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Making the Cut: The Effectiveness of New Teacher Screening and Hiring in the Los Angeles Unified School District

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Teacher hiring is important…

- Teachers vary in effectiveness in important ways (Chetty, Friedman, & Rockoff, 2014; Hanushek & Rivkin, 2012).
- School & district administrators often have considerable discretion when hiring (Cowan, Goldhaber, Hayes, & Theobald, 2016; Engel, Jacob, & Curran, 2014).
- Administrators may have less discretion to select teachers post-hire.

…but we don’t know a lot about it.

- Teacher quality is hard to predict (Buddin & Zamarro, 2009; Chingos & Peterson, 2011).
- Teacher hiring is often rushed (Liu & Johnson, 2006).
- Few studies link information collected during the hiring process to teacher outcomes (Goldhaber, Grout, & Huntington-Klein, 2016; Jacob, Rockoff, Taylor, Lindy, & Rosen, 2016).

In 2014-5, LAUSD implemented the Multiple Measure Teacher Selection Process (MMTSP)

The Challenge

- LAUSD receives approximately 10,000 applicants for certificated positions each year, but will hire fewer than 2,000.
- How to efficiently screen applicants to bring in the highest quality teachers?

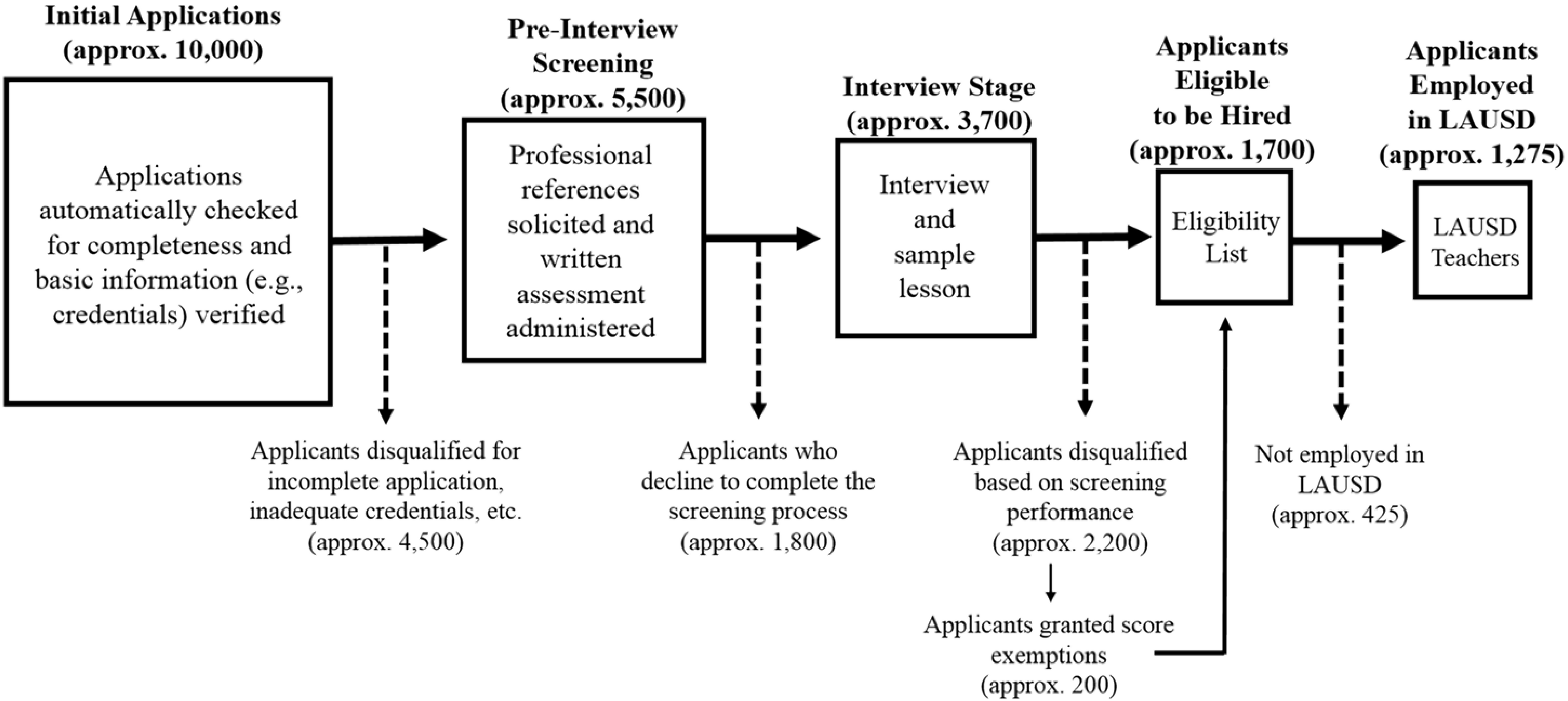
Goals of MMTSP Adoption in 2014-15

- Standardize screening instruments
- Align screening instruments to district priorities
- Collect more and better information on applicants
- Make more informed hiring decisions that lead to a more effective teacher workforce

Applicants are screened using 8 individual assessments

Assessment	Minimum Possible Score	Maximum Possible Score	Minimum Passing Score	Employed Teachers	
				Mean Score	Standard Deviation
Interview	0	25	20	21.53	1.42
Professional References	0	20	16	18.15	1.84
Sample Lesson	0	15	11	12.29	1.57
Writing Sample	1	15	11	12.74	1.11
GPA	1	10	N/A	8.64	1.40
Subject Matter	8	10	N/A	8.91	0.61
Preparation	0	3	N/A	54%	50%
Background	0	2	N/A	57%	49%
Overall	**10**	**80**	**100**	**85.01**	**4.27**

Annual Applicant Progression through LAUSD's Multiple Measures Teacher Selection Process



Research Questions

RQ1

Is the information collected during screening predictive of teacher effectiveness?

RQ2

Could the information collected during screening be used more effectively?

RQ3

Have hiring outcomes improved in LAUSD since the adoption of the MMTSP?

Preview of Results

RQ1

- Screening performance is predictive of VAMs, attendance, and evaluation outcomes, but not mobility.
- Teacher sorting appears modest, but selection effects can’t be ruled out.

RQ2

- Weighting screening assessments to better predict one outcome comes at the cost of predicting other outcomes.

RQ3

- The relationship between newly-hired teachers and school level achievement shows signs of relative improvement in LAUSD schools post-reform.

We use LAUSD administrative data from SY 2014-15 and 2015-16 to answer RQs 1 & 2

- **5,476 applicants eligible to be hired**
  - Overall and individual assessment scores
  - Certification area
  - Possession of graduate degree
  - Date of first eligibility to be hired
- **Student and school characteristics**

- **Employed teacher outcomes**
  - Math and ELA VAMs
  - Absence rates, protected and unprotected absences
  - Evaluations: below standards; average observation rating (range 1-3)
  - Mobility: stay vs. switch vs. exit

- We do not observe performance of applicants who are deemed ineligible, specific job offers, or outcomes for non-hired teachers.

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Screening performance is predictive of both ELA and math VAM.

OLS Regressions of Teacher VAMs on Standardized Screening Scores

	Overall Score	Interview	Sample Lesson	Writing	Reference	GPA	Subject Matter	Received Backg. Points	Received Prep. Points	Received Score Exception
ELA VAM (N = 870)	**0.16* (0.06)**									-0.06 (0.22)
		-0.07 (0.05)	**0.17** (0.07)**	0.01 (0.04)	-0.06 (0.12)	0.07 (0.05)	0.04 (0.05)	0.10 (0.09)	**0.18* (0.08)**	0.02 (0.23)
Math VAM (N = 703)	**0.10^{+} (0.06)**									0.01 (0.19)
		-0.01 (0.05)	0.08 (0.06)	0.00 (0.04)	-0.02 (0.10)	0.03 (0.05)	-0.01 (0.05)	**0.16^{+} (0.09)**	**0.14^{+} (0.08)**	0.05 (0.21)

Note. Standard errors clustered on teachers in parentheses. All models include school demographic controls as well as indicators for years since the teacher was hired, possession of a graduate degree, school level, district region, and school year. $^{+}$ p<.1, * p<.05, ** p<.01, *** p<.001

Screening performance is predictive of teacher evaluations.

Regressions of Teacher Evaluation Outcomes on Standardized Screening Scores

	Overall Score	Interview	Sample Lesson	Writing	Reference	GPA	Subject Matter	Received Backg. Points	Received Prep. Points	Received Score Exception
Average Focus Area Rating (1-3) (N = 2,766)	**0.05*** (0.01)**									-0.04 (0.04)
		0.04** (0.01)	**0.04** (0.01)**	-0.00 (0.01)	0.01 (0.01)	**0.02** (0.01)**	-0.01 (0.01)	0.00 (0.01)	0.02 (0.01)	0.01 (0.04)
Logistic Regression, coefficients are odds ratios										
"Below Standard" Final Evaluation Rating (N = 2,668)	**0.43*** (0.09)**									1.35 (0.69)
		0.86 (0.13)	**0.60** (0.11)**	0.94 (0.13)	**0.61** 0.10**	**0.73** (0.09)**	**0.75^{+} (0.12)**	1.48 (0.48)	0.71 (0.22)	0.76 (0.51)

Note. Standard errors clustered on teachers in parentheses. All models include school demographic controls as well as indicators for years since the teacher was hired, possession of a graduate degree, school level, district region, and school year. $^{+}$ *p*<.1, * *p*<.05, ** *p*<.01, *** *p*<.001

Screening performance is predictive of teacher attendance.

OLS Regressions of Teacher Absences on Standardized Screening Scores

	Overall Score	Interview	Sample Lesson	Writing	Reference	GPA	Subject Matter	Received Backg. Points	Received Prep. Points	Received Score Exception
Unprotected Hours Absent (N=3,168)	**-3.11^{*} (1.31)**									2.47 (4.74)
		1.49 (1.09)	1.38 (1.03)	0.25 (0.58)	**-7.76^{+} (4.29)**	**-1.94^{*} (0.88)**	**-1.74^{*} (0.87)**	-0.07 (1.47)	**-4.06^{**} (1.48)**	3.06 (4.67)
Protected Hours Absent (N=3,168)	0.57 (1.23)									-1.01 (3.60)
		-0.51 (1.24)	0.63 (1.03)	0.26 (0.95)	-0.01 (1.17)	0.58 (0.85)	1.10 (0.87)	-2.55 (1.73)	0.14 (1.68)	-0.04 (3.90)

Note. Standard errors clustered on teachers in parentheses. All models include school demographic controls as well as indicators for years since the teacher was hired, possession of a graduate degree, school level, district region, and school year. $^{+}$ *p*<.1, * *p*<.05, ** *p*<.01, *** *p*<.001

Research Questions

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Have hiring outcomes improved in LAUSD since the adoption of the MMTSP?

RQ3: Have hiring outcomes improved since the MMTSP was adopted?

- If newly-hired teachers are more effective in LAUSD post MMTSP, then the relationship between newly-hired teachers and school-level achievement should become more positive (or less negative) in LAUSD schools relative to schools elsewhere.
- Use a **difference-in-difference analysis**, comparing the relationship between the % of new teachers in a school and student achievement in LAUSD vs. comparison schools
- **Three comparison groups:**
  - TPSs in nine next largest districts
  - Other TPSs in Los Angeles County
  - Charter schools in LAUSD
- **Public school-level data from the California Department of Education:**
  - Identifies teachers in first year in the district
  - School-level achievement and student demographic data

The relationship between newly-hired teachers and achievement is less negative in LAUSD TPS than before.

	Ten Largest Districts (TPS Only)				Los Angeles County (TPS Only)				LAUSD TPS vs. LAUSD Charters			
	ELA		Math		ELA		Math		ELA		Math	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
%age New	-0.005**	-0.000	-0.008**	-0.000	-0.001	0.000	-0.003	0.000	-0.002*	-0.001	-0.004***	-0.002*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
%age New x	-0.001	0.001	-0.005*	0.002	-0.004**	-0.000	-0.008**	0.001	-0.004**	0.000	-0.010***	0.003
LAUSDTPS	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
%age New x Post-	**0.014****	**0.008***	**0.020***	**0.009**	**0.012*****	**0.004**	**0.022*****	**0.006**	**0.006+**	**0.001**	**0.017****	**0.002**
Reform x LAUSDTPS	**(0.004)**	**(0.003)**	**(0.007)**	**(0.006)**	**(0.003)**	**(0.002)**	**(0.005)**	**(0.004)**	**(0.003)**	**(0.003)**	**(0.005)**	**(0.004)**
School Time Trends	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14959	14959	14883	14883	17382	17382	17234	17234	9157	9157	9083	9083
Schools	1482	1482	1481	1481	1850	1850	1847	1847	1050	1050	1050	1050
R-sq	0.91	0.95	0.81	0.91	0.93	0.96	0.86	0.93	0.88	0.94	0.80	0.92

Note. Standard errors clustered on districts or schools in parentheses. All models include student demographic controls and school and year fixed effects. + *p*<.1, * *p*<.05, ** *p*<.01, *** *p*<.001

Implications

For Districts

- Collecting more and better information about prospective teachers may be worthwhile; can improve ability to hire "high quality" teachers.
- More intensive teacher screening also entails trade-offs in terms of:
  - cost,
  - aspects of teacher quality, and
  - adequate teacher supply.

For Policymakers

- Districts may require support to invest in screening systems.
- Invest in statewide data systems to:
  - make more applicant information available to districts and
  - facilitate the evaluation of hiring processes, and
  - understand impacts of hiring policies and decisions.

Thank you!

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Research Questions

RQ1

Is the information collected during screening predictive of teacher effectiveness?

RQ2

Could the information collected during screening be used more effectively?

RQ3

Have hiring outcomes improved in LAUSD since the adoption of the MMTSP?

Reweighting screening scores to better predict one outcome reduces the ability to produce other outcomes.

Coefficients on Standardized Reweighted Overall Screening Scores

		Screening Scores Weighted to Predict:			
Predicted Teacher Outcome	*Unadjusted*	*ELA VAM*	*Unprotected Hours Absent*	*Leave District*	*Unsatisfactory Final Evaluation*
ELA VAM	0.16*	0.18**	0.10	0.15*	0.14*
	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)
Unprotected Hours Absent	-3.11*	-0.43	-7.70**	-2.18	-2.59*
	(1.31)	(0.86)	(2.49)	(1.42)	(1.07)
Leave District[a]	0.90	0.91	0.83+	0.75*	0.90
	(0.11)	(0.10)	(0.10)	(0.09)	(0.11)
Unsatisfactory Final Evaluation[b]	0.43***	0.51***	0.61*	0.51***	0.42***
	(0.09)	(0.09)	(0.14)	(0.10)	(0.09)

Note. Standard errors clustered on teachers in parentheses. All models include school demographic controls as well as indicators for years since the teacher was hired, possession of a graduate degree, school level, district region, and school year. $^{+}$ p<.1, * p<.05, ** p<.01, *** p<.001
[a] ML regressions. Coefficients are relative risk ratios compared to staying in the same school. [b] Logistic regressions. Coefficients are odds ratios.

Models

Predicting Teacher Outcomes Using Screening Performance

$$outcome_{ist} = \theta_0 + \theta_1 S_i + \theta_2 X_{ist} + \theta_3 D_{st} + \sum_{c=1}^{C} \alpha^c C_i^c + \gamma_t + \varepsilon_{ist}$$

- S_i – Standardized screening score(s)
- X_{ist} – Teacher characteristics
  - Indicators of graduate degree, years since hire
- D_{st} – School characteristics
  - Student demographics, indicators for level and district region
- $\sum_{c=1}^{C} \alpha^c C_i^c$ - Certification area indicators
- γ_t – School year indicators
- Standard errors clustered on teachers

RQ1: Is Screening Performance Predictive of Teacher Effectiveness?

Approach

- Regress teacher outcomes on screening score(s)
  - Controls:
    - School demographics
      - Race, EL status, FRL eligibility, & SPED eligibility
    - Indicators for
      - School level
      - District region
      - Teacher subject area
      - Years since hire
      - Possession of graduate degree
      - School year
  - Standard errors clustered on teachers

RQ2: Could the information collected during screening be used more effectively?

Logic

- Screening assessments are differentially predictive of outcomes.
  - Can the scores be reweighted?

Approach: Canonical Correlation

- Identify coefficients to maximize the linear relationship between screening scores and specific teacher outcomes.

Models

Difference-in-Difference

$$score_{sdt} = \beta_1 newteach_{sdt} + \beta_2(newteach * lausdtps * post)_{sdt} + \beta_3(newteach * post)_{sdt} + \beta_4(newteach * lausdtps)_{sdt} + \beta_5(lausdtps * post)_{sdt} + +\beta_6 post_{sdt} + \beta_7 D_{sdt} + \delta_s + \gamma_t + \mu_{sdt}$$

- *score* – Average school achievement (math & ELA)
- *newteach* – Percentage of teachers in school who are new to the district
- *post* = 1 if 2014-15 or later
- *laustps* = 1 if LAUSD traditional public school
- D_{sdt} – student race, FRL, EL, & SPED
- δ_s – School fixed effect
- γ_t – Year fixed effect

RQ3: Have hiring outcomes improved since the MMTSP was adopted?

Approach: Difference-in-difference

- Predict average school math and ELA achievement
  - Three-way interaction between
    - Percentage of teachers new to district
    - Indicator of post-hiring reform period (2014-15+)
    - Indicator of LAUSD TPS
  - Control for student:
    - Race
    - EL status
    - FRL eligibility
    - SPED eligibility
  - School and year fixed effects
  - Standard errors clustered on districts or, within LAUSD, schools

Annual Applicant Progression through LAUSD's Multiple Measures Teacher Selection Process