Information Frictions and the Labor Market for Public School Teachers (Online Appendices)

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B Data Appendix

B.1 Calculation of v

For post-ETI periods, we take each teacher's average of their instructional practice and professional expectations component scores and define this average as v'. Unlike EVAAS scores, which measure teacher value-added to standardized tests, v' may reflect both teacher traits and school-level factors.[1] To account for this, we regress v' on teachers' EVAAS scores, teacher characteristics x, year dummies, and school dummies. Our measure of v is v' net of the estimated coefficients on the school dummies, standardized to be mean 0 and standard deviation of 1 in each year.

Before ETI, a direct score of v is not available, unfortunately. If a teacher has a post-ETI v measure, we use her first v from the post-ETI period as her pre-ETI v. If a teacher does not have a post-ETI v measure, we need to make additional assumptions and impute their v based on information we have at hand. Note that in 2010-11, teachers began to receive the ETI scores. However, as these scores were recorded during the school year, they were not available for schools when they made their hiring decisions at the beginning of the 2010-11 school year. That is, the hiring decisions in 2010-11 were made under the same informational environment as those made in earlier years. Therefore, we assume the conditional distribution of v (conditional on teacher and school characteristics) is the same between 2009-10 and 2010-11. Given these assumptions, we use data from 2010-11 among teachers who had a v measure to gauge the correlation between v and teacher and school

[1] For example, in most cases, a teacher's appraiser is an administrator in her school; differences in v' can therefore reflect differences in administrators' grading generosity.

traits via OLS regression models. Among all the specifications we have tried, the following OLS model captures the correlation the best

$$v = \beta_1 q + \beta_2 exp + \beta_3 grad + \beta_4 \mathbb{I}\left(exp \leq 2\right) + \beta_5 \mathbb{I}\left(exp \leq 2\right) \times q + \beta_6 exp \times q + \beta_7 z_s + \varepsilon.$$

For all pre-ETI teachers without a v measure, we use the estimated β from the above regression to impute their v using their observed (q, x, z_s) in 2009-10.

B.2 The Initial Distribution of Teacher Characteristics

To simulate the model, we need the initial joint distribution of teachers' characteristics (q, v, x, s_0). We are not allowed to export this information at the teacher level for confidentiality reasons; instead, we are allowed to export, for each school s_0, the average and variance of q and v by experience-education groups for cells of size larger than 4.

Using information we are allowed to export, we approximate the distribution $F\left(x, q, v, s_0\right)$ as follows. We assume that $F\left(q, v | x, s_0\right)$ is distributed as a truncated bivariate normal distribution:

$$\begin{gathered}\left[\begin{array}{c} q \\ v \end{array} | \left(x, s_0\right)\right] \sim N\left(\left[\begin{array}{c} \mu_q\left(x, s_0\right) \\ \mu_v\left(x, s_0\right) \end{array}\right], \left[\begin{array}{cc} \sigma_q^2\left(x, s_0\right) & \rho_{qv}\left(x, s_0\right) \\ \rho_{qv}\left(x, s_0\right) & \sigma_v^2\left(x, s_0\right) \end{array}\right]\right) \\ s.t.,\ q \in \left[qlow_{s_0}, qhigh_{s_0}\right],\ v \in \left[vlow, vhigh\right]\end{gathered}$$

We set $qlow$ $(vlow)$ as the minimum value of q (v) in the data minus 0.5 standard deviations of q (v). We set $qhigh$ $(vhigh)$ as the maximum value of q (v) in the data plus 0.5 standard deviations of q (v).

To estimate the distribution as flexibly as the sample size allows, we allow the conditional means $\mu_q(x, s_0)$ and $\mu_v(x, s_0)$ to vary across (x, s_0) cells, where x represents an education-experience group. However, for any (x, s_0) cell with fewer than 4 teachers, we assume that μ_q and μ_v are common across all teachers within the same experience-education group who taught in schools within the same quartile of z_{s1}. We assume $\rho_{qv}\left(x, s_0\right)$, $\sigma_v^2\left(x, s_0\right)$ and $\sigma_q^2\left(x, s_0\right)$ are common for all teachers within an experience group who taught in schools within the same quartile of z_{s1}, but allow these values to differ otherwise. We estimate these μ, ρ and σ^2 parameters jointly via maximum likelihood, separately for the post- and pre-ETI periods. Together with the exported information on (x, s_0), these estimates give us the joint distribution $F\left(q, v, x, s_0\right)$.

C Policy Details

C.1 ETI Timeline

2010–2011 The ETI evaluation framework was designed and formally approved. Teachers received their first classroom-observation-based performance ratings.

2011–2012 The assessment system was revamped to include two key components: instructional practice and professional expectations. Both components were based on in-person observations.

Instructional Practice: This component measured a teacher's effectiveness to teach and interact with students.

Professional Expectations: This component measured how a teacher interacted with colleagues, how well they complied with policies, and the extent they participated in professional development.

2012–2013 Student performance metrics were formally integrated into ETI ratings.

C.2 ASPIRE

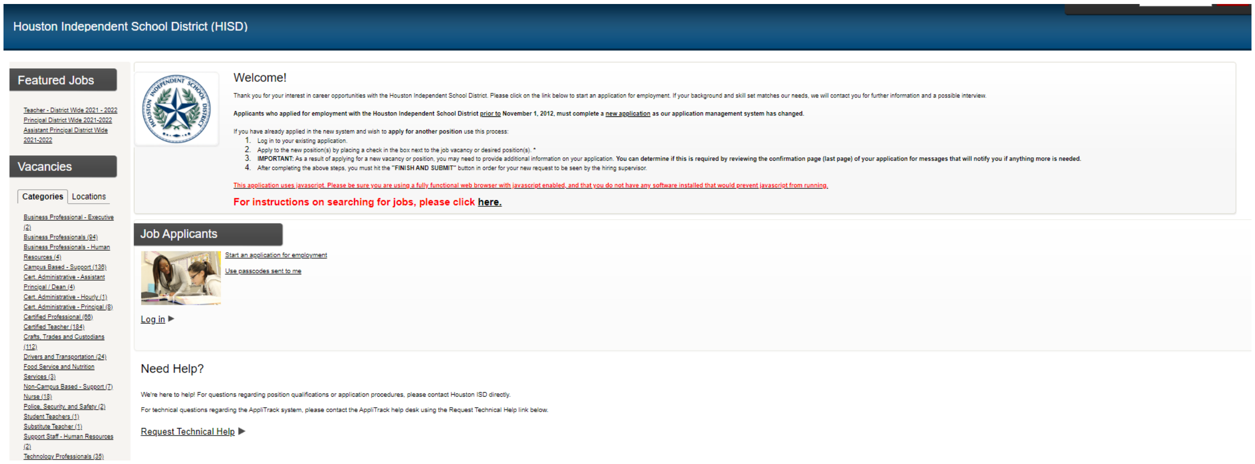
This section details the ASPIRE performance pay amounts for the year we use for our estimation and validation samples. We focus on the individual and campus awards provided for core teachers in grades 3-5 who are assigned value-added scores.

2010-11 Campuses are assigned a campus level VA score, known as a Campus Composite Gain. Teachers at elementary schools in the first quartile of campus value added are awarded $1500. Teachers in elementary schools in the second quartile are awarded $750. However, teachers with very low EVAAS VA scores (a cumulative gain index of less than or equal to -2.00) are ineligible for campus awards.

Individual awards are based on teachers' VA scores in each subject they teach. Teachers receive cash awards for any subjects in which their VA score places them in the first or second quartile of teachers in the same grade and subject, up to a maximum award of $7000. In general, awards for the first quartile are twice as much as awards for the second quartile.

2013-14 Teachers in elementary schools in the top *quintile* of campus VA received a campus award of $2000. Teachers with EVAAS scores less than -2.00 were ineligible for this award.

Figure B2: Screenshot of HISD Job Posting Website (April 2021)



Teachers with a Composite EVAAS score greater than 1.0 and less than 2.0 received an individual reward of $5,000. Teachers with a Composite EVAAS score greater than 2.0 received an individual reward of $10,000.

C.3 Teacher Job Application Portal

Figure B2 shows a screenshot of the HISD job posting website (`https://www.applitrack.com/houstonisd/onlineapp/`) from April 2021.

D Additional Results

D.1 Schools' Preferences: Illustration of Parameter Identification

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 at least some schools are selective (i.e., they do not make offers to all teachers), accounting for teacher preference shocks, this predicted distribution of teacher-school matches will be systematically different from the observed matches, because a teacher can choose a school s only if they have an offer from s. That is, given teachers' preferences, schools' offer decisions—which are governed by schools' preferences—must rationalize the realized match distribution.

For example, consider the simpler case where two teachers i and j both prefer school 1 over school 2. If we observe i working in school 1 and j working in school 2, it must be the case that school 1 prefers i over j. The same argument applies when teachers have 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 (the coefficient for q is normalized).

Figure B3 illustrates this identification argument with a simple example. There are two schools, s_1 and s_2, that make offer decisions. There is a unit of teachers who vary only in their (q, v). Both schools have the same capacity, 0.5, and identical preferences over teachers:

$$B(q, v) = q + bv,$$

where b is the importance of v relative to q. Teachers' preferences for school $s = s_1, s_2$ are given by

$$I(s = s_1) + \epsilon_s,$$

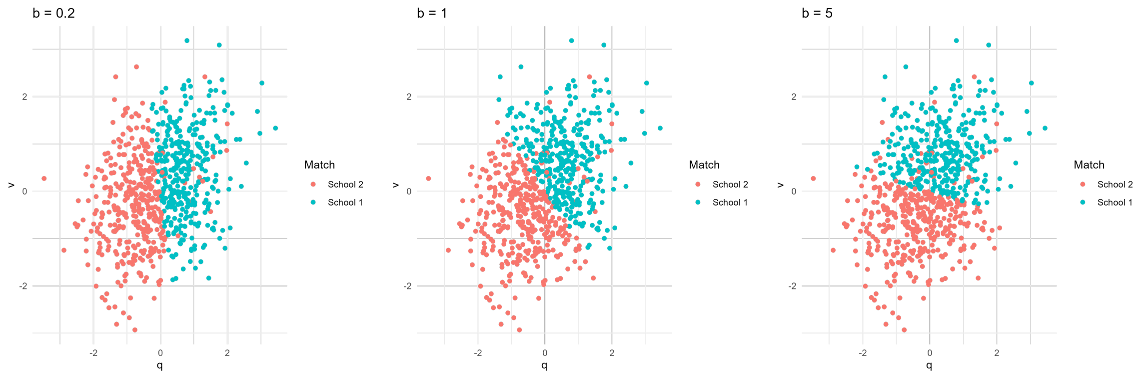
where ϵ_s's are type-1 extreme-value preference shocks that are i.i.d. across school-teacher pairs with mean 0 and a scale parameter of 1. That is, teachers prefer s_1 over s_2 on average, but they are subject to their preference shocks.

To maximize the expected total $B(q, v)$ among their hires, s_1, the more desirable school, extends offers to its favored teachers, those with higher $B(q, v)$, until it reaches its capacity; s_2, the less desirable school, extends offers to every teacher. Panels (a), (b) and (c) in Figure B3 plot three cases with $b = 0.2$, 1, and 5, respectively. Were teachers able to choose freely, we would see most teachers, regardless of their (q, v), end up working in s_1. However, given schools' preferences and capacity constraints, s_1 only makes offers to a subset of teachers. In each panel, the green dots are teachers who end up working in school s_1, and the red dots are teachers who end up working in s_2. Because teachers are subject to preference shocks, there are teachers with higher (q, v) working in s_2 than those who work in s_1; however, the opposite is never true, because s_1 is selective. For example, when $b = 0.2$ ($b = 5$), low-q (low-v) teachers are not observed in s_1 whereas in s_2 we see teachers across the whole (q, v) distribution. Moreover, differences in the overall distribution of (q, v) between s_1 and s_2 identifies b.

D.2 ASPIRE Information Counterfactual

Table B2 compares market equilibria under symmetric information and in which prospective employers have information contained in ASPIRE award outcomes.

Figure B3: Identification in Simple Example



(a) $b = 0.2$ (b) $b = 1$ (c) $b = 5$

Note: Illustration of identification in simple example with three different values of b.

Table B2: Symmetric vs ASPIRE Information Equilibrium

	Symmetric	ASPIRE
A. Job Mobility (%)		
Exit Rate	20.7	20.6
Job Switch Rate	6.4	5.6
$\frac{\#Entrants}{\#Stayers}$	22.8	22.6
B. Average Entrant Characteristics		
q	-0.36	-0.38
v	-0.55	-0.56

C. Teacher Quality	q		v	
	Symmetric	ASPIRE	Symmetric	ASPIRE
Overall	-0.057	-0.057	-0.080	-0.083
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	0.21	0.06	0.02
Gap (Q4-Q1)	0.75	0.73	0.31	0.30

Panel A shows simulated job mobility statistics under symmetric information and in which prospective employers have information contained in ASPIRE award outcomes. Panel B shows average entrant characteristics under symmetric information and asymmetric (ASPIRE) information. Panel C shows average q and v of teachers overall and within school quartiles under symmetric information and asymmetric (ASPIRE) information.

Table B3: Teacher Bonus Program Compensation Details

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

Average wages and bonus received under symmetric and asymmetric information.

D.3 Teacher Bonus Program Compensation Details

Table B3 reports the average wages, bonuses, and percentage wage reductions (τ) under the counterfactual bonus schemes in symmetric information and asymmetric information cases.

D.4 Counterfactual Bonus Experiments without Changing Base Wages

Table B4 reports the effects on within-district sorting of introducing teacher bonus programs without changing base wages.

Table B5 reports the costs and average wages when we introduce teacher bonus programs without changing base wages.

D.5 ETI Introduction and Teacher Effort and Effectiveness

In this section, we look for evidence that the introduction of the ETI led to changes in teacher effort and effectiveness. Specifically, letting y_{it} denote a given measure of teacher effort or effectiveness for teacher i in year t, we estimate the following fixed effects regression model:

$$y_{it} = \alpha \cdot \text{Post}_t + \gamma_i + \beta X_{it} + \varepsilon_{it} \tag{1}$$

where Post_t is an indicator for years after 2011 (when ETI was implemented), γ_i represents teacher fixed effects, and X_{it} is a vector of time-varying teacher characteristics.

Table B4: Effects of Non-Budget-Neutral Bonus Programs

		Symmetric		Asymmetric	
		Δq	Δv	Δq	Δv
A. $\chi(q, v) = q$					
Overall		0.07	0.01	0.07	0.02
By school z_1:	Quart 1	0.25	0.05	0.23	0.07
	Quart 2	0.01	-0.02	0.04	0.01
	Quart 3	0.04	0.02	0.03	0.01
	Quart 4	0.02	0.00	0.03	0.01
B. $\chi(q, v) = q + v$					
Overall		0.06	0.02	0.06	0.03
By school z_1:	Quart 1	0.21	0.10	0.18	0.11
	Quart 2	0.00	-0.02	0.03	0.02
	Quart 3	0.04	0.02	0.02	0.01
	Quart 4	0.02	0.00	0.03	0.01
C. $\chi(q, v) = v$					
Overall		0.03	0.02	0.03	0.04
By school z_1:	Quart 1	0.11	0.14	0.08	0.14
	Quart 2	-0.01	-0.02	0.02	0.01
	Quart 3	0.02	0.01	0.01	0.01
	Quart 4	0.01	0.00	0.01	0.01

Simulated changes in average q and v of teachers overall and within school quartiles when adding teacher bonus programs without changing base wages.

Table B5: Non-Budget-Neutral Bonus Program Compensation Details

	Symmetric	Asymmetric
A. Baseline (No Bonus)		
$W(\cdot)$ (\$1,000/teacher)	53.9	53.9
B. $\chi(q, v) = q$		
Bonus (\$1,000/teacher)	0.5	0.5
$W(\cdot)$+bonus (\$1,000/teacher)	54.6	54.7
C. $\chi(q, v) = q + v$		
Bonus (\$1,000/teacher)	0.5	0.5
$W(\cdot)$+bonus (\$1,000/teacher)	54.5	54.6
D. $\chi(q, v) = v$		
Bonus (\$1,000/teacher)	0.6	0.6
$W(\cdot)$+bonus (\$1,000/teacher)	54.5	54.6

Average wages and bonus received with non-budget-neutral bonus.

Table B6: Parameter Permutation Exercise

	EVAAS Score			**Teaching Hours Present**		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-ETI (α)	-0.048	-0.053	-0.036	0.001	0.001	0.001
	(0.057)	(0.057)	(0.057)	(0.001)	(0.001)	(0.001)
Experience Controls:						
Linear	Yes	Yes	No	Yes	Yes	No
Quadratic	No	Yes	No	No	Yes	No
Categorical	No	No	Yes	No	No	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,687	16,687	16,687	74,994	74,994	74,994

OLS estimates of α from (1). Standard errors in parentheses.

Table B6 presents estimates of α for two outcome measures: the teacher's average EVAAS score (columns 1–3) and the proportion of total teaching hours for which the teacher is present (columns 4–6). The specifications vary by experience controls: columns 1 and 4 control for linear experience; columns 2 and 5 add a quadratic experience term; and columns 3 and 6 replace these with categorical dummies for each experience level.

The results consistently show no statistically significant effect of ETI on either measure of teacher performance. However, we caution that this analysis cannot conclusively rule out potential effects of ETI on teacher effort or effectiveness.

D.6 The Impact of Changes in Parameter Values on Auxiliary Models

We provide more evidence on the mapping between data and parameters via a perturbation exercise. We adjust each parameter one at a time and measure responses of the predicted auxiliary models we use for estimation.

To be specific, let $\widehat{\Theta} = \{\widehat{\theta}_n\}_{n=1}^{N}$ be the vector of estimated structural parameters and $\{\widehat{\sigma}_{\theta_n}\}_{n=1}^{N}$ be the vector of their standard errors. We re-simulate our model N times. In the n^{th} simulation, we use the perturbed parameter vector

$$\widetilde{\Theta}^{(n)} \equiv \left\{\widehat{\theta}_1, \widehat{\theta}_2, \ldots, \widehat{\theta}_{n-1}, \widehat{\theta}_n + 0.1\widehat{\sigma}_{\theta_n}, \widehat{\theta}_{n+1}, \ldots, \widehat{\theta}_N\right\},$$

where the n^{th} parameter is perturbed by one-tenth of its standard error. We obtain new estimates of the auxiliary models and compare them with the baseline. This procedure generates a matrix of dimension $J \times N$, where J is the number of auxiliary parameters and

Table B7: Parameter Permutation Exercise

	Parameter Group			
	Teacher	Outside Option		School
Auxiliary Model:	Preferences	Incumbents	Entrants	Preferences
Aux 1a	11.8%	14.9%	8.6%	2.7%
Aux 1b	12.3%	9.5%	1.1%	2.4%
Aux 2	10.1%	4.3%	4.4%	4.8%
Aux 3:				
Entrant Moments	15.8%	4.6%	50.8%	5.2%
Exit rate	37.9%	25.0%	8.8%	4.0%
Switch Rate	53.5%	59.0%	4.9%	13.4%

Average percentage changes in auxiliary model contributions to GMM criterion when we perturb the estimated structural parameters by .1 standard error.

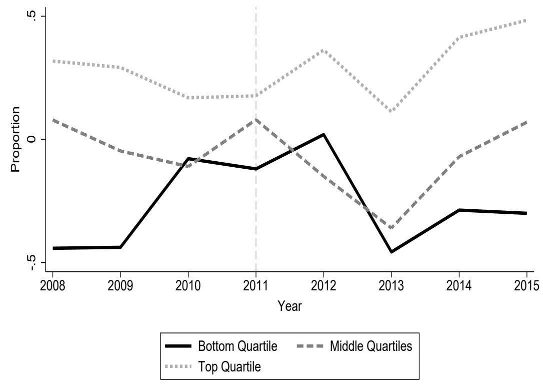
N is the number of structural parameters. Each element (j, n) quantifies how perturbing the n^{th} structural parameter affects the contribution to the objective function associated with the j^{th} auxiliary parameter.

To present these results more clearly, we aggregate the matrix by taking averages within sub-blocks. The auxiliary parameters are divided into six groups, following the structure outlined in the paper: Aux 1a, Aux 1b, Aux 2, and Aux 3—with Aux 3 further split into parameters governing teacher entry, exit rates, and school-switching rates. The model parameters are grouped into four categories: (1) teacher preferences (excluding outside options), (2) the outside option parameters for incumbent teachers, (3) the outside option parameters for entrants, and (4) school preferences. This grouping yields a 6×4 summary matrix (Table B7), where each cell reports the weighted average percent change across the relevant auxiliary parameters and model parameters within the corresponding sub-block, where each auxiliary parameter's weight is equal to it's weight in the estimation objective function.

Column 1 of Table B7 shows that teacher preference parameters (excluding outside options) significantly influence all auxiliary models, particularly the exit rate and switching rate. It is unsurprising that Aux 1a and Aux 1b are closely related to teachers' preferences, as these regressions are designed to mimic a conditional logit model of teachers' choices. Moreover, the strong impact on switching and exit rates also makes sense, since switching costs penalize departures from a teacher's initial school—whether to the outside option or another district school.

Column 2 shows that outside option parameters most strongly affect the switching and exit rates, while having little effect on entry rates and Aux 2 (which capture teacher sorting across school performance quintiles). Column 3 shows that the entrant outside option parameters primarily affect auxiliary parameters related to entry rates and characteristics.

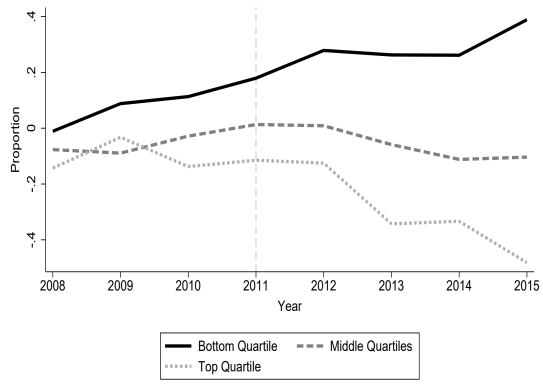
Figure B4: Yearly Teacher Effectiveness by Campus Performance



Note: Teacher effectiveness is measured by the EVAAS score in a given year for a given teacher. The dotted line corresponds to the elementary schools with the most students who met standards before 2011, the solid line corresponds to the elementary schools with the least students who met standards before 2011, and the dashed line with the middle quartiles.

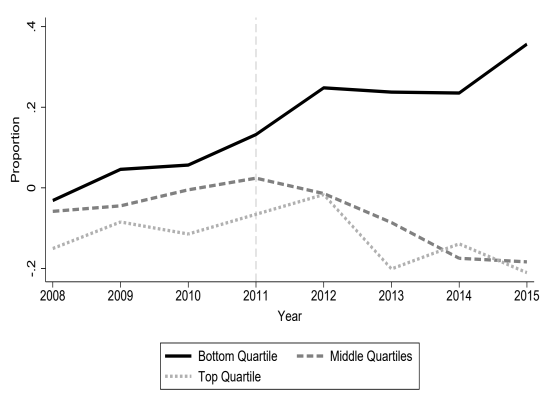
Finally, Column 4 shows that school preference parameters disproportionately affect entrant moments, Aux 2, and the switching rate.

Figure B5: Average Teacher Effectiveness by Campus Minority Percentage



Note: Teacher effectiveness is measured the average EVAAS score across all years for a given teacher. The solid line corresponds to the elementary schools with the fewest minority students before 2011, the dotted line corresponds to the elementary schools with the most minority students before 2011, and the dashed line with the middle quartiles.

Figure B6: Average Teacher Effectiveness by Campus Economically Disadvantaged Percentage



Note: Teacher effectiveness is measured the average EVAAS score across all years for a given teacher. The solid line corresponds to the elementary schools with the fewest economically disadvantaged before 2011, the dotted line corresponds to the elementary schools with the most economically disadvantaged before 2011, and the dashed line with the middle quartiles.

Table B8: Summary Statistics (Pre-ETI)

A. Teacher Characteristics	All		Incumbents		Entrants	
Experience (x_1)	10.78	(9.17)	11.39	(9.09)	2.38	(5.21)
Graduate Degree (x_2)	0.30		0.31		0.20	
q	0.00	(1.01)	0.03	(1.00)	-0.43	(1.11)
v	-0.05	(0.73)	-0.04	(0.71)	-0.28	(0.92)
$corr(q, x_1)$	0.00		-0.03		0.09	
$corr(v, x_1)$	0.07		0.05		0.20	
$E(q \mid x_2 = 1)$	-0.01	(0.96)	0.01	(0.94)	-0.53	(1.13)
$E(v \mid x_2 = 1)$	0.00	(0.72)	0.01	(0.72)	-0.29	(0.81)
$E(q \mid x_1 < 3)$	-0.12	(1.04)	0.03	(0.96)	-0.50	(1.15)
$E(v \mid x_1 < 3)$	-0.19	(0.80)	-0.12	(0.69)	-0.38	(1.00)
$corr(q, v)$	0.21		0.19		0.32	
# Teachers	1,970		1,837		133	
B. School Characteristics	**All**		**Bottom Quartile z_1**		**Top Quartile z_1**	
z_1(Frac. students meeting std.)	0.75	(0.12)	0.59	(0.09)	0.90	(0.03)
Funding per teacher ($1,000)	19.61	(4.42)	19.84	(5.05)	18.89	(4.01)
Capacity (#teaching slots)	10.77	(4.20)	10.76	(4.61)	11.74	(3.83)
School-level incumbent teacher characteristics ($s_0 = s$)						
Average Experience	11.22	(4.03)	11.53	(4.10)	11.46	(4.31)
Fraction w/ Grad Degree	0.30	(0.17)	0.35	(0.18)	0.30	(0.15)
Average q	0.05	(0.51)	-0.17	(0.74)	0.15	(0.35)
Average v	-0.03	(0.27)	-0.08	(0.32)	0.05	(0.25)
# Schools	171		42		42	

Panel A shows teacher-level statistics with cross-teacher standard deviations in parentheses. 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 parentheses.

Table B9: Outcome Sorting, Entry, and Exit (pre-ETI)

A. Average School Employee Characteristics[a]						
School Group by z_1	Experience		q		v	
Quartile 1	10.88	(4.02)	-0.18	(0.71)	-0.08	(0.32)
Quartile 2	10.40	(3.97)	0.08	(0.37)	-0.11	(0.29)
Quartile 3	10.33	(3.18)	0.11	(0.40)	-0.02	(0.40)
Quartile 4	10.74	(4.13)	0.14	(0.30)	0.03	(0.33)

B. Job Mobility			
Incumbents		Entrants	
Exit HISD	7.1%	$\frac{\#Entrants}{\#Stayers}$	7.2%
Within-HISD Job Switch	5.3%		

[a] School-level teacher characteristics, cross-school std dev in parentheses.

Table B10: 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

	Exiter (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 B11: Robustness: OLS with Alternative Inferred Offer Sets

	Baseline	Robustness
wage	0.001	0.001
funding	0.00005	0.00005
$I(s = s_0)$	0.839	0.915
$I(s = s_0)\times$experience	0.0002	0.000
z_1	0.004	0.005
$z_1 \times q$	-0.002	-0.003
$z_1 \times v$	-0.002	-0.004
$I(s = 0)$	0.264	0.275
$I(s = 0)\times$experience	-0.004	-0.004
$I(s = 0)\times$retirement age	0.104	0.111
$I(s = 0)\times$grad degree	0.034	0.033
$I(s = 0) \times q$	-0.002	0.00003
$I(s = 0) \times v$	-0.027	-0.020
#Obs.	139,452	105,514

$a(b)$: OLS specified in Aux 1a, teacher fixed effects included: data vs model, post-ETI. In the second column, we recalculate these auxiliary models using alternative inferred offer sets in which we only add a given school to $\widetilde{O}_i$ if teacher i's values of both q and v exceed those of the seed teacher by 0.3 standard deviations.