferences is revealed from their choices within $\widetilde{O}_i$, we can predict the probability that a teacher would choose to work in each school if they had offers from all schools. As long as (some) schools are selective (i.e., they do not make offers to all teachers), this predicted distribution of teacher-school matches will be systematically (accounting for teacher preference shocks) different from the observed matches, because a teacher can choose a school s only if they had an offer from s. That is, this discrepancy is driven by schools' offer decisions, which are governed by schools' preferences.

This argument can be illustrated as follows. In the simple case where all teachers prefer School 1 over School 2, the fact that i works in School 1 while j works in School 2 implies that School 1 prefers i over j. The same argument applies when teachers have preference shocks: Accounting for teachers preference shocks, if teachers systematically prefer School 1 over School 2, then, School 1 must prefer their hires over (most) teachers working in School 2. As long as the distribution of (x, q, v) in School 1 does not systematically dominate the distribution of (x, q, v) in School 2 in all dimensions, we can infer how much School 1 cares about x and v relative to q. In other words, given teachers' preferences, the realized distribution of teacher-school matches identifies schools' preferences.

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 $\widetilde{O}_i$.

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.

[23]Notice the constructed $\widetilde{O}_i$ across incumbent teachers serves to summarize teacher characteristics that are acceptable by each school: A teacher must be acceptable to s if $s \in \widetilde{O}_i$.

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-construct inferred offer sets based on a stricter rule: From an observed "seed" school-teacher pair (s, i), we include s in teacher j's offer set only if j has q and v at least 0.3 standard deviations higher than those of i, rather than just weakly higher. Doing so significantly lowers the size of $\widetilde{O}_i$, however, our auxiliary models remain robust (Table A8).

Third, we assume that there is no job posting costs. This assumption is plausible because in reality vacancies in HISD are posted publicly online.[24] 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.[25]

5.2 Auxiliary Models

The identification argument in Section 5.1 suggests targeting statistics summarizing 1) teachers' choices within the inferred offer subset $\widetilde{O}_i$ and 2) the realized distribution of teacher-school matches. Notice that, although certain auxiliary models are intuitively more informative about certain structural parameters than others (as we explained above), the identification of the model relies on using information extracted from all auxiliary models and we target the following auxiliary models *jointly*.

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

[25] If it is costly for teachers to apply for jobs (more so for jobs in schools other than one's current school), then these costs would be absorbed in teachers' moving costs in our model.

Aux 1 Coefficients from two regressions of the following form

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

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.[26] 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.

Aux 2 Average school-level teacher characteristics within each group of schools by quartiles of z_{s1}, which supplement Aux 1b.

Aux 3 Moments capturing job mobility:

(a) Average entrants' characteristics and the characteristics z_{s1} of schools where an average entrant works: $E(z_1|entrants)$;

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

(c) Incumbent teachers' exit rate and within-district job switching rate, which supplement Aux 1a;

(d) The ratio between the number of entrants and the number of incumbents who stayed.

[26] 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 two linked data sets from HISD at the teacher and school levels for years 2007 to 2015. Data are reported by academic year, and referenced using the calendar year of the spring 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 Online Appendix B, we provide further details and additional summary statistics.

Teacher Data For information on district incumbent teachers, we use administrative data from HISD, covering all individuals employed by HISD between 2008 and 2015. This panel contains information about teachers' education, years of teaching experience, EVAAS scores, school and class identifiers, and grades and subjects taught. For post-ETI years, we also observe each teacher's yearly ETI component scores. For information on potential entrants, we use data from the Texas Academic Performance Reports, which provide campus-level data on public schools in 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).[27]

School Data: We use information provided by the Common Core and the Texas Education Agency on school characteristics, including funds received and proportions of students in each grade meeting state-set satisfactory levels in standardized tests.

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 analysis, we use data from 2014, allowing three years for the market to adjust following the introduction of ETI in 2011. Additionally, since teachers began receiving all three ETI component scores in 2013, prospective employers had information on all three ETI component scores when making hiring decisions in 2014. To validate the estimated model, we simulate the market equilibrium under initial conditions in 2011. ETI scores were assigned to teachers starting at the *end* of the 2011 academic year, allowing us to observe ETI scores of market participants in 2011; however, hiring in 2011 was made in the pre-ETI information environment.

[27] Ideally, we would also use the information on private-school teachers to construct the distribution of potential entrants. Unfortunately, we do not have information on these teachers, who account for a small fraction of teachers in Texas (e.g. lower than 10% in 2020).

In both 2011 and 2014, we focus on the market for public-school non-substitute full-time math and reading teachers in Grades 3-5 for the following reasons.[28] 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 it hard to identify individual teacher contributions (Kane and Staiger, 2008; Chetty et al., 2014). Among elementary school teachers, value-added measures (EVAAS scores) 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. In addition, we dropped 295 teachers who had missing values for key variables. 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.

Although all qualified individuals can be counted as potential entrants, it is reasonable to focus on the group who have non-trivial probabilities of entering the market as defined above. Therefore, for potential entrants, we focus on teachers employed in all 64 non-HISD districts within the Houston MSA. Among these, we use information on non-substitute full-time teachers with lower than 30 years of experience who taught Grades 3-5 in 2013.[29]

Schools *School Characteristics* z_s include three variables: the fraction of the school's students who passed the state's standards on standardized math tests (z_{s1}), total funding per teacher net of teacher salaries (z_{s2}) (henceforth funding per teacher), and the school's previous-year campus award eligibility (z_{s3}) as discussed in Remark 1.

School Capacity κ_s Assuming that the data are generated from an equilibrium and therefore schools' capacity constraints bind, κ_s is the number of teachers in our estimation (validation) sample who worked in s in 2014 (2011).

Teachers *Teacher Characteristics* x include experience (x_1) and an indicator of whether has a graduate degree (x_2). For data confidentiality reasons, we model x_1 in coarse experience groups: 0 (new teachers), 1-2, 3-4, 5-8, 9-13, 14-29, and 30 or more years (retirement-age

[28] We require that teachers teach at least 75% of total classroom hours for a class of a year to be included in our sample. Substitute teachers make up fewer than 1% of public school teachers in Texas.

[29] The dataset we use does not contain information on the subjects taught by the teachers. The exclusion of teachers with over 30 years of experience from potential entrants is largely consistent with the data: Among those who entered HISD as a full-time Grade 3-5 math/language teacher in 2014, only 3 had over 30 years of experience.

teachers).[30] This grouping respects the experience-education wage schedule in HISD and is comparable with previous literature. It should be noted that both the incumbent and potential entrant pools include new teachers with no experience and experienced teachers.

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, as this was the most recent measure available at the time of making offer decisions. We standardize q to be of mean zero and standard deviation 1 within each year among all Grade 3-5 math and reading teachers in the district. To construct v, we combine ETI's two in-person evaluation measures: instructional practice and professional expectations. We describe this procedure, and how we calculate v for teachers' in pre-ETI years, in Online Appendix B.1. This procedure gives us (q, v) for all HISD incumbents and those who entered, and hence the joint distribution of (x, q, v) among HISD teachers.

For potential entrants who did not enter, we do not observe their (q, v). To obtain the joint distribution of $F(q, v, x)$ for all potential entrants, we use the distribution of their x and the conditional distribution of $F(q, v|x)$ among HISD teachers, the latter assumed to be the same as that among all *potential* entrants. That is, we assume $F(q, v|x)$ is common for all districts within the Houston MSA. Notice that the distribution $F(q, v|x, entrant)$ is endogeneous and therefore would be different from the distribution $F(q, v|x)$ among all *potential* entrants. We will use our model to explain the endogenous distribution $F(x, q, v|entrant)$.

Teacher's Origin School (s_0) : We define district incumbent teachers in year t as those who had worked in HISD before t since 2008. An incumbent teacher's s_0 is their most recent employer in the district prior to t. We define district entrants in t as those who entered HISD but had never worked in HISD before t (since 2008). Entrants and other potential entrants have $s_0 = 0$.

6.2 Summary Statistics

Table 2 summarizes our post-ETI sample. Panel A shows average characteristics among all HISD teachers, HISD incumbents, and entrants; cross-teacher standard deviations are in parentheses.[31] Compared to incumbent teachers, entrants have lower experience, education,

[30] To save on the number of structural and auxiliary model parameters, we use the median within each experience group as x_1 in teachers' moving cost function and in deriving summary statistics and auxiliary models. Online Appendix B.2 explains how we construct the initial joint distribution of teachers across schools without being able to export teacher-level data.

[31] We standardize q and v using all math and reading teachers in Grades 3-5, some of whom are excluded from our sample as explained earlier. Therefore, the q and v in our estimation sample do not have exactly mean 0 and standard deviation of 1.

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)
$corr\,(q, x_1)$	0.06		0.02		0.01	
$corr\,(v, x_1)$	0.18		0.12		0.02	
$E\,(q\|x_2 = 1)$	-0.03	(0.96)	0.03	(0.93)	-0.30	(1.05)
$E\,(v\|x_2 = 1)$	0.00	(0.87)	0.10	(0.82)	-0.49	(0.97)
$E\,(q\|x_1 < 3)$	-0.30	(1.02)	-0.26	(1.01)	-0.35	(1.04)
$E\,(v\|x_1 < 3)$	-0.45	(0.75)	-0.33	(0.74)	-0.59	(0.75)
$corr\,(q, v)$	0.27		0.25		0.23	
# Teachers	2,033		1,620		413	
B. School Characteristics	**All**		**1st Quart. z_1**		**4th Quart. 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)
# Schools	169		42		42	

Panel A shows teacher-level statistics. Cross-teacher standard deviations in parenthesis. Panel B shows school-level statistics for all schools, and schools in the top and bottom quartiles of percent of students meeting testing standards. Cross-school standard deviations in parenthesis.

and quality as measured by q and v. Overall, the correlation is rather weak between teachers' quality (q, v) and readily observable characteristics—experience and education. However, consistent with previous literature on value-added, teachers' quality tends to be lower among young teachers ($x_1 < 3$). The two quality measures, q and v, are weakly correlated.

Panel B of Table 2 summarizes school-level statistics, 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 (high-performing henceforth). Schools with fewer high-performing students tend to have fewer teaching slots but larger funding per teacher. The latter arises partly because of the district's "targeted interventions" favoring low-performing schools.[32]

Table 3 shows the equilibrium teacher-school sorting, entry and exit in 2014. Treating each school as an observation, Panel A shows school-level teacher characteristics among schools in different quartiles of the z_1 distribution (cross-school std dev shown in parentheses).

[32]School funding from the district is determined by a formula which accounts for number of students, demographic composition of students, and "targeted interventions."

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

A. Average Employee Characteristics post-ETI (Aux 2)						
School Group by z_1	Experience		q		v	
Quartile 1	8.00	(3.67)	-0.46	(0.58)	-0.24	(0.36)
Quartile 2	8.85	(2.94)	-0.18	(0.43)	-0.15	(0.30)
Quartile 3	9.99	(4.07)	0.01	(0.37)	-0.09	(0.29)
Quartile 4	10.49	(3.63)	0.24	(0.26)	0.03	(0.21)

B. Job Mobility			
Incumbents		Entrants	
Exit HISD	18.8%	$\frac{\#Entrants}{\#Stayers}$	23.9%
Within-HISD Job Switch	6.6%		

Panel A shows teacher-level statistics with cross-teacher standard deviations in parenthesis. Panel B shows school-level statistics for all schools, and schools in the top and bottom quartiles of percent of students meeting testing standards. Cross-school standard deviations are shown in parenthesis.

Teacher-school matching exhibits a strong assortative pattern, in terms of experience, q, and v. Panel B shows that in 2014, 18.7% of district incumbent teachers exited HISD and 6.6% of them switched schools within HISD. Among all teachers working in our 2014 market, the ratio between entrants and incumbents was 23.9%.

7 Estimation Results

7.1 Parameter Estimates

Table 4 shows estimates of selected model parameters and their standard errors (in parentheses) derived numerically via the Delta Method; other parameter estimates are reported in Table A1. Panel A of Table 4 shows teacher preferences for schools. Schools with higher fractions of students meeting the state standard (z_1) are, on average, more desirable. Moreover, coefficients of the interactions between z_1 and both measures of teacher quality—q (VA) and v (in-person evaluation of one's teaching and professional practice)—are estimated to be positive. That is, higher-quality teachers have stronger preferences for schools with academically stronger student bodies. For example, a teacher with average values of q and v would put a premium of \$4,636 on a school with $z_1 = 0.9$ over an otherwise identical school with $z_1 = 0.5$; this premium is \$16,105 (-\$6,833) for a teacher whose q and v are both ranked at the 90^{th} (10^{th}) percentile. In other words, although most teachers prefer high-performing schools, low-quality teachers have the opposite preference.

Teachers also prefer schools with larger (non-teacher salary) funding per teacher (z_2), *all*

else being equal. Recall that Table 2 shows a negative correlation between a school's student body (z_1) and its funding (z_2). Since teachers value both of these factors, Texas's funding formula, which favors low-z_1 schools, has increased the attractiveness of such schools, but only to a limited extent. For example, at the status quo, an average teacher places a \$3,800 premium on an average school in the top quartile of z_1 compared to an average school in the bottom quartile of z_1; if we remove the cross-school funding (z_2) difference, this premium would increase to \$4,300.

Finally, consistent with findings from previous studies on worker mobility (e.g., Kennan and Walker, 2011), we find that teachers have high moving costs, which grow with teacher experience, and that they face highly-dispersed preference shocks (σ_ϵ): High average moving costs help explain the lack of teacher mobility in general, while preference shocks absorb idiosyncratic reasons for mobility.

Panel B shows school-side parameter estimates, which tend to have larger standard errors than those in Panel A because we have many more teachers than schools. We find that schools highly value teachers' VA q; the strength of this preference increases with a school's fraction of high-performing students (z_1). Relative to q, a teacher's quality as measured by v (in-person evaluation scores) is less valuable to schools in general; however, v is relatively valued more by schools with more low-achieving students (lower z_1). *Conditional* on teacher quality q and v, we find that schools directly care about whether or not a teacher has ever taught but care little about a teacher's additional years of experience and education.

Although our model is silent about why schools put different weights on various traits of a teacher, the resulting estimates are reasonable. For example, given the general emphasis on test scores as performance measures for both students and schools, it is unsurprising that schools care a lot about teachers' VA (q) relative to any other teacher trait. Similarly, it is also reasonable to find that a teacher's quality v is valued more by schools with more low-achieving students: These schools are more likely have students with behavioral problems (e.g., Tippett and Wolke, 2014; Mahvar et al., 2018; Badger et al., 2023), making a teacher's classroom management skills (a key component of v) very important.

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: Teachers, especially high-quality teachers, prefer high-performing schools, high-q teachers are strongly preferred by all schools but more so by high-performing schools. 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 frictions, as schools are reluctant to hire teachers from other schools in fear of the winner's curse.

Table 4: Parameter Estimates

A. Teacher Preferences				
wage ($1,000)	1	-	funding ($1,000 per teacher)	0.10
z_1 (Frac. students meeting standard)	11.59		$I(s \neq s_0)$ (moving)	-70.24
$z_1 \times q$	15.29		$I(s \neq s_0)\times$ experience	-1.11
$z_1 \times v$	7.11		σ_ϵ	10.08
B. School Prefs $B(x,q,v,z_s) = xb_0 + \exp(b_1 z_{s1})\ln(q-\underline{q}) + \exp(b_2 + b_3 z_{s1})\ln(v-\underline{v})$				
q:			Yrs of Experience:	
b_1	1.01		1-2	1.16
v:			3-4	1.48
b_2	-0.63		5-8	1.48
b_3	-0.43		9-13	1.68
Graduate degree	0.09		$\geq$14	1.68

Std errors (in parentheses) are derived numerically via the Delta Method.

7.2 Model Fit and Model Validation

Model Fit Table A2 shows within-sample model fits of auxiliary regressions (Aux 1 in Section 5.2) that characterize the allocation of incumbent teachers across district schools and the outside option. With a few exceptions, the model closely matches these targeted coefficients. Table A3 shows model fits for the moments of teacher characteristics by school groups (Aux 2) and job mobility (Aux 3). The overall fit is good, although the model slightly overpredicts the exit rate and the assertiveness of teacher-school matches.

Model Validation As described in Table 1, in pre-ETI periods, a teacher's current employer was the only school fully informed of the teachers' quality; other schools had no information on v and might have some information on q, captured by a function $A(q)$. We have estimated the pre-ETI outside value parameters by matching only entry and exit moments for each of the two $A(q)$ specifications described in Section 5: Case 1) $A(q) = q$, i.e., prospective employers know q, and Case 2) $A(q)$ is such that prospective employers know about q up to the information revealed by the ASPIRE award outcomes. Using these parameter estimates (Appendix Table A1), together with the non-outside value parameters from Stage-1 estimation, we simulate the model under each given $A(q)$ and the initial conditions from 2011 data.

Tables A4 to A6 contrast model-predicted 2011 equilibrium outcomes, for each of the $A(q)$ cases, with the data.[33] Although both these models fit well the targeted moments (entry and

[33]With asymmetric information, a teacher's expected value $\overline{B}_s(\cdot)$ for school s is not necessarily monotone in (x,q,v) and one cannot construct meaningful inferred offer sets, and hence Aux 1a is not applicable to

Table 5: 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

Column 1 gives the current employer school's information set about a teacher. Column 2 gives other schools' information set about a district incumbent teacher. Column 3 gives all schools' (common) information set about a potential entrant.

exit), Case 2) is closer to the pre-ETI environment, as measured by the data-model distance of non-targeted auxiliary models.[34] Under Case 2), our model match reasonably well the pre-ETI distribution of teacher-school matches, as captured by the pre-ETI non-targeted Aux 1 and Aux 2. For example, although it under-predicts the average teacher quality in low-performing schools pre-ETI, overall, it replicates the fact that the assortativeness of teacher-school allocation was much weaker in the pre-ETI period than the post-ETI period.

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 Equity-Efficiency Implications of Information

Holding all the other initial conditions fixed at their post ETI levels, we compare two market equilibria, each arising from an information environment displayed in Table 5: the baseline symmetric-information environment versus a counterfactual environment where prospective employers have no information on a teacher's (q, v).[35]

Table 6 presents the results. Panel A shows that information increases the within-district job switching rate: 6.4% in the symmetric-info case versus 5.1% in the asymmetric-info case. In contrast, entry and exit rates are very similar between these two cases. Despite its null effect on entry and exit rates, information does affect the composition of teachers: Panel

pre-ETI periods.

[34] Using the inverse of variance of each target as the weights, the overall data-model distance of non-targeted auxiliary models is 51% higher under Case 1) compared to Case 2).

[35] We have also conducted a counterfactual where prospective employers know q up to the ASPIRE award results. As expected, the equilibrium outcomes in that case line in between those in the two environments shown in Table 5. These results are available upon request.

B shows that relative to a market with asymmetric information, a market with symmetric information attracts higher-quality teachers to enter. As a result, Panel C shows that the overall teacher quality in the district, as measured by both q and v, is higher when information is symmetric.

Panel C also zooms into quartiles of schools ranked by a school's fraction of high-achieving students (z_1) . Making information symmetric across employers improves the average teacher quality in the top and the bottom 25% of schools, while decreasing it in the middle two quartiles. These non-monotonic effects arise for the following reasons. First, with symmetric information, all schools are better at identifying high-quality teachers, but it is the top schools that are best able to poach high-quality teachers from other schools because they are preferred by most teachers and more so by high-quality teachers (Table 4). Second, schools in the middle lose more to top schools than bottom schools do because fewer high-quality teachers initially work in bottom schools.[36] Third, as shown in Panel B, symmetric information induces higher-quality teachers to enter the market. These entrants, although less effective than incumbent teachers on average, are more effective than many teachers working in low-performing schools; therefore, these schools benefit most from this extensive-margin effect.

8.2 Teachers' 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, including providing bonuses to high-quality teachers working in low-performing schools.[37] We design counterfactual teachers' bonus programs in the same spirit.

Specifically, letting $\chi(q, v)$ be a measure of teacher quality, our program incentivizes higher-χ teachers to teach in schools ranked in the bottom 25% of the z_1 distribution (i.e., schools with the lowest fraction of high-achieving students). We consider three quality measures: 1) $\chi(q, v) = q$, 2) $\chi(q, v) = q + v$, and 3) $\chi(q, v) = v$. Table 7 specifies the amount of bonus a teacher (incumbent or entrant) receives for working in a given school as a function of teacher quality $\chi(q, v)$ and school characteristics z_1.

Remark 3 *Bonuses are typically rewarded to qualifying teachers at the end of the academic year, as is the case for ASPIRE awards. Following this practice, our bonus programs do not*

[36]Only 17% of teachers initially working in the bottom-quartile schools are in the top quartile of q, this fraction is 21% in the second-quartile schools and 27% in the third-quartile schools.

[37]For example, in 2016, the Dallas Independent School District introduced the Accelerating Campus Excellence program, which provided up to a $10,000 stipend for high-performing teachers who worked in disadvantaged schools.

Table 6: Symmetric vs Asymmetric Information Equilibrium

	Symmetric	Asymmetric
A. Job Mobility (%)		
Exit Rate	20.7	20.7
Job Switch Rate	6.4	5.1
$\frac{\#Entrants}{\#Stayers}$	22.7	22.6
B. Average Entrant Characteristics		
q	-0.36	-0.39
v	-0.55	-0.56

C. Teacher Quality	q		v	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Overall	-0.057	-0.062	-0.080	-0.084
By school z_1: Quart 1	-0.50	-0.52	-0.25	-0.28
Quart 2	-0.19	-0.17	-0.16	-0.14
Quart 3	0.06	0.08	-0.03	-0.01
Quart 4	0.25	0.20	0.06	0.02
Gap (Q4-Q1)	0.75	0.72	0.31	0.30

Panel A shows simulated job mobility statistics under symmetric information and assymetric information. Panel C shows average entrant characteristics under symmetric information and assymetric information. Panel B shows average q and v of teachers overall and within school quartiles under symmetric information and assymetric information.

Table 7: Teacher Bonus ($/year)

	School z_1		
Teacher χ	1st 12.5%	2nd 12.5%	other schools
4th quartile	10,000	5,000	0
3rd quartile	8,000	4,000	0
below median	0	0	0

Size of teacher bonus as function of teacher quality measure, χ, and school's fraction of high achieving students, z_1.

require that the district observe a teacher's quality upfront (e.g., the district may not observe a teacher's quality upon entry).

Given the role of information frictions in shaping equilibrium teacher-school matches, it is natural to hypothesize that the impacts of bonus programs could also vary with the market's information environment, although it is not clear how. To shed light on this, we examine the effects of our counterfactual bonus programs separately on a market with symmetric information and an otherwise-identical market with asymmetric information, as described in Table 5. Furthermore, to explore the possibility of improving educational efficiency and equity at no additional monetary costs, 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 a teacher bonus program is in place; τ is calibrated for each counterfactual simulation such that the district's total expenditure on teacher compensation is the same with and without the bonus program.[38]

The effects of these bonus programs are shown in Table 8. Panels A, B, and C correspond to bonus programs using each of the three quality measures, respectively. Within each panel, the first two columns show the program effect (i.e., the difference in each outcome with versus without the bonus) on a market with symmetric information; the next two columns show the program effect on a market with asymmetric information. Our main findings are as follows:

Result 1: Under both types of market informational environments, all of our bonus programs improve both equity and efficiency. By making the targeted (low-performing) schools more attractive than they used to be, these programs increase teacher quality at targeted schools. Moreover, by attracting higher-quality teachers to enter the market, all of these programs also improve the overall teacher quality in the district. As a result, the improvement at targeted schools is accompanied with very small, and mostly positive, changes in other schools, except for the highest-performing school group, which tends to experience slight decreases in their teacher quality.

For example, in Panel A, we set $\chi(q, v) = q$, i.e., the bonus is based only on EVAAS scores. On a market with symmetric information, this bonus program leads to an increase in overall q (v) by 0.05 (0.003), thus improving efficiency or total teacher quality. As intended, the program is especially successful at attracting high-q teachers to low-performing schools.

Result 2: Quantitatively, all of our programs are more effective at improving teacher quality in targeted schools when implemented in a market with symmetric information, suggesting

[38]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 requires the district to spend more. Unsurprisingly, the overall effect is larger with additional costs (results available upon request).

Table 8: Effects of Bonus Programs

		Symmetric		Asymmetric	
		Δq	Δv	Δq	Δv
A. $\chi(q,v) = q$					
Overall		0.05	0.003	0.05	0.01
By school z_1:	Quart 1	0.22	0.05	0.19	0.05
	Quart 2	0.02	0.01	0.03	0.01
	Quart 3	0.003	-0.01	0.01	-0.002
	Quart 4	-0.02	-0.02	0.01	-0.01
B. $\chi(q,v) = q + v$					
Overall		0.04	0.02	0.04	0.02
By school z_1:	Quart 1	0.18	0.10	0.14	0.09
	Quart 2	0.02	0.01	0.02	0.02
	Quart 3	0.003	-0.01	0.01	0.001
	Quart 4	-0.02	-0.02	0.01	-0.002
C. $\chi(q,v) = v$					
Overall		0.01	0.02	0.01	0.03
By school z_1:	Quart 1	0.09	0.13	0.04	0.12
	Quart 2	0.01	0.004	0.004	0.01
	Quart 3	-0.01	-0.01	-0.001	0.002
	Quart 4	0.01	-0.01	0.001	0.002

Simulated changes in average q and v of teachers overall and within school quartiles when adding teacher bonus programs.

a fruitful interaction between targeted teachers' bonus policies and information intervention policies.

Comparing Columns 1 and 2 (symmetric information) with Columns 3 and 4 (asymmetric information), the improvement in teacher quality in targeted (the bottom quartile) schools is larger in the former case across all three panels. This occurs because with symmetric information, targeted schools can identify and use their bonus advantages to poach high-quality teachers working in other schools more effectively.

Result 3: Due to the positive correlation between q and v, all three bonus programs improve average teacher quality in both dimensions for targeted schools and at the district level. This holds even when only one of the two measures is used in the bonus formula (Panels A and C). However, the improvement in q tends to be larger than that in v, except when bonuses depend only on v; this is largely driven by schools' preferences, who value q more than v.

Specifically, as expected, when bonuses are tied to q only, average teacher v improves much less than q in targeted schools (Panel A). In Panel B, we reward both q and v equally by setting $\chi(q, v) = q + v$. Although this program is more successful than the first bonus program (Panel A) at increasing the average v in targeted schools, its effect on q is still larger than its effect on v. This is because, whenever possible, schools—including the low-performing schools—prioritize hiring higher-q teachers.[39] Moreover, given that q is more valued by schools, this bonus program is also more successful at attracting high-q teachers to enter the market, resulting a larger overall district-level improvement in q than in v. Given these findings, we further examine the case when bonuses are based only on v, i.e., $\chi(q, v) = v$ in Panel C. This bonus program is able to "counteract" schools' preferences and induce a larger improvement in v than in q both in targeted schools and at the district level.

9 Conclusion

Accounting for the salient and complex equity-efficiency implications of information frictions on teachers' labor market, we have built an equilibrium model of the teachers' labor market. The estimated model reveals that breaking the information asymmetry between current and prospective employers improves average teacher quality overall and in the bottom and the top 25% of schools ranked by student performance, but hurts schools in the middle. This result highlights the role of information frictions in shaping the market equilibrium at the intensive margin (teacher-school sorting) and the extensive margin (teacher entry and exit).

[39] It is true that, relative to high-performing schools, low-performing schools care more about v. However, all schools care about q more than v.

Moreover, our counterfactual policy experiments reveal fruitful interactions between information interventions and teachers' compensation policies to improve educational efficiency and equality.

Our framework leaves several extensions for future work. The first extension, which requires additional data, is to incorporate decisions by the private education sector and consider competition not only among public schools, but also between public and private sectors. A second extension is to incorporate household sorting (e.g., Epple and Sieg, 1999; Epple and Romano, 2003; Ferreyra, 2007; Epple and Ferreyra, 2008), which would allow for a more comprehensive evaluation of targeted programs in the long run. A third extension is to add teachers' effort choices into our framework, which is another dimension along which teacher incentive programs may improve efficiency and equity.

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A Appendix

A.1 Optimal Job Offer Decisions

The school's problem is given by

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

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:

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

and

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

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.

A.1.1 $P_s\left(x,q,v,s_0\right)$, $h_s\left(\Gamma_s\left(x,q,v,s_0\right)\right)$ 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

$P_s(x,q,v,s_0) =$

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

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

$\overline{B}_s(\Gamma_s(x,q,v,s_0)) = E[B(x,q,v,z_s)\,|\Gamma_s(x,q,v,s_0),accept] =$

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

A.2 Detailed Functional Forms

A.2.1 Teachers' Payoff from the Outside Option

The teachers' payoff from the outside option is allowed to be different for districts incumbents and potential entrants, given by

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

A.2.2 Schools' Preferences

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.[40] 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.[41] 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.

[40] 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.

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

Table A1: Other Parameter Estimates: Outside Option Values

Period:	Post-ETI	Pre-ETI	
Information:	Full Info	q Known	Aspire Known
Outside option for incumbents			
Constant	110.33	98.71	99.26
Experience	1.84	1.77	1.76
Retirement age	6.73	2.06	1.87
Graduate degree	5.00	0.43	0.44
q	17.25	16.22	16.15
v	4.02	4.91	4.92
Outside option for potential entrants			
Constant	53.16	52.00	52.03
Experience	0.93	3.03	2.95
Graduate degree	2.26	0.93	0.97
q	16.87	18.36	18.36
v	9.63	6.57	6.57

Each columns shows estimates of parameters governing the outside option under alternative information environments. Std errors (in parentheses) are derived numerically via the Delta Method. The columns labeled "q known" shows the case when $A(q) = q$. The columns labeled "Aspire Known" shows the case when $A(q)$ gives the Aspire reward outcomes.

Table A2: 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	0.00005	0.00008	0.00001	-0.00001
$I(s = s_0)$	0.839	0.887	0.708	0.662
$I(s = s_0)\times$experience	0.0002	-0.002	0.0031	0.006
z_1	0.004	0.004	0.002	0.0005
$z_1 \times q$	-0.002	-0.001	0.0007	0.002
$z_1 \times v$	-0.002	-0.002	-0.00009	0.0008
$I(s = 0)$	0.264	0.256	0.236	0.230
$I(s = 0)\times$experience	-0.004	-0.001	-0.003	-0.002
$I(s = 0)\times$retirement age	0.104	0.094	0.088	0.106
$I(s = 0)\times$grad degree	0.034	0.037	0.034	0.033
$I(s = 0) \times q$	-0.002	0.003	-0.001	-0.013
$I(s = 0) \times v$	-0.027	-0.026	-0.048	-0.036
#Obs.	139,452	-	275,400	-

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

Table A3: 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	7.90	-0.46	-0.45	-0.24	-0.25
Quartile 2	8.85	8.87	-0.18	-0.17	-0.15	-0.15
Quartile 3	9.99	9.67	0.01	0.07	-0.09	-0.03
Quartile 4	10.49	10.56	0.24	0.26	0.03	0.06

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

	Entrant (x,q,v)		Entrant $(x,q,v)\times z_1$	
	Data	Model	Data	Model
Experience	4.54	4.51	3.14	3.24
Grad Deg.	0.23	0.20	0.15	0.14
q	-0.34	-0.36	-0.20	-0.22
v	-0.53	-0.55	-0.38	-0.38

	Data	Model
$E(z_1\|entrants)$	0.70	0.72
$\frac{\#Entrants}{\#Stayers}$	23.9%	22.8%
Exit rate	18.8%	20.7%
Switch Rate	6.6%	6.4%

Panel A shows auxiliary model 2: data vs model, post-ETI.

Panel B shows auxiliary model 3: data vs. model, post-ETI.

Table A4: Model Validation: Untargeted OLS of Teacher-School Match (pre-ETI)

	Data	Model	
		q Known	Aspire Known
wage	-0.0001	-0.0001	0.0001
funding	-0.0001	0.00001	0.00001
$I(s=s_0)$	0.8660	0.7739	0.7840
$I(s=s_0)\times$experience	0.0024	0.0076	0.0072
z_1	0.0001	0.0010	0.0012
$z_1 \times q$	0.0006	0.0023	0.0017
$z_1 \times v$	-0.0001	0.0007	0.0005
$I(s=0)$	0.0959	0.0968	0.1052
$I(s=0)\times$experience	-0.0028	-0.0025	-0.0025
$I(s=0)\times$retirement age	0.0820	0.0624	0.0641
$I(s=0)\times$grad degree	-0.0210	-0.0111	-0.0094
$I(s=0)\times q$	-0.0195	-0.0237	-0.0186
$I(s=0)\times v$	-0.0097	-0.0125	-0.0109

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

The column "q known" shows the case when $A(q)=q$.The column

"Aspire Known" shows the case when $A(q)$ gives the Aspire reward outcomes.

Table A5: Model Validation: Untargeted Outcome Sorting (pre-ETI)

	q			v		
School Group by z_1	Data	q Known	Aspire Known	Data	q Known	Aspire Known
Quartile 1	-0.18	-0.27	-0.26	-0.08	-0.11	-0.11
Quartile 2	0.08	0.08	0.09	-0.11	-0.08	-0.07
Quartile 3	0.11	0.10	0.09	-0.02	-0.05	-0.05
Quartile 4	0.14	0.18	0.16	0.03	0.03	0.02

	Experience		
School Group by z_1	Data	q Known	Aspire Known
Quartile 1	10.88	10.84	11.01
Quartile 2	10.40	10.42	10.47
Quartile 3	10.33	10.40	10.35
Quartile 4	10.74	10.54	10.36

Auxiliary model 2: data vs model, pre-ETI. Each entry shows the average value of teacher characteristics for schools in a given quartile of z_1 for a given information environment. Columns labeled "q known" shows the case when $A(q) = q$. Columns labeled "Aspire Known" shows the case when $A(q)$ gives the Aspire reward outcomes.

Table A6: Model Validation: Targeted Entry and Exit Moments (pre-ETI)

	Entrant (x, q, v)			Entrant $(x, q, v) \times z_1$		
	Data	q Known	Aspire Known	Data	q Known	Aspire Known
Experience	2.37	2.50	2.55	1.81	1.89	1.94
Grad Deg.	0.20	0.20	0.21	0.15	0.15	0.16
q	-0.43	-0.40	-0.35	-0.27	-0.28	-0.26
v	-0.28	-0.27	-0.28	-0.19	-0.20	-0.21

	Exiters (x, q, v)		
	Data	q Known	Aspire Known
Experience	10.06	10.13	10.07
Retirement Age	0.07	0.07	0.07
Grad Deg.	0.24	0.26	0.27
q	-0.25	-0.31	-0.25
v	-0.15	-0.17	-0.15

	Data	q Known	Aspire Known
$E(z_1 \mid entrants)$	0.75	0.75	0.77
$\frac{\#Entrants}{\#Stayers}$	7.2%	7.1%	7.2%
Exit rate	7.1%	7.2%	7.2%

Simulated average characteristics of district entrants and exiters under alternative information environments in pre-ETI period. Columns labeled "q known" shows the case when $A(q) = q$. Columns labeled "Aspire Known" shows the case when $A(q)$ gives the Aspire reward outcomes.

Table A7: Teacher Bonus Program Compensation Details

	Symmetric	Asymmetric
A. No Bonus		
$W(\cdot)$+bonus ($1,000/teacher)	53.9	53.9
Bonus ($1,000/teacher)	0	0
Wage reduction $\tau(\%)$	0	0
B. $\chi(q, v) = q$		
$W(\cdot)$+bonus ($1,000/teacher)	53.9	53.9
Bonus ($1,000/teacher)	0.5	0.5
Wage reduction $\tau(\%)$	1.6	1.4
C. $\chi(q, v) = q + v$		
$W(\cdot)$+bonus ($1,000/teacher)	53.9	53.9
Bonus ($1,000/teacher)	0.4	0.4
Wage reduction $\tau(\%)$	1.3	1.3
D. $\chi(q, v) = v$		
$W(\cdot)$+bonus ($1,000/teacher)	53.9	53.9
Bonus ($1,000/teacher)	0.6	0.6
Wage reduction $\tau(\%)$	1.2	1.2

Average wages and bonus received under symmetric and assymetric information.