Local Labor Markets and Selection into the Teaching Profession

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Abstract

Using administrative data from Texas, I track individuals from high school through college to the workforce to determine the effects of local labor markets on occupational choice. I find local labor market conditions are countercyclical with selection into teaching. Individuals sorting into teaching because of poor local labor market conditions are of higher ability (standardized tests) and have higher productivity (value-added). The findings suggest local labor market fluctuations shape career decisions well before individuals participate in the labor market, and increasing the relative economic standing of teaching as a career has the potential to improve the future supply of teachers.

JEL: E32, H75, I20, J24, J45

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1 Introduction

Selection into teaching has long been studied given the importance of teachers on students' long-run outcomes and the difficulty in maintaining a large workforce of high-quality teachers (Jackson, 2012; Chetty et al., 2014b; Chingos et al., 2014; Koedel et al., 2015; Jackson, 2018; Hoxby and Leigh, 2004; Bacolod, 2007; Britton and Propper, 2016; Fraenkel, 2018; Nagler et al., 2020). However, studying selection into teaching is difficult because open questions remain on what information individuals use to choose occupations and when preferences are formed. Career choice may be affected by information received about labor markets, and business cycles in particular make salient features of some occupations over others. Given occupational decisions are often made well before individuals participate in the labor market, could business cycles experienced during adolescence influence the supply and quality of potential teachers?

A priori, it is not obvious whether high ability individuals facing adverse economic conditions would gravitate away from a low-wage career like teaching or towards it due to its stability. To explore these possibilities, I combine Texas administrative data with variation in unemployment rates (URs) at the commuting zone (CZ) level to jointly estimate business cycle effects on teacher supply and quality outcomes of adolescents. Using a fixed-effects strategy, I find that higher URs influence adolescents' future entry into the teaching profession and these individuals are more effective teachers in both aptitude and productivity.

Specifically, I create a longitudinal dataset for the entire state of Texas that follows 2.6 million adolescents from high school through college and into teaching employment. The data comprise a long panel structure and produce insights into decisions made along several junctures well before individuals begin their job search. This is a particularly valuable contribution given the time span between selecting a career path and entering the labor force (Freeman, 1975; Bettinger, 2010). In contrast to previous studies, I observe the entire pipeline of progression toward occupation - including college major, licensing, and employment. I also construct two versions of quality including a proxy for ability, standardized test scores, and a teacher-specific productivity measure, value-added.

To measure the strength of the local economy, I use URs at the CZ-level, with CZ defined by where an individual graduated high school. Combining these datasets, I employ a fixed-effects empirical strategy. This is akin to a natural experiment comparing individuals who incur better or worse local economic conditions in adolescence due to factors such as differential impacts of macroeconomic shocks, local factories closing, or fracking booms (Nagler et al., 2020; Weinstein, 2020; Acton, 2021). Further, I allow the local URs to be experienced at different ages from late adolescence through young adulthood to determine when economic conditions matter the most.

I find higher local URs increase pursuit of teaching, and this effect begins to fade as individuals age out of high school. This result is consistent across several definitions of interest in teaching including future receipt of a bachelor's degree in an education major, future completion of a Pedagogy and Professional Responsibilities (PPR) license exam (a requirement for classroom certification in Texas), and employment in Texas public schools (TPS). In my primary specification, the reduced-form results suggest that the probability of taking a PPR exam is a little less than 1 percent more likely when high schoolers experience a 1 percentage point increase in URs experienced in high school. During higher levels of local URs, the share of bilingual/English as a second language certifications increases. Thus, teacher candidates certify more frequently in a subject area where there are commonly shortages.

Those individuals who are more likely to sort into teaching due to poor labor market conditions are also of higher quality as measured by individual math standardized exams and math value-added estimates. A 1 percentage point increase in local URs increases the average score on 10th grade math standardized exams among potential teachers by about .01 standard deviations. Further, employed teachers who experienced a 1 percentage point higher UR during high school improve their students' standardized math scores by approximately .005 standard deviations more than the typical individual selecting into teaching. This means that the effects on teacher ability translate to realized gains for the next generation of students. Consistent with earlier results, I find that local labor market effects experienced during high school are the most influential on quality sorting.

Interpreting the core results as causal relies on the assumption that local URs, conditional on fixed-effects and controls, change in plausibly exogenous ways with respect to individuals' potential career choices. My results are robust to different definitions of local labor market conditions and alternatively defined outcome variables, among others.

There are several mechanisms through which local labor market fluctuations could assert influence over college major or career choice. Two potential candidates are changes in expected risk or employment probabilities. Recent research shows that business cycles have the ability to change long-run behavior and perceptions, likely through updated beliefs or risk preferences (Malmendier and Nagel, 2011). Further, risk aversion has been associated with sorting into safer careers, and risk aversion can change with emotional states (Saks and Shore, 2005; Meier, 2022). This, coupled with finding sorting into in-demand subject areas within teaching and increased selection into teaching during times of volatile employment conditions, suggests these two mechanisms are plausible. More discussion follows in Section 7.

The results demonstrate that individuals form preferences about careers and are influenced by new information well before they accept employment in a particular occupation, and this has implications for the ability distribution within occupations. While relatively modest, the results suggest scope for policy makers to attract more and better able individuals into the teaching profession by increasing the economic standing and by promoting the relative stability of teaching (Nagler et al., 2020; Kraft et al., 2020). Further, finding that preferences are malleable pre-college suggests career interventions may be more successful pre-college than post-high school.

My paper adds to the disparate literatures of college major choice and teacher labor markets. In particular, I make four contributions. First, I jointly estimate supply and quality changes as business cycles fluctuate. This simultaneous estimation informs both the private and public sectors, offering insights into the most efficient and effective timing for recruiting highly capable individuals and understanding job match quality. Beyond general interest in the joint estimation of supply and quality, estimating both simultaneously also helps tease out potential mechanisms.

Previous work on college major choice does not consider ability or productivity measures (Bradley, 2012; Liu et al., 2019; Ersoy, 2020; Weinstein, 2020; Foote and Grosz, 2020; Blom et al., 2021; Acton, 2021).[1] These studies generally find that sector-specific shocks influence

[1] Other works study changes to information over wages or real changes in wages and its effects on college

decisions to major in related fields, and that recessionary periods reduce interest in lower-wage or high-unemployment majors. My work complements this literature by showing that teaching, a stable occupation, attracts more individuals during recessions and by providing evidence on how this affects the distribution of abilities among majors.[2]

Conversely, previous work on teachers has examined quality effects of teachers hired during recessionary periods or when relative economic conditions worsen for the teaching profession (Figlio, 2002; Hoxby and Leigh, 2004; Bacolod, 2007; Leigh, 2012; Fraenkel, 2018; Nagler et al., 2020). Nagler et al. (2020) shows that value-added changes positively if there is a recession in the year a teacher starts, while Fraenkel (2018) shows that the average college selectivity of those hired when state-wide unemployment rates are higher also improves. While neither paper has direct evidence of the potential supply, both papers argue that quality changes are unlikely to be coming from demand side changes because the overall number of hired teachers remains fixed. In other words, school districts hire the same number but select slightly higher average candidates from this larger and higher quality supply.

Relative to the teaching literature, my study offers better measures of supply-side effects and uses multiple quality indicators, including both standardized test scores and value-added. I also focus on a different period—pre-entry into the labor market. Specifically, I demonstrate that recessionary periods are associated with an increase to potential supply via increases in pre-employment measures of teacher interest: majoring in education and taking a teacher license exam. But I also additionally show that employment levels for these individuals increase as well, suggesting that they are more likely to also be employed as a teacher. Rather than inferring that supply has changed, I directly measure it, complementing previous findings. This is especially important in my setting, where employment conditions could change by the time individuals are seeking employment.

Second and relatedly, I contribute to a long-running and large literature that researches the connection between teacher pay and teacher retention or student outcomes, such as

major choice (Beffy et al., 2012; Berger, 1988; Wiswall and Zafar, 2015a; Long et al., 2015; Xia, 2016).

[2]Blom et al. (2021) finds individuals sort away from education majors. However, in subsequent analysis for a subset of their cohorts that more closely mimics my sample or using fixed-effects at the state-level across their sample, I find consistency between our papers. Because I find consistency when using similar methods and cohorts across samples, I believe this suggests that the results are robust across our papers.

Loeb and Page (2000), Clotfelter et al. (2008), Clotfelter et al. (2011), Goldhaber et al. (2011), Hendricks (2014), Britton and Propper (2016), and Biasi (2021), among many others. Typically, these papers study how to *keep* effective teachers in the classrooms, or they cannot distinguish effort versus selection with wage increases. I ask how to *attract* effective teachers to the classroom.

Third, most papers have not considered a longer time horizon for effects of business cycles on future occupational choices. This is primarily due to a lack of data that connects adolescents to their future occupations.[3] The timing of when individuals make important career decisions is of great policy relevance. For example, to encourage more women to enter STEM fields, knowing whether to target them during their senior year of high school or sophomore year of college is important. I credibly demonstrate that individuals may have a forward thinking attitude toward career changes and may make adjustments prior to entering the workforce.

Finally, I focus on localized geographies which is not a feature of most prior work.[4] However, this is of particular importance given most individuals', and especially teachers', preferences to work close to home (Reininger, 2012). For example, in my sample 63 percent of high school graduates, who became teachers after college, teach in the same CZ from which they graduated and 30 percent teach in the same district.[5]

[3]As part of robustness, Blom et al. (2021) study flexible ages, but it is not a defining feature of their study, nor can they observe exactly when individuals graduate from high school or enter college.

[4]Few exceptions include work that focuses on other types of majors and economic conditions. For example, focusing on geology, business, and computer science degrees, Weinstein (2020) studies macro-industry shocks (i.e., the dot-com bust) and finds they differentially affect fields of study in colleges located in concentrated sectors (i.e., computer science majors in Silicon Valley). Foote and Grosz (2020) and Acton (2021) study enrollment in community colleges as a function of local mass layoffs.

[5]Reininger (2012) shows that non-teaching BA earners over a ten-year period move a median distance of 54 miles from their high school while teachers move a median of 13 miles. An alternative statistic from the same study finds that 42 percent live within 20 miles of where they attended high school, while 60 percent of teachers do Reininger (2012). Of those who graduated both from high school and college in Texas, from UI data, approximately 38 percent had their modal county-of-business in the same county from which they graduated high school, and 50 percent worked mostly in commuting zones identical to the one in which they graduated high school.

2 Setting and Conceptual Framework

2.1 Requirements for Becoming a Teacher in Texas

Becoming a classroom teacher in Texas requires 1) obtaining a bachelor's degree, 2) completing an educator preparation program, 3) passing a Pedagogy and Professional Responsibilities (PPR) exam and a content-specific exam (elementary grades, math, art, etc.), and 4) since 2008, completing a background check including fingerprinting (Agency, 2022c,d).[6]

Thus, the typical process a student takes to become a teacher begins with enrollment in an education preparation program affiliated with a university. During college, students concurrently make progress towards their bachelor's degree and the requirements of the education preparation program. Depending on their program, they may take their PPR or content-specific exams during college or immediately after graduating college.

However, Texas also offers enrollment in education preparation programs that are unaffiliated with universities. The requirements for certification are identical across education preparation programs, but these alternative educator preparation programs are typically targeted towards individuals who are making career changes and already have a bachelor's degree. Still, alternative certification pathways enroll undergraduates or recently graduated students. In my sample, described in Section 3, about 28 percent and 67 percent of students become certified through alternative educator preparation programs and university-affiliated preparation programs, respectively.[7]

2.2 Conceptual Framework

I focus on individuals in their late adolescence and young adulthood. Practically, the majority of individuals who ultimately obtain a bachelor's degree enter college immediately after graduating high school or in their early 20s.[8] As such, most students finalize college going and career decisions during this time.

[6]For the detailed list of information, see Appendix C.

[7]The remaining 5 percent is categorized as other.

[8]More than 62 percent of bachelor's degrees earned in Texas were earned by people 26 years old or younger at time of conferral.

Given the focus on adolescents, how might local economic conditions change their career trajectories? If individuals have perfect foresight and know the entire distribution of expected wages and employment opportunities, we would not expect experiencing a shock to matter (Berger, 1988; Beffy et al., 2012). However, individuals have incorrect beliefs over the expected wage profiles and risks associated with careers and they may access the most recent experiences associated with a major when making a decision (Wiswall and Zafar, 2015b; Patterson et al., 2019; Hastings et al., 2016; Baker et al., 2018; Conlon, 2021; Xia, 2016).

As such, labor market shocks have multiple channels through which they could influence a student's occupational choice. For instance, students may update their distribution of subjective probabilities over employment opportunities across occupations. This may be because they become aware of new information and revise previous expectations or because they differentially seek out new information. In any case, this revision may change their subjective expected lifetime earnings in a way that could tip the subjective expected utility of one major over another.

Furthermore, experiencing a negative shock may make individuals more cautious, especially when experienced at a younger age (Malmendier and Nagel, 2011; Meier, 2022). Thus, they may weigh expected job stability more heavily than if they had not experienced a negative shock. Job stability has the potential to affect both their expected earnings as well as stand on its own - individuals prefer income smoothing so any expected periods of zero income could be particularly unappealing.

With respect to changing economic conditions, teacher employment tends to be *relatively* more stable than the private sector (Kopelman and Rosen, 2016; Nagler et al., 2020). Figure 1 plots the year-over-year change in total private employment and year-over-year change in employment in the education industry. This figure illustrates that cyclical changes in total private employment are unmatched by the education sector.

Given this stability, individuals experiencing a negative shock may be more receptive to the teaching profession for any of the reasons above. To gauge the health of the local labor market, I use URs which are salient measures of labor market conditions. Since teachers have a strong preference for proximity to their childhood homes, I select commuting zones to represent the locality of the labor markets (Reininger, 2012). Furthermore, information may diffuse through family members or peers, and this channel may be especially relevant for adolescents (Xia, 2016). Commuting zones are county clusters defined to represent where people tend to live and work, and as such define narrow but naturally occurring local labor markets.

Using these definitions, I test the reduced-form net effects of experiencing differential local economic conditions on students' decision to ultimately become a teacher and the quality of these individuals using the data and methods described in more detail below. While my main specification reports overall effects, I explore potential mechanisms in Section 7.

3 Data

Using individual-level identifiers, I link Texas administrative datasets together to create one longitudinal dataset that follows individuals from high school into college and into the workforce. I begin with the set of high school graduates and define measures of interest in teaching along the progressive pipeline including college major, licensing, and employment outcomes. I additionally connect these individuals with several measures of quality. Finally, I match these individuals to the economic conditions they experienced throughout adolescence and young adulthood.

High school graduates: My sample construction begins with all high school graduates of a public or charter school in Texas from 1996-2010. I assign their high school graduation district to a CZ which remains fixed as their relevant local labor market. Additionally, I allow their high school graduation year to define their cohort. The high school graduation files include students' race/ethnicity and sex. Henceforth, cohort refers to the spring year of the academic year in which a student graduated high school (2001-02, denoted 2002). For some analyses, I also consider college enrollment and graduation. See Appendix B for more details.

Interest in teaching: My primary measure of interest in teaching is based on teacher license exams housed by the SBEC. I define "completed a license exam" if an individual has taken a Pedagogy and Professional Responsibilities (PPR) exam within eight years of graduating high school. For whether the individual ever became a teacher in Texas, I map occupational employment data for teachers from the TEA back to the high school graduates. I then create an indicator that determines if an individual ever became employed as a teacher in a Texas Public Schools (TPS) within eight years of their high school graduation year.[9]

My final measure of interest in teaching come from college graduation data. College majors in THECB datasets are defined by the nationally representative CIP codes maintained by the National Center for Education Statistics. I harmonize college majors to the 2020 CIP classification for consistency across years. Because there is no clearly defined "education" major in Texas, I construct my own based on the most common majors among teachers employed in Texas. Specifically, I define an education major as a CIP code for interdisciplinary studies - general, two-digit category for parks, recreation, leisure and fitness, and two-digit category for education.[10] See Appendix B for more details. Thus, I measure whether an individual graduated with an education major within six years of graduating high school.

Quality measures: I use three standardized exams and two value-added estimates to measure quality. Two of the standardized exams are math and reading exams taken by high school graduates in the 10th grade. These are standardized (mean zero and standard deviation one) based on the full set of 10th grade exams in a subject-academic year. For high schoolers who take the PPR, I additionally use their standardized score from the PPR exams. The PPR exams have been standardized at the academic-year for all PPR exam takers, not just among those in my subsample - additional details available in Appendix B. Finally, for those individuals who obtained employment in TPS and worked in certain grades and subjects, I additionally calculate value-added. I report the comparison of these quality measures in Section 5.2.

Calculating Value-Added:

[9] Many private school teachers take a PPR exam to be competitive, so I still capture many private school teachers in my analysis (Dennis, Earl, 2023). For those I don't observe, private school teachers represent less than 6 percent of all teachers in Texas, suggesting the bias would be negligible.

[10] Table A11 and A12 list the most common majors among employed teachers.

Using data on more than 3.5 million students in grades 3-8 in math and reading subjects, I link students and teachers via a classroom ID available for academic years 2012-2019. To obtain an estimate of value-added for math or reading for a given teacher, I estimate the following model for each subject *sub* (math or reading):

$$A^{sub}_{ijkgst} = \alpha_1 A^{sub}_{it-1} + \alpha_2 A^{-sub}_{it-1} + \gamma X_{it} + \lambda C_{kgst} + \nu_{gt} + \zeta S_{st} + \mu^{sub}_j + \epsilon_{ikgst} \tag{1}$$

where A^{sub}_{ijkgst} is student i's standardized math or reading score in year t, grade g, classroom k, and taught by teacher j in school s. Student i's A^{sub}_{it-1} and A^{-sub}_{it-1} represent lagged standardized math and reading scores and their squares and cubes, and X_{it} are student characteristics (economic disadvantage, ethnicity/race, sex, whether they are in special education, whether they are at risk, and whether they are gifted). Classroom characteristics, C_{kgst}, and school characteristics, S_{st}, include the mean individual characteristics, mean lagged standardized test scores in math and reading and their squares and cubes for all students in classroom k and school s, respectively. To control for grade-year specific factors affecting all students, I include ν_{gt}. Finally, the teacher fixed effects μ^{sub}_j give the value-added estimate for teacher j. The value-added (VA) estimate predicts the expected *sub* test score change if a student were assigned to teacher j in subject *sub* compared to an average teacher teaching the same subject. Table A3 reports descriptive statistics for this sample. My value-added equation estimation follows standard methods and is robust to alternative estimates (Koedel et al., 2015; Nagler et al., 2020). For more details on value-added construction see Appendix B.

Economic conditions: I merge the high-school-graduating-district to its associated county via the TEA's specification, and finally the county to its 1990 commuting zone (CZ). The CZ-cohort is matched with various employment measures, calculated during a calendar year in relationship the HS graduation cohort year (a HS graduate of the 2001-02 school year connected with employment conditions in calendar year 2002, and so on). Employment conditions include unemployment rate (UR) which I calculate from Texas Labor Market Information data of BLS LAUS for Texas counties. I also obtain CZ population and demographic population estimates from Census Population and Housing Units by defining working age population to be those ages 20 to 64. Further details are found in Appendix B.

3.1 Summary Statistics

There are 2.6 million individuals graduating high school between academic years 1996-2010 across 56 CZs. Of these, 1.9 million enroll in a Texas non-Independent college within six academic years of their high school graduation date, and of these college enrollees, about 519,000 graduate with a bachelor's degree within six years. I observe about 116,000 individuals taking a PPR within eight years of graduating high school - see Tables A1 and A2 for more descriptive details.

4 Empirical Specification and Identification

Do worse economic conditions increase the potential supply of teachers? To answer this question, I relate unemployment rates with multiple outcomes measuring interest in teaching by estimating the following linear probability model:

$$\text{Teach}_{izc} = \alpha + \beta \text{UR}_{zc} + \gamma_z + \eta_c + \theta X_{izc} + \epsilon_{izc} \tag{2}$$

where z indexes CZs, c represents high school graduating cohort, and i references individuals. Standard errors are clustered at the CZ-level. The outcomes, Teach_{izc}, are binary variables indicating whether a teacher has passed a teaching license exam, PPR, within eight years of graduating high school. For additional robustness, I consider two other important measures of interest in teaching: graduating college with an education major (within six years of graduating high school) and being employed as a teacher in a Texas public school (within eight years of graduating high school). These regressions use the full sample of high school graduates and do not account for changes in college enrollment or completion. This regression specification estimates the reduced-form net effects, capturing various potential mechanisms explored further in Section 7.

My primary independent variable of interest is UR_{zc}, which represents the unemployment rate in an individual's CZ of high school graduation. In separate specifications, I allow UR_{zc} to represent the unemployment rate faced at various points in time in relation to an individual's high school graduation year. For instance, UR_{zc} could reference the unemployment rate in relevant CZ in the year prior to an individuals' high school graduating year or one year after high school graduation. This effectively tests which years are the most instrumental in influencing selection into teaching. Practically, I report the unemployment rates over different years calculated from separate regressions.

The CZ fixed-effects, γ_z, control for differences across CZs in the average probability of becoming a teacher and for average differences in URs. For instance, college graduates from rural areas are more likely to take PPR exams than college graduates from urban areas. Cohort fixed-effects, η_c, control for overall conditions that are similar across cohorts - like the declining preference to become a teacher over time and macroeconomic conditions.

To isolate the effect of local URs on teacher supply, I add several additional demographic controls, though I also report estimates without them. The demographic controls include white population share in the CZ-cohort, Black population share in the CZ-cohort, Hispanic population share in the CZ-cohort, Asian population share in the CZ-cohort, total working population the CZ-cohort, and whether individual is white, Black, Hispanic, Asian, and/or male, denoted by X_{izc}. Demographic controls are important additions to consider because demographic changes to a CZ over time can mechanically influence the UR. The extent to which the demographic makeup also influences occupational choice either directly (compositional changes) or indirectly (through role models, etc), excluding demographics could bias estimates of $\hat{\beta}$.[11]

4.1 Identification

The estimated parameter $\hat{\beta}$ represents the average effect of unemployment rates on the future decision to become a teacher. This estimate is causal under the assumption that the CZ-year unemployment rates are plausibly exogenous with respect to individuals' future decision to become a teacher, after controlling for fixed-effects and controls. Whether the URs are plausibly exogenous depends in part on the dynamics of URs and omitted variables. Note, there is no chance for reverse causality - it cannot be that an individual's decision to become a teacher in a future period can affect past CZ employment levels.

[11] If URs change demographics, compositional changes represent a mediator. However, understanding effects of URs excluding any compositional changes requires demographic controls.

Then, threats to identification primarily stem from omitted factors that co-move with CZ-year URs in direction and magnitude but also influence the future decision to become a teacher. There are several factors that have been shown to affect career choice such as ability, role models, or family (Patnaik et al., 2020). However, it is unlikely any of these factors move in relationship with local changes in economic conditions unless they work as a mediator. For instance, it is possible URs influence an individual's expectations and their expectations influence career choice. Here, expectations act as a mechanism instead of a potential confounder.

One possible exception is changes to demographics in the broader regional area. As discussed above, I include both demographic CZ- and individual-level controls in the primary specification. I also estimate balance tests on the set of 10th graders and high school graduates - see the first two columns of Table 1. In general, I do not find demographics of the set of 10th graders or high school graduates to significantly change, though there is some evidence of changes in college graduates. I further explore compositional changes in demographics in Section 7.

I explore the variation in URs used to identify $\hat{\beta}$ in Figure 2, which shows the residuals of the moving average UR (averaged from sophomore year to high school graduation year) after accounting for fixed-effects and demographic controls for four representative CZs. Because CZs experience alternating periods of higher or lower unemployment relative to each other conditional on macroeconomic trends, this variation aids in identifying $\hat{\beta}$. For example, in the mid-1990s, the College Station area had relatively better economic conditions compared to other CZs. By the early 2000s, it was performing relatively worse. If the share of teachers per high school graduate increased in College Station relative to the other CZs during this period, this would suggest a positive relationship between local unemployment rates and the decision to pursue teaching. For a broader view of all CZs and time periods, Figure A1 shows the histogram of residuals of the moving average UR. The standard deviation of these residuals is about 0.01, while the overall standard deviation of unemployment rates across CZs and time periods is about 0.03.

Additionally, local unemployment rates may be subject to measurement error. In further analyses, I test the robustness of my estimates using alternative measures of local employment conditions, which may have varying levels or types of measurement error (see Table A5). The results are consistent with the main findings, reducing concerns that measurement error in the UR is driving the results.[12]

5 Effects of Local Unemployment Rates on the Supply and Quality of Teachers

5.1 Supply

The URs occurring prior to an individual graduating high school have a positive and statistically significant relationship with all indicators of future interest in teaching. Figure 3 graphs point estimates and 95 percent confidence intervals of URs that were experienced during different years of adolescence for each teacher outcome as in equation 2. For comparability across outcomes and samples, the point estimates and confidence intervals in Figure 3 are rescaled by their respective mean. Taking a teacher PPR license exam, at some point in the eight years following graduation, increases when a student experiences higher unemployment rates during high school. These effects seem to fade in the first few years following high school graduation. Both majoring in education and becoming employed as a teacher in Texas demonstrate similar patterns.

To obtain a single point estimate, I use a three-year moving average of URs across sophomore through high school graduation year. With a 1 percentage point (UR std. dev.: 3 percentage points) increase in moving average UR in a student's CZ during their formative years, the probability a high school graduate takes the PPR increases by slightly less than 1 percent over the mean - see Table 2. I additionally present estimates of heterogeneity by demographics (male, female, Black, etc.) and local area characteristics (urbanicity) in Table A13. While some of the point estimates are larger than others, in most cases they are not economically or statistically different in a way that leads me to place strong conclusions on

[12] I also examined the largest CZs which would be least likely to suffer from measurement error and found consistent results. Further, I examined only URs post-2000, after a change in methodology for calculating LAUS, and similarly found results consistent with my main specification.

differences by subgroup.

Why do the local labor market effects diminish as individuals leave high school? First, as individuals progress further into their bachelor's degree, the likelihood of major switching becomes practically more challenging (Patterson et al., 2019).[13] This is likely to be more binding for my sample and specification as I censored the outcome to be taking a PPR within eight years of graduating high school. Second, recall the CZs are assigned based on students' high school graduation location. Assuming that this is the location students would like to return to, this is the optimal definition of their relevant local labor market. However, as students move away from home to attend college, the labor market conditions in an area where they are not currently located may mean less or be less salient for them.[14]

I investigate whether the individuals who took the PPR exam were interested in high demand shortage subjects or non-shortage subjects. Since 1999, Texas has reported bilingual/English as a second language, special education, math, technology, and science subjects as areas in which districts across the state faced substantial difficulty in employing fully qualified teacher candidates (U.S. Department of Education, 2017).[15] I estimate equation 2, with the outcome variable being binary for content type, where zero represents both not taking any content exam (i.e. not interested in teaching) or not taking that specific content exam. I present the coefficients and confidence intervals of moving average URs in Figure 4. There is an increased probability of taking bilingual/English as a second language exams and a slightly increased probability of taking a special education exam. There seems to be little change in more popular subjects like elementary education. These findings could represent different preferences among those marginally pushed into teaching or a shift in preferences towards subjects that are more stable. Individuals - regardless of whether they were pushed

[13] Only about 30 percent of students change their major (Leu, 2017). I find similar estimates in my data as well.

[14] Blom et al. (2021) also find effects of macroeconomic conditions on changes in majors for high school aged individuals - see their figure 8. Further, Acton (2021) finds effects of local mass layoffs during year of high school graduation. Thus, the results here are consistent with other work.

[15] Those who were specifically trained in the subject are qualified. To determine what subject a potential teacher was interested in, I obtain and categorize content subject exams for those students who took them in addition to taking the PPR exam.

into the teaching profession - may want to hedge against unemployment by selecting a subject that they know is persistently high in demand. I cannot differentiate these or other explanations.

It may be concerning if the individuals who sort into teaching due to depressed labor markets create additional churn. To test whether these individuals are less likely to stay in teaching, I create a variable that defines whether an individual has worked for at least two years and for at least six years in the teaching profession. *Only* for individuals who worked in TPS, I estimate the likelihood these outcomes change with respect to local labor markets. As shown in Figure 5, there are mostly insignificant differences in probability of staying for at least six years with respect to differences in local labor markets prior to high school graduation. It is important to note that these regressions reduce the number of identifying cohorts, and statistically insignificant relationships should be interpreted as suggestive evidence of no effect. The probability of staying at least two years seems to increase when there are higher unemployment rates experienced closer to college graduation. Given the persistence in unemployment rates over time, it is possible that these individuals face a difficult labor market during college graduation and stay in teaching for longer.

I estimate a back-of-the-envelope estimate of the size of the supply effect. A 2 percentage point increase in local URs for every CZ implies approximately 133-315 more individuals interested in teaching. On average, there are about 22,000 newly hired teachers across the entire state in a given year. Thus, about 1 percent of newly hired teachers could enter the profession due to a recession.[16] This estimate is likely an under-count. Data restrictions such as completing a PPR within eight years of high school graduation remove individuals who may have been induced into teaching but took longer to complete, for instance.

[16] 2,624,145 high school graduates averaged over 15 years is approximately 174,943 graduates per year. A 2 percentage point increase in local URs is 2(.038 or .09)(174,943)= 133-315 more potential teachers. Then (133 or 315)/22,000= about 1 percent. I chose 2 percentage point increase based on the approximate change in URs in Texas for recessions occurring in the time frame studied in this paper. Newly hired is based on the first observed year in as a teacher in TPS. I calculate first observed year as a teacher by taking current year minus total experience years. I take the mode of this number across observations within a given individual and consider this their career start year.

5.2 Changes in Quality

Now that I have established a relationship between local labor market conditions and the likelihood of becoming a teacher, I turn to the question of whether these individuals are more effective instructors.

5.2.1 Measures of Quality

I employ several proxies for the quality of potential teachers, including their *own* standardized test scores for 10th grade math, 10th grade reading, and PPR exams. I have these measures for anyone who chooses teaching regardless of the subject they wish to teach or future employment in TPS. The 10th grade test scores have the obvious advantage of being comparable not only among teachers but also across other majors and career paths. To the extent that 10th grade test scores are reflective of underlying ability and higher ability is rewarded in all sectors, but especially non-teaching sectors, this proxy of quality is informative. In general among college graduates, those who select into teaching score lower on standardized exams on average - see Figure 6.

However, standardized test scores have the major drawback that they do not necessarily represent a person's innate teaching ability, skills learned on the job, or effort. In addition to the standardized test scores, I also calculate value-added for the subset of potential teachers who gain employment in TPS and work in grades 4-8 instructing math or reading subjects. Value-added is a well-validated measure of teacher effectiveness of raising students' test scores - one dimension of quality teaching (Kane and Staiger, 2008; Chetty et al., 2014a,b; Koedel et al., 2015). Furthermore, Chetty et al. (2014b) has shown that test score value-added is predictive of long-run outcomes including educational attainment. However, it's important to note that test score value-added does not capture other ways in which teachers influence students, such as through soft skills (Jackson, 2018). Another limitation of using value-added in my context is that it is restricted to only a subset of employed teachers and as such cannot directly speak to the full set of potential teachers. Nevertheless, it is an informative measure of productivity that has been shown to predict important outcomes.[17]

[17] Figures A2 show the raw scatters between math 10th grade test scores and math value-added and similarly for reading for comparability.

5.2.2 Effects of Local Unemployment Rates on the Quality of Teachers

If an increase in potential teacher supply is among higher quality individuals, then a draw at random will provide school districts with, on average, higher quality candidates. Thus, the ideal experiment compares the average quality of potential teachers as the pool of potential teachers changes with local labor markets. I adapt equation 2 so that the outcomes are quality measures and the sample is among PPR exam takers only. Specifically, I replace outcome $Teach_{izc}$ in equation 2 with $OwnTestScore_{izc}$ and $ValueAdded_{izc}$. I keep the controls the same except for the case of value-added as an outcome. For these regressions, I additionally include fixed-effects for total experience years in teaching because value-added typically increases with experience (Wiswall, 2013).

Figure 10 maps point estimates and 95 percent confidence intervals of URs experienced during different times relative to high school graduation for all the ability measures *among* those who have taken the PPR exam. Similar to the supply results, when significant effects exist, they are concentrated during high school. These estimates find that 10th grade math and math value-added are higher among PPR takers who experienced higher local URs when they were in high school. However, 10th grade reading scores, PPR exam scores and reading value added are mostly not significantly related to local labor market conditions.[18]

As an additional test, I divide high school graduates by quartile of score on their standardized 10th grade math and reading exams, and I estimate equation 2 separately by quartile. I present the point estimates and 95 percent confidence intervals in Figure 7. Disproportionately more people in the upper quartiles of math ability take the PPR when they experience higher levels of URs during high school. For individuals scoring in the bottom two percentiles of math scores, there are not significantly more individuals taking a PPR exam. Together this points to evidence that the average math ability is increasing. Meanwhile, the increased

[18]To test robustness to my value-added, I estimate math value-added based on Chetty et al. (2014a). This method estimates value-added for each teacher-year. I average the yearly estimates to obtain an overall estimate for the career of each teacher. The effect of moving average URs on student math exam scores is nearly identical to the one estimated under equation 1. This is expected given that the value-added estimates are highly correlated across estimation strategies. The results for math value-added estimated in this manner are presented in Table A6.

likelihood of selecting into teaching across reading quartiles is similar, suggesting that the average reading ability of PPR takers does not change.

Table 2 presents the core results across the quality measures with three year moving average URs as described before. A 1 percentage point increase in local moving average UR increases the average score on 10th grade math standardized exams among potential teachers by about .01 standard deviations. In value-added outcomes, I compare teachers' value-added scores across CZ-cohorts who experienced differential local labor markets. I find that a 1 percentage point increase in URs increases the teachers' math value-added score by .005 on average. This means that recessionary teachers improve their students' math standardized scores by .005 standard deviations more than teachers typically sorting into the profession. Due to small sample sizes, I do not assume the heterogeneity across demographic characteristics provides informative underlying trends. However, for completeness they can be found in Table A13.

6 Robustness

In addition to the balance tests, my results are robust to different definitions of local labor market conditions, alternative sample selections and alternative functional forms. In general, I find the teacher quality results to be more sensitive than supply results to alternatives to my primary specifications but are generally robust. This may be due to smaller sample sizes.

6.1 Alternative methods

Finding a positive association between UR and completing the PPR exam is not limited to a linear probability model - see Table A4. Qualitatively, I find large increases in the log odds using logistic regression.[19] Similarly, OLS of equation 2 with outcome being (log) share of PPR completions per college graduates for a given CZ-cohort similarly give statistically significant positive relationships (1 percent increase in share PPR corresponding to a 1 per-

[19] I prefer OLS estimation to the non-linear models because I employ a fixed-effects strategy. Due to the incidental parameter problem, non-linear models with fixed-effects could produce a large bias (Kennedy, 2008).

centage point increase in moving average UR). How do these relate to the total number of PPR completions over time? Without the inclusion of demographic controls, log PPR count points to evidence of an increased total number of teachers in CZ-cohorts that experience elevated levels of UR on the order of a significant 3.6 percent increase. Controlling for CZ-cohort demographics renders the estimates on log PPR insignificant at conventional levels.

Cross-sectional only variation: I also use only cross-sectional variation and find similar results. Specifically, for each cohort separately, I estimate the effect of URs in that year across CZs. The results, presented in Figure A3, show a positive effect of URs in every year. Notably, there are higher rates of entry into the teaching profession in areas that have higher unemployment rates either for that year or persistently.

6.2 Sample selection and variable choices

Alternative employment measures: Using data from the QCEW on employment, I calculate four alternative measures of local labor markets. The first two are based on the total employment (aggregated by county up to the CZ), including the actual employment per total working population five years prior and the total employment 5 year growth rate. In case URs or actual employment are endogenous, I also create a Bartik/shift-share instrument based on the industry structure in the CZ. The details of the construction of these variables are found in Appendix B.

In all cases, the effects on supply and quality are qualitatively consistent with estimates using URs (point estimates on *employment* are negative). For instance, a 1 percentage point decrease in the 5 year growth rate during an individual's high school graduation year, calculated via my Bartik instrument, implies an increase in the probability of taking the PPR exam by 0.13 percentage points and an increase of 0.08 standard deviations in 10th grade math scores among PPR takers. Math value-added is insignificant for this measure of employment - see Table A5 for details. Further, Figure A4 demonstrates the same pattern as the primary results. Specifically, employment effects exist until around high school graduation year and then fade out or weaken thereafter.

Some previous work has shown mass layoffs matter for college enrollment decisions and for enlisting in the military (Acton, 2021; Foote and Grosz, 2020; Murphy et al., 2020). I also use mass layoffs as an alternative to URs. The downside to using mass layoffs is that it only takes advantage of negative economic shocks. Contrastingly, the QCEW and UR data take advantage of both booms and busts. In any case, I relate mass layoffs divided by total working population with probability of taking a PPR exam. I find insignificant effects using mass layoffs on taking PPR. It is possible there is not enough variation or enough mass layoff events for identification. The quality results are still in the right direction, however, those condition on taking a PPR, so they are representative of a smaller and more targeted subgroup of individuals.

Sample choices, misc.: I additionally check the sensitivity of my primary results to changes in construction of my sample. I find no meaningful difference when I exclude 2003 (2003 had particularly large missing values for 10th grade test scores due to the change in testing regimes from TAAS to TAKS). I find no change when I include the CZs I originally dropped due to small sample sizes for employment characteristics (about 15,000 individuals total). Further, I find no qualitative or economically meaningful differences in the main results using 2000 defined CZs instead of 1990 defined CZs. Additionally, I expand the period around high school graduation year to exceed 3 years prior and post - see Tables A14 and A15. The evidence paints a similar picture accross all these modeling changes.

6.3 Attrition

Once people leave the state of Texas, I am unable to observe them. How might this bias the results? First, any high school graduate who leaves the state because of economic conditions in my primary specification will be counted as not becoming a teacher. Thus, if people are more likely to leave the state during poor economic conditions, this will increase the number of non-teachers based on my variable construction. This should downward bias my results.

To provide an upper bound for my estimates, I flag whether I can see a high school graduate in any data set in Texas post-graduation. Specifically, this is whether an individual completed college or is employed in Texas within six years of high school graduation. This makes up 97 percent of my high school graduation sample. The other 3 percent I will assume leave the state (although they could still live in the state and opt out of employment or additional schooling). Then I create an upper bound by re-coding this 3 percent as PPR completers (instead of non-PPR completers in primary specification). I then re-run equation 2 for probability of taking the PPR conditional with results presented in Table A7. For a 1 percentage point increase in URs, my upper bound suggests a 1.5 percent increase. This is close to my primary specification which finds a little less than 1 percent increase for similar changes to local economic conditions.

Finally, movement across CZs within Texas will not generally bias my results because I observe outcome variables across the entire state. Instead, this type of movement bias results if families differentially moved across CZs during economic fluctuations *and* their high-school-aged children were more or less likely to become teachers. As an additional robustness, I constrain my sample to those individuals who have been at their high school for exactly four years to remove the possibility that their family moved because of economic conditions. The results presented in Figure A5 demonstrate that the conclusions are similar to the main results.

Overall, all of these tests suggest that the effect of attrition out of the sample entirely or across CZs seems unlikely to significantly bias my primary results.

7 Discussion

7.1 Mechanisms

While my setting does not allow for definitive tests of mechanisms, supporting evidence implies that some mechanisms are more plausible than others. A supply mechanism that alters students' risk preferences or updates their subjective expectations regarding job security is consistent with some of the evidence provided in this section. There is less support that the supply results are driven by compositional changes in college enrollment.[20][21] In general, there are no definitive conclusions on the ability mechanisms. In what follows, I present implications of each mechanism for supply and quality changes and provide what evidence is available for its validity.

Risk preferences and expected employment:

Changes to subjective expected probability of finding employment and to risk preferences are two potential mechanisms that are observably similar in this context while being distinct. Recessionary periods might change individuals' perception about availability of jobs (possibly accurately or inaccurately) or make riskier career paths less attractive through changes to risk preferences. However, it is unclear how this affects ability changes. Some work in the teaching literature suggests that teaching fits a simplified Roy model, where ability is rewarded less in teaching than in non-teaching careers, leading to an increase in average ability in teaching during recessions (Nagler et al., 2020).[22]

[20] I additionally correlated teacher wages and non-teacher wages and URs as well as added them to my main regression. In general, the URs and wages were not statistically significantly related, suggesting that they potentially capture different employment outcomes or that wages, given their stickiness, may not have enough variation in this setting to be meaningful. Given this, it is difficult to glean how informative the wages are in prediction and as such I do not present formal results. However, the regression results were in expected directions (i.e., an increase in non-teaching wages decreases the likelihood of taking a PPR) whether they held significance or not.

[21] Other possible mechanisms include changes in perceptions of role models or perceived discrimination (Carrell et al., 2010; Mansour et al., 2018; Porter and Serra, 2020). It has been shown these affect college major choice, and it is plausible that business cycles present better or worse opportunities across gender and/or racial lines (i.e. dot-com bubble hurt tech businesses, but the Great Recession affected construction and real estate more.) However, these mechanisms are ultimately untestable here. Other attributes that affect college major choice, like exposure to courses or differential tuition costs, are unlikely to co-move with local URs and, as such, are unlikely to be plausible mechanisms. However, it's possible that individuals sort toward cheaper majors to reduce costs.

[22] Here, it is assumed that ability is uni-dimensional and is valued by employers in both teaching and non-teaching careers. Further, it is assumed individuals only care about wages (and are risk neutral), and wages are determined by an average for the occupation plus an ability-adjusted bonus. It is also assumed that returns for ability matter less in teaching than non-teaching. Because teaching does not reward much

Previous research is consistent with both mechanisms. Past work has demonstrated that risk aversion correlates with selecting safer careers, including teaching, emotions play a large role in risk preferences, and that individuals are affected in a variety of long-term ways when experiencing recessionary periods (Saks and Shore, 2005; Dohmen and Falk, 2010; Meier, 2022; Malmendier and Nagel, 2011). To the extent that a booming labor market can induce positive outlooks or that weak labor markets can induce fear, even if only temporarily, this line of research supports the findings in this paper. Further, students may become more aware of information on employment prospects or seek out information differentially (Xia, 2016; Blom et al., 2021). As additional supporting evidence of both channels, my results imply an increased share of in-demand subject certifications during higher URs suggesting that individuals sort towards higher need areas *within* teaching as well.

If the risk channel is at play, individuals may be also influenced by the overall volatility of the labor market rather than the specific direction of the business cycle. To descriptively test this, I measure volatility using the standard deviation of URs adolescents faced over their four year high school period. I find that as the standard deviation increases, so does interest in teaching - see Table 3.

College composition:

Changes in the composition of my sample are crucial for determining whether the supply and quality changes result from occupational selection or shifts in who attends college due to economic conditions. I test whether demographic changes (e.g., race, gender, economic disadvantage) or the total number of college enrollees and graduates are affected by URs (see Table 1). Notably, the overall share of college graduates declines, especially among economically disadvantaged students. In general, a decline in on-time college graduates should work against my findings, making it more difficult to detect an *increase* in PPR exam takers. Further, disadvantaged students are more likely to become teachers, suggesting that this decline would bias the results downward too. Overall, it seems like the results appear

for ability (or, in other words, has a compressed wage schedule relative to non-teaching), there is sorting along ability lines where higher ability individuals sort into non-teaching wages and lesser ability sort into teaching. See working paper version of Nagler et al. (2020) and Bacolod (2007) for more details.

in spite of changes to college composition.

How might these compositional changes affect quality? Since economically disadvantaged students tend to have lower test scores on average, negative selection out of graduating college could imply increases in ability among both teachers and non-teachers. Based on evidence in Table A8, which reports the changes in shares to college majors *among* on-time college graduates, there are across-the-board increases in math ability across all majors. However, this explanation alone does not match the findings perfectly either. If the majority of students who decide not to graduate on-time were among the lowest ability, there would be larger declines in total students in majors with the highest share of low ability students. In fact, I find the opposite: education majors gain while STEM majors lose.

Finally, another possibility related to the extensive margin is whether economic conditions push individuals into differentially selective colleges. Different colleges may influence the availability or encouragement of specific college majors and may impact an individual's choice based on peer effects. I consider this possibility with three distinctions: first enrolling in a community college, first enrolling in the highly selective public universities in Texas (University of Texas at Austin or Texas A&M University), or first enrolling in another four year college or university.

There is a statistically significant drop in enrollment in four year colleges associated with the moving average URs experienced toward the end of high school - see Table A9. I do not detect statistically significant changes in enrollment in flagship universities or community colleges.

Next, I observe how URs affect selecting into teaching conditional on where an individual first enrolled in college. Specifically, I condition each equation by whether a person first started in each of the three categories outlined above. Ex ante, like the demographics, it is expected that regardless of where an individual first enrolls, they would be more likely to become teachers if they had experienced recessionary periods. Thus, the relative size of the effect on URs illustrates any interaction effects between first attending college at a particularly selective institution and having experienced recessionary periods prior to enrollment.

The strongest effect is in four year universities, followed by community colleges. This would suggest that students may be slightly more likely to take a PPR if they had first enrolled in a four-year college (thus, downward biasing if there is sorting away from four-years), or that this smaller subgroup of four-year students is more likely to be interested in teaching (i.e., negative selection out of four-year). However, the point estimates across institutional types is similar enough that it's unlikely to have driven results significantly.

7.2 Policy Implications

In terms of external validity, I am focusing on a specific time period and age group which may alter policy implications. However, within this scope, the mechanisms described above are consistent with the notion that teaching is a relatively stable profession. In fact, Dohmen and Falk (2010) find that teachers tend to be more risk averse and prefer fixed payment schemes over variable pay, and stability is one of the most emphasized benefits of current teachers in numerous surveys and colloquially (Lang and Palacios, 2018; Warner-Griffin et al., 2018; Markow and Pieters, 2012; Johnston, 2020). In this case, policy makers may reduce future teacher supply if certain aspects of stability are removed without a compensating differential provided in its place. Examples include stricter tenure laws, covid-19, school shootings, and accountability - all these shape the perception of teaching as a relatively safe career. In fact, recent work by Kraft et al. (2020) shows that the introduction of accountability laws decreases supply which is consistent with the results here.[23]

The concentration of effects before students leave for college suggests that high school-targeted programs could be effective. This is not an entirely new concept for the teaching profession, and recently there have been expansions in local "grow-your-own" programs. These programs aim to retain high school graduates or paraprofessionals as teachers by offering dual credit or financial support for tuition and license exams (Garcia, 2020; Reininger, 2012). Texas has recently introduced competitive grants for these programs to address teacher shortages and promote diversity (AIR, 2018). While these programs show promise, there is limited quantitative evidence on their effectiveness.

[23]They also find one measure of quality - selectivity of colleges teachers graduate from - to increase (Kraft et al., 2020).

8 Conclusion

Using administrative data from Texas and two-way fixed-effects methods, I find that local labor market conditions are countercyclical with selection into the teaching profession. Among college graduates, a 1 percentage point increase in local URs during the time of college entry increases the probability of taking a teacher license exam by a little less than 1 percent. Further, the same increase in URs improves the average ability of those taking the teacher license exam as measured through standardized exams and value-added. Overall, my estimates imply that adolescence is a crucial period of career preference formation.

I find that these results are consistent with the notion that individuals view teaching as a stable profession. Local labor market shocks may change individuals' expectations over employment probabilities or may additionally update their risk preferences. These results suggest a modest ability for policy makers to influence recruitment to teaching via increased economic standing. The results are also consistent with the notion that policy makers should be cautious about implementing changes that may make teaching appear as a less stable profession. Overall, previous work and this paper together paint a clearer picture of the challenges the teaching profession faces in losing quality candidates to non-teaching professions.

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9 Tables

Table 1: Probability of Racial, Ethnic, Sex, and Economic Disadvantage and Local Unemployment Rates Across the Set of 10th Graders, High School Graduates, College Enrollees, and College Graduates

	All 10th Graders	All High School Graduates	Enrolled in College	College Graduates
Outcomes - dependent variable				
Black	-0.108**	-0.107	-0.076	-0.089
	(0.052)	(0.064)	(0.088)	(0.079)
Hispanic	0.210*	0.137	0.146*	-0.070
	(0.116)	(0.084)	(0.080)	(0.192)
White	-0.138	-0.069	-0.100	0.172
	(0.112)	(0.105)	(0.124)	(0.236)
Econ. Dis.	-0.341	-0.427	-0.555**	-0.888***
	(0.364)	(0.319)	(0.258)	(0.191)
Male	0.028	-0.041	-0.054	-0.048
	(0.031)	(0.034)	(0.048)	(0.088)
Tot Obs	3,642,749	2,624,145	1,915,488	519,016
Log total count				
MA UR	0.492	0.260	-0.567	-2.100**
	(0.524)	(0.520)	(0.575)	(0.988)
Tot Obs	840	840	840	840
Outcome Mean	9.37	8.98	8.66	7.33

Notes: *Outcomes* - refers to the binary outcome of whether an individual is Black, Hispanic, white, economically disadvantaged, and/or male. These outcomes replace teacher outcomes in equation 2. Columns distinguish the samples the equations are estimated over. For high school and college, they are defined as in the main text. For 10th grade sample, this refers to the total number of 10th graders (who took the 10th grade math and reading exam) and assigned a cohort based on year-in-10th-grade + 2, or their approximate high school graduation date assuming they would graduate. The associated labor market condition is a moving average UR that correspond to their assigned cohort and CZ. *Logs* - this specification logs the collapsed total number of individuals in each of the czone-cohort cells. The regressions are weighted by the total number of high school graduates in 1996. Total observations refers to the total number of cz-cohorts. All standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All include the following controls: white population share in CZ-year, Black population share in CZ-year, Hispanic population share in CZ-year, Asian population share in CZ-year, total working population CZ-year. Data sources: TEA, THECB, BLS, Census. Further details about data construction can be found in Appendix B.

Table 2: Probability of Taking a PPR Exam, Quality of PPR Test Completers, and Local Unemployment Rates

	Supply		Quality									
	PPR Completion Exam (0/1)		10th Grade STD Math Exam		10th Grade STD RE Exam		PPR STD Score		Value-Added Math		Value-Added Reading	
MA UR	0.090***	0.038	0.442**	0.987**	-0.643***	-0.200	0.074	0.214	0.293***	0.521***	0.082	0.203
	(0.028)	(0.048)	(0.169)	(0.419)	(0.096)	(0.273)	(0.390)	(0.565)	(0.101)	(0.174)	(0.072)	(0.140)
Controls	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
Tot Obs	2,624,145	2,624,145	115,520	115,520	115,520	115,520	115,520	115,520	16,841	16,841	16,506	16,506
Outcome Mean	0.04	0.04	0.58	0.58	0.56	0.56	0.01	0.01	-0.00	-0.00	0.00	0.00

Notes: These are OLS regressions of equation 2. MA UR refers to the three year moving average UR as defined in text. Columns represent the outcome. The quality are conditional on having taken the PPR. Controls include white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Value-added estimates additionally control for number of experience years in teaching. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, Census.

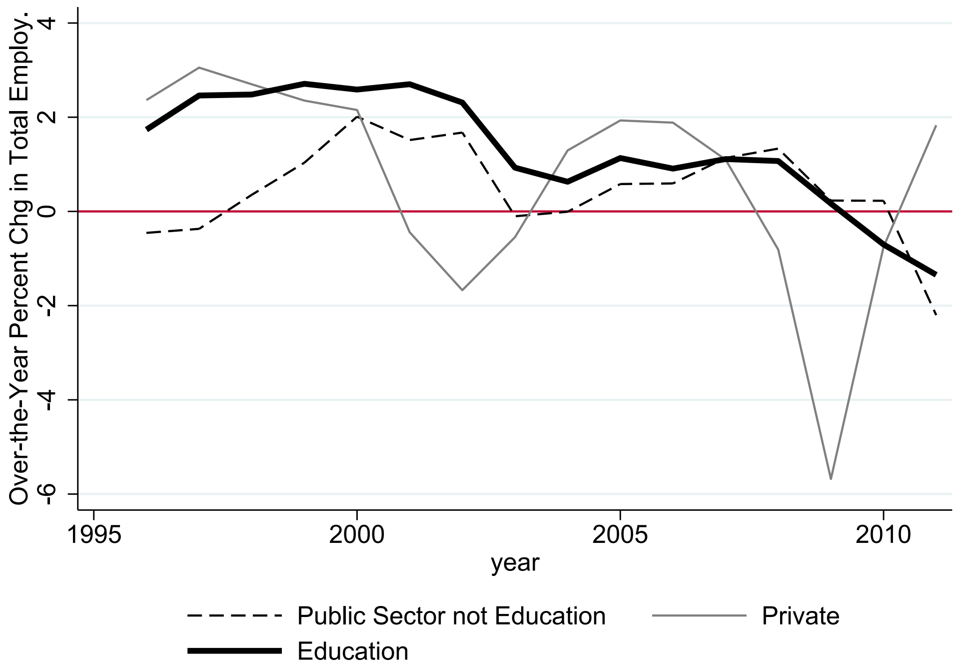
Table 3: Propensity to Select into Teaching, Quality of Teachers, and Volatility of Unemployment Rates

	PPR	Educ Grad	Employ	STD-M	VA-M	VA-R
St. Dev. UR	0.162***	0.012	0.162***	1.009*	0.039	-0.293
	(0.046)	(0.032)	(0.053)	(0.599)	(0.274)	(0.255)
Control	yes	yes	yes	yes	yes	yes
Tot Obs	2,624,145	2,624,145	2,624,145	115,520	16,841	16,506

Note: The outcomes are probability that an individual completes a PPR exam, graduates with an education major, or has employment in TPS; standardized math exams, math value-added and reading value-added, respectively. Controls include: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ level. Value-added regressions also include experience years. Data: TEA, THECB, SBEC, BLS, Census.

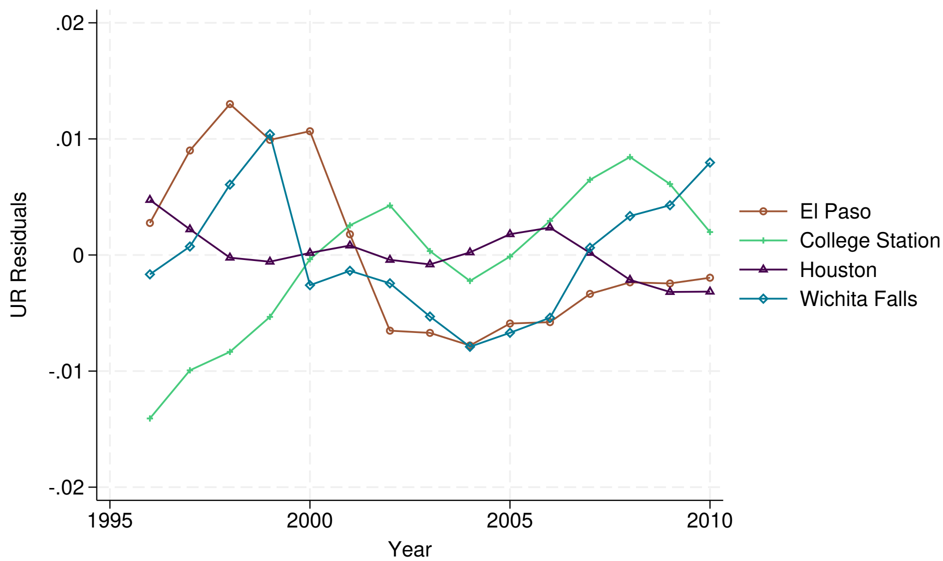
10 Figures

Figure 1: Over-the-Year Percent Change in Total Private Employment and Total Education Industry Employment in Texas



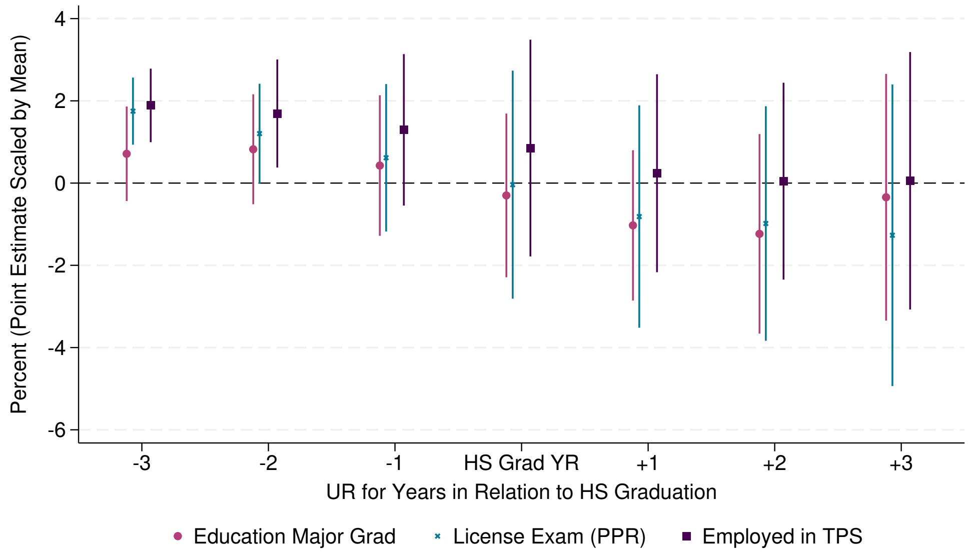
Note: Annual average of total Texas private employment plotted as a one-year percentage change. Education sector is industry NAICS 61 total employment across private, state government or local government, plotted as a one year percentage change. Data from the QCEW for calendar years 1996-2010.

Figure 2: Unemployment Rate Residuals for Four Commuting Zones



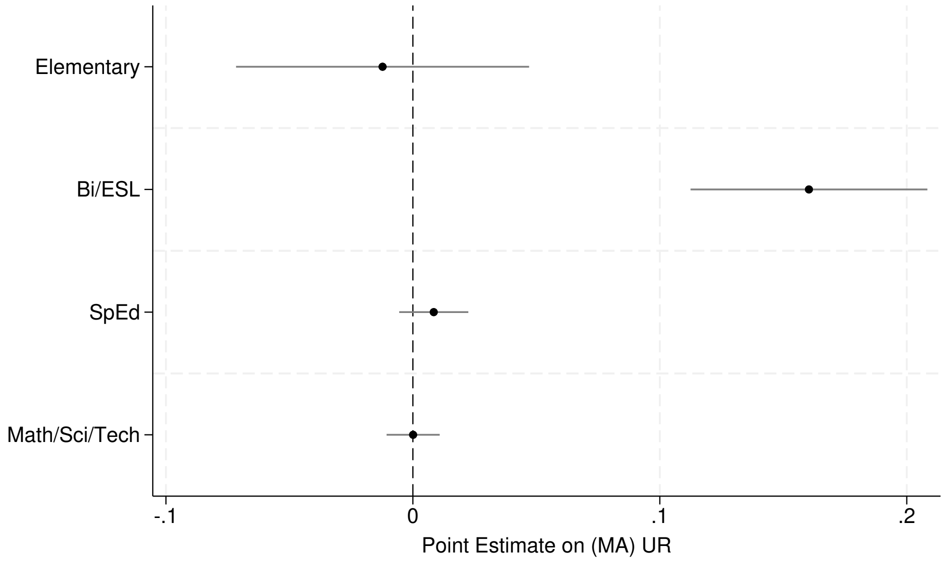
Note: Specific CZs are chosen based on 1996 population in CZs and to be representative of different population sizes and a variety of locations. CZs listed by a metro- or micro-politan city within the CZ. Working age population in 1996: Houston 2.5 million; El Paso 363,072; College Station - 116,851; and Wichita Falls - 86,407. Residuals from unemployment rates regressed on commuting zone and year fixed effects for the full sample of commuting zones and years. Data: BLS.

Figure 3: Effect of a One Percentage Point Increase in Local Unemployment Rates on Likelihood of Becoming a Teacher



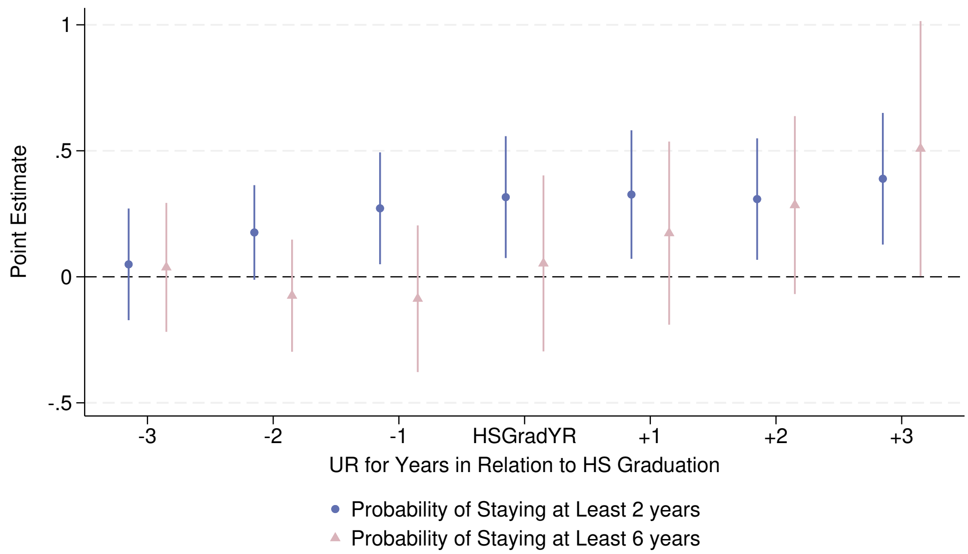
Note: Each point and bar are the point estimate on UR and confidence interval, respectively, *re-scaled* by the mean of the outcome so as to be comparable across outcomes. Each point estimate is a unique regression using equation 2 whereby the UR is assigned in a year relative to an individual's high school graduation year. All regressions control for the variables in the text, and Table A14 reports regression output. Data: TEA, THECB, SBEC, Census.

Figure 4: Probability of Completing Different Subject Content Exams and Local Unemployment Rates



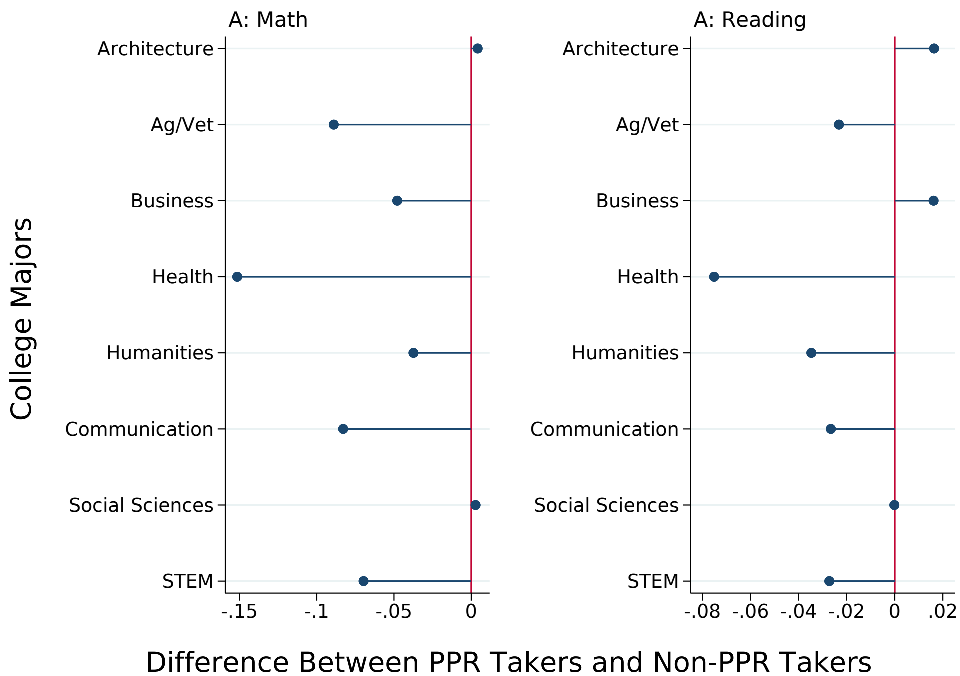
Note: Plotted are point estimates and confidence intervals for moving average URs for the corresponding content exam in the SBEC. Outcomes include whether the content exam was for elementary, bilingual/ESL, math/science/technology, or special education subjects. Outcomes are formatted (0/1), where 0 indicates that either the high school graduate did not take a content exam or took a content exam but in a different subject. See Table A19 and footnote for the regression output in more detail. Data sources: TEA, SBEC, THECB, BLS, Census.

Figure 5: Probability Employed Teachers Have at Least Two or Six Years of Experience in Education and Local Unemployment Rates



Note: These are point estimates and confidence intervals for unemployment rates in different calendar years with respect to high school graduation year from equation 2 where outcomes have been replaced. Outcomes are binary - 1 if an individual reported having at least two or six years of experience and zero otherwise. Run on only individuals who were employed in Texas public schools within eight years of graduating high school. All regressions control for the variables in the text. The probability of staying at least six years uses cohorts from 1996-2004 (2018-(8yrs to observe employment + 6)=2004). The probability of staying at least two years uses cohorts from 1996-2008 (2018-(8yrs to observe employment + 2)=2008). Data sources: TEA, SBEC, THECB, BLS, Census.

Figure 6: Difference in Math and Reading Standardized Exams Between PPR Takers and Non-PPR Takers by College Major



Note: The droplines represent the mean difference in 10th grade standardized math and reading scores between PPR takers and non-PPR takers for the college graduate sample described in text. They are split by the college graduation major. For instance, for those individuals who obtained a business degree, the individuals that ended up taking a teacher license exam were about -.05 standard deviations lower scoring on their tenth grade math exam and about .02 standard deviations higher scoring on their 10th grade reading exam. See Tables A11 and A12 for information on the major-to-teaching mapping in Texas. Total observations: 519,016. Data sources: TEA, SBEC, THECB.

Figure 7: Local Unemployment Rates and Completing the PPR by Quartile of Math and Reading Ability

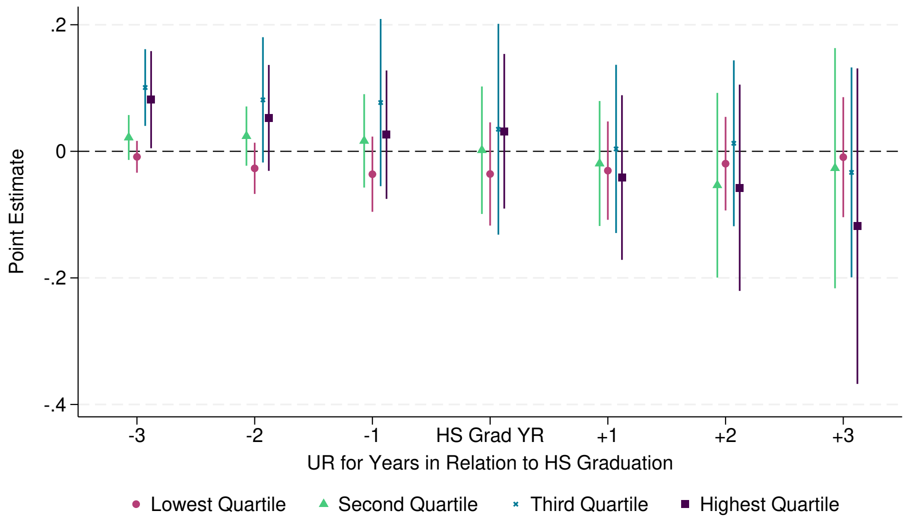


Figure 8: Math

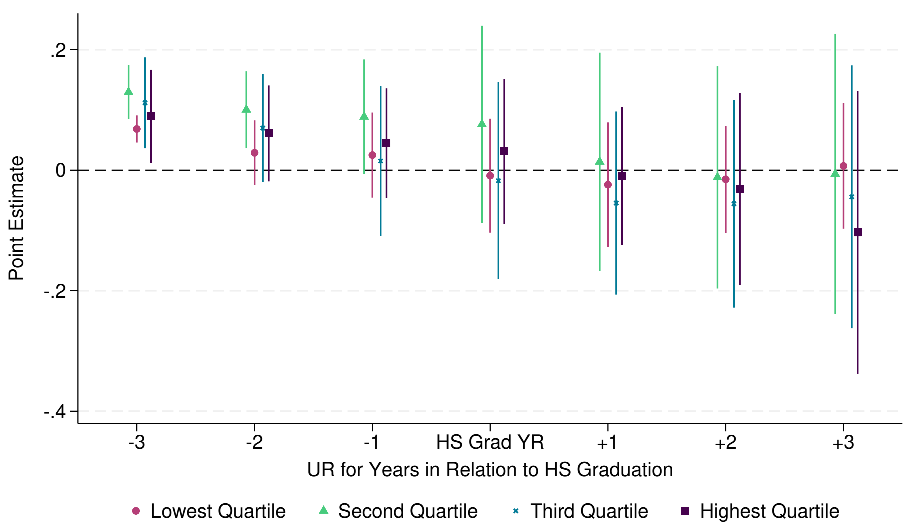
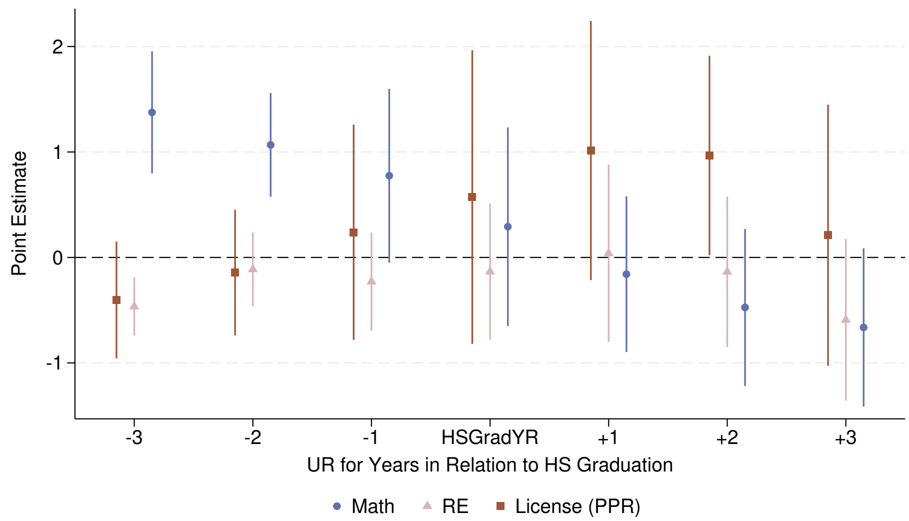
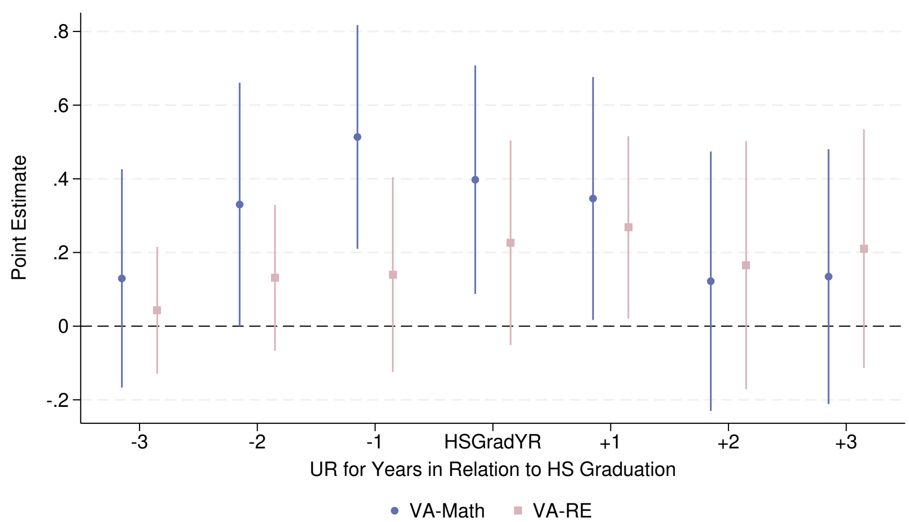


Figure 9: Reading

Note: Each point and bar are the point estimate on UR and confidence interval, respectively. Each point estimate is a unique regression using equation 2 whereby the UR is assigned in a year relative to an individual's high school graduation year. The lowest quartile corresponds to being in the 24th or lower percentile ranking of math/reading score among high school graduates. Second quartile is 25-49th percentile. Third quartile is 50-74th percentile. Highest quartile is 75+ percentile ranking. All regressions control for the variables in the text, and Table A15 reports regression output. Data: TEA, THECB, SBEC, Census.

Figure 10: Local Unemployment Rates and Quality Measures for Individuals who Completed the PPR Exam





Note: The outcomes are 10th grade standardized math and reading exams, standardized PPR exam scores and math and reading value-added as described in text. Each point and bar is the point estimate and confidence interval of separate regressions of modified equation 2. These are conditional on having taken the PPR exam or have a value-added score. Divide by 100 to get the effect of a 1 percentage point increase in local URs (URs in decimals). All regressions control for the variables in the text, and Table A15 reports regression output. Data: TEA, THECB, SBEC, Census.

Appendices - Online Publication Only

A Tables and Figures

Table A1: Descriptive Statistics

Samples:	HS Grads mean/sd	Ever Enroll mean/sd	College Graduates mean/sd	PPR Takers mean/sd
Completed PPR	0.04	0.06	0.16	1.00
	(0.21)	(0.23)	(0.37)	(0.00)
Male	0.48	0.46	0.41	0.19
	(0.50)	(0.50)	(0.49)	(0.40)
Economic Disadvantage	0.31	0.27	0.15	0.19
	(0.46)	(0.44)	(0.36)	(0.40)
White	0.52	0.54	0.65	0.65
	(0.50)	(0.50)	(0.48)	(0.48)
Black	0.12	0.12	0.08	0.07
	(0.33)	(0.32)	(0.27)	(0.26)
Hispanic	0.32	0.30	0.20	0.25
	(0.47)	(0.46)	(0.40)	(0.43)
Asian	0.03	0.04	0.07	0.02
	(0.18)	(0.19)	(0.25)	(0.13)
10th Grade Reading	0.17	0.29	0.61	0.56
STD Test Score	(0.84)	(0.74)	(0.49)	(0.51)
10th Grade Math	0.17	0.29	0.73	0.58
STD Test Score	(0.91)	(0.85)	(0.64)	(0.66)
Reading Value-Added				0.00
				(0.16)
Math Value-Added				0.00
				(0.23)
Experience Years in				6.49
Teaching (if VA Score)				(4.27)
Total Obs	2,624,145	1,915,488	519,016	115,520

Notes: Means and standard deviations split by sample. "HS Grads" refers to the baseline high school graduating set of students as described in the text. "Ever Enroll" is whether an individual ever enrolled in any Texas public college or university within 6 years of graduating high school. "College Graduates" refers to the set of individuals I define as on-time college graduates in Section 3. "PPR Takers" is a subset of the college graduates who additionally take the PPR exam. For high school graduating cohorts from 1996-2010. Data sources: TEA, THECB, SBEC.

Table A2: Descriptive Statistics of Local Labor Market Conditions and Population

	mean/sd
MA UR	0.06
	(0.03)
White Population Share	0.57
	(0.20)
Black Population Share	0.07
	(0.06)
Hispanic Population Share	0.33
	(0.23)
Asian Population Share	0.01
	(0.01)
Total Working-age population	232,922
	(522,248)
Total CZ-years	840

Notes: Labor Market Averages show the employment and population data for the CZs, unweighted across the 56CZ*15cohorts = 840 cells. MA UR refers is defined in the text. Working age population counts individuals ages 20-64. White population share is the share total working age population who are working age and white - similarly for the rest. Data: BLS and Census.

Table A3: Value-Added Summary Statistics

	mean/sd	count
VA Math	-0.01	79,614
	0.24	
VA Reading	0.00	85,949
	0.17	
Standardized VA	0.00	79,614
Math	1.00	
Standardized VA	0.00	85,949
Reading	1.00	

Note: Value-added estimates and their descriptives from estimating equation 1 for years 2013-2019. Data: TEA. For more description on the sample construction see Appendix B.

Table A4: Probability of Taking the PPR Exam and Local Unemployment Rates Under Alternative Functional Forms

	OLS-PPR (0/1)		Logit-PPR (0/1)		LnSharePPR		SharePPR		LnPPR	
MA UR	0.090***	0.038	1.262**	0.075	1.428**	0.575	0.089***	0.054	3.602**	0.835
	(0.028)	(0.048)	(0.607)	(1.008)	(0.590)	(0.916)	(0.028)	(0.048)	(1.468)	(1.005)
Controls?	no	yes	no	yes	no	yes	no	yes	no	yes
Tot Obs/Cells	2,624,145	2,624,145	2,624,145	2,624,145	784	784	784	784	784	784
Mean	0.04	0.04	0.04	0.04	-3.13	-3.13	0.04	0.04	5.85	5.85

Notes: Regressions first to last: OLS on whether an individual completed the pedagogy and professional responsibilities (PPR) exam (0/1), logit on whether an individual completed the PPR exam (0/1), OLS on the log share of number of PPR takers per high school graduates, OLS with the share of number of PPR takers per high school graduates, OLS on the natural log of count of PPR takers. OLS PPR and logit PPR are estimated at the individual level data with(out) CZ and individual controls (white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male). The other regressions are collapsed to CZ-cohort level and weighted by number of high school grads in the CZ in cohort 1996 and exclude cohort 1996 (56CZ*14cohorts = 784). These are estimated with(out) CZ controls (white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, and total working population CZ-cohort). I ran probit as well, but not reported due to the similarities between it and the logit model. MA UR refers to the three-year moving average UR as described in text. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data sources: TEA, THECB, SBEC, BLS, Census.

Table A5: Probability of Completing the PPR Exam and Quality of PPR Test Takers by Alternative Local Employment Statistics

	Takes PPR Exam (0/1)		10 Grade Math Score		PPR Test Score		Value-added Math		Value-added Reading	
Bartik Emp/Pop	-0.040**	-0.034**	-0.283*	-0.198	0.221	0.408	0.005	0.057	-0.008	0.039
	(0.017)	(0.017)	(0.164)	(0.208)	(0.246)	(0.268)	(0.060)	(0.080)	(0.049)	(0.063)
Total Emp/Pop	-0.034***	-0.036***	-0.421***	-0.410***	-0.133	0.070	-0.081	-0.103*	-0.056	-0.050
	(0.008)	(0.009)	(0.105)	(0.152)	(0.094)	(0.140)	(0.078)	(0.057)	(0.049)	(0.053)
Bartik 5-year GR	-0.143***	-0.128***	-1.012***	-0.822*	0.061	0.625	-0.210	-0.022	-0.149	-0.123
	(0.042)	(0.035)	(0.352)	(0.480)	(0.495)	(0.502)	(0.199)	(0.258)	(0.142)	(0.178)
Total 5-year GR	-0.007	-0.004	-0.244***	-0.189**	-0.224*	-0.104	-0.106**	-0.086*	-0.054	-0.057
	(0.011)	(0.012)	(0.059)	(0.084)	(0.113)	(0.130)	(0.044)	(0.046)	(0.042)	(0.041)
Mass Layoffs	0.134	-0.241	2.357	2.318	1.248	1.096	3.339***	3.221**	1.304	1.491
	(0.153)	(0.190)	(2.890)	(3.515)	(2.301)	(2.684)	(1.249)	(1.389)	(0.851)	(0.896)
Controls	no	yes	no	yes	no	yes	no	yes	no	yes
Tot Obs	2,624,145	2,624,145	115,520	115,520	115,520	115,520	16,841	16,841	16,506	16,506
Outcome Mean	0.04	0.04	0.58	0.58	0.01	0.01	-0.00	-0.00	0.00	0.00

Notes: These are OLS regressions of equation 2 run with alternative employment predictors. The quality measures are conditional on having taken the PPR. Total employment and total employment growth are the actual values reported by QCEW while Bartiks are proxies. Specifically, the "Bartik" refers to a Bartik or shift-share instrument described in equations 3 and 4 in Appendix B. Employment levels are divided by total working population with a 5 year lag. The growth rate regressions control for white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Value-added estimates additionally control for number of experience years in teaching. The total employment per population and mass layoffs regressions control for White population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, whether individual is White, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, QCEW, Census.

Table A6: Local Unemployment Rates and Alternatively Estimated Math Value-Added

	VA-M	
MA UR	0.171***	0.476***
	(0.060)	(0.146)
Controls	no	yes
Tot Obs	11,265	11,265
Outcome Mean	0.01	0.01

Notes: Regression output of main quality equations estimated on alternatively calculated value-added for math. These value-added estimates are based on Chetty et al. (2014a) using Stata program `vam`. The value-added for each teacher-year are averaged to create an overall estimate for a given teacher. Controls include white population share in CZ-year, Black population share in CZ-year, Hispanic population share in CZ-year, Asian population share in CZ-year, total working population CZ-year, whether individual is white, Black, Hispanic, Asian and/or male and total experience years in teaching. Standard errors are clustered at the CZ level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data sources: TEA, THECB, SBEC, BLS, Census. Further details about data construction can be found in Appendix B.

Table A7: Probability of Taking a PPR and Moving Average Unemployment Rates with Alternative Definitions for Potential Leavers from Texas Administrative Data

	Primary Specification		Upper Bound	
MA UR	0.090***	0.038	0.137***	0.092**
	(0.028)	(0.048)	(0.039)	(0.043)
Controls	no	yes	no	yes
Tot Obs	2,624,145	2,624,145	2,624,145	2,624,145
Outcome Mean	0.04	0.04	0.06	0.06

Note: Primary specification represents the results specified in main text. Upper bound treats anyone who is not observed working in or graduating from college in Texas within 6 years of graduating high school as a PPR completer. Controls: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, BLS, Census.

Table A8: CZ Labor Market Conditions and Probability of Majoring in Various Field Categories

	Educ	Soc	Comm	Human	Health	Bus	Math	STEM	Econ	Other
Panel A - Major										
MA UR	0.195*	0.135	0.020	0.162*	0.019	-0.165	0.024	-0.308**	-0.015	-0.085
	(0.099)	(0.111)	(0.068)	(0.089)	(0.103)	(0.150)	(0.019)	(0.133)	(0.031)	(0.059)
Tot Obs	519,016	519,016	519,016	519,016	519,016	519,016	519,016	519,016	519,016	519,016
Outcome Mean	0.13	0.12	0.10	0.12	0.06	0.21	0.01	0.17	0.01	0.03
Panel B - STD Math										
MA UR	1.338**	0.595	1.369*	0.272	1.787***	1.130*	2.209***	1.534***	0.796	1.185*
	(0.584)	(0.774)	(0.734)	(0.514)	(0.595)	(0.598)	(0.650)	(0.405)	(0.893)	(0.654)
Tot Obs	69,322	63,337	49,665	62,795	30,203	109,557	5,671	90,047	7,075	16,330
Outcome Mean	0.53	0.70	0.61	0.68	0.66	0.79	1.16	1.07	0.97	0.31
Panel C - STD Reading										
MA UR	0.014	0.293	0.971***	-0.191	1.737***	0.321	2.706***	0.857**	-0.200	-0.310
	(0.354)	(0.240)	(0.348)	(0.520)	(0.362)	(0.479)	(0.891)	(0.353)	(0.854)	(0.676)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Tot Obs	69,322	63,337	49,665	62,795	30,203	109,557	5,671	90,047	7,075	16,330
Outcome Mean	0.50	0.66	0.63	0.67	0.60	0.59	0.70	0.72	0.69	0.35

Notes: OLS estimates of equation 2, where outcome is probability (0/1) of graduating with a bachelor's in the major category in the columns among those who graduated college within six years of completing high school. The output for quality include standardized tests for math and reading as the outcome conditional on having majored in the category in the column. For descriptions of the major categories and their corresponding CIP codes see Table A10. Controls include white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, Census.

Table A9: Probability of First Enrolling in a Community College, Flagship University, or Four Year University and Moving Average Unemployment Rates

	Community College		Flagship		Four Year	
Panel A - Enroll						
MA UR	-0.033	-0.166	-0.078***	-0.016	-0.426***	-0.336**
	(0.124)	(0.157)	(0.020)	(0.018)	(0.102)	(0.132)
Tot Obs	2,624,145	2,624,145	2,624,145	2,624,145	2,624,145	2,624,145
Outcome Mean	0.44	0.44	0.03	0.03	0.24	0.24
Panel B - Takes PPR						
MA UR	0.084	0.156***	0.173	0.109	0.150	0.292***
	(0.066)	(0.047)	(0.167)	(0.112)	(0.092)	(0.041)
Tot Obs	1,164,596	1,164,596	82,524	82,524	636,418	636,418
Outcome Mean	0.04	0.04	0.10	0.10	0.09	0.09

Note: The outcomes in Panel A are probability that an individual enrolls first in a community college, a flagship (UT Austin or Texas A&M) or a four year public college or university (not flagship). Outcomes in Panel B are whether a person takes a PPR exam conditional on having first attended a school in each category in the columns. Controls include: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ level. Data: TEA, THECB, SBEC, BLS, Census.

Table A10: Broad Major Categories and 2-digit CIP Codes

Major Category	CIP Code	Description
Agriculture	1	Agriculture/Animal/Plant/Veterinary Science and related fields
	3	Natural resources and conservation
Architecture	4	Architecture and related services
Business	52	Business, management, marketing, and related support services
Communication	9	Communication, journalism and related programs
	10	Communications technologies/technicians and support services
	19	Family and consumer sciences/ human sciences
	35	Interpersonal and social skills
	44	Public administration and social services professions
Education	13	Education
	31	Parks, recreation, leisure, fitness, and kinesiology
Health	51	Health professions and related programs
Humanities	16	Foreign languages, literatures, and linguistics
	23	English language literature/letters
	24	Liberal arts and sciences, general studies and humanities
	38	Philosophy and religious studies
	39	Theology and religious vocations
	50	Visual and performing arts
	54	History
Social Studies	5	Area, Ethnic, Cultural, Gender and Group Studies
	42	Psychology
	45	Social Sciences
STEM		
Computer Sci	11	Computer and information science and support services
Engineering	14	Engineering
	15	Engineering/engineering-related technologies/technicians
Math	27	Mathematics and statistics
Science	41	Science technologies/technicians
	26	Biological and biomedical sciences
	40	Physical sciences
Other	12	Culinary, entertainment, and personal services
	22	Legal professions and studies
	25	Library science
	28	Military science, leadership and operational art
	29	Military technologies and applied sciences
	32	Basic skills and developmental/remedial education
	34	Health-related knowledge and skills
	36	Leisure and recreational activities
	37	Personal awareness and self-improvement
	43	Homeland security, law enforcement, firefighting and related protective services
	46	Construction trades
	47	Mechanic and repair technologies/technicians
	48	Precision production
	49	Transportation and materials moving
*Multiple**	30	Interdisciplinary

Notes: This table represents the aggregation of 2-digit CIP codes, based on 2020 specification, to broader major degree categories. *- Majors in Interdisciplinary are separated into several other broad categories based on their 6-digit CIP code. A list of these is available upon request.

Table A11: Major Categories for (Matched) Employed Teachers

	Count of Teachers Matched	Percent of Major for Teachers	Share of All Majors
Interdisciplinary	139,349	37	10
Parks/Leisure/Fitness	27,953	7	4
English	21,768	6	3
Business	21,371	6	20
Arts	19,890	5	4
Psychology	14,763	4	5
History	13,925	4	2
Health	12,856	3	8
Social Sci	12,718	3	8
Biology	11,987	3	6
Education	11,961	3	1
Communication	9,775	3	5
Foreign Lang	9,513	3	1
Liberal Arts	8,894	2	2
Math/Stat	8,796	2	1
Family Studies	8,415	2	2
Ag/Vet	6,643	2	2
Other	5,585	1	6
Physical Sci	2,389	1	1
Public Admin	2,354	1	1
Engineering	1,806	<1	6
Nat Resources	935	<1	1
Computer Sci	871	<1	2
Engineering Tech	810	<1	1
Architecture	720	<1	1
Philosophy	581	<1	<1
Ethnic Studies	477	<1	<1
Religious Stud	329	<1	<1
Communication Tech	70	<1	<1
Total	377,504	100	100

Notes: Of employed teachers who are matched to college graduation file, this gives the proportion that they fall into each of the 2-digit major CIP categories. For instance, 3 percent of matched employed teachers majored in biology fields while nearly 37 percent majored in interdisciplinary studies. I have categorized "education" as either explicitly denoted education (technically not allowed for bachelor's degrees), interdisciplinary studies, general, and the 2-digit category parks, recreation, leisure and fitness studies. The final column provides comparison of how popular each major is among the entire share of bachelor degree earners in Texas files graduating from years 1996-2019. Sources include: THECB and TEA.

Table A12: Proportion of Completed Bachelor's Degrees that Become Employed as Teachers by Major Category

Major Category	Count	Percent
Education	8,470	66
Interdisciplinary	98,226	66
Math/Stat	5,962	41
Parks/Leisure/Fitness	20,623	40
Foreign Lang	7,250	38
History	10,054	33
English	15,783	31
Family Studies	6,421	27
Arts	14,119	26
Liberal Arts	6,656	25
Psychology	10,994	15
Ag/Vet	4,767	14
Biology	8,866	11
Ethnic Studies	373	11
Social Sci	9,665	11
Physical Sci	1,632	10
Communication	7,636	10
Public Admin	1,781	10
Religious Stud	283	10
Other	4,147	9
Health	9,040	9
Communication Tech	51	8
Philosophy	442	8
Nat Resources	707	8
Business	16,521	5
Architecture	583	4
Engineering Tech	574	3
Computer Sci	642	2
Engineering	1,328	1

Notes: Data are from matching bachelor degrees (graduation years 1996-2013) to the teacher employment file (1996-2019), and calculates the proportion of each major category that is matched to teacher employment file. For instance, 66 percent of the education majors in the bachelor files ultimately show up as employed teachers during the same time period. The proportions are calculated over all years aggregated together. Count refers to the raw count of matched-major-category-to-employed teacher for reference. Sources include: THECB and TEA.

Table A13: Probably of Taking PPR and Corresponding Quality and Local Unemployment Rates by Demographic Characteristics

	PPR	10th-M	10th-RE	VA-M	VA-R
Male	0.278*	-0.110	-1.172**	0.556	0.337
	(0.151)	(0.622)	(0.514)	(0.538)	(0.474)
Tot Obs	211,229	15,115	15,115	1,551	888
Outcome Mean	0.07	0.72	0.54	-0.04	-0.02
Female	0.838***	1.623***	0.279	0.528*	0.279
	(0.125)	(0.448)	(0.330)	(0.297)	(0.217)
Tot Obs	307,787	67,062	67,062	10,678	11,108
Outcome Mean	0.22	0.57	0.58	0.01	0.00
Black	0.498	0.528	-1.051	0.824	1.484
	(0.374)	(2.145)	(1.640)	(1.411)	(1.075)
Tot Obs	41,397	5,821	5,821	961	1,002
Outcome Mean	0.14	0.29	0.41	0.00	0.00
Hispanic	0.543**	1.280	0.010	0.195	0.257
	(0.268)	(0.776)	(0.603)	(0.498)	(0.362)
Tot Obs	103,100	20,443	20,443	3,519	3,456
Outcome Mean	0.20	0.50	0.45	0.05	0.01
White	0.216**	0.416	0.031	0.819**	0.359
	(0.107)	(0.551)	(0.275)	(0.367)	(0.254)
Tot Obs	337,617	54,194	54,194	7,507	7,365
Outcome Mean	0.16	0.66	0.63	-0.02	-0.00
EconDis	0.511	0.747	-0.455	1.522**	0.007
	(0.374)	(0.701)	(0.618)	(0.714)	(0.407)
Tot Obs	77,636	15,004	15,004	2,664	2,534
Outcome Mean	0.19	0.50	0.41	0.04	0.01
NEconDis	0.432***	1.002*	-0.011	0.347	0.451**
	(0.094)	(0.522)	(0.263)	(0.235)	(0.206)
Tot Obs	440,123	66,993	66,993	9,540	9,438
Outcome Mean	0.15	0.62	0.61	-0.01	-0.00
Rural	0.694	-0.343	1.967	-1.685	-3.623***
	(0.587)	(2.272)	(2.884)	(2.207)	(1.045)
Tot Obs	11,994	2,536	2,536	387	349
Outcome Mean	0.21	0.66	0.61	-0.05	-0.01
Urban	0.625***	1.210***	0.085	0.623**	0.372*
	(0.117)	(0.417)	(0.349)	(0.251)	(0.188)
Tot Obs	507,022	79,641	79,641	11,842	11,647
Outcome Mean	0.16	0.60	0.57	0.00	0.00

Note: The outcomes of each OLS regression from equation 2 are represented in the columns and point estimates are from the three-year moving average UR. The panel variables (male, female, etc.) refer to the sample the regressions are run on. For instance, column one row one presents the point estimate of equation 2 on probability of taking a PPR conditional on being male. The quality measures are additionally conditional on having taken the PPR. All regressions include as controls: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort. Value-added estimates additionally control for number of experience years in teaching. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, BLS, Census.

Table A14: Probability of Ever Graduating with Education Major, Completing the PPR Exam, and Ever Working in TPS and Local URs

	Graduated with Education Major	Completed PPR	Employed in TPS
5-year prior UR	0.004	0.110***	0.104***
	(0.012)	(0.019)	(0.018)
4-year prior UR	-0.001	0.104***	0.105***
	(0.012)	(0.017)	(0.017)
3-year prior UR	-0.000	0.077***	0.086***
	(0.012)	(0.018)	(0.020)
2-year prior UR	-0.001	0.053*	0.077**
	(0.014)	(0.027)	(0.030)
1-year prior UR	-0.010	0.027	0.059
	(0.017)	(0.039)	(0.042)
UR HS grad year	-0.023	-0.002	0.039
	(0.020)	(0.061)	(0.060)
1-year post UR	-0.033*	-0.036	0.011
	(0.018)	(0.059)	(0.055)
2-year post UR	-0.034	-0.043	0.002
	(0.024)	(0.063)	(0.054)
3-year post UR	-0.012	-0.056	0.003
	(0.029)	(0.081)	(0.071)
4-year post UR	-0.030	-0.092	-0.009
	(0.042)	(0.126)	(0.109)
5-year post UR	-0.040	-0.027	0.030
	(0.030)	(0.106)	(0.091)
Tot Obs	2,624,145	2,624,145	2,624,145
Outcome Mean	0.03	0.04	0.05

Note: Table formatting of point estimates displayed in Figure 3 from equation 2. Each column and row is output from a unique regression. Columns represent outcomes while rows represent primary independent variable. Independent variables are NOT included in the same regression. Independent variables are the UR in an individuals' CZ the year before or after their high school graduation year. For instance, prior 1 and post 1 are the years before and after the student graduates high school, respectively. All regressions include as controls: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, BLS, Census.

Table A15: Quality Measures and Local Unemployment Rates Over Time Conditional on Completing PPR Exam

	10th Grade Math	10th Grade Read	PPR Score	VA-M	VA-RE
5-year prior UR	1.647***	0.171	-0.384	-0.077	0.049
	(0.270)	(0.150)	(0.334)	(0.142)	(0.087)
4-year prior UR	1.499***	-0.175	-0.371	0.091	0.086
	(0.312)	(0.146)	(0.229)	(0.113)	(0.085)
3-year prior UR	1.375***	-0.465***	-0.403	0.130	0.043
	(0.289)	(0.137)	(0.276)	(0.148)	(0.086)
2-year prior UR	1.067***	-0.113	-0.143	0.330*	0.131
	(0.245)	(0.175)	(0.297)	(0.165)	(0.099)
1-year prior UR	0.775*	-0.229	0.239	0.514***	0.140
	(0.411)	(0.232)	(0.509)	(0.152)	(0.132)
UR-HS grad year	0.292	-0.135	0.573	0.398**	0.226
	(0.470)	(0.322)	(0.695)	(0.155)	(0.139)
1-year post UR	-0.158	0.040	1.014	0.347**	0.268**
	(0.368)	(0.419)	(0.613)	(0.165)	(0.123)
2-year post UR	-0.474	-0.136	0.966**	0.122	0.166
	(0.372)	(0.357)	(0.472)	(0.176)	(0.168)
3-year post UR	-0.663*	-0.592	0.211	0.134	0.211
	(0.374)	(0.383)	(0.618)	(0.173)	(0.162)
4-year post UR	-1.752**	-0.925*	-0.510	0.266	0.521**
	(0.690)	(0.506)	(1.302)	(0.325)	(0.214)
5-year post UR	-2.316**	-0.511	-0.556	-0.357	0.597**
	(1.046)	(0.476)	(1.269)	(0.325)	(0.239)
Tot Obs	115,520	115,520	115,520	16,841	16,506
Outcome Mean	0.58	0.56	0.01	-0.00	0.00

Note: Table formatting of point estimates displayed in Figure 10 from equation 2. Each column and row is output from a unique regression. Columns represent outcomes while rows represent primary independent variable. Independent variables are NOT included in the same regression. Independent variables are the UR in an individuals' CZ the year before or after their high school graduation year. For instance, prior 1 and post 1 are the years before and after the student graduates high school, respectively. Outcomes from left to right: 10th grade standardized math scores, 10th grade standardized reading scores, standardized PPR scores, value-added for math, value-added for reading. All regressions are conditional on having taken the PPR. All regressions include as controls: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Value-added estimates additionally control for experience year fixed effects. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, BLS, Census.

Table A16: Ever Graduating with Education Major, Completing the PPR Exam, and Ever Working in TPS and Local Employment-Population Ratios

	Graduated with Education Major	Completed PPR	Employed in TPS
5-year prior Emp	-0.089	-0.054**	-0.041*
	(0.069)	(0.026)	(0.022)
4-year prior Emp	-0.071	-0.055**	-0.042**
	(0.080)	(0.023)	(0.019)
3-year prior Emp	-0.071	-0.057***	-0.047***
	(0.086)	(0.019)	(0.017)
2-year prior Emp	-0.080	-0.064***	-0.057***
	(0.082)	(0.018)	(0.016)
1-year prior Emp	-0.065	-0.069***	-0.066***
	(0.056)	(0.015)	(0.015)
Emp in HS grad year	-0.099*	-0.069***	-0.068***
	(0.053)	(0.015)	(0.015)
1-year post Emp	-0.087*	-0.056***	-0.052***
	(0.047)	(0.015)	(0.014)
2-year post Emp	-0.065	-0.050***	-0.045***
	(0.050)	(0.014)	(0.014)
3-year post Emp	-0.038	-0.047***	-0.043***
	(0.052)	(0.013)	(0.014)
Tot Obs	519,016	2,624,145	2,624,145
Outcome Mean	0.13	0.04	0.05

Note: Table formatting of point estimates displayed in Figure A4 from equation 2. Each column and row is output from a unique regression. Columns represent outcomes while rows represent primary independent variable. Independent variables are NOT included in the same regression. Independent variables are the total employment per population in an individuals' CZ the year before or after their high school graduation year. For instance, prior 1 and post 1 are the years before and after the student graduates high school, respectively. All regressions include as controls: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, BLS, Census.

Table A17: Completing the PPR by Percentile of Math Ability Exam Score

	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
5-year prior UR	-0.000	0.010	0.151***	0.163***
	(0.011)	(0.017)	(0.026)	(0.036)
4-year prior UR	-0.004	0.031*	0.150***	0.117***
	(0.011)	(0.016)	(0.023)	(0.037)
3-year prior UR	-0.009	0.022	0.101***	0.082**
	(0.013)	(0.018)	(0.030)	(0.038)
2-year prior UR	-0.027	0.024	0.081	0.053
	(0.020)	(0.023)	(0.049)	(0.042)
1-year prior UR	-0.036	0.017	0.077	0.026
	(0.030)	(0.037)	(0.066)	(0.051)
UR HS grad year	-0.036	0.002	0.035	0.032
	(0.041)	(0.050)	(0.083)	(0.061)
1-year post UR	-0.030	-0.019	0.004	-0.041
	(0.039)	(0.049)	(0.066)	(0.065)
2-year post UR	-0.019	-0.054	0.013	-0.058
	(0.037)	(0.073)	(0.065)	(0.081)
3-year post UR	-0.009	-0.027	-0.033	-0.118
	(0.047)	(0.095)	(0.083)	(0.124)
4-year post UR	0.012	0.033	-0.092	-0.235
	(0.045)	(0.108)	(0.181)	(0.149)
5-year post UR	0.068**	0.067	-0.010	-0.025
	(0.029)	(0.088)	(0.159)	(0.140)
Tot Obs	635,788	653,876	682,815	651,666

Note: Outcome is taking a PPR and estimated on equation 2. Split by quartile of math score in 10th grade among all high school graduates. Controls include: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ level. Data: TEA, THECB, SBEC, BLS, Census.

Table A18: Completing the PPR by Percentile of Reading Ability Exam Score

	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
5-year prior UR	0.036***	0.142***	0.177***	0.160***
	(0.011)	(0.025)	(0.031)	(0.049)
4-year prior UR	0.061***	0.142***	0.167***	0.142***
	(0.009)	(0.021)	(0.033)	(0.038)
3-year prior UR	0.068***	0.130***	0.112***	0.089**
	(0.011)	(0.022)	(0.038)	(0.039)
2-year prior UR	0.029	0.100***	0.070	0.061
	(0.027)	(0.032)	(0.045)	(0.040)
1-year prior UR	0.025	0.089*	0.015	0.045
	(0.035)	(0.048)	(0.062)	(0.045)
UR HS grad year	-0.009	0.076	-0.017	0.031
	(0.047)	(0.082)	(0.082)	(0.060)
1-year post UR	-0.024	0.014	-0.055	-0.010
	(0.052)	(0.090)	(0.076)	(0.057)
2-year post UR	-0.015	-0.012	-0.056	-0.031
	(0.044)	(0.092)	(0.086)	(0.079)
3-year post UR	0.007	-0.006	-0.044	-0.103
	(0.052)	(0.116)	(0.109)	(0.117)
4-year post UR	0.020	-0.029	-0.076	-0.262
	(0.084)	(0.147)	(0.189)	(0.189)
5-year post UR	0.002	0.020	-0.043	-0.041
	(0.058)	(0.137)	(0.179)	(0.191)
Tot Obs	661,498	648,142	625,664	688,841

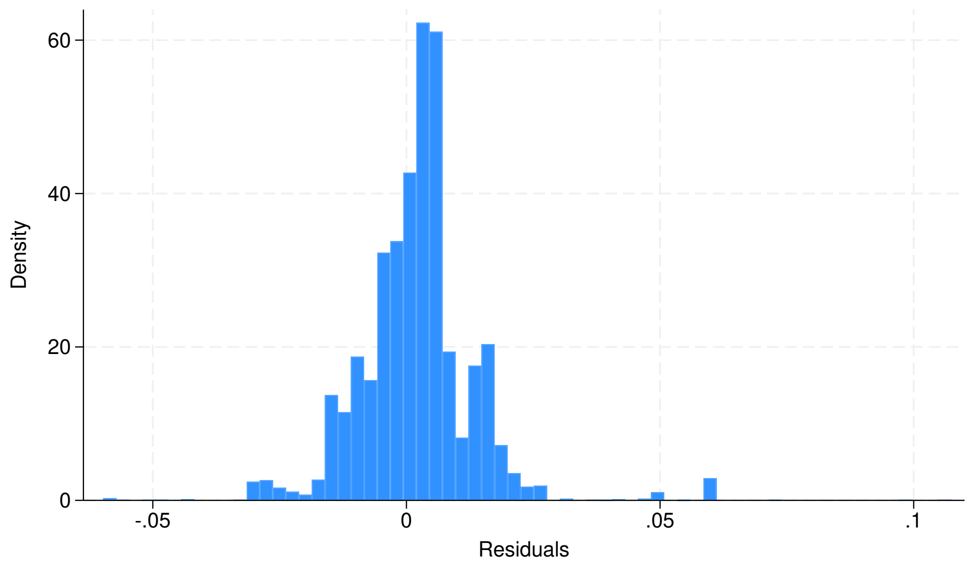
Note: Outcome is taking a PPR and estimated on equation 2. Split by quartile of reading score in 10th grade among all high school graduates. Controls include: white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ level. Data: TEA, THECB, SBEC, BLS, Census.

Table A19: Probability of Taking a Content Test in Elementary Education, Bilingual/English as a Second Language, Special Education or Math/Science/Technology with Local Unemployment Rates

	Elt	Bi/ESL	SPED	M/S/T
MA UR	-0.012	0.160*	0.008	0.000
	(0.030)	(0.024)	(0.007)	(0.005)
Controls	yes	yes	yes	yes
Tot Obs	2,624,145	2,624,145	2,624,145	2,624,145
Outcome Mean	0.03	0.01	0.00	0.00

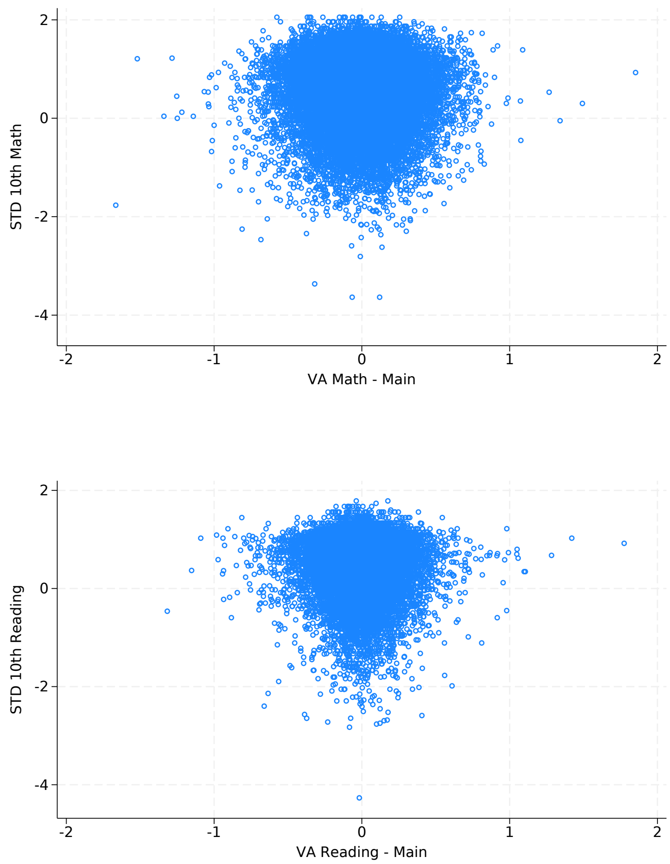
Notes: This is the regression output as illustrated in Figure 4. These are estimated from equation 2. Outcomes include whether the content exam was for elementary, bilingual/ESL, Math/Science/Technology, or Special Ed subjects all in binary formatting (0/1), where zero is representative of not becoming a teacher or taking a different subject exam. MA refers to the three-year moving average UR described in text. Controls include white population share in CZ-cohort, Black population share in CZ-cohort, Hispanic population share in CZ-cohort, Asian population share in CZ-cohort, total working population CZ-cohort, whether individual is white, Black, Hispanic, Asian and/or male. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data sources: TEA, THECB, SBEC, BLS. Further details about data construction can be found in Appendix B.

Figure A1: Histogram of UR Residuals



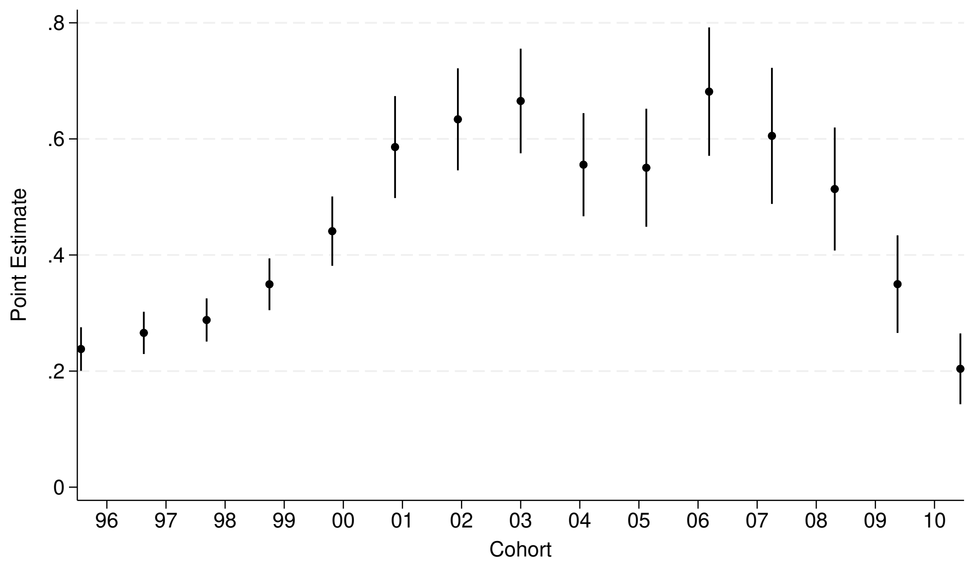
Note: The residuals of URs after year (cohort) and CZ fixed-effects. Data: BLS.

Figure A2: Tenth Grade Test Scores and Value-Added for Math and Reading



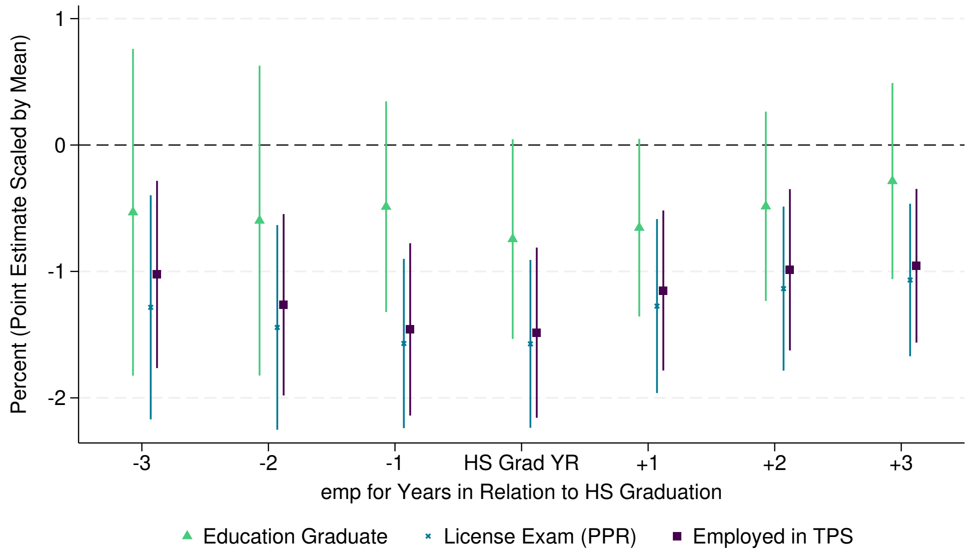
Note: Scatters of the standardized 10th grade math scores and math value-added (top) as well as for reading (bottom). Data: Data: TEA, THECB, SBEC.

Figure A3: UR Cross-sectional Variation Effect on PPR Exams



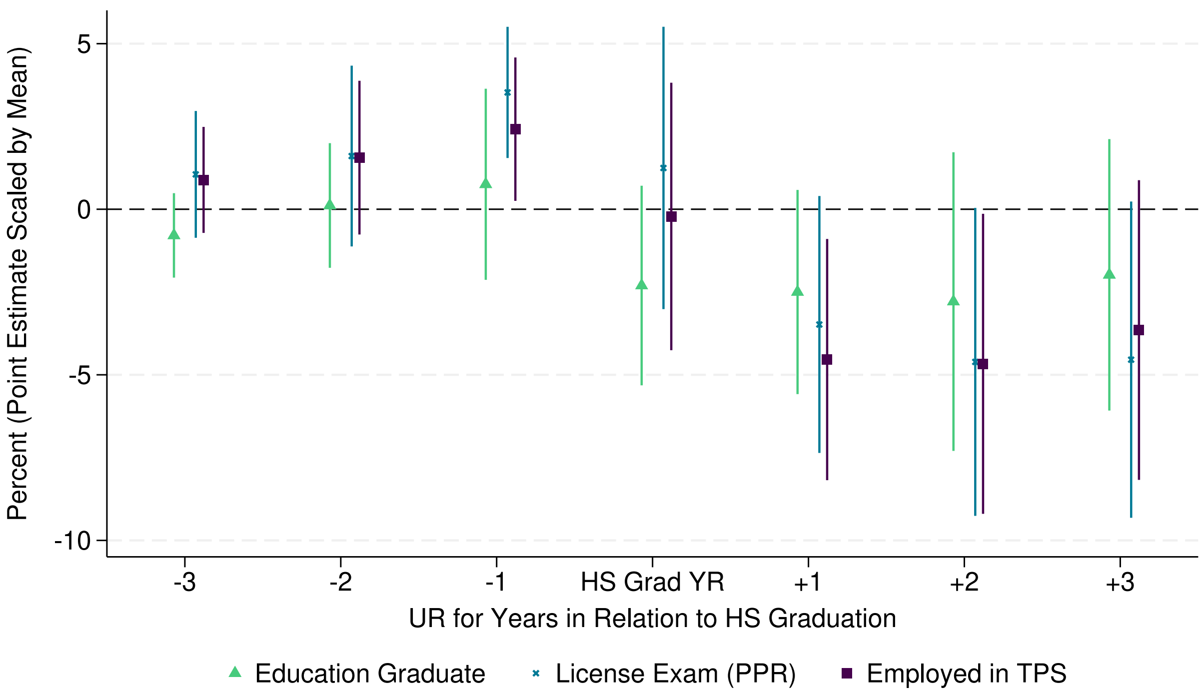
Note: Each point and bar are the point estimate on UR and 95 % confidence interval. Each point estimate is a unique regression using only cross-sectional variation in UR within the cohort-year. All regressions control for the variables in the text. Data: Data: TEA, THECB, SBEC, BLS, Census.

Figure A4: Propensity to Select into Teaching and Employment-Working Population Ratios at Different Ages



Note: Independent variable is the total employment divided by total working population. Each point and bar are the point estimate on employment ratio and confidence interval, respectively, *re-scaled* by the mean of the outcome so as to be comparable across outcomes. Each point estimate is a unique regression using equation 2 whereby the employment ratio is assigned in a year relative to an individual's high school graduation year. All regressions control for the variables in the text. Data: TEA, THECB, SBEC, BLS, Census.

Figure A5: PPR Exam Takers Among Students Who Attended Their HS for Four Years



Note: Results estimated only on students who attended the same high school for four years. All regressions control for the variables in the text. Data: Data: TEA, THECB, SBEC, BLS, Census.

B Data Details

I connect individuals and their characteristics together using Texas Education Agency (TEA), Texas Higher Education Coordinating Board (THECB), and Texas State Board for Educator Certification (SBEC) datasets, all housed in the Texas Education Resource Center.

High school graduation file: I remove any observations that are flagged as having an identifier that may not be acceptable for linkage across datasets. This exclusion drops approximately 7 percent of the initial high school graduate file. I also additionally drop high school graduating years 1993-1995 because I do not have an associated 10th grade math or reading score for these cohorts. I additionally drop any individuals from 1996-2010 who do not have both a 10th grade math and reading score. I also remove those whose 10th grade exam dates were strictly more than 2 years from their expected graduation date – this represents less than 1 percent of sample.

SBEC - Teacher License Exams and Teacher Certifications: The ERC houses tests and corresponding certification scores from the State Board for Educator Certification (SBEC) which was formed in 1995 (Templeton et al., 2020). The SBEC files include the universe of certification exams from 1990 to present, though some of their exams date back to 1986. This file includes exams for content, pedagogy, and other certification exams such as librarian or principal. It includes the raw score and the program (alternative, university based, etc.) through which the individual was trained. At the time of my data request, inclusive exams ended in 2018. Hence, the end of PPR exams at cohort 2010 (allowing for 8 years to observe in the SBEC files).

PPR exams differ by grade level, typically elementary, secondary or all grades. Despite being different across grades and having changes year-to-year,[24] this exam ascertains the same information: the extent the teacher is effective at providing an environment conducive for learning and maintaining professional conduct (Hendricks, 2016). From the master file,

[24] Namely, a change in 2003 of the teacher certification program from the Examination for the Certification of Educators in Texas (ExCET) to the Texas Examinations of Educator Standards(TExES) and year-over-year tweaks to exams (Hendricks, 2016).

I standardize the PPR exam across academic year and individual exam (differing by grade level) so as to have comparable scores across years and grade levels. The standardization includes all tests except those where the individual is deemed out of state prepared or had a missing value for out of state designation. Thus the standardization is within all individuals who were participating in educator preparation programs within Texas. I keep individuals' first-time standardized exam score and the corresponding academic year and preparation program (alternative, university-based, or other). I exclude individuals who explicitly report that their educator program was out-of-state. This dataset of individuals' first time PPR exam contains over 630,000 test takers from academic years 1986 to 2018, some of whom never become teachers in Texas.

Student Standardized Exams - 10th Grade Math and Reading Ability: From 1994 to graduating class of 2003 (9th grade as of January 2001), students were required to pass exit level exams in math, reading and writing administered during 10th grade under the TAAS test taking regime (Digest, 2019).[25] I standardize all 10th grade raw exam scores for each subject- school year (this excludes students retaking the exam as 11th graders). The data are unique at the student ID-subject-year level.

During the TAKS testing regime, 2003 to 2012, students were required to take 10th grade math and reading exams.[26] Note that 10th graders in 2012 are expected to graduate high school in 2014, and as such my sample of high school graduates ending with graduating year in 2013 are fully covered by TAAS or TAKS. I standardize all 10th grade raw exam scores for each subject-school year. The final data are unique at the student ID-subject-year level.

Finally, I construct a data set of one 10th grade exam per subject per unique student ID. I append the 10th grade TAAS and 10th grade TAKS datasets, and when there are multiple subject exams for a given individual, I retain only their first (via year) observed standardized test score. Practically, this is relevant for the transition between TAAS and TAKS testing

[25] More info here: https://web.archive.org/web/20080822040221/http://www.tea.state.tx.us/student.assessment/resources/techdig07/Chapters/Chapter20-TexasAssessmentofAcademicSkillsExitLevel.pdf

[26] https://web.archive.org/web/20080810182753/http:/www.tea.state.tx.us/student.assessment/taks/booklets/index.html

regimes, namely 2003. Math and reading must have been completed in the same years.

Economic disadvantage: Economic disadvantage is defined to be a student receiving free or reduced-price lunch or other disadvantage in the 10th grade - specifically from the test files. TEA defines other economic disadvantage as: a) from a family with an annual income at or below the official federal poverty line, b) eligible for Temporary Assistance to Needy Families (TANF) or other public assistance, c) received a Pell Grant or comparable state program of need-based financial assistance, d) eligible for programs assisted under Title II of the Job Training Partnership Act (JTPA), or e) eligible for benefits under the Food Stamp Act of 1977.

College enrollment and graduation (THECB): THECB reports enrollment in each semester and year and completed degrees across all Texas Public Universities, Texas Community, Technical and State Colleges, and Texas Health-Related Institutions for years 1992 to 2018. They additionally report enrollment and degrees earned for Texas Independent Colleges and Universities from 2003 to 2018. As stated in the main text, I do not include the Independent Colleges and Universities in my primary analysis, but do in certain robustness checks. THECB also reports information on college majors. In the case of dual majors/degrees earned, I prioritize first bachelor's earned. In the case of multiple majors in the same degree year, I randomly select one to be representative. Across my sample, about 3 percent of individuals have multiple degrees/multiple majors within a year. Once first degree conferred year is selected on, approximately 2 percent of degrees earned in a given year are accompanied by a secondary major.

"Education" Majors and CIP codes: I harmonized the CIP codes to the 2020 specification. The National Center for Education Statistics creates CIP codes, see https://nces.ed.gov/ipeds/cipcode/Default.aspx?y=56 for details.

In Texas, prior to 2019, there was no official "education" major - see Texas House Bill 3217 for change. To capture majors most closely associated with teaching elementary or secondary education, I match the teacher employment files to the bachelor graduation files.

Shown in Table A11, the most common majors are interdisciplinary studies (37 percent of matched teachers), and parks, recreation, leisure, and fitness studies (7 percent of matched teachers). All other majors represented 6 percent or less of matched individuals and were not highly representative of majors expected of teachers (such as business). As such I have categorized education as either explicitly denoted education (technically not allowed for bachelor's degrees), interdisciplinary studies - general, and the 2-digit category parks, recreation, leisure and fitness studies. Alternatively, Table A12 shows the percentage of each two digit major that is observed in the teacher employment file.

Unemployment Rates - LAUS/BLS: I download from Texas Labor Market Information BLS LAUS data for Texas counties.[27] I then aggregate labor force counts by county to the CZ equivalent and derive unemployment rates by calendar year and by CZ by dividing the total unemployed people in a CZ by the total count of individuals in the labor force.

QCEW: I obtain county-level public Quarterly Census of Employment and Wages (QCEW) program data from 1990-2019. From these, I aggregate total (private and government) annual employment and annual wages up to the commuting zone-year and commuting zone-industry-year level.[28] The QCEW publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs.[29] With this data I construct four measures of employment in each Texas commuting zone: total actual employment, a proxy (Bartik) total employment, an actual employment growth rate, and a proxy (Bartik) employment growth rate.

Total actual employment and actual employment growth rate: These are calculated from the county, total covered annual employment measures reported by the QCEW - aggregation code 70. Total employment is aggregated across counties within a CZs. I divide total em-

[27] https://texaslmi.com/LMIbyCategory/LAUS

[28] I make the distinction here because QCEW suppresses small cells which happen more frequently at the county-industry level than at the county level. Thus adding the industries within a county would unnecessarily introduce measurement error.

[29] https://www.bls.gov/cew/overview.htm/

ployment by total working population in the CZ five years prior to account for the large differences in size of CZs in my sample. Employment growth is the 5 year growth rate of the total covered employment.

Bartik employment growth rate: I construct a Bartik employment growth instrument using the fact that overall labor demand shocks can be written as a weighted average of industry-specific demand shocks where the weights are representative of the prevalence of the industry in a given CZ. Instead of using own CZ-industry growth rate, this measure is replaced by a growth rate of all U.S. states excluding Texas to prevent endogeneity. For CZ z and cohort year c, predicted employment growth rates are calculated as:

$$\text{BartikGR}_{zc} = \sum_{ind} \text{Share}^{Ind}_{z,c-5} gr^{Ind}_{-z,c} \tag{3}$$

where $\text{Share}^{Ind}_{z,c-5}$ represents the share of NAICS industry Ind in CZ z during time c-5.[30] The choice of updating the industry share overtime is to make the instrument more predictive. The $gr^{Ind}_{-z,c}$ term represents industry-specific employment change over 5 years that is calculated by using total growth rate from each state-industry excluding Texas entirely.

Bartik total employment: The Bartik employment measure gives a proxy employment *level* for a CZ-year based on the (5 year) lagged total employment in industry Ind for CZ z times the ratio of employment in that industry occurring in all states *excluding* Texas to its (5 year) lagged employment for industry Ind. These are added up over all industries to create a total predicted employment measure:

$$\text{BartikEMP}_{z,c} = \sum_{I \in Industry} \text{Employ}^{I}_{z,c-5} \left(\frac{\text{Employ}^{I}_{-z,c}}{\text{Employ}^{I}_{-z,c-5}} \right) \tag{4}$$

Where -z represents all aggregate employment of all states excluding Texas.

The basic intuition is that the ratio of non-Texas employment in a industry is a predicted value of how much employment in Texas in that industry should change over a 5 year period. This multiplied by the original employment in CZ z generates a predicted employment level.

[30] I exclude 2 digit industry 99 - unclassified which was added in 2001.

It is akin to the Bartik growth rate calculated above. This predicted level of employment is divided by total working population in the CZ five years prior to account for the large differences in size of CZs in my sample.

Caveats to using QCEW data: "To preserve the anonymity of establishments, BLS withholds publication of data for any geographic industry level in which there are fewer than three firms or in which the employment of a single firm accounts for over 80 percent of the industry. At the request of a State, data are also withheld where there is reason to believe that the "fewer than three" rule would not prevent disclosure of information pertaining to an individual firm or would otherwise violate the State's disclosure provisions. Information concerning Federal employees, however, is fully disclosable."[31] Using counties results in data suppression particularly among certain industries. In particular, industries 21, 22, 61, and 62 have several suppressed (0s for employment levels) at the county level across all U.S. counties. Thus there may be more measurement error created in the smaller CZs as a result of cell suppression. Across the whole Texas dataset of included CZs about 5 percent of the industry-CZ-year cells are suppressed.

Population Estimates: County population estimates are from Census Population and Housing Units.[32] I download the 1990-2015 data from `https://www.nber.org/research/data/us-intercensal-county-population-data-age-sex-race-and-hispanic-origin` and condition on 20-64 year olds for a working age population estimate. I have also split the 20-64 year old population into white, Black, Asian, and other non-Hispanic and Hispanic subgroups. In years 2000 and later, other non-Hispanic includes those who are two or more races (non-Hispanic).

Mass Layoffs: I obtain county level estimates of extended mass layoffs from the BLS page listed on this site: `https://www.bls.gov/mls/cntyicmain.htm`. I aggregate up the coun-

[31] `https://www.bls.gov/cew/publications/additional-publications/archive/old-handbook-of-methods.htm`

[32] `https://www.census.gov/programs-surveys/popest.html`

ties to CZs total extended mass layoffs. I then divide by the total population to get mass layoff incidence. In the regressions I run, I do a moving average by taking total mass layoffs the average of the year prior, year of , and year after high school graduation and dividing it by the average of total population during the same three periods.

Definition of Rural CZ: I select CZs that have no micropolitan or metropolitan county's within the CZ based on Office of Management and Budget's (OMB) June 2003 delineation of micro- and metro- counties in Texas found here: https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/historical-delineation-files.html.

Additional data cleaning restrictions: I merged the above datasets by individuals' unique identifier (SSNREP). I make the following additional sample edits. I remove any high school graduates who report inexplicable college-going characteristics such as those who have a bachelor's degree within six years of graduating high school from a Texas college, but for which I never observe enrolled in a Texas public college within the same period. I also remove observations who have any missing values in the following variables: high school graduation year, district, sex, race/ethnicity, birth year, county, commuting zone. Finally, I remove 11 CZs that cross the state border (CZs are not confined within the state) or because they have sufficiently small numbers making their employment data prone to measurement error. This represents only 15,000 high school graduates total, and my results are impervious to including them. Altogether, all of the restrictions remove less than 1 percent of the high school data file.

Construction of Value-Added Data: Beginning in the 2012 school-year, the TEA data reports a class identifier for each student-course-year and similarly reports a class identifier for each teacher-course-year. This class ID allows for the connection of students to teachers at a classroom level.

To construct the value-added (VA) estimates, I begin by standardizing raw scores for students in grades 3-8 by grade-subject-school year to account for differences across years in difficulty of exam. In the cases where some grades-school years allow retakes, I keep only individuals' first exam score. This standardization takes place *before* any sample selection is made on students for VA estimation. In practice, these test scores were completed under the STAAR testing regime in Texas and comprise academic years 2012-2019. I then select student observations that have all the demographic variables (economic disadvantage, ethnicity/race, sex, whether they were in special education, whether they were at risk, and whether they were gifted), both concurrent math and reading test scores, and lagged math and reading test scores. This includes over 3.7 million students.

Next, I match these standardized exam scores to their class IDs. The class IDs include only courses starting during the typical school year (excluding May, June, July, and December). I exclude any courses that were 3 or 4 semesters an academic year, and I retain only the class ID for the first semester of two semester long courses (in practice the assigned teacher rarely changes over the second semester). In the instances where there are more than one subject-course-year class IDs listed for a given student, I prioritize the ones in which Service ID indicates a math/reading/ELA related subject over "generalist". When a student has multiple subject-class IDs, I randomly select one teacher to be representative.

Finally, these student-class ID-subject-year observations are connected to teachers via the class ID variable. In total, there are more than 9.8 million observations, more than 3.6 million student IDs, and more than 79,000 unique teachers for the calculation of math VA. For reading VA, there are 8.8 million observations, 3.5 million unique students and 85,000 unique teachers.

C Steps to Becoming a Classroom Teacher in Texas

The basic requirements for becoming a teacher in Texas include (Agency, 2022c):

1. Obtain a Bachelor's Degree
2. Complete an Educator Preparation Program (EPP)
3. Become certified by passing appropriate license exams
4. As of January 1st, 2008, complete background check (Agency, 2022d)

There are two types of EPPs depending on whether the individual would like to obtain their bachelor's degree concurrently (University-based Program - UBP) or post bachelor's degree (alternative certification program). The Alternative Certification Programs (ACPs) were allowed under the SBEC starting in year 1999, and are quite common in Texas (Templeton et al., 2020).[33]

Requirements for a UBP EPP (Agency, 2022a):

1. Select a Texas University that has an approved EPP program and meet the requirements for entry
2. Complete course work and secure student teaching or teaching internship (internship for Post-Baccalaureate Candidates only)
3. Apply for a Probationary Certificate *if a teaching position has been secured for an internship*
4. Complete examination requirements for a Standard Certification

[33]TEA describes alternative programs as, "Alternative certification programs (ACP's) offer a nontraditional route to certification that may allow you to teach while completing the requirements. These programs are located in universities, school districts, education service centers, community colleges, and private entities." TEA describes University-based programs as, "University programs offer a route to educator certification while earning a degree at the same time. These programs also allow a person with a bachelor's degree or higher to complete the requirements for an educator certificate with university coursework. In some cases, people with a bachelor's degree can earn an advanced degree in addition to completing the requirements for a certificate."

- Student must be recommended through program

5. Apply for a Standard Certificate

Requirements for a ACP EPP (Agency, 2022b):

1. Select an approved ACP and meet the requirements for entry
2. Obtain a Teaching Position
   - Depends on appropriate progress in ACP and program is required to provide an eligibility statement
   - A certified mentor is assigned to work along with the ACP student
3. Apply for a Probationary Certificate
4. Finalize any further requirements for ACP (coursework, exams, etc), then apply for a Standard Certificate

To become certified in Texas, teachers must pass both a content and a Pedagogy and Professional Responsibilities (PPR) exam (Templeton et al., 2020; Hendricks, 2016). The content exams test knowledge of subject material at relevant grade levels such as mathematics for grades 8-12 or art for grades EC-12. The PPR exam measures four dimensions: designing instruction and promoting student learning, creating a positive classroom environment, implementing effective instruction and assessment and fulfilling professional roles and responsibilities (Agency, 2018). The PPR exam changed in 2003 from Examination for the Certification of Educators in Texas (ExCET) to the Texas Examinations of Educator Standards(TExES) but they tested the similar material over the course of this change (Hendricks, 2016).

Individuals may complete a student teaching before becoming fully certified. About 80 percent of non-standard certifications, student teaching or emergency certifications, have not passed a PPR exam strictly prior to being able to enter a classroom. However, these non-standard certifications are only valid for one year typically and cannot be renewed. About

70 percent of individuals have passed a PPR exam strictly before their first observed employment spell. The overall share of non-standard certifications in Texas has been declining over time.