Discussion Paper Series

IZA DP No. 18572

April 2026

Does Training Teachers Locally Affect Teacher Shortages? Evidence from Regional Public Universities

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IZA@LISER NETWORK
ISSN: 2365-9793

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Abstract

We study whether training teachers locally increases nearby teacher supply. We use the historical assignment of normal schools and insane asylums to identify the effect of university proximity. Normal schools, built to train teachers, became regional universities while asylums mostly continue as small psychiatric facilities. Our evidence suggests greater teacher supply in normal school counties: lower teacher wages and more teachers per student. Asylum counties have more teachers with emergency credentials and fewer who majored in education—suggesting they mitigate lower supply by hiring in different pools. Normal school counties have higher high school test scores and graduation rates.

JEL classification

I2, J61, J31

Keywords

teacher shortages, regional universities, teacher training, geographic frictions in the labor market

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* We would like to thank conference participants at the MidSouth Education Policy Workshop, the Association for Public Policy Analysis and Management Fall Research Conference, the UIUC Center for Advanced Study seminar series, and the Association for Education Finance and Policy annual conference for helpful comments.

1 Introduction

Many people believe that the supply of teachers is lower than socially optimal, especially in STEM subjects, in special education, and in school districts with disadvantaged students (Nguyen, Lam and Bruno, 2024; Cowan et al., 2016). This paper estimates the effects of an important policy lever: does the proximity to a regional public university increase the supply of teachers to nearby school districts? This is a lever of particular interest because regional public universities enroll roughly 40 percent of all undergraduate students in the U.S. (Fryar, 2015), including many prospective teachers in teacher education programs.[1] Understanding the local geographic effects of one of the most common training programs for future teachers helps inform the potential impacts of these and other programs aimed at relieving teacher shortages.

We begin by outlining a conceptual framework in which teachers are trained by universities, and are subject to geographic frictions in future employment. This implies that the supply of teachers will be higher in places that train teachers than in places that do not. In equilibrium, this will lead to more teachers and lower wages in locations that train teachers.

We test these predictions with an identification strategy that we use in Howard, Weinstein and Yang (2024) and Howard and Weinstein (Forthcoming) to study the impacts of proximity to a regional public university on other outcomes (local economic resilience and economic mobility).[2] We compare counties that, in the 19th and early 20th centuries, were assigned normal schools to train teachers versus counties that were assigned insane asylums by the state legislature. Legislatures selected locations for these institutions using very similar criteria, including political factors, geographic accessibility, and natural beauty.

The identification strategy is especially well-suited to this study on teachers. Nearly all the normal schools later evolved into teachers colleges, and today are regional public

[1]In fact, based on IPEDS data (U.S. Department of Education, National Center for Education Statistics, 2020) our sample of roughly 200 regional public universities produces roughly 17% of all bachelor's degrees in the U.S., but 28% of all bachelor's degrees in education.

[2]Howard, Oh and Weinstein (2026) uses a similar strategy to identify the effects of HBCUs on local economic mobility.

universities that continue to award many degrees in education. Asylum properties mostly continue to have state-owned psychiatric facilities, and—importantly—these continue to be small in size relative to their county's population. Normal school counties look different than all other counties in the state, underscoring the importance of a strong control group. We show both qualitative and empirical evidence in this paper and in previous papers (Howard, Weinstein and Yang, 2024; Howard and Weinstein, Forthcoming) that normal school counties were very similar to asylum counties—and assignment of a normal school instead of an asylum appears effectively random. Our identification assumption is that counties assigned asylums are a good counterfactual for teacher labor markets and K-12 education in counties assigned normal schools, had they received a different state institution instead.

We construct a comprehensive dataset on teacher labor markets from a variety of sources, including district-level data on the fraction of teachers with emergency or provisional credentials from the U.S. Department of Education. To the best of our knowledge, this is the first paper to use these data.[3] We use data on all public school districts from the Common Core of Data (CCD), and individual-level data from the American Community Survey (ACS).

We find that proximity to a regional university increases the number of teachers per student, reduces the fraction of teachers with emergency or provisional credentials, and reduces teacher wages, all consistent with a larger supply of teachers. Further, the characteristics of teachers in normal school counties reflect the student characteristics and training offered at the local universities. Teachers in these counties are more likely to have majored in education, and subject-area education like STEM education and special education. They are less likely to have majored in STEM fields, humanities (english and history), and foreign languages. Teachers in normal school counties may also have lower SAT/ACT scores, as we show that universities in normal school counties enroll students with lower test scores. However, we do not directly measure teachers' standardized test scores. Combined with the modest effects on teacher-student ratios, these results suggest asylum counties may partially

[3]Other papers study emergency credentials during the Covid pandemic, but focus on data from one state (Bacher-Hicks et al., 2023; Backes and Goldhaber, 2023).

mitigate the lower supply of teachers by searching in different applicant pools.

Finally, the evidence suggests children in normal school counties have higher proficiency rates on eighth grade and high school tests, and our previous work found they are more likely to graduate from high school (Howard and Weinstein, Forthcoming).

While proximity to regional public universities could affect local K-12 education in many ways, our results are consistent with proximity increasing teacher supply. If proximity to these universities affected district characteristics and demand for quality K-12 education, we would expect to see these differences in district characteristics and higher teacher wages. However, normal school districts look very similar to asylum districts, and we find a negative effect on wages and no statistical difference in expenditures per student, which are both inconsistent with higher demand in normal school counties.

Several types of policies have been enacted that appear motivated by the relationship between geographic proximity to teacher education programs (TEPs) and teacher hiring difficulties. One response has been to explore greater partnerships between teacher education programs and farther-away districts.[4] A second response has been to provide funding for building or expanding teacher education programs in areas expected to have teaching shortages. The federal Teacher Quality Partnership Program, previously funded at 70 million dollars per year, included funds for expanding TEPs with clinical components in high-needs school districts.[5] Finally, some states allow community colleges to award bachelor's degrees in fields with high demand. Illinois is currently considering legislation that would allow this for early childhood education degrees, among others (Illinois Community College Board, 2026; Bragg and Harmon, 2024). However, other policies to reduce teacher shortages are not targeted based on proximity to teacher education programs, such as teacher loan for-

[4] The state of Washington funded a report on creating student-teacher placements in districts farther from TEPs (E2SHB 1139, 2019).

[5] Louisiana also has a program that financially supports greater partnerships between TEPs and school districts (Louisiana Department of Education, 2024). Another set of related policies ("grow-your-own") aim to increase interest in the teaching profession among high school students or paraprofessionals in districts with hiring difficulties (Aragon, 2018; Motamedi, Leong and Yoon, 2017; Educators Rising, 2024; Edwards and Kraft, 2024).

giveness programs. Understanding the causal impact of proximity to teaching programs has implications for the effectiveness of these policies.

Our results suggest geographic frictions in the labor market for teachers, which is consistent with several facts about geographic mobility. First, a large share of college students stay close to home for college, implying these regional universities will have a greater number of local students.[6] Second, a large share of students stay close to their university after college.[7] Third, there are frictions in the labor market for teachers. Several papers focusing on data from single states find teachers are more likely to teach in districts close to their hometown, and also independently more likely to teach in districts close to their university.[8]

Taken together, our results are consistent with the many local students at regional universities increasing the local supply of teachers, given that recent graduates are likely to stay close to their hometown and college town. These frictions also imply some non-local students will stay close to the regional university to teach, additionally raising local supply of teachers around regional public universities. These frictions could emanate from preferences or information. School districts may advertise and recruit locally, the university may have relationships with local districts, or local job postings may be more salient because of local networks.[9]

Several papers show relationships between proximity to teacher education programs and school or district hiring difficulties.[10] However, these estimates may be biased due to differ-

[6] Students growing up next to the regional universities in our sample are also more likely to go to college, and conditional on college attendance they are more likely to attend local universities (Howard and Weinstein, Forthcoming). Mattern and Wyatt (2009) show 16% of students attend a college in a state not bordering their home state, using a match between College Board data and the National Student Clearinghouse.

[7] Conzelmann et al. (2023) find 50% of recent college graduates are living and working in the metro area closest to the college they attended. Weinstein (2022) shows the importance of geographic proximity for firms recruiting on college campuses.

[8] This includes Boyd et al. (2005) using data from New York state, Reininger (2012) who uses national survey data but does not look at distance to college, Fowles et al. (2014) who use data from Kentucky, and Boyd et al. (2013) who use data on five metropolitan areas in New York state. Bates et al. (2023) analyze teacher and principal preferences in one large school district and policy implications for raising student achievement.

[9] Engel and Cannata (2015) discuss several papers showing that school districts recruit and advertise for positions locally, and among graduates of the district.

[10] These include Edwards et al. (2024) using data from Tennessee, Goldhaber et al. (2018) using data from California, and Goldhaber et al. (2021) using data from Washington. Bruno (2025) shows that rural

ences between districts that are closer and farther from teaching programs. Districts near regional universities may have different risks of hiring difficulties even in the absence of the regional university.

We see our paper as making several contributions. First, our empirical strategy allows us to identify the causal impact of regional university locations on teacher supply, using data on districts across the continental U.S.[11] We are able to quantify the impact on various district characteristics, which is important for policymakers considering a cost-benefit analysis. Second, we show that the characteristics of the teachers in normal school counties reflect the characteristics of the students at the local university. This is an important result for policymakers interested in expanding teacher education programs in teacher shortage areas. It underscores the importance of considering the types of students who will be attracted to the new teacher training programs, as well as the training they would receive. Finally, our research provides insights into sources of differences in teacher subject-specific education versus general education, an area in which there is limited research.[12]

2 Framework

We start by discussing a simple framework for understanding the impact of proximity to a regional public university on teacher labor markets. This model motivates why we might expect to find lower wages, more teachers, and a higher concentration of characteristics of regional-university-educated teachers in normal school counties.

Assume that teachers graduate from universities j and can choose to work in districts i.

districts within a county have higher teacher vacancy rates during the pandemic using data from Illinois. Acton, Orr and Rogers (2023) find rural districts in Wisconsin mostly allocate an increase in state aid to non-instructional spending. James, Kraft and Papay (2023) study teacher hiring in Boston.

[11] Our paper also relates to a long literature on estimating compensating differentials, including in the teacher labor market. See Antos and Rosen (1975), Levinson (1988), Goldhaber, Destler and Player (2010), Chambers (1995), Boyd et al. (2013), Rosen (1986), Toder (1972), Kenny and Denslow Jr (1980); Brown (1980); Hwang, Mortensen and Reed (1998); Lang and Majumdar (2004). Biasi, Fu and Stromme (2022) study how teacher labor markets are affected by allowing districts to adjust individual teacher wages flexibly.

[12] A 2005 report of the American Educational Research Association (AERA) noted that there is very limited research on the effect of subject-area education (Cochran-Smith and Zeichner, 2009).

A teacher n from university j receives indirect utility v

$$v_n(j) = \max_i \{w_i + a_i - \delta_{ji} + \epsilon_{ni}\}$$

where w is wages, a is amenities including cost of living, δ_{ji} is a moving cost, and ϵ_{ni} is a Gumbel distributed i.i.d. shock. There is a mass S_j of teachers from university j. Because of the Gumbel assumption, the number of teachers who choose location i is

$$L_i = \sum_j S_j \frac{\exp(w_i + a_i - \delta_{ji})}{\sum_{i'} \exp(w_{i'} + a_{i'} - \delta_{ji'})}. \tag{1}$$

For each school district, production exhibits decreasing returns to scale, and the wage is equal to the marginal productivity:

$$w_i = F_i'(L_i), \tag{2}$$

where F_i' is a decreasing function. Equilibrium is defined as the set of L_i and w_i that satisfy the system of equations given by (1) and (2).

Consider the following experiment. Suppose we lower the moving costs for one university j school-district i pair, δ_{ji}, while holding the wages in all other districts $k \neq i$ constant. This is meant to correspond to the thought experiment of the difference between a normal school county and an asylum county. We think of these counties as having similar competition for teachers from other locations and occupations, similar amenities, and similar teaching production functions, but differing in the proximity of a large supply of teachers.

Proposition 1. *In that experiment, the wage w_i decreases, and the number of teachers L_i increases. In addition, location i will have a larger share of workers from university j.*

Proof: We will proceed by contradiction. Suppose wages weakly increase. By equation (1), the supply of teachers will increase, since wages did not decline and δ_{ji} decreased. By equation (2), wages will fall. This is a contradiction. So it must be that wages decrease.

Because wages decrease, then by equation (2), the number of teachers increases.

Because wages decrease, the number of teachers from every other university decreases. But since the overall number of teachers increases, the number of teachers from j must increase. Therefore, the share from j must also be higher. $\square$

In Appendix A, we extend this model to allow for a more general teaching production function, along with a constraint that teacher wages must be the same regardless of productivity.

3 Data and Summary Statistics in Normal School, Asylum, and All Other Counties

In this section we show three main facts. First, normal school counties train many more teachers than same-state asylum counties, making this a relevant sample in which to study the effects of universities on local teacher labor markets. Second, asylum counties have characteristics thought to be correlated with hiring difficulties, relative to all other counties in the state. This is important for external validity – our effect is identified among a sample of counties at risk of teacher shortages. Third, we show that while asylum counties look quite different from all other counties, they look very similar to normal school counties. This suggests asylum counties are a strong counterfactual for teacher labor markets in normal school counties, had they received an institution other than the normal school.

The location of normal schools and asylums were determined using very similar criteria, and political influence was of primary importance. Consistent with this, counties that received normal schools looked very similar to same-state counties that received asylums in the mid-1800s (Howard, Weinstein and Yang, 2024; Howard and Weinstein, Forthcoming). In this section we focus on county characteristics today that would be especially relevant for understanding teacher supply in asylum counties as a counterfactual for teacher supply in normal school counties.

We identify the institutions that had been normal schools using Ogren (2005), asylums using Furbush et al. (1926), and normal school and asylum counties as in Howard and Weinstein (Forthcoming). We identify school districts in normal school and asylum counties using the county FIPS code in the U.S. Department of Education EDGE school district geocode dataset (U.S. Department of Education, National Center for Education Statistics, 2024*b*), and merging to our set of normal school and asylum counties.

The normal schools evolved into today's regional public universities. While these are comprehensive universities offering degrees in many fields other than education, they continue to produce a large fraction of education degrees in the U.S. Our sample includes 205 normal school counties, roughly 6.5% of all counties in the U.S. There are currently 188 institutions of higher education that evolved from the normal schools in our set of normal school counties. In 2018, these 188 institutions that had been the normal schools produced roughly 17% of all bachelor's degrees in the U.S., but roughly 28% of all bachelor's degrees in education in the U.S.[13]

Throughout the paper we estimate a simple specification, regressing county-level outcomes or characteristics Y_i on an indicator for normal school county, including state fixed effects, α_s. We include only normal school and asylum counties, and we cluster standard errors at the state level.

$$Y_i = \beta \text{Normal School County}_i + \alpha_s + \epsilon_i \tag{3}$$

Table 1 shows that universities in normal school counties produce more total bachelor's degrees and more bachelor's degrees in education per person than asylum counties. The point estimate suggests that on average normal school counties produce 3.5 times the number of total degrees per person than asylum counties, and more than 7 times the number of

[13]These statistics are based on 2018 IPEDS data (U.S. Department of Education, National Center for Education Statistics, 2020), and do not count degrees produced at universities in the local total if most of the students are enrolled exclusively in distance education. Universities in asylum counties produce 14% of all degrees in the U.S. and 11% of all bachelor's degrees in education. See Appendix C for details.

Table 1: Difference in Bachelor's Degrees Produced in Normal School and Asylum Counties

	(1)	(2)
	Bachelor's Degrees per County Population	
	All Degrees	Education Degrees
Normal school county	0.0145**	0.00157**
	(0.00219)	(0.000258)
Observations	315	315
R-squared	0.334	0.345
Mean DV, Asylum Counties	0.00576	0.000246

Notes: $^{+}$ $p < 0.1$, * $p < .05$, ** $p < .01$. Observations are at the county level, and the outcome is based on university-level data from IPEDS for 2018 aggregated to the county level. Standard errors are clustered at the state level. See text for details.

education degrees per person relative to asylum counties. To put the education degrees in perspective, a .00157 degrees per capita increase corresponds to about one additional education degree per 100 students per year, indicating the potential to have large effects on local public school districts if many of these degree-holders become teachers locally.[14] Among the universities that originated as normal schools, the average fraction of bachelor's degrees awarded in education is roughly 9.4%, much higher than the 4.2% of all bachelor's degrees in the U.S. that are awarded in education. Together, these facts show that our setting is a relevant one for understanding the impact of universities on K-12 teacher labor markets.

Table 2 shows county-level demographics from Chetty and Hendren (2018), in normal school counties, asylum counties, and all other counties. Asylum counties look different from all other counties, and in ways that the literature has discussed as being correlated with lower supply of teachers or teacher hiring difficulties (e.g., Engel, Jacob and Curran (2014); Jackson (2012)). Asylum counties have higher population density, a higher share of Black residents, higher levels of racial and income segregation, and higher fraction of children with single mothers. The fraction of parents with incomes below the 50th national income percentile is 3.8 percentage points, or roughly 7.5%, lower than in all other counties.

[14]Based on data from U.S. Census Bureau (2025) and U.S. Census Bureau (2026), about 15.8 percent of the population was enrolled in K-12 schools in 2025.

Table 2: Difference in County Characteristics between Normal School and Asylum Counties

	(1)	(2)	(3)	(4)	(5)
	Normal School	Asylum	All Other	Diff Asyl - All Other	Diff Normal Sch - Asyl
Log population density	4.874	5.156	3.622	1.206**	-0.307
	(1.683)	(1.628)	(1.6)	(0.146)	(0.187)
Frac. Black residents	0.095	0.089	0.072	0.04**	-0.002
	(0.149)	(0.119)	(0.13)	(0.01)	(0.01)
Racial segregation	0.118	0.136	0.068	0.062**	-0.010
	(0.097)	(0.105)	(0.079)	(0.013)	(0.013)
Income segregation	0.053	0.055	0.022	0.03**	0.001
	(0.036)	(0.038)	(0.027)	(0.004)	(0.005)
Frac. children with single mothers	0.218	0.211	0.186	0.029**	0.006
	(0.065)	(0.059)	(0.064)	(0.006)	(0.006)
Frac. parents below median income	0.447	0.414	0.500	-0.038**	0.019
	(0.136)	(0.144)	(0.152)	(0.012)	(0.014)

Notes: $^{+}$ $p < 0.1$, * $p < .05$, ** $p < .01$. Variables are from Chetty and Hendren (2018), with observations at the county level. Column 4 shows differences between asylum counties and all other counties in the same state, and column 5 shows differences between normal school and asylum counties in the same state, using regressions with state fixed effects. Standard errors are clustered at the state level. See text for details.

Thus, with the possible exception of this last variable, our set of counties has characteristics suggesting they may be at risk of teacher shortages, which is relevant for the external validity of our results and policy implications.

However, asylum counties look very similar to normal school counties. There are not statistically significant differences between normal school and asylum counties in any of the variables in Table 2. Similarly, we also show the overall income distribution for parents is very similar in normal school and asylum counties in Howard and Weinstein (Forthcoming). These results suggest the asylum counties are a much stronger control group for the normal school counties.

Finding that the counterfactual normal school counties have characteristics often associated with shortages also suggests that simply comparing regions close to teacher education programs and those farther away may yield an underestimate on the impact of proximity. This also underscores the importance of our identification strategy.

4 Regional Universities Increase Local Teacher Supply

In this section we show evidence consistent with regional universities increasing local teacher supply: lower teacher wages, more teachers per student, and fewer teachers with emergency and provisional credentials.

4.1 Teacher Wages in Normal School and Asylum Counties

Following the framework in Section 2, we are interested in whether teacher wages are lower in normal school districts. This would be consistent with a large number of teachers at regional universities willing to work for lower wages in normal school districts, and those districts willing to hire them over graduates without those location preferences.

We use 2012-2019 one-year ACS samples, each of which is a 1% random sample of the population. The smallest identifiable geographic unit in these samples is the public use microdata area (PUMA). To be consistent with the rest of the paper, as well as our previous research using this identification strategy, we would like to know differences at the county level, between normal school and asylum counties. Using the PUMA Equivalency Files, we link each respondent's PUMA to all of the counties associated with the PUMA. We then collapse at the county level.

Nearly all of the normal school and asylum counties are associated with PUMAs that are not associated with any other normal school or asylum county. However, for those that are not in this group, when we collapse at the county level, for individuals in PUMAs that are associated with both normal school and asylum counties, their observation will be included in the county average for both counties. This will bias our results towards finding no difference in normal school and asylum counties. As an alternative, we include only counties associated with PUMAs that are not associated with other normal school or asylum counties, or only associated with normal school and asylum counties of the same type.

The ACS asks about wage income from the previous year, but asks about current occupation, industry, and location. We mitigate concerns that the wage income last year is from an occupation other than teaching, and from a location other than the current normal school or asylum county. First, to make it more likely that current-year teachers were also reporting wage income from teaching last year, we restrict the sample to individuals who were full-time workers last year (usual hours worked equal to at least 35, and at least 40 weeks worked last year). We also restrict to those earning at least 7000 dollars (in 1999 dollars). This is based on the federal minimum wage in 2016 (7.25 dollars per hour in 2016 dollars, times 35 hours per week, times 40 weeks per year, converted to 1999 dollars which is the same as the wage income basis, is roughly 7000 dollars). We also included only individuals who are currently employed, had at least a bachelor's degree, and reported that they were not enrolled in school within the past three months.

To reduce the likelihood that we are capturing wages last year when the individual was a student, we include people 26 to 65 years old. To reduce the likelihood that we are capturing wage income last year when the respondent lived in a county other than their current normal school or asylum county, we include only individuals who report living in the same house last year or moved within the migration PUMA (MIGPUMA).[15] Finally, we exclude people living in group quarters.

We identify teachers as those whose industry is elementary and secondary schools (based on IND1990), with occupations listed as preschool and kindergarten teachers; elementary and middle school teachers; secondary school teachers; and special education teachers (based on OCC2010). We present results pooling these teachers, as well as separating by type of teacher. We weight observations using the person weight in the ACS and construct county averages.

We find that on average, teacher wages in normal school counties are roughly 2.2% lower than in asylum counties in the same state (Table 3). This includes the counties associated with PUMAs that are associated with both normal school and asylum counties, which we

[15] MIGPUMAs may correspond to one or multiple PUMAs.

discussed will bias the results toward zero. Excluding these counties, the difference is 2.7%, significant at the 5% level (Table A3).

Tables A4 and A5 show the wage results separately for elementary and middle school teachers, and separately for high school teachers. Without controls, magnitudes are larger and more precise for the elementary and middle school teachers, but for both the magnitudes are roughly 2-3%.[16]

Magnitudes in Table A3 suggest most of the lower wages in normal school districts are not explained by differences in the fraction of teachers with at least a master's degree or difference in teacher age, though these are also endogenous regressors. The coefficient on wages falls slightly but the magnitude is roughly similar (around a 2% difference), although it is not significant at the 10% level. Including county characteristics from Opportunity Insights (Chetty et al., 2018) yields coefficients with magnitudes generally around 1-1.5% (Tables A3, A4, A5).[17] The results for elementary school teachers continue to be significant at the 5% level with these controls, although the pooled results are not significant at the 10% level.[18]

Our finding that teacher wages are lower in normal school counties is consistent with teachers from regional universities having location preferences and districts hiring those teachers with local preferences. This could be because the applicant pool is comprised mainly of people with these preferences, or because districts are screening on proximity to the applicant's college in order to pay lower wages, or because they think those teachers would be more productive at their school. This is also consistent with the literature on

[16]One potential concern in separating by level of teacher is that roughly 30% of schools that are high schools or combined middle and high schools are combined (U.S. Department of Education, 2016), and there may be differences in this likelihood across normal school and asylum districts.

[17]Given our assumption that assignment of these institutions was as-good-as random, identifying the impact of proximity should not require the inclusion of control variables, though they may reduce the standard errors. In theory, interpretation of the results with the control variables is not straightforward, as they may endogenously have responded to effects on K-12 education. In general our results are similar including and excluding control variables, which is consistent with minimal differences between normal school and asylum counties historically and today.

[18]Interestingly, the coefficient on log population density is very positive and significant, and explains about half of the decline in the coefficient from 2% to 1% in the pooled results

Table 3: Difference in Teacher Labor Markets in Normal School and Asylum Counties

	(1) Log(Wage) Teachers	(2) Student-Teacher Ratio	(3) Top Quartile Emergency Cred
Normal school county	-0.0215*	-0.347**	-0.0728+
	(0.0101)	(0.108)	(0.0362)
Observations	315	315	303
R-squared	0.824	0.844	0.546
Mean DV, Asylum Counties	10.45	16.13	0.282

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Column 1 uses pooled one-year ACS samples from 2012-2019, with observations at the county-level. Column 2 uses CCD data from 1997-1998 through 2018-2019 on students and teachers to construct county-level student teacher ratios. Column 3 uses Department of Education data on teachers with emergency credentials from 2017-2018 through 2021-2022 to construct the county-level fraction of teachers with emergency credentials. All columns include state fixed effects, clustering standard errors at the state level. See text for details.

teacher hiring which suggests schools have preferences for candidates with local ties (Engel and Cannata, 2015).

4.1.1 Placebo Analysis

We are interested in whether teacher wages are lower because of greater supply of teachers due to the nearby regional public university nearby. If this is the reason for the lower wages, we would not expect lower wages in occupations for which the supply is unaffected by the local regional public university. In implementing this placebo analysis, we also want to compare to an occupation that is similar to teaching in that it is fairly similar regardless of where it is performed. We present results from two placebo exercises, in which we test for differences between normal school and asylum counties in wages of police officers and firefighters, and cashiers.

We find that wages of police and fire occupations are lower in normal school counties, but the magnitudes are smaller than the wage differences for teachers and they are not statistically significant (Tables A6 and A7). Further, there are also small and insignificant differences in wages for cashiers in normal school and asylum counties. This evidence is consistent with the lower wages of teachers in normal school counties coming from greater supply of new teachers from the local regional public university.

4.2 Student-Teacher Ratio in Normal School and Asylum Counties

In this section, we test whether student-teacher ratios are lower in normal school counties, consistent with the framework in Section 2. We do this using data from the CCD (U.S. Department of Education, National Center for Education Statistics, 2024*a*) and the methods described in Section 3, and also using ACS data (Ruggles et al., 2024).

We obtain district-level data from the Common Core of Data (CCD), for the 1997-1998 school year through the 2018-2019 school year.[19] We calculate student-teacher ratios based on the number of students and teachers from pre-Kindergarten to grade 12, and drop districts in which the number of students or teachers is zero.[20] We keep only regular public school districts or independent charter districts. We drop districts for which the student-teacher ratio or the teacher-student ratio is twice the 99th percentile across all states and years in our sample after the restrictions described above.

There are no data for some districts in some years. Aggregating at the county level would give greater weight to districts that report more often. To avoid this, we first obtain the district-level mean number of students and teachers across all years in our data. We calculate the county-level number of students and teachers by adding these district-level means, and then construct the county-level student-teacher ratio.

We estimate specification (3), in which the dependent variable is the number of students

[19]While the data are available in later years, we use 2018-2019 as the final year of our analysis to avoid including the Covid years and any interpretation difficulties that may introduce.

[20]The data on pre-Kindergarten only becomes available in 2010, and so before 2010 our measure is based on the number of students and teachers from Kindergarten to 12th grade. We also estimate specifications using only Kindergarten to 12th grade, and so to ensure comparability in all specifications, we drop districts for which the number of students or teachers from pre-Kindergarten to 12th grade is zero, or the number of students or teachers from Kindergarten to 12th grade is zero. Further data details can be found in Appendix B.

divided by the number of teachers, and we cluster standard errors at the state level. Table 3 shows that on average the student-teacher ratio in normal school counties is lower by roughly .35, using the CCD data. The mean in asylum counties is roughly 16, so this implies that the student-teacher ratio in normal school counties is roughly 2.2% lower than in asylum counties. Another way to put this number in context is that normal school counties have a higher teacher-student ratio by 0.00164 (as opposed to a lower student-teacher ratio as reported in the table). We can compare that to the increase in education degrees from Table 1 which was approximately 0.01 degrees per student per year, suggesting that a positive but small fraction of those degrees are translating into a differential increase in local teachers in the same county as the university. This could reflect limited geographic frictions, or that asylum counties are partially substituting by hiring different types of teachers, which we will address in Section 5.1.

Appendix G shows additional analysis of student-teacher ratios using the number of school-age children and teachers in ACS data, also finding lower student-teacher ratios in normal school counties. While the magnitudes are larger in the ACS data, the confidence intervals include the point estimate using the CCD data.

Appendix K shows there are not statistically different expenditures per pupil in normal school and asylum counties. This is consistent with the higher wages and fewer teachers per student in asylum relative to normal school counties. If asylum counties wanted student-teacher ratios similar to normal school counties, we would likely see higher expenditures per student given the higher teacher wages. Similar expenditures per student is also inconsistent with greater demand for high-quality education in normal school counties, providing further support for the supply-side mechanism.

4.3 Teacher Credentials: District-Level Data from the Every Student Succeeds Act

As a measure of hiring difficulties, we use district-level data on teachers reported by the U.S. Department of Education. As part of the federal Every Student Succeeds Act (ESSA), signed into law in 2015, public school districts are required to annually report the number of teachers who are teaching with emergency or provisional credentials. These data are made available through district report cards, and were also published on the website of the U.S. Department of Education, ED Data Express, for the 2017-2018 through 2021-2022 school year (U.S. Department of Education, ED Data Express, 2024). Teachers with emergency or provisional credentials have received significant attention in recent years, and have been discussed in connection with teacher shortages. Goldhaber et al. (2021) use these credentials as a proxy for hiring difficulties.

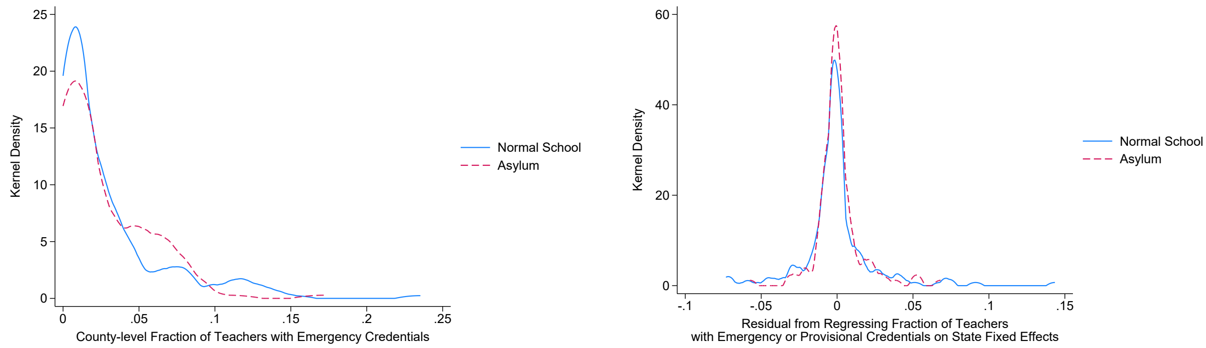
Similar to our construction of county-level student-teacher ratios, we first obtain the district-level means for the number of teachers and the number of teachers on emergency credentials.[21] We obtain the county-level total number of teachers, and number with emergency credentials, by summing the district-level means, and then construct the county-level fraction with emergency credentials.

We first show that the fraction of teachers with emergency and provisional credentials is correlated with other variables associated with teacher hiring difficulties. Figure A1 shows a binned-scatter plot of the relationship between the fraction of teachers in the county with emergency or provisional credentials and several covariates. The plots include state fixed effects.[22] We show these relationships among normal school and asylum counties in states with both types of institutions. There is a clear positive relationship between the fraction of teachers with emergency or provisional credentials and fraction of parents in the county below the 50th national income percentile, fraction of Black residents in the county,

[21] Details on the data construction are described in Appendix E.

[22] We use the binsreg command in Stata to construct the plot, and include the fixed effects.

Figure 1: **Teacher Credentials in Normal School and Asylum Counties**



(a) Emergency and Provisional Credentials

(b) Residualized Emergency and Provisional Credentials

Notes: Kennel density plots using Epanechnikov kernel.

and fraction of children in the county with single mothers. These are all consistent with previous research on the types of districts most affected by teacher hiring difficulties. This provides supportive evidence that the fraction of teachers in the county with emergency or provisional credentials reflects difficulty in hiring teachers. We see a U-shaped relationship with log population density.

Figure 1a is a kernel density plot of the county-level fraction of teachers with emergency credentials, for normal school and asylum counties in states with both types of institutions. Normal school counties are more likely to have fewer than 5% of teachers with emergency or provisional credentials, and less likely to have between roughly 5 and 10% of teachers with emergency or provisional credentials.

Figure 1b shows a similar plot of the residuals from regressing the fraction of teachers with emergency or provisional credentials on state fixed effects, when including normal school and asylum counties in the regression. We plot the residuals for states that have both normal schools and asylums. It is clear that this measure of teacher shortages is lower in normal school than asylum counties – with asylum counties more likely to have values above the prediction (specifically in the range from 0 to .05 above the prediction).

The 75th percentile of the county-wide fraction of teachers with emergency or provisional credentials is roughly 3.7%. These highest values may be most indicative of hiring difficulties or most impactful on students, and so we focus on whether the county-level fraction is greater than or equal to the 75th percentile of the distribution that year among normal school and asylum counties. We also discuss results using the fraction of teachers with emergency or provisional credentials as the dependent variable.

We compare normal school and asylum counties within the same state, and estimate equation (3) with the dependent variable indicating whether the county-level fraction of teachers with emergency or provisional credentials is in the top quartile.

While the magnitude suggests the fraction with emergency or provisional credentials is roughly 7% lower in normal school counties, it is not statistically significant. Including county characteristics the coefficient becomes larger, and is statistically significant at the 5% level (Table A2).

Table 3 shows that the fraction of teachers with emergency credentials in normal school counties is seven percentage points (roughly 25%) less likely in the top quartile relative to asylum counties. This is significant with $p = .051$. Table A1 shows the coefficient increases in magnitude and precision when including county characteristics as control variables.

5 Regional Universities Affect Local Teacher Specialization and the Quality of Education

In this section we show regional universities affect the areas of specialization (college major) of local teachers, as well as raise student test scores.

5.1 Teacher College Majors from the ACS

We test the prediction from Section 2 that teachers in normal school counties more likely have characteristics that are similar to graduates of universities in normal school counties. This would be consistent with proximity increasing teacher supply, specifically among the teachers who graduated from the nearby university, who may differ from the average teacher. Combined with the modest effects on teacher-student ratios, this would also be consistent with asylum county districts partially mitigating the lower supply by hiring from different applicant pools.

We test for differences in college major.[23] We follow a similar methodology to our analysis of wages in the ACS in Section 4.1, but relax some of the sample restrictions. In the wage analysis, our measure of wage income was from the previous year, and so we placed extra restrictions on the sample to mitigate concerns that the individual was working in a different county or in a different occupation in the previous year. Our measures in this section all refer to the current period, and so those restrictions can be relaxed. We include individuals who are 22 to 69 years old, currently employed, working as a teacher in an elementary or secondary school for at least 35 hours per week, and not enrolled in school in the past three months. This last restriction ensures we are not capturing student teachers.

There are several subject areas that have been shown to experience higher levels of hiring difficulties, including special education and STEM (Nguyen, Lam and Bruno, 2024; Cowan et al., 2016; Edwards et al., 2024). We are particularly interested in whether districts in closer proximity to a regional public university experience less difficulty hiring teachers with these majors.

Individuals do not have to major in education in order to become a teacher, and there are often multiple pathways for non-education majors to become teachers. Sometimes these non-education majors can complete the necessary teacher preparation requirements while in college. Alternatively, non-education majors may complete an alternative pathway to education licensure after completing college, which in some cases may lead to a master's degree. Finally, there are some settings in which individuals may teach even without licensure, through provisional or emergency licenses. If school districts in normal school counties are more likely to hire graduates of the local regional university, then teachers in those counties

[23]We also test separately for differences in master's degree attainment and age.

should look more like the graduates of those universities rather than the average graduate that becomes a teacher. Thus, if regional universities have a greater fraction of education majors, or subject-area education majors (e.g., Math teacher education), then the teachers in normal school counties should be more likely to have those majors.

We first show in Table A9 that a greater share of the bachelor's degrees produced at universities in normal school counties are in education, subject-specific education (e.g., Math teacher education), and special education relative to degrees produced at universities in all other counties in the state. These data are based on 2017-2018 IPEDS completions data, and we aggregate to the county level. These include only counties that produce any bachelor's degrees. We weight counties by total degrees awarded in the county to reflect the pool of potential teaching applicants across the state.

Next, we test for differences in teacher college major, between normal school and asylum counties using the ACS. We weight individuals using the survey weights, collapse at the county level, and then estimate our main regression clustering standard errors at the state level. We estimate these specifications pooling teachers in elementary and secondary schools, and also separately by type of teacher, because of differences in the relevant areas of subject knowledge. One area of particular interest is the difference in teachers' STEM preparation, which may be especially different in secondary schools given the STEM classes taught in high school.

We first discuss the results from the sample of Elementary and Middle School teachers, which are similar to the pooled results in Appendix A10 given this is the largest group of teachers.[24] Table 4 shows teachers in normal school counties are about 1.3 percentage points less likely to have a bachelor's degrees in a general teacher education field (general education, elementary education, or secondary education), and roughly 1.1 percentage points more likely to have a bachelor's degree in subject-area education field. This is consistent with Table A9 showing that the former normal schools have a larger fraction of majors in

[24]Table A11 shows the results in this section are similar when we exclude the counties that are part of PUMAs associated with both normal school and asylum counties.

subject-area education. Adding together the coefficients in columns 1 and 2 also shows that teachers in normal school counties are similarly likely to have majored in the broad field of education as teachers in asylum counties.

We then analyze subject-area education fields in which there are differences between normal school and asylum county teachers. Column 3 shows elementary and middle school teachers in normal school counties are more likely to have a bachelor's degree in STEM Teacher Education (Math Teacher Education, or Science, Computer Science Education) ($p = .101$). There is no statistically significant difference in the fraction with any STEM, humanities, or special needs education major.[25] Table A14 shows the full decomposition of broad degree fields, and additionally shows a smaller fraction of teachers majoring in social sciences and in foreign languages in normal school counties.[26]

Panel B shows the results for secondary school teachers. The fraction of secondary school teachers in asylum counties who major in general teacher education or subject-area teacher education is much lower than for elementary school teachers (54 vs. 70%). Secondary school teachers in normal school counties are 4 percentage points more likely to have majored in subject-area teacher education than in asylum counties (column 2), but there is no difference in likelihood of majoring in general teacher education (column 1). This implies an overall greater likelihood of majoring in education among secondary school teachers in normal school counties. Roughly a quarter of the greater likelihood of subject-area education majors is explained by greater likelihood of STEM teacher education majors.[27]

Column 4 shows that secondary school teachers in normal school counties are roughly 1.8 percentage points less likely to have majored in a STEM field (roughly a 12% difference). We see this effect only among secondary school teachers, consistent with greater demand for

[25]See Appendix H for classification details.

[26]Appendix Table A13 shows the full decomposition of subject-area education majors. There is a statistically significant .8 percentage point increase (35%) in the fraction of teachers majoring in physical and health education in normal school counties.

[27]Similar to the elementary and middle school teacher results, we also see a large increase (1.5 percentage points or 34%) in the fraction of secondary school teachers majoring in physical and health education in normal school counties (Table A13).

this subject-area knowledge among secondary schools. Secondary school teachers in normal school counties are also 2.5 percentage points (16%) less likely to have majored in humanities (including english, history, and fine arts). Table A14 also shows that secondary school teachers in normal school counties are less likely to major in business and communications (1.2 percentage points, or 16%, and less likely to major in foreign languages (.7 percentage points or 24%). There is no difference in the fraction with special needs education majors.

These results are consistent with normal school districts attracting teachers who obtain teaching credentials through an undergraduate degree in education, as opposed to alternative pathways for people not majoring in education. For example, Appendix Table A16 column (5) shows that secondary school teachers in normal school counties are less likely to have a master's degree, which is consistent with non-education majors in asylum counties obtaining credentials through a master's rather than an undergraduate program.[28,29]

In panel C we additionally show differences in college major among special education teachers. While some states require an individual to major in special education in order to work as a special education teacher, many do not.[30] Table A9 shows that a greater fraction of degrees produced in normal school counties are produced in special needs education. Thus, if there are geographic frictions in the labor market, this would make it easier for local districts to hire special education teachers with a major in the subject.

An important caveat for this analysis is that most of the counties in our sample have a small number of special education teachers. Of the 329 counties that have any special education teachers, the median is 10 special education teachers and the average is 19. We find that special education teachers in normal school counties are roughly 4 percentage points more likely to have majored in this field ($p < .1$), which is roughly a 13% increase relative to the mean of the dependent variable in asylum counties.

[28] Goldhaber and Walch (2014) show that there has been an increase in the fraction of teachers who obtain teaching credentials through a graduate program rather than an undergraduate degree in education.

[29] Appendix Table A16 shows no statistically significant difference in teacher age between normal school and asylum counties.

[30] Some states instead require passing a test, while others instead only require a certain number of course hours (between 24 and 36 hours) (Special Education Resource Project, Vanderbilt University, 2025).

There are several counties with a small number of secondary teachers. When limiting the specification to secondary school teachers, roughly 5% of the counties in the regression have fewer than 15 teachers. For robustness, we drop states for which at least half of normal school counties or half of asylum counties have fewer than 15 teachers. This drops three states from the sample, but yields similar results to those in Table 4.[31]

Table 4: Difference in Teacher College Major in Normal School and Asylum Counties

	(1) General Teacher Ed.	(2) Subj. Area Teacher Ed.	(3) STEM Teacher Ed.	(4) STEM	(5) Humanities	(6) Special Needs Ed.
Panel A: Elementary and Middle School Teachers						
Normal school county	-0.0130*	0.0112+	0.00322	0.00121	0.00241	0.00118
	(0.00630)	(0.00608)	(0.00192)	(0.00365)	(0.00445)	(0.00294)
Observations	315	315	315	315	315	315
R-squared	0.701	0.561	0.393	0.404	0.719	0.443
Mean DV, Asylum Counties	0.526	0.175	0.0214	0.0562	0.0834	0.0461
Panel B: Secondary School Teachers						
Normal school county	-0.00301	0.0391**	0.0106+	-0.0180*	-0.0245**	-0.000616
	(0.0110)	(0.0111)	(0.00606)	(0.00777)	(0.00772)	(0.00472)
Observations	315	315	315	315	315	315
R-squared	0.306	0.467	0.300	0.309	0.432	0.167
Mean DV, Asylum Counties	0.267	0.276	0.0628	0.147	0.155	0.0206
Panel C: Special Education Teachers						
Normal school county	0.0183	0.0339	0.00114	-0.00986	-0.00520	0.0403+
	(0.0250)	(0.0242)	(0.00313)	(0.00665)	(0.0143)	(0.0209)
Observations	314	314	314	314	314	314
R-squared	0.216	0.340	0.121	0.131	0.334	0.345
Mean DV, Asylum Counties	0.323	0.381	0.00557	0.0323	0.0736	0.317

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level, based on aggregated individual-level data from the 2012-2019 one-year ACS samples. All samples include teachers working in elementary and secondary schools. Standard errors are clustered at the state level. See text for details and variable definitions.

Appendix J additionally shows that the universities in normal school counties enroll students with lower SAT/ACT scores, relative to other universities in the state. If teachers in normal school counties are more likely to have graduated from the local university, this may be another dimension along which teachers differ.

[31] While the magnitude of the effect on STEM Teacher Education major is similar, it is no longer statistically significant. Table A12 shows similar results to Table 4 when including county-level covariates. In general the results are similar, though coefficients are often slightly smaller in magnitude and less precise, though many of the effects are still statistically significant.

5.2 Student Test Scores in Normal School and Asylum Counties

The effects of proximity to regional universities on teacher labor markets may have implications for student achievement.[32] Our previous work shows higher high school graduation rates in normal school counties relative to same-state asylum counties (Howard and Weinstein, Forthcoming). In this section, we use school-level state assessment data from EdFacts to test for differences in test scores. While these assessments differ by states, with different proficiency thresholds, these concerns are mitigated in our setting given that our analysis is within state. EdFacts has data on the fraction of students proficient in math and separately in reading and language arts (RLA), for assessments in 3rd through 8th grade, and in high school. Using the number of students participating in the assessment, and the fraction proficient, we calculate the total proficient by school. We merge the school data with school-level geographic data, and analyze test scores in 2015-2016 through 2018-2019.[33]

Consistent with our previous analysis, we first obtain the school-level mean number proficient and number taking the test by subject and grade-level. We then aggregate to the county-subject-grade level by summing the number proficient and number taking the test for all schools in the county.

We estimate equation (3) separately for math and reading/language arts, and separately for 3rd grade, 8th grade, and high school. We may expect nonlinear effects that are greater in areas with lower proficiency, as there is more room for improvement.[34] To explore this possibility, we aggregate separately when the school is in an above-median state for proficiency in the subject-grade-year, and when the school is in a below-median state. This

[32] Recent work using data from Boston Public Schools, show that schools that attract more applicants do hire teachers with better credentials on paper, but they are not differentially likely to hire teachers that are better in the classroom or that have longer tenure at the school (James, Kraft and Papay, 2023).

[33] For some schools the fraction proficient is reported in ranges given concerns about confidentiality. We use the median of the range, except when the range is greater than or equal to 50, less than 50, or the sample is so small that no range is given. In these instances we do not impute any fraction; however, the number of students in these schools is very small. For the high school assessments it is relevant that the dropout rate is lower in normal school counties, as shown in Howard and Weinstein (Forthcoming).

[34] To address this issue when studying fraction proficient as an outcome, Papke (2005) splits the sample based on whether the district was above or below median proficiency.

yields a maximum of two observations per county. We estimate specification (3) separately for the above- and below-median observations. Thus, some of the differences in the effects could reflect treatment-effect heterogeneity across states that is not causally related to the lower proficiency levels in those states. For example, for high school math there are 15 states that are always above median, 15 states that are always below median, and 10 states that are sometimes above and sometimes below median. With this caveat, we think it is reasonable to expect larger impacts of proximity in places where there is more room for test-score improvements.

Table 5: Difference in K-12 Proficiency Rates in Normal School and Asylum Counties

	(1) RLA	(2) Math	(3) RLA Above Median State-Years	(4) Math Above Median State-Years	(5) RLA Below Median State-Years	(6) Math Below Median State-Years
Panel A: Third-Grade Test Scores						
Normal school county	-0.00126	-0.000539	-0.00510	-0.00379	0.00383	-0.00206
	(0.00995)	(0.00984)	(0.0112)	(0.0118)	(0.0134)	(0.0136)
Observations	315	315	214	203	228	206
R-squared	0.691	0.635	0.662	0.600	0.378	0.388
Mean DV, Asylum Counties	0.501	0.528	0.591	0.610	0.411	0.448
Panel B: Eighth-Grade Test Scores						
Normal school county	0.00299	0.00830	0.00590	0.00174	0.0103	0.0122
	(0.00995)	(0.0124)	(0.0132)	(0.0179)	(0.0133)	(0.0156)
Observations	315	315	181	170	200	194
R-squared	0.720	0.701	0.509	0.627	0.513	0.307
Mean DV, Asylum Counties	0.502	0.431	0.607	0.536	0.412	0.315
Panel C: High School Test Scores						
Normal school county	0.0124	0.0188	0.0153	-0.00655	0.0219	0.0342*
	(0.0102)	(0.0122)	(0.0110)	(0.0150)	(0.0176)	(0.0151)
Observations	315	315	200	207	176	177
R-squared	0.871	0.879	0.810	0.827	0.569	0.475
Mean DV, Asylum Counties	0.576	0.462	0.690	0.607	0.431	0.276

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level, and constructed using school-level data from the CCD for years 2015-2016 through 2018-2019. Columns 1 and 2 do not allow for heterogeneity by state proficiency rates. Columns 3 and 4 include above-median states for proficiency rates in the subject-grade-year, and columns 5 and 6 include states at or below the median in the subject-grade-year. Standard errors are clustered at the state level. See text for details.

We first discuss the results without allowing for heterogeneity by proficiency level. Table 5 columns 1 and 2 show the magnitudes suggest a non-trivial positive effect on the fraction proficient in eighth grade math and high school RLA and math in normal school counties, although these are not statistically significant. The fraction proficient in high school math is higher by roughly 2 percentage points, or 4%. When we include county-level controls, the effects on 8th grade and high school test scores are statistically significant (Panel B of Table

A18).

Table 5 columns 3 through 6 show the effects when we allow for different effects in state-years with lower proficiency levels. In state-years with lower proficiency levels, we see a nontrivial 1.0 percentage point increase in the fraction proficient in eighth grade RLA and 1.2 percentage point increase for eighth grade math (not significant). We see even larger effects in high school. There is a 2.2 percentage point increase in the fraction proficient in high school RLA (not significant) and a 3.4 percentage point (12%) increase in the fraction proficient in high school math (significant at the 5% level). The effects in above-median state-years are generally close to zero. Table A18 shows similar results when including county-level characteristics, but many of the magnitudes are slightly larger and the standard errors smaller.

6 Conclusion

This paper studies whether training teachers locally raises the local supply of teachers and eases teacher shortages in the local community. We use a novel identification strategy that compares counties assigned normal schools to train teachers to same-state counties that were instead assigned an asylum in the 1800s or early 1900s. Conditional on receiving one of these institutions, it was effectively random which counties received the normal school and which received the asylum. The normal schools became regional universities that maintain a focus on training teachers, while the asylums mostly continue as state-owned psychiatric institutions. This allows us to identify the causal impact of proximity to a regional university, as the asylum counties are a strong counterfactual for what the normal school counties would have looked like if they had received a different state institution.

We find evidence for normal school assignment raising the local supply of teachers today: teacher wages in normal school counties are about 2% lower, student-teacher ratios are roughly 2% lower, and the fraction of teachers with emergency or provisional credentials is about 25% less likely to be in the top quartile. We further see that this proximity yields more teachers with characteristics that reflect the students at the nearby university. Teachers in normal school counties are more likely to have subject-area education majors (such as STEM teacher education and special needs education), and less likely to major in the disciplines themselves (such as STEM, humanities, and foreign languages). We see suggestive evidence of positive effects on eighth grade and high school proficiency on state assessments in normal school counties, and our previous work shows lower high school drop-out rates (Howard and Weinstein, Forthcoming).

While we show that normal school counties are producing many more education majors per year, we estimate modest effects on teacher wages and student-teacher ratios. This suggests that the local supply shock was not as strong as we may have expected. Our results suggest that asylum counties may have partially mitigated the lower supply of teachers by hiring teachers from different applicant pools – hiring teachers with emergency or provisional credentials, as well as teachers who were less likely education or area-specific education majors.

Our results are relevant given the current debate and discussion surrounding teacher shortages. Expanding teacher education programs in shortage areas may increase teacher supply in those areas. Importantly, this will yield increased supply of teachers with characteristics like those who would enter a training program in the shortage area, and their training will reflect the offerings available in the local teacher training program.

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A Model with Heterogeneity and Common Wages

In this appendix, we extend the model from the main paper to incorporate heterogeneity in teacher abilities, in terms of the education production function. However, we also model the common situation in teacher labor markets that wages are similar for all teachers within a district conditional on years of experience and levels of education, regardless of marginal productivity. Our goal will still be to prove that if two counties were identical but for their distance to a nearby regional public university, the one with the regional public university would have lower wages and a higher share of teachers from that university.

Suppose that teachers graduating from each university are distinct; hence there are J types of teachers $j = 1, ..., J$ corresponding to the J universities, that may contribute to the teaching production function in different ways.

Within each county i, there are a continuum of competitive school districts with identical production functions $F_i(L_{i1}, ..., L_{iJ})$. As before, teachers choose counties based on wages, amenities, moving costs, and idiosyncratic shocks, but are indifferent between districts within a county. Assume that districts are unable to screen, so that when they hire, they hire a random local teacher. Because there are a continuum of teachers, they effectively hire in proportion to the local stock of teachers of each type J. All districts within a county are identical and offer the same competitive local wage w_i, so the teachers themselves are not selective in which offers they accept, conditional on location.

Define $L_i = \sum_j L_{ij}$ and define $s_{ij} = L_{ij}/L_i$ to be the share of teachers in location i that originate from j. Note that $\sum_j s_{ij} = 1$. The school will hire additional teachers until the expected marginal productivity of an additional teacher is equal to the marginal cost (the wage):

$$\sum_j s_{ij} \frac{\partial F_i}{\partial L_{ij}}(L_{i1}, ..., L_{iJ}) = w_i$$

As in the main text, teachers choose locations to maximize utility that depends on wages, amenities, moving costs, and a Gumbell demand shock.

$$L_{ij} = S_j \frac{\exp(w_i + a_i - \delta_{ji})}{\sum_k \exp(w_k + a_k - \delta_{jk})}$$

It will be helpful to define $\phi_{ij} = \frac{\exp(w_i+a_i-\delta_{ji})}{\sum_k \exp(w_k+a_k-\delta_{jk})}$, the share of teachers from j that go to i (this is distinct from s_{ij}, the share of teachers in i from j).

We make a series of three technical assumptions for our proof, but we think these are fairly innocuous. First, assume that F_i is homogeneous of degree λ, with $\lambda \in (0, 1)$, meaning that if we increase the number of each type of teacher by 1 percent, the teaching output would increase by λ percent. F_i therefore has decreasing returns to scale.

Second, suppose that for the school of interest j,

$$\frac{\partial F_i}{\partial L_j}(L_{i1}, ..., L_{iJ}) \leq \frac{1}{\lambda} w_i$$

This assumes that the marginal productivity of teachers from j is less than the average productivity times a constant $\frac{1}{\lambda}$, which is greater than one. This assumption is not restrictive.

Third, suppose the initial equilibrium is stable, in the sense that raising wages will not bring in so many high-productivity workers such that wages rise even further.

For the purposes of our exercise, we will focus on changing the moving costs from a nearby college to a school district i (e.g. bringing a regional university from a county close to district i's county into the same county as district i), in the sense that the college is already sending a large share of its teachers to the county. Formally, suppose that for district-university pair (i, j), that $\phi_{ij} > \sum_k s_{ik}\phi_{ik}$, the share of teachers from j choosing i is bigger than the average such share for other universities k.

Proposition: Under these conditions, if moving cost δ_{ji} decreases, and holding wages w_k constant for $k \neq i$, then s_{ij} increases and w_i decreases.

Proof: We will start by showing that wages decrease. Because of the logit assumption,

$$d \log L_{ij} = (1 - \phi_{ij}) dw_i - (1 - \phi_{ij}) d\delta_{ji}$$

By Euler's homogenous function theorem, $\lambda F_i = \sum_{j=1}^{J} L_{ij} \frac{\partial F_i}{\partial L_{ij}}$. So

$$w_i = \lambda \frac{F_i(L_{i1}, ..., L_{J1})}{L_i}$$

If we totally differentiate,

$$dw_i = -\lambda \sum_k \left(\frac{F_i}{L_i^2} - \frac{1}{L_i} \frac{\partial F_i}{\partial L_{ik}} \right) dL_{ik}$$

Combining with the logit assumption,

$$dw_i = -\lambda \frac{1}{L_i} \sum_k \left(\frac{F_i}{L_i} - \frac{\partial F_i}{\partial L_{ik}} \right) (1 - \phi_{ij}) L_{ik} dw_i + \lambda \frac{1}{L_i} (1 - \phi_{ij}) \left(\frac{F_i}{L_i} - \frac{\partial F_i}{\partial L_{ij}} \right) L_{ij} d\delta_{ji}$$

Note that for the equilibrium to be stable in the sense described above, it must be that $-\lambda \frac{1}{L_i} \sum_k \left(\frac{F_i}{L_i} - \frac{\partial F_i}{\partial L_{ik}} \right) (1 - \phi_{ij}) L_{ik} < 1$. We would typically expect the left-hand side to be negative, so we would not expect this assumption to be a very restrictive one.

Solving,

$$dw_i = \frac{\lambda s_{ij} (\frac{F_i}{L_i} - \frac{\partial F}{\partial L_{ij}})(1 - \phi_{ij})}{1 + \lambda \sum_k [s_{ik} (\frac{F_i}{L_i} - \frac{\partial F_i}{\partial L_{ik}})(1 - \phi_{ik})]} d\delta_{ji}$$

By the inequality above, the denominator is positive. And because $\frac{\partial F}{\partial L_{ij}} < \frac{1}{\lambda} w_i = \frac{F}{L_i}$, the numerator is positive. So a decrease in δ_{ji} causes a decrease in w_i.

Because $s_{ij} = \frac{L_{ij}}{\sum_k L_{ik}}$, then

$$d \log s_{ij} = (1 - \phi_{ij}) dw_i - (1 - \phi_{ij}) d\delta_{ji} - \sum_k s_{ik} (1 - \phi_{ik}) dw_i$$

Combining the terms on w_i,

$$d \log s_{ij} = -\left(\phi_{ij} - \sum_k s_{ik}\phi_{ik}\right) dw_i - (1 - \phi_{ij}) d\delta_{ji}$$

By assumption, $\phi_{ij} > \sum_k s_{ik}\phi_{ik}$, so when moving costs declines and wages decline, the share increases.

$\square$

B Data details

There are four normal schools listed in Ogren (2005) for which the listed location was different from the original location of the school. For one of these schools, the second location was still in the same county (the school in Framingham, MA). For the other three, the school opened in the new location soon after the original opening. One opened in its new location five years after the initial location (Westfield, MA). The San Jose, CA school opened in San Jose nine years after its original opening in San Francisco; though they started looking for new locations after 6.5 years (Gilbert, 1957). The school originally in Marion, AL opened in Montgomery, AL 14 years after its original opening, though they started looking for a new location after 12.5 years (Caver, 1982). Given the short time between the original and new location, we include both the original and the second county as normal school counties for these three schools.

The CCD geographic files provide the county of the district based on the mailing address. In 2022-2023, roughly 96% of all districts reporting schools and enrollment (not limiting to normal school and asylum districts) operated schools in a single county (National Center for Education Statistics, 2024). Of the 4799 unique districts in normal school and asylum counties, three have a district address in a state other than the state in which they are operating as a district.

There are some instances in which the county reported for the district varies across years. We assign the modal county to the district, and then identify whether the district is in a normal school or asylum county based on this modal county.

The data on pre-Kindergarten only becomes available in 2010, and so before 2010 our measure of student-teacher ratios is based on the number of students and teachers from Kindergarten to 12th grade. We also estimate specifications using only Kindergarten to 12th grade, and so to ensure comparability in all specifications, we drop districts for which the number of students or teachers from pre-Kindergarten to 12th grade is zero, or the number of students or teachers from Kindergarten to 12th grade is zero.

After applying the sample restrictions in our wage analysis in Section 4.1, in our sample of teachers in elementary and secondary schools, less than 3% of elementary and middle school, and secondary school teachers have less than a bachelor's degree. In contrast, for preschool and kindergarten teachers, roughly 14% do not have a bachelor's degree, and for special education teachers this is roughly 10%.

C Further Details on Bachelor's Degree Composition

The statistics in Table 1 are based on 2018 IPEDS data (U.S. Department of Education, National Center for Education Statistics, 2020). Because we are interested in students staying locally after graduation, we exclude from the county-level totals degrees awarded by universities where the percent of students who are enrolled exclusively in distance education is 50% or higher. We do include these degrees when calculating the total degrees produced in the country. We obtain 2018 county-level population data from the U.S. Census intercensal population estimates (U.S. Census, 2024). In 2018, two of the 188 institutions that had been normal schools are not included in these statistics – one because most of the students were enrolled exclusively in distance education, and one was missing from the data. However, the degree data for that university was not missing in 2017, and it awarded 195 degrees, so this is not expected to alter the results.

Normal school counties produced roughly 29% of all bachelor's degrees in the U.S., and 35% of all bachelor's degrees in education. There are a number of large universities in normal school counties that did not evolve from the normal school, explaining the difference between the 29% of degrees produced in normal school counties and 17% at the institutions that had been the normal schools.

D Results Controlling for County Characteristics

Table A1: Difference in Teacher Labor Markets in Normal School and Asylum Counties, Controlling for County Characteristics

	(1) Log(Wage) Teachers	(2) Student-Teacher Ratio	(3) Top Quartile Emergency Cred
Normal school county	-0.00973	-0.167+	-0.0931*
	(0.00653)	(0.0930)	(0.0377)
Frac. Black residents	0.262**	1.784*	1.109**
	(0.0739)	(0.840)	(0.262)
Racial segregation	0.0338	-1.209	0.173
	(0.0416)	(0.828)	(0.288)
Income segregation	-0.0888	-0.433	-0.614
	(0.173)	(3.509)	(0.627)
Frac. children with single mothers	-0.577*	-2.623	0.633
	(0.222)	(2.056)	(0.513)
Frac. parents below median income	-0.0573	-0.482	-0.107
	(0.0530)	(0.650)	(0.236)
Log population density	0.0210**	0.533**	-0.0565**
	(0.00504)	(0.104)	(0.0194)
Observations	315	315	303
R-squared	0.869	0.903	0.627
Mean DV, Asylum Counties	10.45	16.13	0.282

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Column 1 uses pooled one-year ACS samples from 2012-2019, with observations at the county-level. Column 2 uses CCD data from 1997-1998 through 2018-2019 on students and teachers to construct county-level student teacher ratios. Column 3 uses Department of Education data on teachers with emergency credentials from 2017-2018 through 2021-2022 to construct the county-level fraction of teachers with emergency credentials. County characteristics are from Chetty et al. (2018). All columns include state fixed effects, clustering standard errors at the state level. See text for details.

E Further Details on Emergency Credentials

In each school year there are several states without district-level credentials data. Over time, the number of states with these data increases. In 2017-2018, there were nine states that did not report; in 2018-2019 there were five states; in 2019-2020 there were four states, and in 2020-2021 and 2021-2022 there was just one state.[35] Among the normal school and asylum counties in states that do report the data, on average roughly 96% of the regular and independent charter school districts in the county report the data. The 50th and 25th percentiles of the county-wide fraction of regular and independent charter school districts in the county reporting data on emergency or provisional credentials is one.[36]

Some districts report the number of teachers with emergency or provisional licenses, some report the number of teachers without emergency or provisional licenses, and some report both. In instances where both are reported, we use the number with emergency or provisional licenses. When this is not reported we use the total number of teachers minus the number without emergency or provisional licenses.[37][38]

To avoid counting the total teachers in districts missing data on emergency and provisional credentials, we keep only the districts for which the number of teachers with emergency or provisional licenses, or the number without emergency or provisional licenses, is not miss-

[35]In 2017-2018, these were California, North Carolina, North Dakota, New Jersey, New Mexico, Nevada, Pennsyvlania, Utah, and Vermont, which altogether had 70 normal school and asylum counties (69 without the singleton in Nevada. In 2018-2019, the states were California, New Jersey, Pennsyvlania, Utah, and Vermont, with a total 46 normal school and asylum counties. In 2019-2020, the states were California, New Jersey, Pennsylvania, and Utah, with a total of 41 normal school and asylum counties, and in 2020-2021 and 2021-2022 it was only California with 12 normal school and asylum counties.

[36]There is very little variation in these statistics across year. These statistics are for the normal school and asylum counties in states reporting these data, and excluding California which sometimes reports for zero districts and in some years just for one district. The statistics also exclude roughly five normal school and asylum counties in states with singleton normal school and asylum counties, which are excluded from the regression.

[37]In one year, there are a few cases where the difference between the total and number without emergency or provisional licenses is less than zero but greater than or equal to -.1. We replace these values with zero.

[38]For Louisiana, starting in 2019 the districts reported the fraction with emergency credentials similar to how they had reported the fraction with non-emergency credentials in 2017 and 2018. In 2017-2018 and 2018-2019, the fraction with emergency credentials is close to zero, while starting in 2019-2020 it is close to 100%. Starting in 2019-2020, we replace the county-wide fraction with emergency credentials as one minus the fraction, as it appears this was a reporting error.

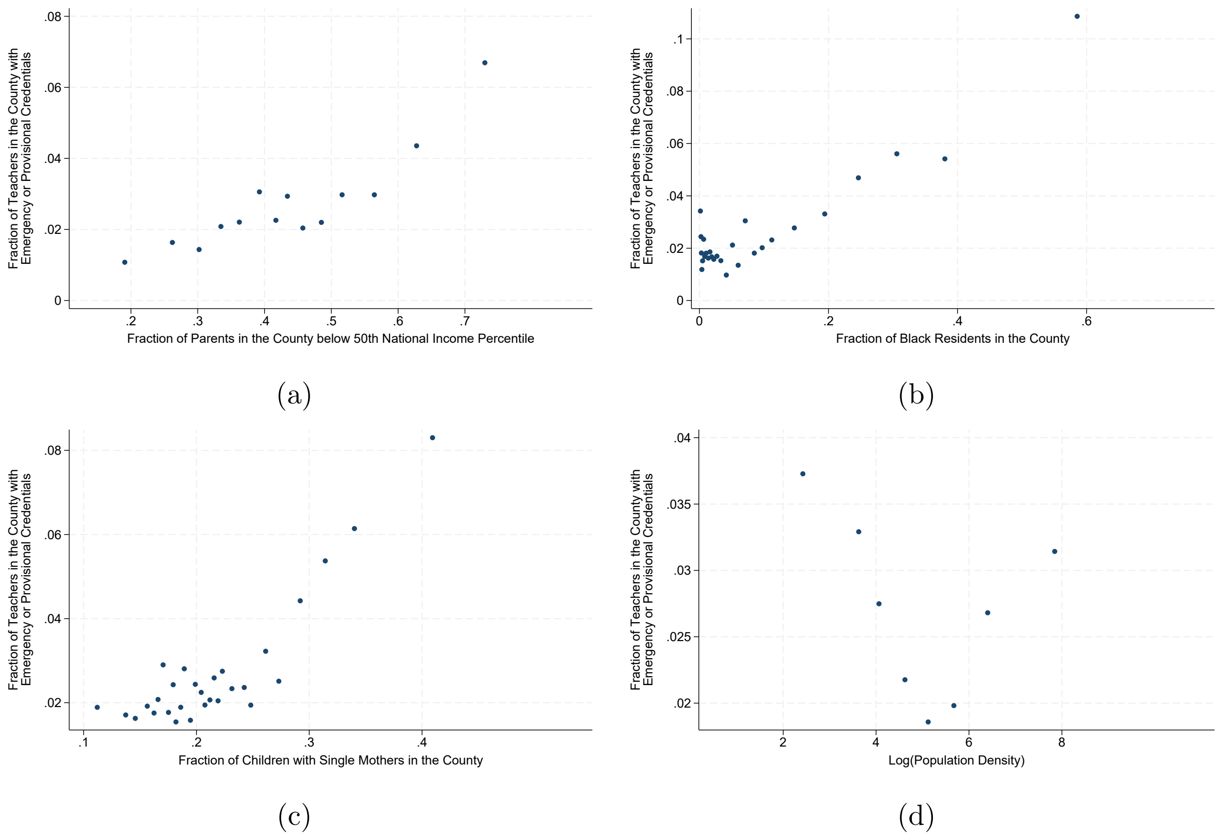

Figure A1: **Binned-Scatter Plot of the Fraction of Teachers in the County with Emergency or Provisional Credentials and County-Level Characteristics** This figure shows binned scatter-plots created using binsreg, and adjusting for state fixed effects. Observations are at the county level. All plots include the 2017-2018 through 2021-2022 school years. The sample includes only regular public school and independent charter districts in normal school and asylum counties.

ing. We also keep only the districts for which the total number of teachers is not missing. We also keep only regular public school districts or independent charter districts. Finally, for districts in which the reported county varies over time, we assign the modal county.

Table A2 shows results when using fraction of teachers with emergency or provisional credentials as the dependent variable, instead of an indicator for the county being in the top quartile of the distribution of the fraction of teachers with emergency or provisional credentials, as in Table 3.

Table A2: Difference in Fraction of Teachers with Emergency or Provisional Credentials

	(1)	(2)
Normal school county	-0.00180	-0.00395*
	(0.00224)	(0.00193)
Frac. Black residents		0.134**
		(0.0309)
Racial segregation		-0.00706
		(0.0178)
Income segregation		0.0413
		(0.0435)
Frac. children with single mothers		0.0674
		(0.0420)
Frac. parents below median income		0.00651
		(0.0135)
Log population density		-0.00467**
		(0.00130)
Observations	303	303
R-squared	0.618	0.805
Mean DV, Asylum Counties	0.0260	0.0260

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. County characteristics are the same as those included in Table A1. Standard errors are clustered at the state level.

F Further Details on the ACS Wage Analysis

There are 280 normal school and asylum counties that are associated with PUMAs that are not associated with any other normal school or asylum county. There are 34 counties that are associated with PUMAs that are also associated with other normal school or asylum counties of the opposite type (e.g., normal school counties associated with PUMAs that are also associated with asylum counties). The remainder of the counties are associated with PUMAs that are associated with other normal school or asylum counties of the same type.

Table A3: Difference in Teacher Wages in Normal School and Asylum Counties, with Controls

	(1) All Counties	(2) All Counties	(3) All Counties	(4) All Counties	(5) Excl. Overlap	(6) Excl. Overlap	(7) Excl. Overlap	(8) Excl. Overlap
Normal school county	-0.0215*	-0.0224*	-0.0174	-0.00973	-0.0265*	-0.0278*	-0.0216	-0.0123
	(0.0101)	(0.0103)	(0.0112)	(0.00653)	(0.0118)	(0.0122)	(0.0135)	(0.00752)
Age		0.00730*	0.00791*			0.00926*	0.00965**	
		(0.00351)	(0.00323)			(0.00386)	(0.00320)	
Frac. teachers with at least master's			0.309**				0.317**	
			(0.0783)				(0.0818)	
Frac. Black residents				0.262**				0.261**
				(0.0739)				(0.0799)
Racial segregation				0.0338				0.0319
				(0.0416)				(0.0421)
Income segregation				-0.0888				-0.123
				(0.173)				(0.192)
Frac. children with single mothers				-0.577*				-0.518+
				(0.222)				(0.268)
Frac. parents below median income				-0.0573				-0.0928
				(0.0530)				(0.0593)
Log population density				0.0210**				0.0201**
				(0.00504)				(0.00495)
Observations	315	315	315	315	271	271	271	271
R-squared	0.824	0.827	0.848	0.869	0.816	0.821	0.844	0.862
Mean DV, Asylum Counties	10.45	10.45	10.45	10.45	10.45	10.45	10.45	10.45

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. Specifications are similar to column (1) of Table 3, but include additional controls. Columns 5 through 8 exclude the counties that are part of PUMAs associated with both normal school and asylum counties. Standard errors are clustered at the state level. See Table 3 and text for details.

Table A4: Difference in Teacher Wages in Normal School and Asylum Counties, by School Grade Level

	(1) Elem and Middle	(2) Elem and Middle	(3) Elem and Middle	(4) Elem and Middle	(5) HS	(6) HS	(7) HS	(8) HS
Normal school county	-0.0246*	-0.0251*	-0.0216+	-0.0133*	-0.0163	-0.0147	-0.00487	-0.00451
	(0.00977)	(0.00986)	(0.0107)	(0.00611)	(0.0134)	(0.0143)	(0.0137)	(0.0115)
Age		0.00709*	0.00710*			0.0110**	0.00989**	
		(0.00299)	(0.00282)			(0.00233)	(0.00206)	
Frac. teachers with at least master's			0.263**				0.275**	
			(0.0661)				(0.0459)	
Frac. Black residents				0.280**				0.142
				(0.0746)				(0.113)
Racial segregation				0.0185				0.101
				(0.0502)				(0.0810)
Income segregation				-0.0993				-0.0181
				(0.176)				(0.286)
Frac. children with single mothers				-0.551*				-0.614*
				(0.216)				(0.295)
Frac. parents below median income				-0.0606				-0.0223
				(0.0525)				(0.0652)
Log population density				0.0202**				0.0217**
				(0.00476)				(0.00759)
Observations	315	315	315	315	315	315	315	315
R-squared	0.822	0.826	0.844	0.864	0.700	0.729	0.766	0.739

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. Specifications are similar to Table A3, but use individual data aggregated to the level of county-teacher type. Standard errors are clustered at the state level.

Table A5: Difference in Teacher Wages in Normal School and Asylum Counties, by School Grade Level, Excluding Overlap Counties

	(1) Elem and Middle	(2) Elem and Middle	(3) Elem and Middle	(4) Elem and Middle	(5) HS	(6) HS	(7) HS	(8) HS
Normal school county	-0.0293*	-0.0300*	-0.0251+	-0.0156*	-0.0217	-0.0204	-0.00922	-0.00658
	(0.0112)	(0.0113)	(0.0126)	(0.00676)	(0.0164)	(0.0172)	(0.0168)	(0.0140)
Age		0.00908**	0.00881**			0.0106**	0.00941**	
		(0.00327)	(0.00295)			(0.00254)	(0.00208)	
Frac. teachers with at least master's			0.264**				0.291**	
			(0.0703)				(0.0459)	
Frac. Black residents				0.280**				0.139
				(0.0806)				(0.119)
Racial segregation				0.0179				0.120
				(0.0510)				(0.0851)
Income segregation				-0.146				-0.0293
				(0.197)				(0.311)
Frac. children with single mothers				-0.497+				-0.542
				(0.260)				(0.345)
Frac. parents below median income				-0.0923				-0.0706
				(0.0586)				(0.0740)
Log population density				0.0194**				0.0215**
				(0.00480)				(0.00747)
Observations	271	271	271	271	271	271	271	271
R-squared	0.813	0.820	0.838	0.856	0.693	0.718	0.762	0.738

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. Specifications are similar to Table A4 but exclude the counties that are part of PUMAs associated with both normal school and asylum counties.

F.1 Wage Differences in Other Occupations, Normal School and Asylum Counties

In this section we present results showing wage differences in other occupations. When looking at police and fire occupations we include first-line supervisors of police and detectives; first-line supervisors of fire fighting and prevention workers; firefighters; police officers and detectives.

Table A6: Difference in Wages in Other Occupations, Normal School and Asylum Counties

	(1) Ln(Wage) Police and Fire	(2) Ln(Wage) Cashier	(3) Ln(Wage) Police and Fire	(4) Ln(Wage) Cashier	(5) Ln(Wage) Police and Fire	(6) Ln(Wage) Cashier
Normal school county	-0.0185	-0.00353	-0.0122	-0.00339	-0.00377	0.00839
	(0.0153)	(0.0194)	(0.0147)	(0.0205)	(0.0133)	(0.0193)
Observations	315	315	315	315	315	315
R-squared	0.742	0.296	0.753	0.324	0.818	0.336
Control for Age	N	N	Y	Y	N	N
Control for County Characteristics	N	N	N	N	Y	Y

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Specifications are similar to Table A3 but use data on police officers and firefighters, and cashiers. County characteristics are the same as those in Table A1. Observations are at the county level. Standard errors are clustered at the state level.

Table A7: Difference in Wages in Other Occupations, Normal School and Asylum Counties, Excluding Overlap Counties

	(1) Ln(Wage) Police and Fire	(2) Ln(Wage) Cashier	(3) Ln(Wage) Police and Fire	(4) Ln(Wage) Cashier	(5) Ln(Wage) Police and Fire	(6) Ln(Wage) Cashier
Normal school county	-0.0242	-0.0108	-0.0187	-0.0101	-0.00716	0.00466
	(0.0173)	(0.0228)	(0.0167)	(0.0234)	(0.0143)	(0.0228)
Observations	271	271	271	271	271	271
R-squared	0.727	0.281	0.734	0.291	0.813	0.326
Control for Age	N	N	Y	Y	N	N
Control for County Characteristics	N	N	N	N	Y	Y

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Specifications are similar to Table A6 but exclude the counties that are part of PUMAs associated with both normal school and asylum counties. County characteristics are the same as those in Table A1. Standard errors are clustered at the state level.

G Further Details on Student-Teacher Ratios

Using the methods described in Section 5.1, we obtain counts of teachers in each county in the ACS (including pre-school and kindergarten teachers; elementary and middle school teachers; secondary school teachers; and special education teachers), who work in elementary and secondary schools. We also obtain counts of 5-18 year-olds in each county in the ACS who are enrolled in kindergarten through 12th grade. We then construct student-teacher ratios, and estimate the following regression at the county level:

$$\frac{Students_i}{Teachers_i} = \beta \text{Normal School County}_i + \alpha_s + \epsilon_i \tag{A1}$$

We find that student-teacher ratios are lower by roughly .78. The mean ratio in asylum counties is roughly 14.96, and so this represents a reduction of roughly 5%. The effect is slightly larger when we exclude counties that are associated with PUMAS that are associated with both normal school and asylum counties. Results are similar when including county-level covariates.

Table A8: Difference in Student-Teacher Ratios in Normal School and Asylum Counties, ACS Data

	(1) All Counties No Controls	(2) Excl. Overlap No Controls	(3) All Counties Controls	(4) Excl. Overlap Controls
Normal school county	-0.782**	-0.912**	-0.844**	-1.019**
	(0.288)	(0.325)	(0.278)	(0.314)
Observations	315	271	315	271
R-squared	0.583	0.581	0.661	0.673
Mean DV, Asylum Counties	14.96	15.28	14.96	15.28

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. The dependent variable is the student-teacher ratio, constructed by aggregating all teachers in OCC2010 codes 2300, 2310, 2320, and 2330 that are working in elementary and secondary schools, and aggregating all 5-18 year-olds that are enrolled in kindergarten through 12th grade. Columns 3 and 4 additionally include the same county-level covariates as in Table A1.

H Further details on ACS teacher characteristics

H.1 Bachelor's degree composition at universities in Normal School Counties

Table A9: Difference in Bachelor's Degree Composition Produced in Normal School counties

	(1) Frac. Ed: All Counties	(2) Frac. Subj. Ed: All Counties	(3) Frac. Spec. Ed: All Counties	(4) Frac. Ed: Norm, Asyl	(5) Frac. Subj. Ed: Norm, Asyl	(6) Frac. Spec. Ed: Norm, Asyl
Normal school county	0.0210**	0.00567**	0.00433**	0.0450**	0.0118**	0.00726**
	(0.00588)	(0.00195)	(0.00144)	(0.00676)	(0.00286)	(0.00164)
Observations	795	795	795	259	259	259
R-squared	0.330	0.257	0.199	0.466	0.418	0.284
Mean DV, not Normal Sch. Counties	0.0590	0.0136	0.00342	0.0408	0.00965	0.00329

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level, and the outcome is based on university-level data from IPEDS for 2018 aggregated to the county level. We exclude universities for which at least 50% of the students are enrolled in distance education. Dependent variables are degrees in the field relative to total degrees. Regressions include state fixed effects. Standard errors are clustered at the state level. Observations in columns (1) through (3) are weighted by total degrees in the county. See text for details.

H.2 ACS field of degree classifications

We generate several classifications related to college majors in the ACS. We create nine broad categories of majors from the ACS field of degrees. We list these, as well as the ACS code in parentheses.

1. Education: Education (23)

2. STEM: Environment and Natural Resources (13), Computer and Information Sciences (21), Engineering (24), Biology and Life Sciences (36), Mathematics and Statistics (37), Physical Sciences (50)

3. Social Science and related: Area Ethnic and Civilization Studies (15), Law (32), Library Science (35), Interdisciplinary and Multi-disciplinary Studies (40), Psychology (52), Criminal Justice and Fire Protection (53), Public Affairs, Policy, and Social Work (54), Social Sciences (55)

4. Technologies and other: Architecture (14), Communication Technologies (20), Cosmetology and Culinary Arts (22), Engineering Technologies (25), Military Technologies (38), Nuclear, Industrial Radiology, and Biological Technologies (51), Construction Services (56), Electrical and Mechanic Repairs and Technologies (57), Precision Production and Industrial Arts (58), Transportation Sciences and Technologies (59)

5. Business and Communications: Communications (19), Business (62)

6. Foreign Languages: Linguistics and Foreign Languages (26)

7. Humanities: English Language, Literature, and Composition (33), Liberal Arts and Humanities (34), Philosophy and Religious Studies (48), Theology and Religious Vocations (49), Fine Arts (60), History (64)

8. Health and Agriculture: Medical and Health Sciences and Services (61), Agriculture (11)

9. Family Science and Recreation: Family and Consumer Sciences (29), Physical Fitness, Parks, Recreation, and Leisure (41)

Table A10: Difference in Teacher College Major in Normal School and Asylum Counties, Pooled Teachers

	(1) General Teacher Ed.	(2) Subj. Area Teacher Ed.	(3) STEM Teacher Ed.	(4) STEM	(5) Humanities	(6) Special Needs Ed.
Normal school county	-0.0135*	0.0196**	0.00467*	-0.00204	-0.00313	0.00360
	(0.00637)	(0.00629)	(0.00192)	(0.00286)	(0.00427)	(0.00289)
Observations	315	315	315	315	315	315
R-squared	0.679	0.613	0.436	0.467	0.733	0.487
Mean DV, Asylum Counties	0.470	0.201	0.0274	0.0705	0.0952	0.0551

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. This table is the same as Table 4, but uses all teachers working in elementary and secondary schools, which includes the samples in Table 4, as well as pre-school and kindergarten teachers working in elementary and secondary schools. Standard errors are clustered at the state level. See text for details and variable definitions.

Table A11: Difference in Teacher College Major in Normal School and Asylum Counties, Excluding Overlap

	(1) General Teacher Ed.	(2) Subj. Area Teacher Ed.	(3) STEM Teacher Ed.	(4) STEM	(5) Humanities	(6) Special Needs Ed.
Panel A: Pooled Teachers						
Normal school county	-0.0131+	0.0219**	0.00458*	-0.00300	-0.00437	0.00429
	(0.00702)	(0.00698)	(0.00210)	(0.00313)	(0.00501)	(0.00329)
Observations	271	271	271	271	271	271
R-squared	0.624	0.590	0.390	0.405	0.715	0.488
Mean DV, Asylum Counties	0.466	0.201	0.0270	0.0715	0.0962	0.0552
Panel B: Elementary and Middle School Teachers						
Normal school county	-0.0126+	0.0125+	0.00330	0.000592	0.00127	0.00133
	(0.00701)	(0.00660)	(0.00201)	(0.00416)	(0.00513)	(0.00338)
Observations	271	271	271	271	271	271
R-squared	0.656	0.532	0.316	0.326	0.715	0.441
Mean DV, Asylum Counties	0.522	0.175	0.0211	0.0574	0.0840	0.0459
Panel C: Secondary School Teachers						
Normal school county	-0.00480	0.0436**	0.00947	-0.0198*	-0.0260**	-0.000470
	(0.0125)	(0.0129)	(0.00701)	(0.00897)	(0.00900)	(0.00551)
Observations	271	271	271	271	271	271
R-squared	0.283	0.452	0.295	0.316	0.395	0.165
Mean DV, Asylum Counties	0.265	0.275	0.0620	0.146	0.157	0.0214
Panel D: Special Education Teachers						
Normal school county	0.0304	0.0318	0.000750	-0.0119	-0.00780	0.0441+
	(0.0281)	(0.0294)	(0.00370)	(0.00766)	(0.0165)	(0.0252)
Observations	269	269	269	269	269	269
R-squared	0.189	0.310	0.124	0.124	0.330	0.326
Mean DV, Asylum Counties	0.314	0.385	0.00642	0.0326	0.0751	0.322

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. This table is similar to Table 4, but excludes the counties that are part of PUMAs associated with both normal school and asylum counties. Standard errors are clustered at the state level. See text for details.

Table A12: Difference in Teacher College Major in Normal School and Asylum Counties, Including County-Level Covariates

	(1) General Teacher Ed.	(2) Subj. Area Teacher Ed.	(3) STEM Teacher Ed.	(4) STEM	(5) Humanities	(6) Special Needs Ed.
Panel A: Elementary and Middle School Teachers						
Normal school county	-0.0167**	0.00776	0.00239	0.000648	0.00519	0.000262
	(0.00617)	(0.00551)	(0.00184)	(0.00329)	(0.00424)	(0.00325)
Observations	315	315	315	315	315	315
R-squared	0.756	0.615	0.417	0.420	0.768	0.462
Mean DV, Asylum Counties	0.526	0.175	0.0214	0.0562	0.0834	0.0461
Panel B: Secondary School Teachers						
Normal school county	-0.00424	0.0350**	0.00817	-0.0162+	-0.0258**	-0.000262
	(0.0114)	(0.0116)	(0.00610)	(0.00803)	(0.00809)	(0.00503)
Observations	315	315	315	315	315	315
R-squared	0.341	0.497	0.338	0.330	0.501	0.178
Mean DV, Asylum Counties	0.267	0.276	0.0628	0.147	0.155	0.0206
Panel C: Special Education Teachers						
Normal school county	0.0159	0.0262	0.000448	-0.00941	-0.00780	0.0316
	(0.0247)	(0.0239)	(0.00299)	(0.00718)	(0.0152)	(0.0210)
Observations	314	314	314	314	314	314
R-squared	0.241	0.353	0.130	0.141	0.369	0.361
Mean DV, Asylum Counties	0.323	0.381	0.00557	0.0323	0.0736	0.317

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is the same as Table 4, but includes the same county-level covariates as in Table A1. See text and Table 4 for details. Standard errors are clustered at the state level.

H.3 Decomposition of Subject-Area Teacher Education Degrees

Table A13 decomposes the coefficient in column (2) of Table 4. We start with the discussion of the results for Elementary and Middle School Teachers, but again these results are very similar to the pooled regression. We see that teachers in normal school counties are more likely to have a degree in math teacher education (.3 percentage points or roughly 30% given the mean of the dependent variable in asylum counties of 1.1%). Teachers in normal school counties are also .7 percentage points more likely to have majored in physical and health education, which is a 35% increase relative to the mean of 2.1% in asylum counties. While the magnitudes suggest positive and non-trivial effects on the fraction majoring in science and computer science education, special needs education, and art and music education, these effects are not statistically significant.

For secondary school teachers, there are non-trivial positive effects on fraction majoring in math teacher education; science, computer science education; and art, music education, but these are not statistically significant from zero. There is a large positive effect on fraction majoring in physical or health education (1.5 percentage points, or roughly 34% relative to the mean of 4.6% in asylum counties).

Table A13: Difference in Subject-Area Teacher Education Degrees, Normal School and Asylum Counties

	(1) College Major: Math Teacher Ed.	(2) College Major: Phys., Health Ed.	(3) College Major: Science, CS Ed.	(4) College Major: Special Needs Ed.	(5) College Major: Soc. Sc. Ed.	(6) College Major: Mult. Levels Ed.	(7) College Major: Language, Drama Ed.	(8) College Major: Art, Music Ed.
Panel A: Pooled Teachers								
Normal school county	0.00357*	0.00851**	0.00139	0.00360	-0.000183	-0.0000905	0.000429	0.00304
	(0.00159)	(0.00207)	(0.00125)	(0.00289)	(0.00156)	(0.00137)	(0.00208)	(0.00215)
Observations	315	315	315	315	315	315	315	315
R-squared	0.340	0.265	0.325	0.487	0.270	0.425	0.304	0.369
Mean DV, Asylum Counties	0.0155	0.0250	0.0129	0.0551	0.0172	0.0188	0.0305	0.0337
Panel B: Elementary and Middle School Teachers								
Normal school county	0.00321*	0.00735**	0.000438	0.00118	-0.000433	-0.0000186	-0.000858	0.00138
	(0.00156)	(0.00208)	(0.00116)	(0.00294)	(0.00147)	(0.00149)	(0.00205)	(0.00251)
Observations	315	315	315	315	315	315	315	315
R-squared	0.317	0.289	0.285	0.443	0.187	0.402	0.248	0.278
Mean DV, Asylum Counties	0.0108	0.0213	0.0116	0.0461	0.0145	0.0204	0.0269	0.0296
Panel C: Secondary School Teachers								
Normal school county	0.00560	0.0153*	0.00516	-0.000616	0.00108	-0.000728	0.00311	0.00788
	(0.00441)	(0.00613)	(0.00463)	(0.00472)	(0.00462)	(0.00253)	(0.00697)	(0.00595)
Observations	315	315	315	315	315	315	315	315
R-squared	0.252	0.256	0.165	0.167	0.227	0.162	0.220	0.317
Mean DV, Asylum Counties	0.0416	0.0456	0.0231	0.0206	0.0311	0.0114	0.0513	0.0626
Panel D: Special Education Teachers								
Normal school county	0.000246	-0.0119	0.000755	0.0403+	-0.00377	0.00134	0.00285	0.00567
	(0.00172)	(0.00842)	(0.00271)	(0.0209)	(0.00486)	(0.00679)	(0.00426)	(0.00467)
Observations	314	314	314	314	314	314	314	314
R-squared	0.0859	0.205	0.135	0.345	0.163	0.153	0.135	0.152
Mean DV, Asylum Counties	0.00224	0.0243	0.00360	0.317	0.0113	0.0120	0.0165	0.00927

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. This table provides the effects separately for each of the majors included in "Subj. Area Teacher Ed." in column (2) of Table 4. See text and Table 4 for details.

Table A14: Difference in Teachers' Field of Degree, Normal School and Asylum Counties

	(1) Education	(2) STEM	(3) Business & Communications	(4) Social Sciences	(5) Humanities	(6) Family Science & Recreation	(7) Health Agriculture	(8) Foreign Languages	(9) Technologies & Other
Panel A: Pooled Teachers									
Normal school county	0.0104	-0.00204	-0.00162	-0.00652*	-0.00313	0.000137	0.00202	-0.00335*	0.000430
	(0.00818)	(0.00286)	(0.00277)	(0.00299)	(0.00427)	(0.00164)	(0.00225)	(0.00129)	(0.00153)
Observations	315	315	315	315	315	315	315	315	315
R-squared	0.775	0.467	0.387	0.698	0.733	0.455	0.253	0.418	0.132
Mean DV, Asylum Counties	0.694	0.0705	0.0574	0.0782	0.0952	0.0206	0.0221	0.0152	0.00476
Panel B: Elementary and Middle School Teachers									
Normal school county	0.00427	0.00121	0.000693	-0.00775*	0.00241	0.000531	0.00177	-0.00282*	0.000540
	(0.00804)	(0.00365)	(0.00299)	(0.00301)	(0.00445)	(0.00187)	(0.00211)	(0.00120)	(0.00118)
Observations	315	315	315	315	315	315	315	315	315
R-squared	0.771	0.404	0.354	0.684	0.719	0.425	0.195	0.320	0.135
Mean DV, Asylum Counties	0.722	0.0562	0.0551	0.0779	0.0834	0.0195	0.0205	0.0121	0.00413
Panel C: Secondary School Teachers									
Normal school county	0.0395**	-0.0180*	-0.0115+	0.00150	-0.0245**	-0.00355	0.00478	-0.00708+	-0.000545
	(0.0134)	(0.00777)	(0.00647)	(0.00549)	(0.00772)	(0.00468)	(0.00429)	(0.00395)	(0.00541)
Observations	315	315	315	315	315	315	315	315	315
R-squared	0.593	0.309	0.260	0.395	0.432	0.257	0.209	0.248	0.157
Mean DV, Asylum Counties	0.573	0.147	0.0700	0.0644	0.155	0.0237	0.0210	0.0301	0.00848
Panel D: Special Education Teachers									
Normal school county	0.0326	-0.00986	-0.00362	-0.0174	-0.00520	0.00585	-0.00810	-0.00491	-0.000545
	(0.0248)	(0.00665)	(0.00701)	(0.0196)	(0.0143)	(0.00467)	(0.0122)	(0.00514)	(0.00541)
Observations	314	314	314	314	314	314	314	314	315
R-squared	0.369	0.131	0.187	0.259	0.334	0.237	0.204	0.236	0.157
Mean DV, Asylum Counties	0.686	0.0323	0.0556	0.121	0.0736	0.0170	0.0494	0.0164	0.00848

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is similar to Table 4, but shows the decomposition of teacher college major by broad field category. See text for details.

Table A15: Difference in Field of Degree, Normal School and Asylum Counties, Excluding Overlap Counties

	(1) Education	(2) STEM	(3) Business & Communications	(4) Social Sciences	(5) Humanities	(6) Family Science & Recreation	(7) Health Agriculture	(8) Foreign Languages	(9) Technologies & Other
Panel A: Pooled Teachers									
Normal school county	0.0134	-0.00300	-0.00248	-0.00736*	-0.00437	-0.0000604	0.00315	-0.00359*	0.000441
	(0.00933)	(0.00313)	(0.00310)	(0.00341)	(0.00501)	(0.00191)	(0.00272)	(0.00151)	(0.00180)
Observations	271	271	271	271	271	271	271	271	271
R-squared	0.740	0.405	0.352	0.640	0.715	0.464	0.226	0.247	0.118
Mean DV, Asylum Counties	0.690	0.0715	0.0594	0.0786	0.0962	0.0213	0.0212	0.0146	0.00478
Panel B: Elementary and Middle School Teachers									
Normal school county	0.00594	0.000592	0.0000144	-0.00813*	0.00127	0.000554	0.00325	-0.00307*	0.000821
	(0.00911)	(0.00416)	(0.00339)	(0.00344)	(0.00513)	(0.00217)	(0.00244)	(0.00140)	(0.00136)
Observations	271	271	271	271	271	271	271	271	271
R-squared	0.740	0.326	0.318	0.624	0.715	0.431	0.174	0.220	0.106
Mean DV, Asylum Counties	0.718	0.0574	0.0570	0.0787	0.0840	0.0201	0.0191	0.0117	0.00392
Panel C: Secondary School Teachers									
Normal school county	0.0449**	-0.0198*	-0.0138+	0.000612	-0.0260**	-0.00494	0.00482	-0.00730	-0.00166
	(0.0155)	(0.00897)	(0.00762)	(0.00670)	(0.00900)	(0.00542)	(0.00505)	(0.00457)	(0.00654)
Observations	271	271	271	271	271	271	271	271	271
R-squared	0.560	0.316	0.249	0.341	0.395	0.262	0.189	0.135	0.198
Mean DV, Asylum Counties	0.568	0.146	0.0727	0.0648	0.157	0.0252	0.0211	0.0299	0.00938
Panel C: Special Education Teachers									
Normal school county	0.0440	-0.0119	-0.0000655	-0.0243	-0.00780	0.00756	-0.00817	-0.00776	0.00316+
	(0.0284)	(0.00766)	(0.00762)	(0.0233)	(0.0165)	(0.00540)	(0.0141)	(0.00552)	(0.00176)
Observations	269	269	269	269	269	269	269	269	269
R-squared	0.314	0.124	0.209	0.211	0.330	0.223	0.185	0.121	0.171
Mean DV, Asylum Counties	0.683	0.0326	0.0552	0.121	0.0751	0.0175	0.0506	0.0147	0.00102

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is similar to Table A14, but excludes the counties that are part of PUMAs associated with both normal school and asylum counties. See text for details.

Table A16: Difference in Teacher Age and Education in Normal School and Asylum Counties, by School Grade Level

	(1) All	(2) All	(3) Elem and Middle	(4) Elem and Middle	(5) HS	(6) HS	(7) Spec. Ed.	(8) Spec.Ed.
	Master's	Age	Master's	Age	Master's	Age	Master's	Age
Normal school county	-0.0170	0.160	-0.0133	0.136	-0.0426*	-0.00930	0.0347	0.597
	(0.0108)	(0.183)	(0.0109)	(0.195)	(0.0169)	(0.322)	(0.0278)	(0.550)
Observations	315	315	315	315	315	315	314	314
R-squared	0.836	0.427	0.822	0.385	0.610	0.271	0.424	0.258
Mean DV, Asylum Counties	0.556	43.03	0.550	43.13	0.588	43.06	0.563	43.25

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. The dependent variables are the fraction of teachers with at least a master's degree, and the average age of the teachers. The abbreviation HS reflects characteristics of secondary school teachers. Specifications are similar to Table 4. Standard errors are clustered at the state level.

Table A17: Difference in Teacher Age and Education in Normal School and Asylum Counties, by School Grade Level, Excluding Overlap Counties

	(1) All	(2) All	(3) Elem and Middle	(4) Elem and Middle	(5) HS	(6) HS	(7) Spec. Ed.	(8) Spec.Ed.
	Master's	Age	Master's	Age	Master's	Age	Master's	Age
Normal school county	-0.0210	0.189	-0.0177	0.161	-0.0495*	0.0314	0.0462	0.393
	(0.0128)	(0.210)	(0.0128)	(0.225)	(0.0199)	(0.367)	(0.0325)	(0.604)
Observations	271	271	271	271	271	271	269	269
R-squared	0.812	0.428	0.795	0.400	0.557	0.221	0.375	0.249
Mean DV, Asylum Counties	0.557	42.95	0.551	43.04	0.590	42.95	0.569	43.49

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level. This table is similar to Table A16, but excludes counties that are part of PUMAs associated with both normal school and asylum counties. The abbreviation HS reflects characteristics of secondary school teachers. Standard errors are clustered at the state level.

I Further details on test scores

Our heterogeneity exercise in Section 5.2 evaluates effects in states with lower overall test scores, where proximity may have larger effects as there is more room for improvement.

We aggregate total proficient and total test-takers at the state-year-grade-subject level, and then obtain the fraction proficient. We also use the state-year-grade-subject fraction proficient to obtain the median state fraction proficient at the year-grade-subject level. For each school-subject-grade level, we can then identify whether the school is in a state that is above the median state proficiency for that grade-subject-year across all states. We then obtain the school-subject-grade level mean separately for observations when the state is above- and below-median proficiency. We aggregate to the county-above state-median level, by summing the mean school-level number proficient and number of test-takers. We calculate the county fraction proficient, and estimate specification (3) separately for the above- and below-median observations.

Results with and without heterogeneity are in Table 5. Results when including county-level characteristics are in Table A18.

Table A18: Difference in K-12 Proficiency Rates in Normal School and Asylum Counties, Including Control Variables

	(1) RLA	(2) Math	(3) RLA Above Median State-Years	(4) Math Above Median State-Years	(5) RLA Below Median State-Years	(6) Math Below Median State-Years
Panel A: Third-Grade Test Scores						
Normal school county	0.00668	0.00849	0.00191	0.00903	0.0113	0.00554
	(0.00720)	(0.00770)	(0.00771)	(0.00895)	(0.00904)	(0.0103)
Observations	315	315	214	203	228	206
R-squared	0.817	0.782	0.756	0.764	0.654	0.621
Mean DV, Asylum Counties	0.501	0.528	0.591	0.610	0.411	0.448
Panel B: Eighth-Grade Test Scores						
Normal school county	0.0114+	0.0175*	0.0105	0.0184	0.0150+	0.0157
	(0.00660)	(0.00849)	(0.00885)	(0.0127)	(0.00773)	(0.0125)
Observations	315	315	181	170	200	194
R-squared	0.845	0.839	0.740	0.789	0.759	0.686
Mean DV, Asylum Counties	0.502	0.431	0.607	0.536	0.412	0.315
Panel C: High School Test Scores						
Normal school county	0.0167*	0.0259**	0.0212*	0.00343	0.0222	0.0410**
	(0.00715)	(0.00862)	(0.00859)	(0.0115)	(0.0130)	(0.0101)
Observations	315	315	200	207	176	177
R-squared	0.933	0.936	0.882	0.904	0.801	0.731
Mean DV, Asylum Counties	0.576	0.462	0.690	0.607	0.431	0.276

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is the same as Table 5, but includes as control variables the same county characteristics as in Table A1.

J Differences in university selectivity

Our evidence is consistent with normal school counties having a greater supply of teachers because of the local regional university. In addition to providing different offerings (e.g., subject-area education majors), these universities may also attract students with different characteristics. In particular, regional universities tend to be less selective than flagship public universities, which may also train future teachers. Using 2009 IPEDS data, we compare measures of admissions selectivity at the universities in normal school counties relative to other counties in the same state. We do not compare only to asylum county universities, as the teachers in asylum counties may come from any university. Our objective is to compare to other universities that produce a lot of teachers, and so we weight by the number of bachelor's degrees awarded in education.

Specifically, we construct county-level averages weighted by first-time undergraduate enrollment, and then estimate specification (3) weighting those county-level averages by the number of bachelor's degrees awarded in education in the county. Table A19 shows students at universities in normal school counties have lower standardized test scores than other students in the state. The 25th and 75th percentile of the Math SAT for incoming students is lower by about 21-22 points (roughly 3-4%), significant at the 5% level. SAT verbal percentiles are lower by about 13-15 points, significant at the 10% level in the case of the 75th percentile. ACT percentiles are lower by about 1.1 to 1.3 points (about 5%), significant at the 1% level.[39] We also see that universities in normal school counties are less likely open admission, but conditional on being non-open admission the fraction admitted is the same, letters of recommendation are less likely required, and test scores are more likely required.

Thus, with the appropriate caveats that we do not observe test scores for teachers working in normal school counties, this evidence suggests they may have lower standardized test scores.

[39] Test score percentiles are conditional on being non-open admission, requiring test scores, and at least 60% of students submitting test scores.

Table A19: Differences in Incoming Student SAT/ACT Scores and Admissions Selectivity: Universities in Normal School Counties vs. Other Same-State Counties, Weighting by Total Bachelor's Degrees Awarded in Education

Panel A: Differences in Standardized Test Scores

	SAT Verbal 25th pctile	SAT Verbal 75th pctile	SAT Math 25th pctile	SAT Math 75th pctile	ACT Composite 25th pctile	ACT Composite 75th pctile
Normal school county	-12.88	-14.87+	-21.81*	-20.63*	-1.145**	-1.289**
	(8.657)	(7.929)	(8.756)	(8.071)	(0.369)	(0.316)
Observations	507	507	513	513	568	568
R-squared	0.184	0.238	0.187	0.215	0.199	0.181
Mean DV, not Normal Sch. Counties	469.3	585.6	480.0	594.3	20.26	25.39

Panel B: Differences in Selectivity

	Public	Open admission	Fraction admitted	Letters of recommendation required or recommended	Test scores required or recommended
Normal school county	0.346**	-0.0591*	0.00162	-0.181**	0.0211**
	(0.0429)	(0.0258)	(0.0185)	(0.0641)	(0.00569)
Observations	646	646	599	599	599
R-squared	0.282	0.249	0.375	0.314	0.118
Mean DV, not Normal Sch. Counties	0.355	0.140	0.681	0.622	0.962

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table uses IPEDS university-level data from 2009 to construct county-level averages weighted by enrollment of first-time undergraduate students. Regressions weight by the total number of bachelor's degrees awarded in education in the county, to compare universities in normal school counties to other universities that award many degrees in education. Fraction admitted, letters of recommendations required or recommended, and test scores required or recommended are conditional on non-open admission. Test score percentiles are conditional on non-open admission, test scores required, and $\geq 60\%$ of enrolled students submitting test scores. Standard errors are clustered at the state level.

Table A20: Differences in Incoming Student SAT/ACT Scores and Admissions Selectivity: Universities in Normal School Counties vs. Other Same-State Counties, Weighting by Total Bachelor's Degrees Awarded in Education, including Control Variables

Panel A: Differences in Standardized Test Scores

	SAT Verbal 25th pctile	SAT Verbal 75th pctile	SAT Math 25th pctile	SAT Math 75th pctile	ACT Composite 25th pctile	ACT Composite 75th pctile
Normal school county	-10.13	-11.93	-18.63*	-17.68*	-0.927**	-1.043**
	(7.388)	(7.582)	(7.628)	(7.884)	(0.318)	(0.291)
Observations	507	507	513	513	568	568
R-squared	0.291	0.327	0.314	0.319	0.335	0.298
Mean DV, not Normal Sch. Counties	469.3	585.6	480.0	594.3	20.26	25.39

Panel B: Differences in Selectivity

	Public	Open admission	Fraction admitted	Letters of recommendation required or recommended	Test scores required or recommended
Normal school county	0.271**	-0.0410+	-0.00369	-0.178*	0.00969+
	(0.0358)	(0.0218)	(0.0168)	(0.0681)	(0.00551)
Observations	646	646	599	599	599
R-squared	0.362	0.286	0.409	0.322	0.141
Mean DV, not Normal Sch. Counties	0.355	0.140	0.681	0.622	0.962

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is the same as Table A19 but includes the same control variables as in Table A1.

K Expenditures per pupil in Normal School and Asylum Counties

Even if the cost of hiring a teacher is higher in asylum counties because of teachers' geographic preferences, the way in which this affects teacher-student ratios, credentials, and student outcomes depends on the decisions those communities make about education quality. For example, asylum counties could decide to hold education quality constant, and hire an equal number of teachers as in normal school counties and spend more per student. The evidence we have presented so far is not consistent with this, as we see lower teacher-student ratios in asylum counties and greater fraction of teachers with emergency credentials. In this section, we directly show differences in district expenditures per pupil in normal school and asylum counties.

We obtain data on total district expenditures, district expenditures on instructional salaries, total district capital outlay expenditures, and number of students, from the CCD Fiscal Survey for the years 2008 through 2019. We follow a procedure similar to the one we use for the student-teacher and credentials analysis, and construct district-level means and then construct county aggregates by summing the district level mean expenditures and number of students. As with the CCD student and teacher data, we keep only regular public school districts and independent charter districts. We drop district-year observations for which any of the expenditure data or student data are zero or missing. We calculate the 1st and 99th percentile of per-pupil total expenditure, expenditure on instructional salaries, and capital outlay expenditure. If any of these district-level measures are greater than or equal to twice the 99th percentile, or less than or equal to half of the 1st percentile, we set all of the district-level expenditures variables to missing, as well as the number of students. In this way, we do not end up with a different set of districts contributing to the county-level average for each variable. We then construct district-level means, and county aggregates, as described in the previous sections. We merge the data to the set of normal school and asylum counties.

We then estimate a regression with log expenditures per student at the county level as the dependent variable, and an indicator for normal school county along with state fixed effects. We cluster standard errors at the state level. Table A21 shows there are no statistically significant differences in expenditures per student in normal school counties versus asylum counties.[40]

Table A21: Difference in K-12 School Expenditures between Normal School and Asylum Counties

	(1)	(2)	(3)
	Ln(Expend./Stud)	Ln(Expend. Instruct. Salaries/Stud)	Ln(Expend. on Capital Outlays/Stud)
Normal school county	0.0144	0.00935	0.0234
	(0.0115)	(0.00964)	(0.0629)
Observations	312	312	312
R-squared	0.879	0.901	0.461
Mean DV, Asylum Counties	9522.1	3216.3	824.1

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. Observations are at the county level, and constructed by using school district-level data from the CCD for years 2008-2009 through 2018-2019. Standard errors are clustered at the state level.

[40] There are three fewer counties in these regressions than in Table 3. This is because of three counties from New York, which are missing data from the finance dataset.

Table A22: Difference in Expenditures in Normal School and Asylum Counties, Controlling for County Characteristics

	(1) Ln(Expend./Stud)	(2) Ln(Expend. Instruct. Salaries/Stud)	(3) Ln(Expend. on Capital Outlays/Stud)
Normal school county	0.0171	0.0114	0.0475
	(0.0114)	(0.00895)	(0.0597)
Frac. Black residents	0.169+	-0.000426	0.148
	(0.0960)	(0.0988)	(0.432)
Racial segregation	0.149+	0.0796	0.156
	(0.0847)	(0.0711)	(0.385)
Income segregation	-0.0725	-0.191	1.357
	(0.415)	(0.281)	(0.996)
Frac. children with single mothers	-0.0994	-0.0263	-0.629
	(0.225)	(0.243)	(1.005)
Frac. parents below median income	0.0152	0.0317	-0.798+
	(0.0825)	(0.0537)	(0.458)
Log population density	0.00493	0.00699	0.0101
	(0.0131)	(0.0105)	(0.0410)
Observations	312	312	312
R-squared	0.886	0.903	0.508
Mean DV, Asylum Counties	9522.1	3216.3	824.1

Notes: + $p < .1$, * $p < .05$, ** $p < .01$. This table is the same as Table A21, but includes control variables. See Table A21 for details.