# 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. I also show these local labor market conditions have the largest influence when experienced during high school. On average, individuals who sort into teaching because of poor local labor market conditions are of higher ability (standardized tests) and have higher productivity (value-added). Further, poor local labor market conditions drive individuals toward certification in at least one shortage area (bilingual/ESL) and weakly away from general elementary studies. The results are consistent with updated beliefs over employment probabilities or changes to risk preferences such that teaching is perceived as a relatively more stable career path. The findings suggest that local labor market fluctuations shape career decisions well before individuals participate in the labor market, and that increasing the relative economic standing of teaching as a career has the potential to improve the future supply of teachers.

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# 1 Introduction

One of the most important labor decisions is occupational choice. This decision requires that individuals have expectations and assess information about various pecuniary and non-pecuniary aspects of occupations in their consideration set. Despite a large body of work on what influences college major and occupation, open questions remain on what information individuals use and when preferences are formed.[1] One way in which individuals may learn about careers is through labor markets, and previous research has found that business cycles experienced during youth affect a variety of long-term outcomes (Malmendier and Nagel, 2011; Stuart, 2022; Blom et al., 2021; Acton, 2021). Given occupational decisions are often made well before individuals participate in the labor market, could business cycles experienced during adolescence influence occupational choice and ability sorting?

I study this question through the lens of one of the largest singular occupations: teachers. 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). Further, the teaching profession is one of the few occupations that has well-validated measures of occupation-specific productivity (value-added), allowing for better understanding of quality sorting. However, 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 answer these questions comprehensively, I combine Texas administrative data with variation in unemployment rates (URs) at the commuting zone (CZ) level to jointly estimate business cycle effects on 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.

Specifically, I begin by creating 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,

[1] For a recent literature review, see Patnaik et al. (2020).

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. Finally, the data characterize both the extensive and intensive margins of educational attainment, allowing me to provide more detail on the mechanisms for career changes.

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. Unemployment rates are a useful gauge of the economy because they are salient. 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 enrollment in an education major, 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 conditional on graduating college on-time is about .5-1 percentage points (3 percent) more likely when individuals experience a 1 percentage point increase in URs at approximate age of college entry. During higher levels of local URs, the share of bilingual/English as a second language certifications increases, and the share of general elementary studies certifications weakly decreases. Thus, teacher candidates certify more frequently in a subject area where there are commonly shortages. Finally, I do not find evidence that these teachers are more likely to leave the profession within a six-year period, which suggests these may be long-term shifts in career paths.

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.

Because local labor market conditions have the ability to influence education at the extensive margin (enrollment or graduation from college), my results represent net effects. However, I also observe college enrollment and graduation counts, which provide important context. There is evidence of a decline in college graduation due to poor local labor market conditions experienced during high school. The potential decline in the number of college graduates works against realized gains in increases in the count of potential teachers. This has ramifications for what school districts may come to expect of future supplies of teachers during business cycles and has implications for other researchers studying college major choice in response to business cycles. However, back-of-the-envelope calculations find that individuals induced into teaching due to recessionary conditions could make up approximately 3 percent of newly hired teachers in a given year.[2]

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. Finally, to account for potential heterogeneity in treatment effects, I estimate a weighted average movers' potential outcome slope and find it to be qualitatively similar to my main results (de Chaisemartin et al., 2022).

There are several mechanisms through which local labor market fluctuations could assert influence over college major or career choice. Two likely 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

[2]See Section 5.1 for more details on how this number was calculated.

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 two disparate literatures of college major choice and teacher labor markets. In particular, I make five contributions. First, I jointly estimate supply and quality changes as business cycles fluctuate. Beyond general interest in the joint estimation of supply and quality, estimating both simultaneously 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).[3] Alternatively the most convincing studies on teachers to date do not provide estimates of the changes in potential teacher supply (Nagler et al., 2020).

Second, the previous teaching literature comes short of separating supply and quality effects of business cycles from potential demand effects of business cycles (Figlio, 2002; Hoxby and Leigh, 2004; Bacolod, 2007; Leigh, 2012; Fraenkel, 2018; Nagler et al., 2020).[4] Because educational funding is often tied to resources that ebb and flow with the business cycle,[5] it can be difficult to ascertain whether poor economic conditions lead to higher value-added teachers because of reductions to hiring (demand) during downturns or because more productive potential teachers are seeking employment (supply). Without further assumptions or better data, we cannot separate the two (Nagler et al., 2020). Motivated by the difficulties in disentangling equilibrium observed number of teachers and their relative quality, I focus on the *flow* of potential teachers and *their* quality. Because I observe individuals and labor market conditions well before they enter the market, I can better separate out the potential supply and demand effects.

Third, most papers have not considered a longer time horizon for effects of business cycles on future occupational choices.[6] The timing of when individuals make important career decisions is of great policy relevance. For example, if we wanted to encourage more women to enter STEM

[3]Other works study changes to information over wages or real changes in wages and its effects on college major choice (Beffy et al., 2012; Berger, 1988; Wiswall and Zafar, 2015a; Long et al., 2015; Xia, 2016).

[4]Leigh (2012) may be one of the closest to achieving this because they study pre-employment outcomes with respect to teacher wages. However, their work does not have teacher employment or value-added, and Australia's process for selecting college majors differs substantially from the U.S.

[5]See Figure A1 for the number of newly hired individuals over time.

[6]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.

fields, knowing whether to target them during their senior year of high school or sophomore year of college is important. With respect to the teaching profession, there is already some movement in this direction. For example, several local school districts across the U.S. are implementing grow-your-own programs to target recent graduates (and paraprofessionals) to become teachers in hopes they will return to that district. In essence, grow-your-own programs are a localized teacher shortage solution.

Fourth, I focus on localized geographies which is not a feature of most prior work.[7] 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.[8]

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

The remainder of the paper is as follows. Sections 2 and 3 discuss the conceptual framework and data. Section 4 outlines the empirical methods. Section 5 discusses the results on the supply of potential teachers and their quality. Section 6 considers robustness of the primary identification strategy. Finally, Sections 7 and 8 conclude with discussions on mechanisms and policy implications.

[7]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.

[8]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).[9] Until 2019, there was no defined education major. As long as an individual completed an education preparation program and license exams, they could become a teacher regardless of their bachelor field of study. Despite the lack of a uniform major regulated by the Texas State Board for Educator Certification, many colleges have specified "education" majors - often categorized under interdisciplinary studies.[10]

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 29 percent and 68 percent of students become certified through alternative educator preparation programs and university-affiliated preparation programs, respectively.[11]

## 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.[12] As such, most students finalize college going and career decisions

[9]For the detailed list of information, see Appendix D.

[10]Table A19 and A20 list the most common majors among employed teachers.

[11]The remaining 3 percent is categorized as other.

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

during this time. Because one particular age or year may not be more influential than the age/year immediately preceding or following, I remain agnostic about when economic conditions could be most influential. Instead, and described in more detain in Section 4, I allow economic conditions to be related in a flexible way across several time periods surrounding this crucial time of decision making.

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, we would not expect 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 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 unemployment rates 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).[13] 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.

## 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. Specifically, 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. I begin with the set of high school graduates and define four measures of interest in teaching along the progressive pipeling 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.[14] Henceforth, cohort refers to the spring year of the academic year in which a student

[13]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.

[14]In some cases, I include two more graduating cohorts 2012-13 in specifications looking at high school graduates or college graduates because I can observe them longer than I can observe PPR test takers. See table footnotes for details.

graduated high school (2001-02, denoted 2002).

*College enrollment and graduation:* I define "graduated with a bachelor's degree", henceforth college graduate or on-time college graduate, as whether the student, within six years of graduating high school, earns a degree conferred at the bachelor's level from a Texas non-Independent college or university.[15] Similarly, I define "ever enroll in college" as one if an individual is recorded attending a non-independent Texas college pursuing any degree award within six years of high school graduation. I do not require that the individual be enrolled for a certain amount of time, only that they ever attend. In Section 6, I show that excluding independent colleges due to their inconsistent data reporting during my sample period does not change the results.

*Interest in teaching:* 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. See Appendix B for more details. With this definition, two of my measures of interest in teaching are whether an individual ever enrolls in an education major within six academic years of graduating high school and whether they graduate with a bachelor's degree in an education major within six years of graduating high school.

My other two measures of interest in teaching come from two additional data files. The first uses the set of 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. Finally, 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

[15] Of high school graduates from 1992-2004 who earn a bachelor's degree (giving approximately 15 years of time for each cohort to "show up" in the college graduate file, after 15 years is very rare), about 64 percent of the degrees are earned within 6 years from high school graduation and 76 percent are earned within 8 years from high school graduation (the maximum year that I check in my robustness). Using all the data that I have, these numbers are 76 percent and 86 percent, respectively.

school graduation year.[16]

*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:*
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):

$$A_{ijkgst}^{sub} = \alpha_1 A_{it-1}^{sub} + \alpha_2 A_{it-1}^{-sub} + \gamma X_{it} + \lambda C_{kgst} + \nu_{gt} + \zeta S_{st} + \mu_j^{sub} + \epsilon_{ikgst} \quad (1)$$

where $A_{ijkgst}^{sub}$ 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 $A_{it-1}^{sub}$ and $A_{it-1}^{-sub}$ 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 $\nu_{gt}$. Finally, the teacher fixed effects $\mu_j^{sub}$ 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 A2 reports descriptive statistics for this

[16] 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.

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. Furthermore, 16 percent of these bachelor's degree completers take a PPR within eight years of graduating high school (82,177) - see Tables 1 and A1 for more descriptive details.

## 4 Empirical Specification and Identification

Do worse (better) economic conditions increase (decrease) 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, $\text{Teach}_{izc}$, are binary variables indicating ever enrolled in an education major within six years of graduating high school, graduated college with an education major within six years of graduating high school, PPR completion within eight years of graduating high school, and employment in Texas public schools within eight years of graduating high school. Moving forward, I consider PPR completion to be the primary measure of interest in teaching. Regressions for enrollment in education are run on individuals who have ever enrolled in college within six years. College graduation in an education major and PPR completion regressions include only individuals who graduate college on-time. Finally, the regressions with employment in TPS as the outcome are run on all high school graduates.

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, $\gamma_z$, 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, $\eta_c$, 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 $\hat{\beta}$.[17]

The variation in URs that identifies $\beta$ stems from two main sources. The first of which is

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

differences *across* cohorts *within* CZs that deviate from the *average* (for all CZs) differences among cohorts. To fix ideas, suppose over a five year period (cohorts 2000 and 2005) the UR in the Houston-area CZ increased substantially relative to all other CZs between cohorts 2000 and 2005. If this is associated with a larger than average increase in the share of students pursuing teaching, this weighs $\beta$ towards a positive relationship.

Figure 2 illustrates this type of variation in URs. For instance, in Figure 2, in each given year, there are macro/statewide trends. For instance, in 2005 all CZs experienced over-the-year declines in their URs. Contrastingly, during the dot-com bust and Great Recession, all CZs increased their URs from the previous year. Looking within a particular over-the-year change in UR, such as in 2009, there is variation in the differences of URs. The fact that some local areas experience booms and busts differentially provides differences in labor markets I can use to identify $\beta$.[18]

The second source of variation is derived from differences in URs *across* CZs in a given cohort that deviate from the *average* (across cohorts) differences between CZs. For instance, suppose within the 2000 high school graduating cohort we observe a difference in URs between the Houston-area CZ and the Dallas-area CZ that is *lower* than it is typically. If the difference in the share of test takers between Houston-area CZ and Dallas-area CZ is also *lower*, then this variation contributes to a positive association between UR and the probability of pursuing teaching.

## 4.1 Identification

The average effect of URs on the future decision to become a teacher is $\beta$. The estimated parameter $\hat{\beta}$ is causal under the assumption that CZ-year URs 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.

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,

[18] Figure A2 and A3 provide other visualizations of over time differences in unemployment rates across select CZs.

expectations act as a mechanism instead of a potential confounder.

One possible exception is changes to demographics. As discussed above, I include both demographic CZ- and individual-level controls in the primary specification. I further explore compositional changes in demographics in Section 7. In general, I do not find demographics to be significantly change with respect to the set of high school graduates - see Table 2. Regardless, my specification ultimately uncovers the net effects conditional on all changes in educational decisions.

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

## 5.1 Supply

To utilize the multiple measures of interest in teaching as well as the long panel structure of the Texas administrative data, I examine the relationship between URs in years relative to an individuals' high school graduation year to various indicators of 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. For comparability across outcomes and samples, the point estimates and confidence intervals in Figure 3 are rescaled by their respective mean. This figure clearly illustrates that the outcomes and their respective samples all show a similar pattern. 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. Local URs in students' assigned CZ are small and insignificant in years after individuals graduate high school. In other words, local labor markets have the potential to shift the future potential supply of teachers, and these effects are concentrated earlier on.

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 both psychologically and practically more challenging (Patterson et al., 2019).[19] This is likely to be more binding for the sample of individuals who graduate college on-time.[20] Second, recall the CZs are assigned based on students' high school graduation location. Assuming that this is the

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

[20] Alternatively, if the sample considered non-traditional students who took several years to graduate, they may have been more likely to switch majors both because of their longer time horizon or mechanically - because switching majors set individuals back in progression to degree.

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.[21]

To obtain a single point estimate, I use a three-year moving average of URs across junior year of high school through one year post-high school graduation. This is likely conservative given fade-out-effects. 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 of taking the PPR increases by about .5-1 percentage point conditional on being a college graduate within six years of high school graduation - see Table 3. This translates to approximately 3 percent increase over the mean.

Figure 4 illustrates the point estimates and confidence intervals for moving average URs and whether an individual takes the PPR exam conditional on graduating college for each subgroup on the y-axis (male, female, Black, etc.). These analyses are conducted separately for each category, comparing PPR completion for students with a specific characteristic to other students with the same characteristic but facing different local labor market conditions. Students living in rural CZs seem to respond more to local labor market conditions than students in urban CZs.[22] Females tend to be more affected by URs than males and non-economically disadvantaged students are affected more than lower income students. Black and Hispanic individuals do not show significant changes in their PPR taking based on URs, but white students do. Some of these dissimilarities are not significantly or economically different, so the heterogeneity results represent suggestive evidence.

I investigate whether the individuals who took the PPR exam were interested in 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).[23] Within the set of individuals who also completed a content exam (a requirement for certification), I estimate equation 2, with the outcome variable being

[21]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.

[22]Definitions for rural listed in Appendix B.

[23]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. This happened to be 93 percent of my PPR test takers.

binary for content type. This is effectively comparing the propensity of potential teachers to take certain subject content exams over others upon experiencing different local labor market conditions.

I present the coefficients and confidence intervals of moving average URs in Figure 5. There is a weak decline in probability of studying elementary subjects and an increased probability of taking bilingual/English as a second language exams. This finding 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 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.

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 550 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 3 percent of newly hired teachers could enter the profession due to a recession.[24] This estimate is likely an under-count. Data restrictions such as completing college within six years of high school graduation remove individuals who may have been induced into teaching but took longer to complete their bachelor's, for instance.

It may be worrisome 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. For individuals who worked in TPS, I estimate the likelihood these outcomes change with respect to local labor markets. As shown in Figure 6, there are not significant differences in probability of staying for at least two or 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 is possible that these individuals face a difficult

[24] 82,177 PPR completions averaged over 15 years is approximately 5,500 completions per year. A 2 percentage point increase in local URs is 2(.05)(5,500)= 550 more potential teachers. Then 550/22,000= about 3 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.

labor market during college graduation and stay in teaching for longer.

## 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 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.

Figure 7 shows the mean 10th grade test score difference between PPR test takers and non-PPR test takers categorized by college major. Recall that up until 2019, there was no required education major in Texas, providing an opportunity for any person interested in becoming a teacher to have a variety of background training. Reading skills are mixed but mostly negative implying that across most majors those who select teaching have lower average reading ability compared to others in the same major. Individuals with lower mathematical skills in a given major are more likely to sort into teaching. This overall aligns with other work that claims lower skilled individuals sort into occupations with more compressed wages (Hoxby and Leigh, 2004; Bacolod, 2007; Nagler et al., 2020).

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.[25] 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,

[25]Hanushek et al. (2019) recently provided evidence that cognitive skills of teachers are related to test scores of students in a cross-country study.

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.[26]

#### 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. 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 8 maps point estimates and 95 percent confidence intervals of URs experienced during different times relative to high school graduation for all the various 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 insignificantly related with local labor market conditions.

Table 3 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

[26] Figures A4 show the raw scatters between math 10th grade test scores and math value-added and similarly for reading for comparability.

more than teachers typically sorting into the profession. Another way of thinking about value-added is how teachers rank in comparison to each other. In Table A3, I re-standardize the value-added estimates such that the outcome is how a teacher ranks compared to the average teacher (across all teachers in Texas with a value-added score). These estimates suggest that a 1 percentage point higher UR implies the average teacher sorting into teaching is .02 standard deviations better at affecting student test scores than a typical teacher. 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 A21.

## 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. Further, I estimate a heterogeneous robust estimator, WAMPOS, and find it to be qualitatively similar to my main results (de Chaisemartin et al., 2022). 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.[27] 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 of nearly identical magnitude (4 percent increase in share PPR corresponding to a 1 percentage 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 percent increase. Controlling for CZ-cohort demographics renders the estimates on log PPR insignificant at conventional levels.

[27] 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).

*Statewide estimates:* For similar reasons, national or statewide economic conditions could also influence career choice (Blom et al., 2021; Nagler et al., 2020). I test whether my local results are consistent with state-level specifications. Qualitatively, I find a positive relationship between URs and completing the PPR conditional on graduating college estimated at the statewide level with linear and quadratic trends.[28] The estimates are slightly attenuated - see Table A5 - compared to the CZ-level estimates. The statewide estimates of log counts of PPR takers suggest approximately 1-2 percent increase in individuals interested in teaching with a 1 percentage point increase in statewide UR, though statistically insignificant at conventional levels. The statewide estimates of quality measures largely support the CZ findings. However, the math value-added estimates lose their significance. Overall, the evidence is reassuring as it presents a different specification that still comes to similar conclusions. It is perhaps unsurprising that these results are more tenuous and weaker because statewide conditions may be less salient to adolescents or because it controls for fewer necessary factors.

*WAMPOS:* de Chaisemartin et al. (2022) propose a weighted average movers' potential outcome slope (WAMPOS). The WAMPOS can be interpreted as an average effect of increasing the moving average URs by 1 percentage point on the share of PPR test takers per college graduates in a given cohort. Specifics on the estimation are provided in Appendix C. Table A6 presents the estimates of WAMPOS. In all cases for which I obtain an estimate, they are positive, implying that an increase in moving average UR corresponds with an increase in the share of PPR takers per college graduate. This implies a small role for sign flipping due to heterogeneous treatment effects.

*Removing comparisons between consecutive cohorts and cross-sectional only variation:* Given the persistent nature of labor market conditions, it may be unreasonable to compare consecutive cohorts. Instead, it is possible to separate the sample into three panels with three year lags between cohorts. Then, the moving average UR is unique to each cohort and does not include any overlapping years, and it is more likely these cohorts face very different economic conditions. Reassuringly, the three separate panels report similar point estimates across PPR exams - see

[28]Specifically, I estimate the following equation (and cluster errors at the cohort level):

$$\text{PPR}_{ic} = \alpha + \beta \text{MAUR}_c + c + c^2 + \theta X_{ic} + \epsilon_{ic} \text{ if } i \text{ is a College Graduate}$$

Table A7. They are qualitatively the same across 10th grade math exams and math value-added compared to the primary specification.

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 A5, show an effect of URs is much larger than regressions that control for time and CZ fixed-effects.

### 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 .4 percentage points and an increase of 0.09 standard deviations in 10th grade math scores among PPR takers. Math value-added is insignificant for this measure of employment. See Table A8 for details. Further, Figure A6 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 - see Appendix B for data details. 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. The results demonstrate an overall similar picture to what occurs with URs – see Table A8. Specifically, there is a positive association between larger mass layoff events and increased likelihood of becoming a teacher, higher standardized test scores among teachers, and higher value-added.

*Binary treatment variable:* I replace the continuous UR with an indicator for whether a CZ increases unemployment rate from cohort-1 to cohort. This effectively redefines a CZ as "treated" if unemployment rate increases year-over-year and assumes high school graduation year as the most relevant age for being influenced by labor markets. For an increase (of any level) in the UR, the estimates suggest an increase in the probability individuals take the PPR conditional on graduating college. However, the binary treatment variable for UR is not significant for quality measures. The continuous UR uses variation in direction and magnitude. As such, removing the flexibility may remove too much variation, and may be an explanation for insignificance of the quality measures.

*Alternative value-added:* There are many ways to estimate value-added (Koedel et al., 2015). To test robustness to my particular definition, 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 results for math value-added estimated in this manner are presented in Table A10. 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.

*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 or impute missing values for 10th grade test scores (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 across specifications that define college graduate as 4 or 8 years from high school graduation or using 2000 defined CZs instead of 1990 defined CZs. Finally, my results are robust to including independent colleges as well. Table A11 lays out the primary estimates using a definition for college graduate including independent colleges.

### 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 graduating college and 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-graduates and non-teachers based on my variable construction. This should on average downward bias my results. If those leaving were disproportionately more likely to become teachers themselves, this would again downward bias results because I treat them as non-teachers. The only situation in which there would be an upward bias is if those who leave due to poor economic conditions are more likely to be college graduates but not teachers and I condition on graduating college (as I did in regressions with PPR completions but unlike regressions for employed teachers).

To provide upper and lower bounds of 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 a bound by re-coding this 3 percent as all college graduates and PPR completers (instead of non-graduates and non-PPR completers in primary specification). To create a lower bound, I re-code the 3 percent to be college graduates but not PPR completers. I then re-run equation 2 for probability of taking the PPR conditional on graduating college with results presented in Table A12. For a 1 percentage point increase in URs, my lower bound estimate suggests an increase in 1.6 percent probability of completing a PPR while the upper bound suggests a 4 percent increase. Both the upper and lower bound estimates are close to my primary specification which finds a 3 percent increase for similar changes to local economic conditions.

I also compare CZs based on whether they border another state under the assumption that individuals may be more likely to move out of the state entirely due to economic conditions if they live close to another state. Then if attrition bias is large, border CZs and strictly-interior CZs would have differential treatment effects. The downside to this test is that border and interior CZs could experience heterogeneous treatment effects for reasons that differ from attrition. Table A13 shows the number of high school graduates completing college on-time after experiencing an economic downturn is slightly higher for border CZs than interior ones, but this effect is not statistically significant. I also find individuals in border CZs are less likely to become teachers during economic downturns. This result is also statistically insignificant. Because the point estimates on the interaction term are insignificant in both cases, this suggests there is unlikely differential attrition across border and interior CZs that would affect my primary outcomes.

Finally, movement across CZs within Texas will not generally bias my results because I observe outcome variables across the whole state. Instead, this type of movement biases 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 reduce 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 A7 demonstrate that the conclusions are nearly identical to the main results.

Overall, all of these tests suggest that the effect of attrition out of the sample entirely or across CZs seem unlikely to significantly bias my primary results.[29]

# 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. The results presented in this study align with a supply mechanism that alters students' risk preferences or updates their subjective expectations regarding job security. There is less support that the supply results are driven by compositional changes in college enrollment or graduation caused by changes in the business cycle or that students are motivated by naturally occurring changes in wages.[30] 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:*

One set of mechanisms is changes to subjective expected probability of finding employment or to risk preferences. While these two are not the same, I include them together because the way they work in changing individuals' career selection is observably similar in this context, so there is

[29] A recent paper, Foote and Stange (2022), compares earnings outcomes using state level administrative data to comprehensive U.S. administrative data. They find Texas to be one of the lowest biased in terms of earnings due to smaller attrition rates. This is another test in favor of small biases using Texas data.

[30] 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.

overlap in evidence.

Updating expected employment implies individuals revise expectations on employment or earnings across majors. This would make riskier career paths seem less appealing if individuals experience a recession. Without further theoretical underpinnings, it is unclear how this might influence expected ability changes. However, some previous work in the teaching literature has argued that teaching fits a simplified Roy model well.[31] This would imply individuals, before experiencing a shock, are sorted by ability with lowest ability in teaching and highest ability in non-teaching. Then the marginal person sorting into teaching because of a recession is both the highest ability among teachers and the least able among non-teachers. This implies teaching shares increase while non-teaching shares decrease and the ability levels in both increase on average.

Risk preferences are similar yet distinct. In essence, people who become more sensitive to risk because of scarring effects of recessions will select into more stable careers. Again this does not have an empirical prediction on what should happen to average ability across different careers. However, it would imply that volatile conditions matter more than just negative recessionary conditions.

Previous research is consistent with both mechanisms. Past work has demonstrated that risk aversion correlates with selecting safer careers, 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; 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 more influenced by the overall volatility of the labor market rather than the specific direction of the business cycle. To test this, I measure

[31] 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 matters less in teaching than non-teaching. Because teaching does not reward much 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.

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 A14.

Finally, evidence is mixed with respect to a simple Roy model. Table A15 presents information on what happens to changes in shares to other majors and their respective changes to ability. While the math ability levels increase in general for non-teaching majors, they increase irregardless of the change in share of the corresponding major, as seen in health majors. In fact, there could be several explanations that are consistent with no change in overall share of health majors that correspond with higher average ability levels. I explore this in more detail in the college composition changes.

*College composition:*

Understanding how the composition of my sample changes is crucial for determining whether the supply and quality changes presented in this study result from occupational selection or from shifts in who attends and pursues college in response to changing economic conditions.

I estimate whether the probability an individual is Black, Hispanic, white, male, or economically disadvantaged changes with URs controlling for fixed effects and CZ-wide demographic changes (i.e. equation 2 with individual demographic outcomes). I run these tests across four distinct samples: 10th graders, high school graduates, college enrollees, and on-time college graduates. I also test whether the total log count of these three samples changes with URs. These results further act as balance tests and are presented in Table 2.

There are two results that are noteworthy. First, the overall share of college graduates declines.[32] Second, these declines seem to be among economically disadvantaged students.

How might this influence the findings on supply? A decrease in college graduates could imply an increase in teaching share if those who are least likely to complete college also would not have selected into teaching. However, the evidence for this is weak. Disadvantaged students are more likely to be teachers suggesting a reduction in their share would actually downward bias results. Further, my finding of increases in the share of teachers was not limited to equations that conditioned on being a college graduate. For example, the estimate on the share of individuals employed in TPS out of all high school graduates was nearly identical in terms of magnitude.

[32]Evidence about whether students who experience downturns have different probabilities of completing college on-time is scant. At least one recent paper finds it decreases long-run attainment (Stuart, 2022). Kovalenko (2023) finds that four year college completion decreases during the fracking boom in Texas and Charles et al. (2018) find no change in bachelor's completion during housing booms. Overall, the evidence is mixed and may be dependent on the type of economic shock.

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 A15, 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 a four year college or university, or first enrolling in University of Texas at Austin or Texas A&M University, the highly selective public universities in Texas. The evidence is in the expected directions - during economic downturns in high school, graduates are more likely to enroll in community colleges and less likely to enroll in four year or selective four year colleges, as shown in Table A16. However, with the addition of controls, these are not significant effects. Regardless, if starting in four year institutions makes individuals less likely to study education, then this could be a plausible mechanism.

*Wages:*

Finally, I consider whether individuals could be influenced by changing wages that coincide with economic fluctuations. Overall, I do not find an effect of wages but there are at least a two caveats. First, it's likely that wages are sticky, and I may not be capturing appropriate wage changes (Grigsby et al., 2021; Grigsby, 2022). Second, there is less variation in wages to use for estimation.

Specifically, I first relate teacher and non-teacher wages with interest in teaching in similar specifications as before. I do not find wages to be significant predictors of completing a PPR exam conditional on graduating college – see Table A17 columns 4-7. In the models where both wages and URs are present, UR always maintains its significance and magnitude. As predicted, my results show that there are not significant changes to either teacher or non-teacher wages when local labor markets fluctuate - see columns 1-3. Altogether, this suggests a limited scope for actual wages working as a direct mechanism in this context.

This is not to say direct relative wage increases are *not* alternative ways to attract more and higher quality teachers into the profession, but rather that local wages do not fluctuate in meaningful ways for there to be a detectable direct effect from wages in this context.

### 7.2 Policy Implications

In terms of external validity, this study focuses on a particular type of student - one who enrolls in and graduates college on-time. The way these individuals react to market changes may be, and likely is, different than non-traditional students or current participants in the workforce. This is non-trivial given the increasing share of alternatively certified individuals; however, the majority of teachers in Texas become first employed in TPS in their 20s and relatively shortly after graduating college.[33] Thus, it is useful to understand the decision making process of this particular group of individuals.

The mechanisms described above are consistent with the notion that teaching is a relatively stable profession. In fact, this 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.[34]

Finally, finding that effects are more concentrated before students leave for college implies targeted programs during high school may be effective. This is not an entirely new concept for the teaching profession. Local districts manage grow-your-own programs with the hopes of retaining high school graduates or paraprofessionals as teachers in their specific district. While grow-your-own programs are heterogeneous in their implementation, their goal is to get individuals interested early in teaching and provide support for any barriers in doing so (Garcia, 2020). For instance,

[33] About 87% of individuals' first teaching year was within five years of graduating college for individuals matched between TPS and Texas college graduation. Additionally, 57% of individuals are 26 years old or younger when they first start teaching and 75% of them are under 30 years old.

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

many grow-your-own programs offer dual credit or financial support for tuition and license exams (Reininger, 2012). Texas just recently began offering competitive grants specifically for grow-your-own programs.[35] The idea behind them is motivated in part by shortages and diversity. For example, rural communities can offer grow-your-own programs to deal with low migration to smaller communities. Further, many districts strive to have diverse staff in line with their student population. To date, there is little quantitative evidence on the effectiveness of grow-your-own programs (AIR, 2018). This is left for future research.

# 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 3 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. I do not find evidence to support a direct wage effect (increased relative wages influence individuals into teaching) but cannot necessarily rule it out. 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. Further, the results herein may support grow-your-own programs, targeted toward recruitment of high schoolers. 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.

[35] https://tea.texas.gov/sites/default/files/2016-21_Strategic-Plan-Signed.pdf

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# 9 Tables

Table 1: Descriptive Statistics

| Samples: | HS Grads<br>mean/sd | Ever Enroll<br>mean/sd | College Graduates<br>mean/sd | PPR Takers<br>mean/sd |
|---|---|---|---|---|
| Completed PPR | 0.03<br>(0.17) | 0.04<br>(0.20) | 0.16<br>(0.37) | 1.00<br>(0.00) |
| Male | 0.48<br>(0.50) | 0.46<br>(0.50) | 0.41<br>(0.49) | 0.18<br>(0.39) |
| Economic Disadvantage | 0.31<br>(0.46) | 0.27<br>(0.44) | 0.15<br>(0.36) | 0.18<br>(0.39) |
| White | 0.52<br>(0.50) | 0.54<br>(0.50) | 0.65<br>(0.48) | 0.66<br>(0.47) |
| Black | 0.12<br>(0.33) | 0.12<br>(0.32) | 0.08<br>(0.27) | 0.07<br>(0.26) |
| Hispanic | 0.32<br>(0.47) | 0.30<br>(0.46) | 0.20<br>(0.40) | 0.25<br>(0.43) |
| Asian | 0.03<br>(0.18) | 0.04<br>(0.19) | 0.07<br>(0.25) | 0.02<br>(0.13) |
| 10th Grade Reading<br>STD Test Score | 0.17<br>(0.84) | 0.29<br>(0.74) | 0.61<br>(0.49) | 0.57<br>(0.49) |
| 10th Grade Reading<br>STD Test Score | 0.17<br>(0.91) | 0.29<br>(0.85) | 0.73<br>(0.64) | 0.60<br>(0.64) |
| Reading Value-Added | | | | 0.00<br>(0.16) |
| Math Value-Added | | | | 0.00<br>(0.23) |
| Experience Years in<br>Teaching (if VA Score) | | | | 7.26<br>(4.17) |
| Total Obs | 2,624,145 | 1,915,488 | 519,016 | 82,177 |

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. Total observations for reading VA, math VA, and experience years are 11,996, 12,229, and 19,377, respectively. Data sources: TEA, THECB, SBEC.

Table 2: 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 | -0.140** | -0.078 | -0.050 | -0.063 |
| | (0.063) | (0.078) | (0.100) | (0.097) |
| Hispanic | 0.153 | 0.079 | 0.033 | -0.197 |
| | (0.122) | (0.093) | (0.108) | (0.200) |
| White | -0.044 | -0.021 | 0.004 | 0.290 |
| | (0.129) | (0.123) | (0.157) | (0.250) |
| EconDis | -0.464 | -0.516 | -0.694** | -1.028*** |
| | (0.369) | (0.324) | (0.272) | (0.223) |
| Male | 0.042 | -0.038 | -0.040 | 0.017 |
| | (0.034) | (0.042) | (0.056) | (0.113) |
| Tot Obs | 3,642,749 | 2,624,145 | 1,915,488 | 519,016 |
| | | | | |
| *Log total count* | | | | |
| MA UR | 0.612 | 0.426 | -0.401 | -2.099* |
| | (0.548) | (0.653) | (0.689) | (1.078) |
| 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.

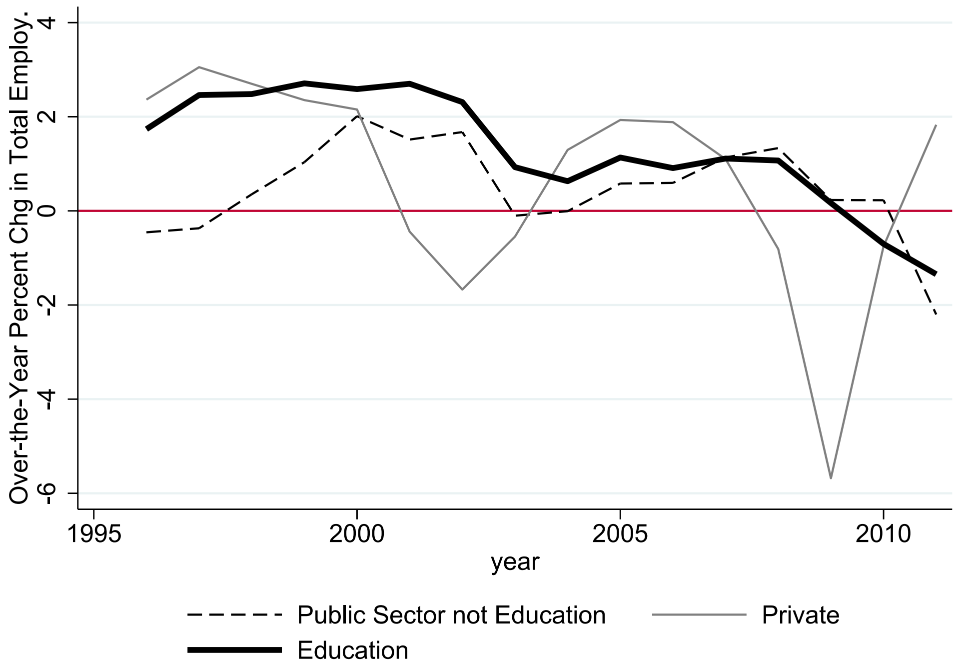
Table 3: Probability of Taking a PPR Exam, Quality of PPR Test Completers, and Local Unemployment Rates

| | 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 | 1.124*** | 0.509** | 0.389* | 0.630 | -0.525*** | 0.024 | 0.176 | 0.478 | 0.317*** | 0.537** | 0.013 | 0.261 |
| | (0.095) | (0.201) | (0.220) | (0.504) | (0.144) | (0.420) | (0.441) | (0.717) | (0.106) | (0.237) | (0.088) | (0.190) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 519,016 | 519,016 | 82,177 | 82,177 | 82,177 | 82,177 | 82,177 | 82,177 | 12,229 | 12,229 | 11,996 | 11,996 |
| Outcome Mean | 0.16 | 0.16 | 0.60 | 0.60 | 0.57 | 0.57 | 0.00 | 0.00 | 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 PPR exam completion outcome is conditional on graduating college on time; the next five outcomes (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.

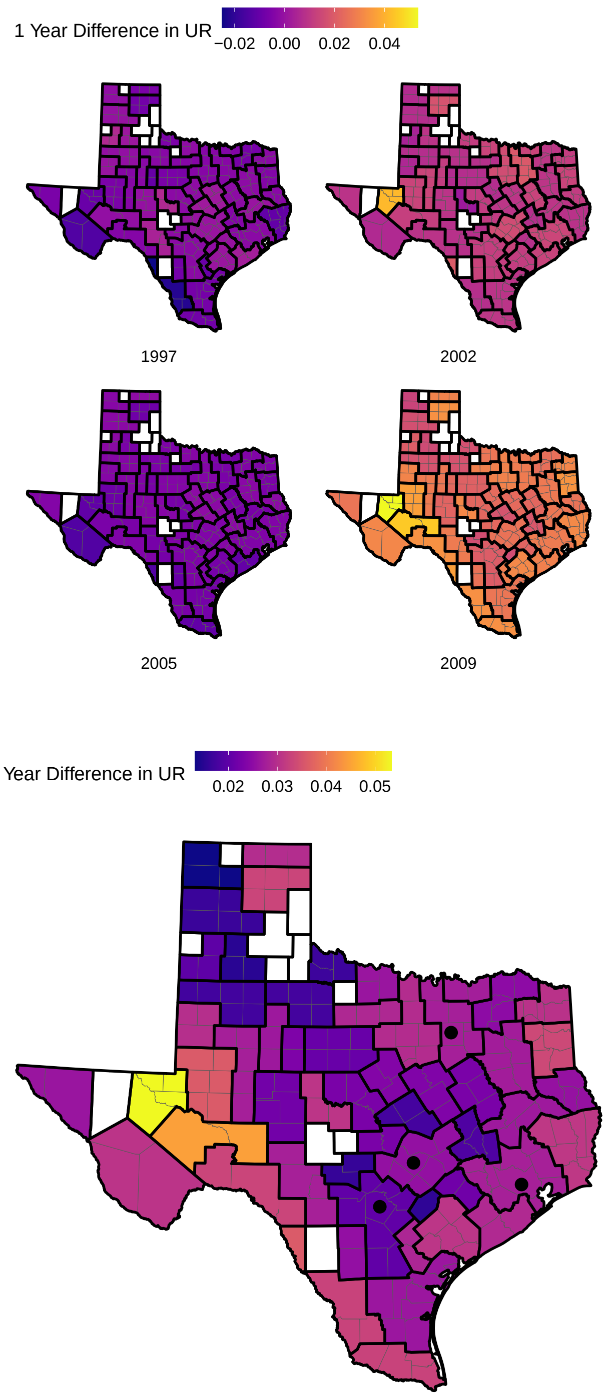
# 10 Figures

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



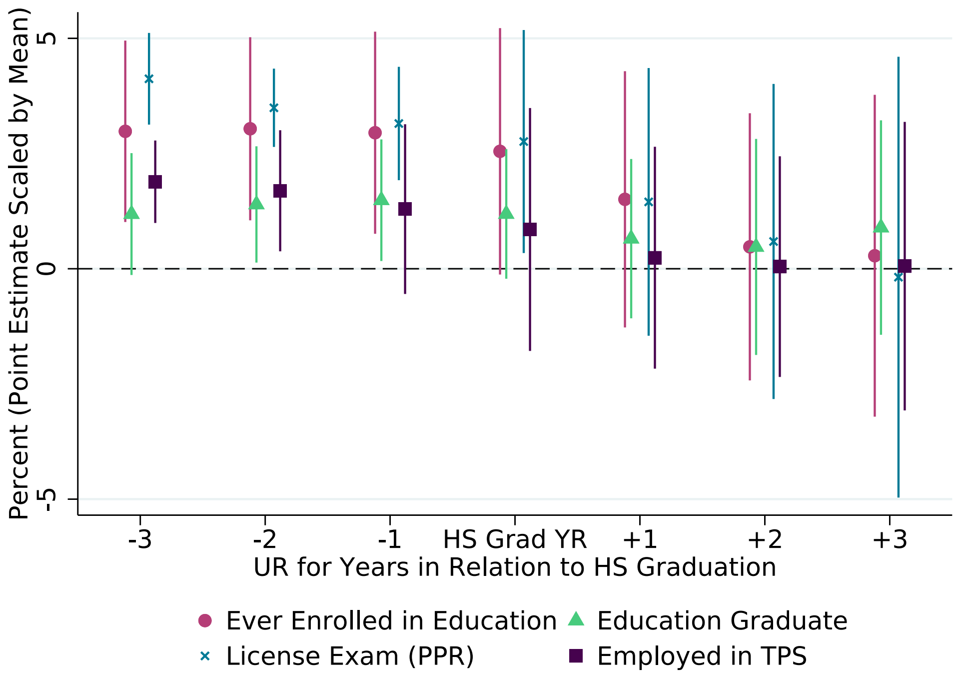

*Note*: Annual average of total Texas private employment plotted as a one-year percentage change. Education sector is industry NAICS 61 total employment across private, state government or local government, plotted as a one year percentage change. Data from the QCEW for calendar years 1996-2010.

Figure 2: One Year Difference in Unemployment Rates by Commuting Zones for Years 1997, 2002, 2005, and 2009



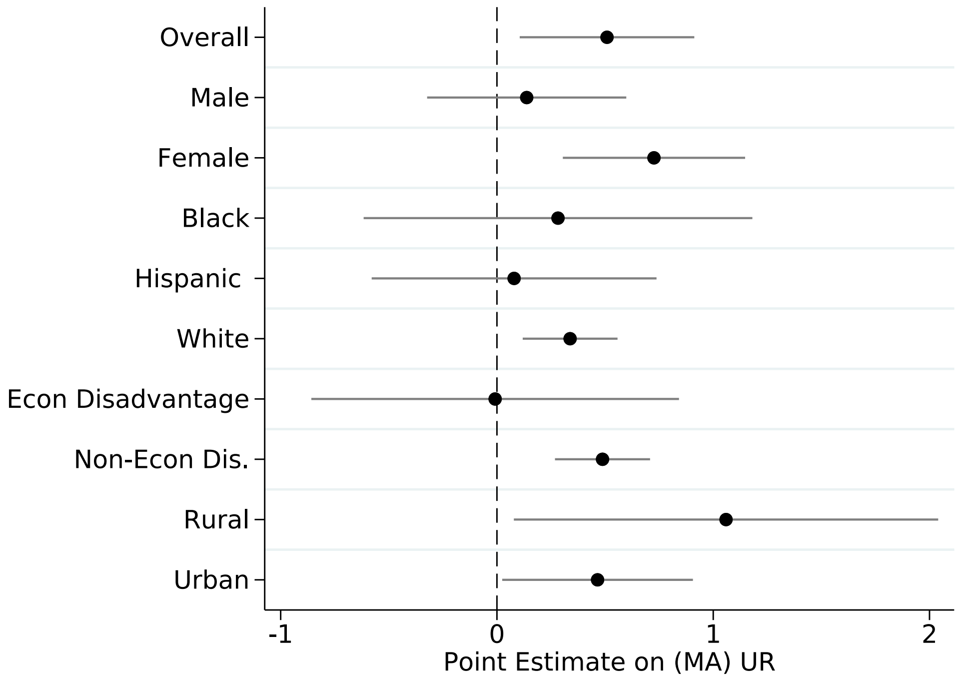

*Note*: One year differences in URs at the CZ level. White counties represent ones excluded from the sample, grey lines denote counties, and black lines trace CZs. Black cities denote Dallas, Austin, Houston, and San Antonio. Data sources: BLS.

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



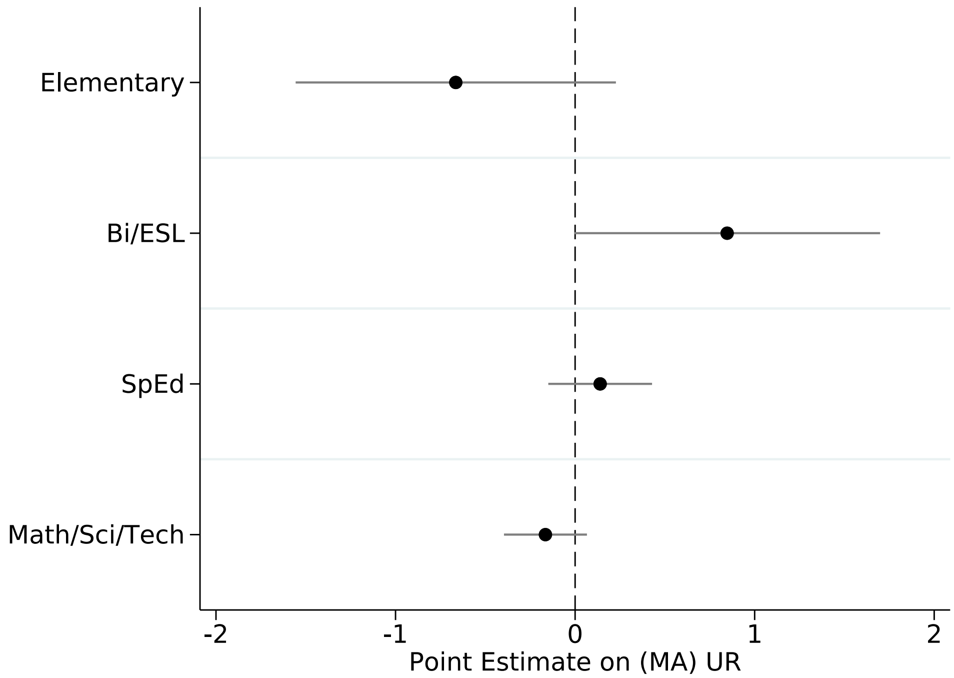

*Note*: Each point and bar are the point estimate on UR and confidence interval, respectively, *re-scaled* by the mean of the outcome so as to be comparable across outcomes. Each point estimate is a unique regression using equation 2 whereby the UR is assigned in a year relative to an individual's high school graduation year. Ever enrolled is a dummy variable for ever enrolled in an education major within 6 years of high school graduation and is run conditional on ever enrolling in college within 6 years. Graduated with education major and takes the PPR are conditional on having graduated college. Finally, employed in Texas public schools is estimated on the *whole* sample of high school graduates - there is no further conditioning on whether they graduated college or enrolled in college. All regressions control for the variables in the text, and Table A22 reports regression output. Data: TEA, THECB, SBEC, Census.

Figure 4: Probability of Completing a PPR Exam and Local Unemployment Rates by Individual Demographic Characteristics Conditional on Graduating College On-time



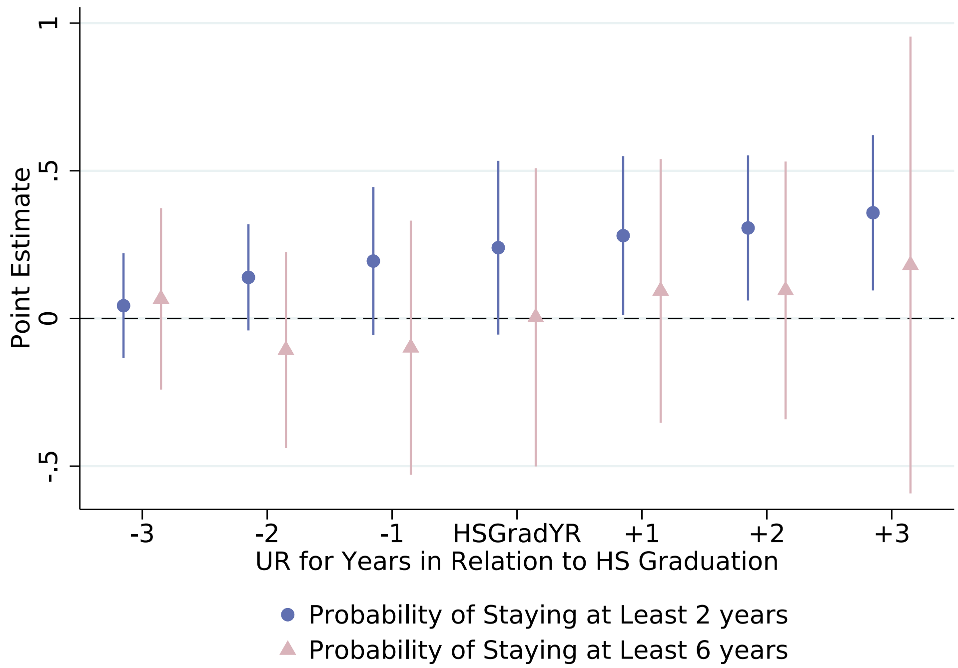

*Note*: These are point estimates and confidence intervals on a moving average UR described in text on whether an individual takes a PPR using equation 2 by different individual characteristics. These are estimated conditional on graduating college on time. Controls include CZ demographics but not individual demographics. See Table A21 and associated footnote for the regression output in more detail. Data sources: TEA, THECB, SBEC, BLS, Census.

Figure 5: Probability of Completing Different Subject Content Exams and Local Unemployment Rates Conditional on Completing the PPR



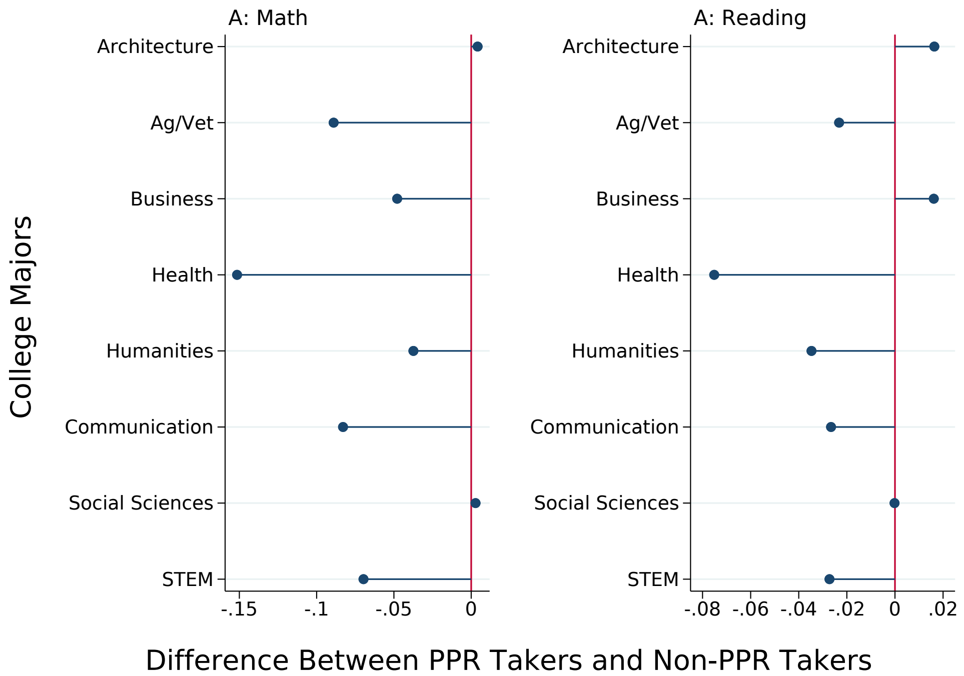

*Note*: Plotted are point estimates and confidence intervals for moving average URs for the sample of PPR exam takers within 8 years of high school graduation date who also had a corresponding content exam in the SBEC. Outcomes include whether the content exam was for elementary, bilingual/ESL, math/science/technology, or special education subjects. Outcomes are formatted (0/1). See Table A24 and footnote for the regression output in more detail. Data sources: TEA, SBEC, THECB, BLS, Census.

Figure 6: Probability Employed Teachers Have at Least Two or Six Years of Experience in Education and Local Unemployment Rates



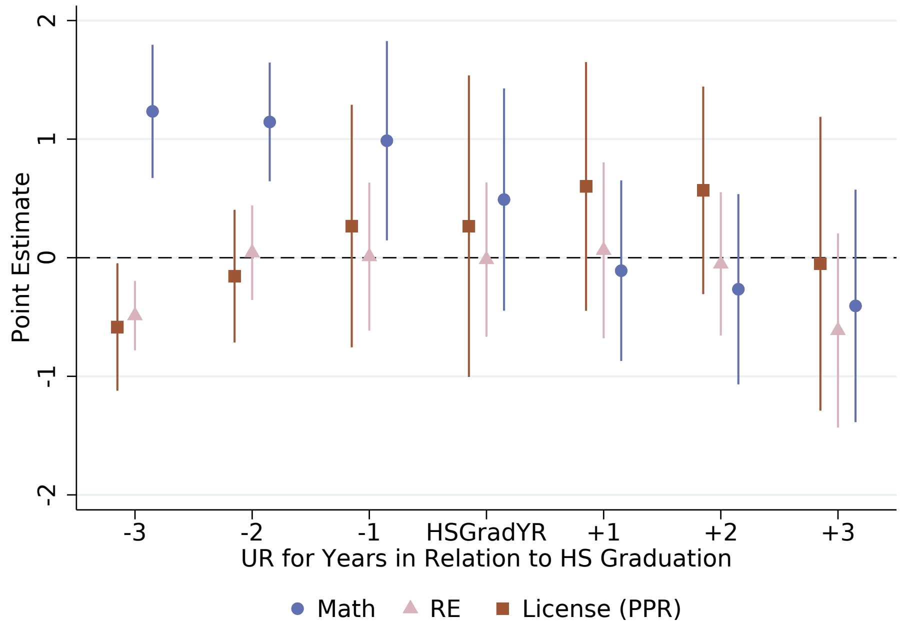

*Note*: These are point estimates and confidence intervals for unemployment rates in different calendar years with respect to high school graduation year from equation 2 where outcomes have been replaced. Outcomes are binary - 1 if an individual reported having at least two or six years of experience 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.

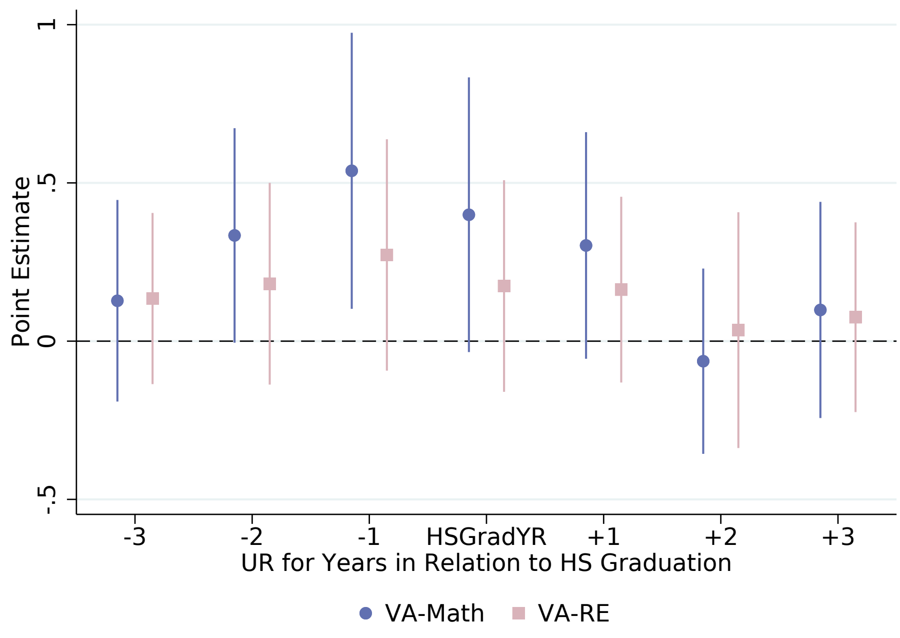
Figure 7: Difference in Math and Reading Standardized Exams Between PPR Takers and Non-PPR Takers by College Major




*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 A19 and A20 for information on the major-to-teaching mapping in Texas. Total observations: 519,016. Data sources: TEA, SBEC, THECB.

Figure 8: 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 A23 reports regression output. Data: TEA, THECB, SBEC, Census.

# Appendices - Online Publication Only

## A Tables and Figures

Table A1: 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 A2: 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 Math | 0.00 | 79,614 |
| | 1.00 | |
| Standardized VA Reading | 0.00 | 85,949 |
| | 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 A3: Standardized Value-Added Estimates and Local Unemployment Rates for Individuals with a Value-Added Score

| | STD VA-M | | STD VA-R | |
|---|---|---|---|---|
| MA UR - CZ | 1.318*** | 2.234** | 0.080 | 1.564 |
| | (0.442) | (0.986) | (0.525) | (1.137) |
| Controls | no | yes | no | yes |
| Tot Obs | 12,229 | 12,229 | 11,996 | 11,996 |
| Outcome Mean | 0.06 | 0.06 | 0.03 | 0.03 |

Notes: *CZ:* OLS regression output of equation 2 with outcomes being the standardized VA for math and standardized VA for reading conditional on taking PPR. 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. The outcome means do not have to be 0 because the standardization was with respect to all teachers with a VA score. The standard errors of the statewide estimates are clustered at the cohort-level while the CZ 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 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 | 1.124*** | 0.509** | 5.202*** | 1.956 | 3.767*** | 1.928* | 1.096*** | 0.633*** | 2.915* | -0.171 |
| | (0.095) | (0.201) | (0.386) | (1.424) | (0.336) | (1.074) | (0.081) | (0.199) | (1.734) | (1.265) |
| Controls? | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs/Cells | 519,016 | 519,016 | 519,016 | 519,016 | 784 | 784 | 784 | 784 | 784 | 784 |
| Mean | 0.16 | 0.16 | 0.16 | 0.16 | -1.83 | -1.83 | 0.17 | 0.17 | 5.50 | 5.50 |

Notes: Regressions first to last: OLS on whether an individual completed the pedagogy and professional responsibilities (PPR) exam (0/1) conditional on being a college graduate, logit on whether an individual completed the PPR exam (0/1) conditional on being a college graduate, OLS on the log share of number of PPR takers per college graduates, OLS with the share of number of PPR takers per college 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 Corresponding Quality Measures on Statewide Unemployment Rates

| | Supply | | | | Quality | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PPR | | Ln PPR | | 10th G Math | | 10th G RE | | PPR Score | | VA-M | | VA-R | |
| MA UR - State | 0.420** | 0.173 | 1.827 | 1.364 | 1.003 | 2.626** | -0.226 | 2.980*** | 1.635*** | 2.510** | 0.343 | -0.165 | -0.053 | 0.065 |
| | (0.185) | (0.114) | (1.519) | (1.751) | (0.756) | (0.921) | (1.046) | (0.886) | (0.530) | (0.940) | (0.200) | (0.271) | (0.174) | (0.207) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 519,016 | 519,016 | 15 | 15 | 82,177 | 82,177 | 82,177 | 82,177 | 82,177 | 82,177 | 12,229 | 12,229 | 11,996 | 11,996 |
| Outcome Mean | 0.16 | 0.16 | 8.60 | 8.60 | 0.60 | 0.60 | 0.57 | 0.57 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Notes: The first column is OLS regression output of equation $Y_{ic} = \alpha + \beta \text{MAUR}_c + c + c^2 + \theta X_{ic} + \epsilon_{ic}$ if $i$ is a College Graduate, where Y is an indicator for completion of a PPR exam. MA UR refers to the three year averaged *statewide* UR averaged over cohort-1 through cohort+1 calendar years. Ln PPR is the total log count of PPR takers in a given cohort run on the statewide URs with linear and quadratic controls. The remaining columns are of the same regression with quality measures, Y, corresponding to columns and conditional on completing the PPR. Cohorts span 1996-2010. Controls include white population share in TX-year, Black population share in TX-year, Hispanic population share in TX-year, Asian population share in TX-year, total working population TX-year, 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 cohort level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Data: TEA, THECB, SBEC, Census.

Table A6: Point Estimates of WAMPOS

| Epsilon | Point Est | Bootstrap Std Err |
|---|---|---|
| .001 | 6.339804 | 223.9893 |
| .002 | 17.84883 | 135.3033 |
| .004 | 7.888262 | 59.74194 |

Notes: WAMPOS estimates and bootstrapped standard errors as described in detail in Appendix C. For .001, the estimate implies an increase of 6 percentage points in the share of PPR completers per college graduates. Data sources: TEA, THECB, SBEC, BLS, Census.

Table A7: Probability of Taking PPR and Corresponding Quality Measures with Local Unemployment Rates: Non-Overlapping Cohorts

| | PPR Comp. | | 10th G Math | | 10th G RE | | PPR Score | | VA-Math | | VA- Reading | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A - 1996* | | | | | | | | | | | | |
| MA UR | 1.059$^{***}$ | 0.521$^{***}$ | 0.650$^{**}$ | 0.286 | -0.765$^{***}$ | -0.286 | -0.131 | -0.003 | 0.163 | 0.762$^{*}$ | -0.155 | 0.508$^{*}$ |
| | (0.107) | (0.123) | (0.301) | (0.648) | (0.150) | (0.380) | (0.412) | (0.796) | (0.168) | (0.425) | (0.148) | (0.302) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 165,255 | 165,255 | 26,816 | 26,816 | 26,816 | 26,816 | 26,816 | 26,816 | 3,871 | 3,871 | 3,844 | 3,844 |
| Outcome Mean | 0.16 | 0.16 | 0.60 | 0.60 | 0.57 | 0.57 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| *Panel B - 1997* | | | | | | | | | | | | |
| MA UR | 1.100$^{***}$ | 0.713$^{***}$ | 0.125 | 1.136 | -0.066 | -0.034 | 0.643 | 0.670 | 0.256 | 0.159 | 0.155 | 0.361 |
| | (0.076) | (0.245) | (0.352) | (0.767) | (0.246) | (0.639) | (0.425) | (0.886) | (0.196) | (0.363) | (0.121) | (0.419) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 174,012 | 174,012 | 27,580 | 27,580 | 27,580 | 27,580 | 27,580 | 27,580 | 4,091 | 4,091 | 4,045 | 4,045 |
| Outcome Mean | 0.16 | 0.16 | 0.60 | 0.60 | 0.58 | 0.58 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Panel C - 1998* | | | | | | | | | | | | |
| MA UR | 1.224$^{***}$ | 0.366 | 0.466$^{*}$ | 0.563 | -0.552$^{**}$ | 0.243 | -0.088 | 0.738 | 0.687$^{***}$ | 0.383 | 0.085 | -0.174 |
| | (0.126) | (0.270) | (0.257) | (0.466) | (0.223) | (0.431) | (0.805) | (0.975) | (0.177) | (0.475) | (0.149) | (0.236) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 179,749 | 179,749 | 27,781 | 27,781 | 27,781 | 27,781 | 27,781 | 27,781 | 4,267 | 4,267 | 4,107 | 4,107 |
| Outcome Mean | 0.15 | 0.15 | 0.60 | 0.60 | 0.56 | 0.56 | -0.01 | -0.01 | -0.00 | -0.00 | -0.00 | -0.00 |

Notes: Each panel represents a different set of cohorts, each three years apart. Panel A reports outcomes of equation 2 for cohorts 1996, 1999, 2002, 2005, and 2008. Panel B reports outcomes of equation 2 for cohorts 1997, 2000, 2003, 2006, and 2009. Panel C reports outcomes of equation 2 for cohorts 1998, 2001, 2004, 2007, and 2010. The column names represent the outcomes. The PPR is whether individuals complete the PPR conditional on graduating college on-time. The next five are quality measures and are run conditionally 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 sources: TEA, THECB, SBEC, BLS, Census.

Table A8: 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 | -0.200** | -0.104 | -0.253* | -0.160 | 0.221 | 0.430 | -0.036 | 0.031 | -0.056 | -0.055 |
| | (0.094) | (0.065) | (0.148) | (0.221) | (0.270) | (0.305) | (0.069) | (0.087) | (0.056) | (0.071) |
| Total Emp/Pop | -0.203*** | -0.156*** | -0.423*** | -0.444*** | -0.196* | -0.055 | -0.068 | -0.098 | -0.091* | -0.136** |
| | (0.057) | (0.036) | (0.127) | (0.159) | (0.117) | (0.143) | (0.088) | (0.065) | (0.054) | (0.063) |
| Bartik 5-year GR | -0.814** | -0.467** | -1.009*** | -0.858* | -0.072 | 0.467 | -0.229 | 0.017 | -0.224 | -0.344 |
| | (0.382) | (0.209) | (0.333) | (0.461) | (0.595) | (0.584) | (0.201) | (0.263) | (0.176) | (0.235) |
| Total 5-year GR | -0.050 | -0.020 | -0.268*** | -0.234** | -0.286** | -0.185 | -0.092* | -0.080 | -0.066 | -0.083* |
| | (0.042) | (0.043) | (0.078) | (0.103) | (0.122) | (0.134) | (0.055) | (0.062) | (0.044) | (0.046) |
| Mass Layoffs | 3.633** | 0.410 | 2.112 | 1.603 | -0.970 | -1.578 | 2.818** | 2.652* | 0.847 | 1.365 |
| | (1.723) | (0.720) | (3.095) | (3.590) | (2.263) | (2.379) | (1.287) | (1.484) | (1.062) | (1.207) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 519,016 | 519,016 | 82,177 | 82,177 | 82,177 | 82,177 | 12,229 | 12,229 | 11,996 | 11,996 |
| Outcome Mean | 0.16 | 0.16 | 0.60 | 0.60 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Notes: These are OLS regressions of equation 2 run with alternative employment predictors. Takes the PPR exam outcome is conditional on having graduated college while 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 A9: Probability of Completing PPR and Corresponding Quality Measures with Binary Treatment for an Over-the-Year Increase in Local Unemployment Rates

| | PPR | | 10th Grade Math | | VA-M | |
|---|---|---|---|---|---|---|
| 1 if UR increases over the year | 0.005** | 0.003 | -0.011 | -0.016 | -0.008 | -0.008 |
| | (0.003) | (0.003) | (0.009) | (0.010) | (0.008) | (0.008) |
| Controls | no | yes | no | yes | no | yes |
| Tot Obs | 519,016 | 519,016 | 82,177 | 82,177 | 12,229 | 12,229 |
| Outcome Mean | 0.16 | 0.16 | 0.60 | 0.60 | 0.00 | 0.00 |

Notes: These are OLS regressions of equation 2 where $UR_{zc}$ has been replaced with a binary variable for UR increasing from cohort-1 to cohort. Takes PPR is conditional on graduating college on time; the next two outcomes (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 A10: Local Unemployment Rates and Alternatively Estimated Math Value-Added

| | VA-M | | STD VA-M | |
|---|---|---|---|---|
| MA UR | 0.231** | 0.551*** | 1.714** | 4.089*** |
| | (0.108) | (0.150) | (0.804) | (1.112) |
| Controls | no | yes | no | yes |
| Tot Obs | 8,266 | 8,266 | 8,266 | 8,266 |
| Outcome Mean | 0.01 | 0.01 | 0.04 | 0.04 |

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 A11: Probability of Completing PPR and Corresponding Quality Measures for Unemployment Rates: Including Texas Independent Colleges

| | PPR | | 10 G Math | | 10 G RE | | PPR Sco | | VA-M | | VA-R | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MA UR - CZ | 1.103*** | 0.532*** | 0.503** | 0.598 | -0.481*** | -0.065 | 0.263 | 0.508 | 0.347*** | 0.602** | 0.030 | 0.284 |
| | (0.096) | (0.179) | (0.194) | (0.493) | (0.147) | (0.391) | (0.484) | (0.717) | (0.119) | (0.241) | (0.083) | (0.179) |
| Controls | no | yes | no | yes | no | yes | no | yes | no | yes | no | yes |
| Tot Obs | 601,729 | 601,729 | 93,804 | 93,804 | 93,804 | 93,804 | 93,804 | 93,804 | 13,650 | 13,650 | 13,422 | 13,422 |
| Outcome Mean | 0.16 | 0.16 | 0.61 | 0.61 | 0.58 | 0.58 | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 |

Notes: CZ panel- OLS regression output of equation 2 under an alternative definition of "college graduate". These repeat results of Tables 3 and A5 for alternatively defined college graduation. In 2003, Independent colleges and universities began reporting their data to THECB. This would correspond approximately to high school graduating cohorts 1999 and after (4 years to degree). The alternative defined college graduate is anyone who is observed in the bachelor's files including those who appear in the Independent colleges/universities post-2003, but no data from Independent college/university graduates prior. I also run results excluding 1996-1999 cohorts for both this sample and using the primary definition of "college graduate" and obtain similar results. 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, 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 of the statewide estimates are clustered at the cohort level and while the CZ 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 A12: Probability of Taking a PPR and Moving Average Unemployment Rates with Alternative Definitions for Potential Leavers from Texas Administrative Data

| | Primary Specification | | Lower Bound | | Upper Bound | |
|---|---|---|---|---|---|---|
| MA UR | 1.124*** | 0.509** | 0.816*** | 0.254 | 1.474*** | 0.916*** |
| | (0.095) | (0.201) | (0.091) | (0.215) | (0.110) | (0.211) |
| Controls | no | yes | no | yes | no | yes |
| Tot Obs | 519,016 | 519,016 | 565,278 | 565,278 | 565,278 | 565,278 |
| Outcome Mean | 0.16 | 0.16 | 0.15 | 0.15 | 0.23 | 0.23 |

Note: Primary specification represents the results specified in main text and treats anyone not observed in my dataset within 6 years from graduating high school as not a college graduate and not a PPR completer. Lower bound treats anyone who is not observed working in or graduating from college in Texas within 6 years of graduating high school as a college graduate but not having completed the PPR. 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 college graduate and 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 A13: Probability of Graduating College and Moving Average Unemployment Rates by Whether the Commuting Zone Borders Another State

| | College Grad | PPR |
|---|---|---|
| MA UR | -0.423*** | 0.526** |
| | (0.096) | (0.211) |
| I(Border state) | 0.235*** | -0.580** |
| | (0.085) | (0.248) |
| (MA UR)*I(Border state) | 0.101 | -0.064 |
| | (0.127) | (0.137) |
| Controls | yes | yes |
| Tot Obs | 2,624,145 | 519,016 |
| Outcome Mean | 0.20 | 0.16 |

Note: A border CZ is defined by whether any county in a CZ borders another U.S. state. The (MA UR)*I(Border state) term is the interaction of a moving average UR and whether a CZ is a border state. 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 BLS, Census.

Table A14: Propensity to Select into Teaching, Quality of Teachers, and Volatility of Unemployment Rates

| | Ever Enroll | PPR | Educ Grad | Employ | STD-M | VA-M | VA-R |
|---|---|---|---|---|---|---|---|
| St. Dev. UR | 0.906*** | 1.210*** | 0.482*** | 0.162*** | 1.028* | -0.094 | 0.068 |
| | (0.319) | (0.183) | (0.163) | (0.053) | (0.554) | (0.327) | (0.365) |
| Control | yes | yes | yes | yes | yes | yes | yes |
| Tot Obs | 1,886,811 | 519,016 | 519,016 | 2,624,145 | 82,177 | 12,229 | 11,996 |

*Note:* The outcomes are probability that an individual enrolls in an education major, 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.

Table A15: 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. 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 A18. 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 A16: Probability of First Enrolling in a Community College, Flagship University, or Four Year University and Moving Average Unemployment Rates

| | Community College | | Flagship | | Four Year | |
|---|---|---|---|---|---|---|
| MA UR | 0.481*** | 0.309 | -0.116*** | -0.041 | -0.452*** | -0.287 |
| | (0.140) | (0.221) | (0.030) | (0.036) | (0.141) | (0.223) |
| Controls | no | yes | no | yes | no | yes |
| Tot Obs | 1,886,811 | 1,886,811 | 1,886,811 | 1,886,811 | 1,886,811 | 1,886,811 |
| Outcome Mean | 0.62 | 0.62 | 0.04 | 0.04 | 0.38 | 0.38 |

*Note:* The outcomes 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. 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 A17: Local Unemployment Rates Affect on Log Wages and Probability of Completing PPR with Employment and Wages

| | Log Average Salary for Newly Hired Teachers | Log Average Salary For All Teachers | Log Non-teacher Average Salary | Completes the PPR Exam | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| MA UR | 0.073 | -0.079 | 0.277 | 0.522*** | 0.505** | | |
| | (0.296) | (0.151) | (0.336) | (0.192) | (0.205) | | |
| Log New Hire Base Pay | | | | -0.056 | | -0.052 | |
| | | | | (0.042) | | (0.046) | |
| Lon Non-Teacher Salary | | | | -0.032 | | -0.026 | |
| | | | | (0.023) | | (0.025) | |
| Log Ratio Salary | | | | | -0.017 | | -0.022 |
| | | | | | (0.025) | | (0.025) |
| Tot Obs | 840 | 840 | 840 | 519,016 | 519,016 | 519,016 | 519,016 |
| Outcome Mean | 10.70 | 10.90 | 10.83 | 0.16 | 0.16 | 0.16 | 0.16 |

Notes: The first three columns relate three-year moving average URs to wages (outcomes) using the two-way fixed effects model in text. These equations are weighted by total working population and for years 1996-2010. The last four columns reports point estimates from equation 2, conditional on having a college degree, jointly added URs and various measures of wages. Log ratio refers to the log ratio of average salary for all teachers divided by average salary of non-teachers based on wage data from QCEW. Log average salary for newly hired teachers is the basepay for teachers who have zero experience years in the TEA file, ie representative of newly hired teachers. 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, BLS, QCEW.

Table A18: 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 A19: 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 A20: 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 A21: Probably of Taking PPR and Corresponding Quality and Local Unemployment Rates by Demographic Characteristics

| | PPR | 10th-M | 10th-RE | VA-M | VA-R |
|---|---|---|---|---|---|
| Male | 0.138 | -0.489 | -1.232* | 0.602 | 0.610 |
| | (0.230) | (0.626) | (0.636) | (0.501) | (0.577) |
| Tot Obs | 211,229 | 15,115 | 15,115 | 1,551 | 888 |
| Outcome Mean | 0.07 | 0.72 | 0.54 | -0.04 | -0.02 |
| Female | 0.726*** | 1.057* | 0.351 | 0.496 | 0.265 |
| | (0.210) | (0.529) | (0.417) | (0.307) | (0.207) |
| 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 | 0.282 | 0.225 | -1.343 | 0.274 | 1.947* |
| | (0.448) | (2.474) | (1.983) | (1.824) | (1.123) |
| Tot Obs | 41,397 | 5,821 | 5,821 | 961 | 1,002 |
| Outcome Mean | 0.14 | 0.29 | 0.41 | 0.00 | 0.00 |
| Hispanic | 0.079 | 0.263 | -0.370 | 0.010 | 0.201 |
| | (0.329) | (0.638) | (0.602) | (0.467) | (0.385) |
| 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 | 0.338*** | -0.103 | -0.087 | 0.821** | 0.402 |
| | (0.109) | (0.672) | (0.337) | (0.393) | (0.293) |
| 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 | -0.008 | 0.554 | -0.638 | 1.770** | -0.207 |
| | (0.424) | (0.808) | (0.734) | (0.744) | (0.447) |
| 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 | 0.488*** | 0.363 | -0.095 | 0.356 | 0.502** |
| | (0.110) | (0.597) | (0.318) | (0.247) | (0.212) |
| 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 | 1.059** | -1.618 | 2.289 | -0.488 | -3.724** |
| | (0.450) | (2.678) | (3.451) | (2.546) | (1.252) |
| Tot Obs | 11,994 | 2,536 | 2,536 | 387 | 349 |
| Outcome Mean | 0.21 | 0.66 | 0.61 | -0.05 | -0.01 |
| Urban | 0.465** | -1.618 | 2.289 | 0.569** | 0.378** |
| | (0.218) | (2.678) | (3.451) | (0.254) | (0.180) |
| Tot Obs | 507,022 | 2,536 | 2,536 | 11,842 | 11,647 |
| Outcome Mean | 0.16 | 0.66 | 0.61 | 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 having a college degree and being male. The quality measures 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. 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 A22: Probability of Ever Enrolling in Education Major, Ever Graduating with Education Major, Completing the PPR Exam, and Ever Working in TPS and Local Unemployment Rates Over Time

| | Ever Enrolled in Education Major | Graduated with Education Major | Completed PPR | Employed in TPS |
|---|---|---|---|---|
| 3-year lag UR | 0.516*** | 0.159* | 0.653*** | 0.086*** |
| | (0.170) | (0.088) | (0.079) | (0.020) |
| 2-year lag UR | 0.526*** | 0.186** | 0.553*** | 0.077** |
| | (0.172) | (0.084) | (0.067) | (0.030) |
| 1-year lag UR | 0.511*** | 0.199** | 0.499*** | 0.059 |
| | (0.189) | (0.088) | (0.097) | (0.042) |
| UR-high school grad year | 0.441* | 0.159* | 0.437** | 0.039 |
| | (0.231) | (0.094) | (0.191) | (0.060) |
| 1-year lead UR | 0.261 | 0.087 | 0.230 | 0.011 |
| | (0.240) | (0.115) | (0.229) | (0.055) |
| 2-year lead UR | 0.082 | 0.063 | 0.094 | 0.002 |
| | (0.250) | (0.156) | (0.270) | (0.054) |
| 3-year lead UR | 0.049 | 0.119 | -0.029 | 0.003 |
| | (0.302) | (0.155) | (0.378) | (0.071) |
| Controls | yes | yes | yes | yes |
| Tot Obs | 1,915,488 | 519,016 | 519,016 | 2,624,145 |
| Outcome Mean | 0.17 | 0.13 | 0.16 | 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, lag 1 and lead 1 are the years before and after the student graduates high school, respectively. Outcomes from left to right: ever enrolled in education is a dummy for ever have education major reported within six years of graduating high school from the college enrollment files. They are conditional on ever enrolling in a Texas college within six years of high school graduation. Graduated with education major and PPR completion are both conditional on having graduated college. Finally, employed in Texas Public Schools is estimated on the *whole* sample of high school graduates. 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 A23: 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 |
|---|---|---|---|---|---|
| 3-year lag UR | 1.234*** | -0.488*** | -0.584** | 0.128 | 0.135 |
| | (0.280) | (0.146) | (0.268) | (0.159) | (0.135) |
| 2-year lag UR | 1.145*** | 0.042 | -0.156 | 0.334* | 0.181 |
| | (0.250) | (0.199) | (0.279) | (0.169) | (0.159) |
| 1-year lag UR | 0.987** | 0.009 | 0.267 | 0.538** | 0.272 |
| | (0.419) | (0.312) | (0.510) | (0.218) | (0.182) |
| UR-HS grad year | 0.490 | -0.016 | 0.266 | 0.399* | 0.174 |
| | (0.468) | (0.325) | (0.634) | (0.217) | (0.167) |
| 1-year lead UR | -0.109 | 0.062 | 0.601 | 0.302* | 0.163 |
| | (0.380) | (0.370) | (0.523) | (0.179) | (0.146) |
| 2-year lead UR | -0.266 | -0.052 | 0.568 | -0.063 | 0.035 |
| | (0.400) | (0.302) | (0.437) | (0.146) | (0.186) |
| 3-year lead UR | -0.406 | -0.614 | -0.051 | 0.099 | 0.076 |
| | (0.489) | (0.409) | (0.618) | (0.170) | (0.150) |
| Controls | yes | yes | yes | yes | yes |
| Tot Obs | 82,177 | 82,177 | 82,177 | 12,229 | 11,996 |
| Outcome Mean | 0.60 | 0.57 | 0.00 | 0.00 | 0.00 |

Note: Table formatting of point estimates displayed in Figure 8 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, lag 1 and lead 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 A24: 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 Conditional on PPR Completion

| | Elt | Bi/ESL | SPED | M/S/T |
|---|---|---|---|---|
| MA UR | -0.665 | 0.847* | 0.140 | -0.165 |
| | (0.445) | (0.425) | (0.144) | (0.115) |
| Controls | yes | yes | yes | yes |
| Tot Obs | 76,202 | 76,202 | 76,202 | 76,202 |
| Outcome Mean | 0.50 | 0.11 | 0.04 | 0.08 |

Notes: This is the regression output as illustrated in Figure 5. These are estimated from equation 2 on the sample of PPR exam takers who additionally had a corresponding content exam. Outcomes include whether the content exam was for elementary, bilingual/ESL, Math/Science/Technology, or Special Ed subjects all in binary formatting (0/1). 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.

Table A25: The Count and Log Count of Newly Hired Teachers with Unemployment Rates

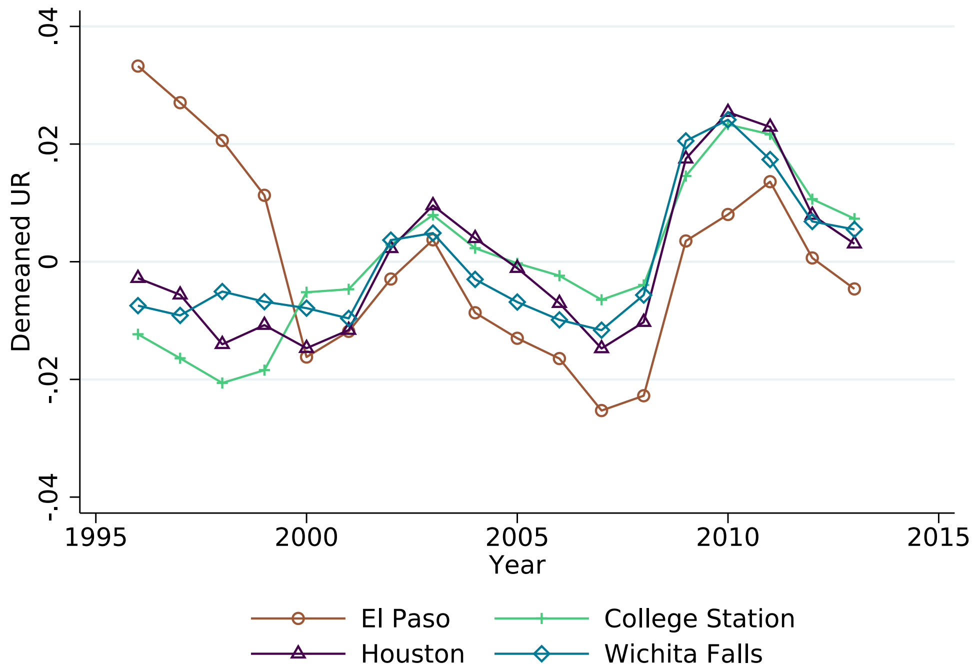
| | Count NH | Ln NH |
|---|---|---|
| *Panel A - Statewide* | | |
| UR - state | -1,884*** | -0.085*** |
| | (434) | (0.022) |
| Tot Obs | 17 | 17 |
| Outcome Mean | 21,914 | 9.988 |

*Note:* Columns are outcomes including count of newly hired teachers and log count of newly hired teachers. Newly hired is defined as an individual and year in which the individual had 0 experience years. Career start year is the calendar year in which the teacher started. URs are the prevailing unemployment rate during the calendar year of the career start year. Panel A regresses the outcomes on linear and quadratic trends for career start year. No additional controls. Both run on career start years 1997-2013.

Figure A1: Count of Newly Hired Teachers in Texas by Calendar Year of Career Start

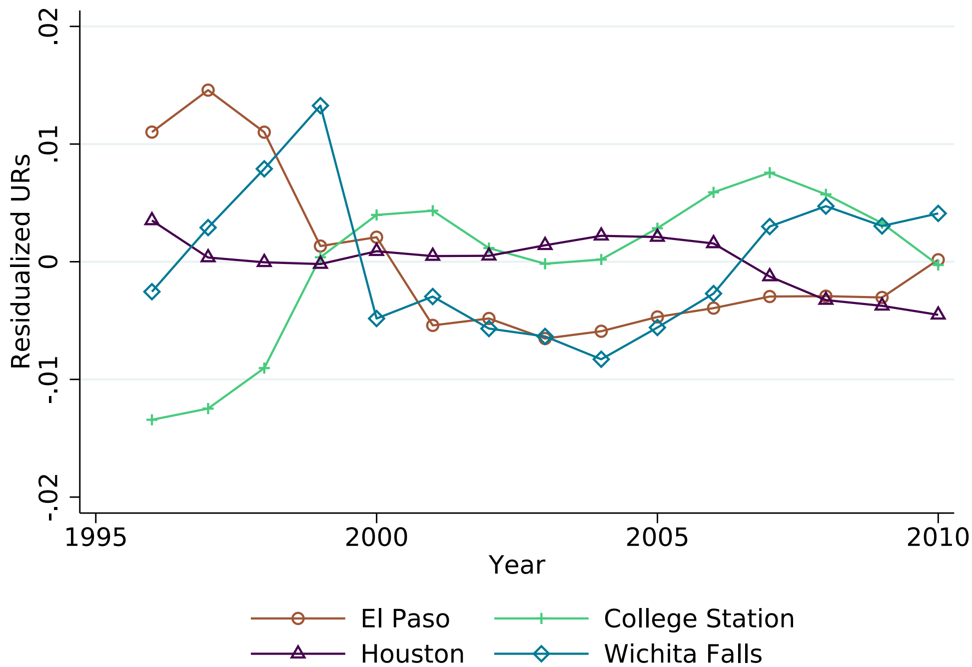

*Note*: Plots the total count of newly hired individuals in Texas public schools. Newly hired year is defined as the first year a teacher would have taught given their experience level. Calendar year refers to the year in which they would have started. For example, if a teacher started in 2001-02 school year, they are counted as newly hired in 2001 calendar year. Data: TEA. See Table A25 for regression output of newly hired and current employment conditions.

Figure A2: De-meaned Unemployment Rates for Four Commuting Zones from 1996-2010



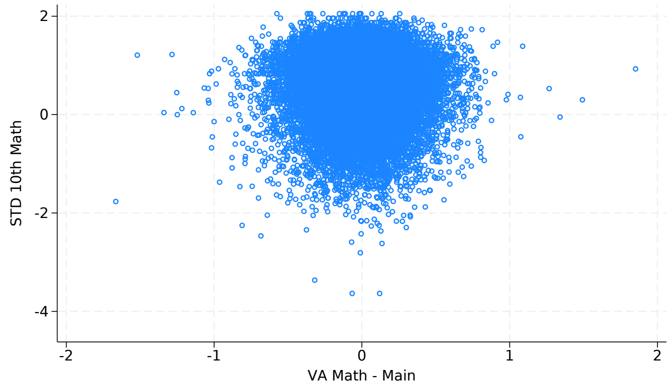

*Note*: Specific CZs are chosen based on 1996 population in CZs and to be representative of different sizes and a variety of locations. CZs listed by a metro- or micro-politan city within the CZ. Working age population in 1996: Houston 2.5 million; El Paso 363,072; College Station - 116,851; and Wichita Falls - 86,407. URs demeaned based on data from the whole period. Data: BLS.

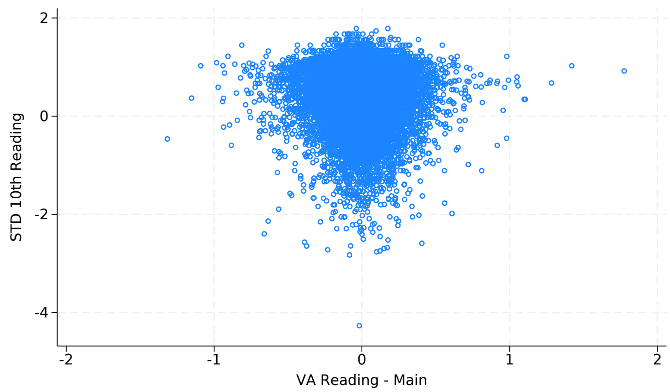
Figure A3: Unemployment Rate Residuals for Four Commuting Zones




*Note*: Specific CZs are chosen based on 1996 population in CZs and to be representative of different 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.

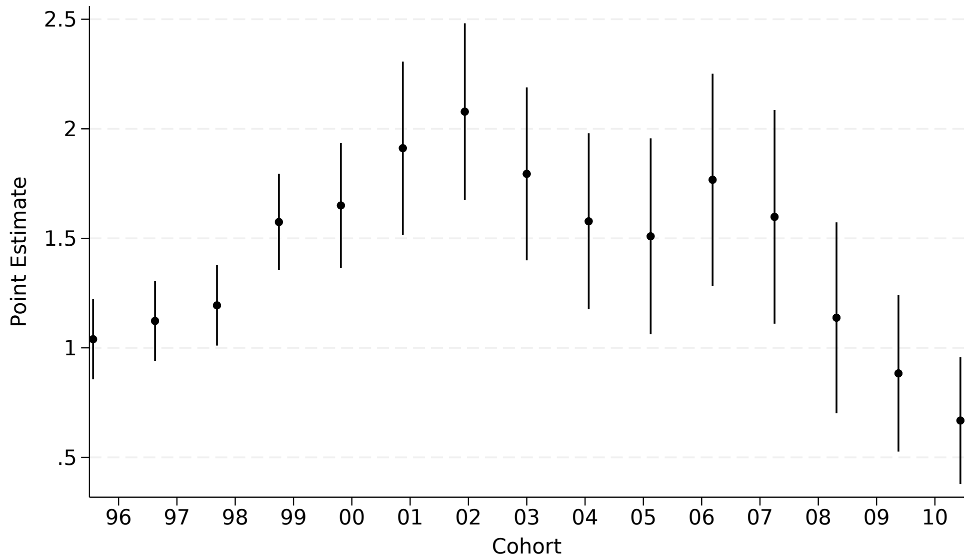
Figure A4: Tenth Grade Test Scores and Value-Added for Math and Reading



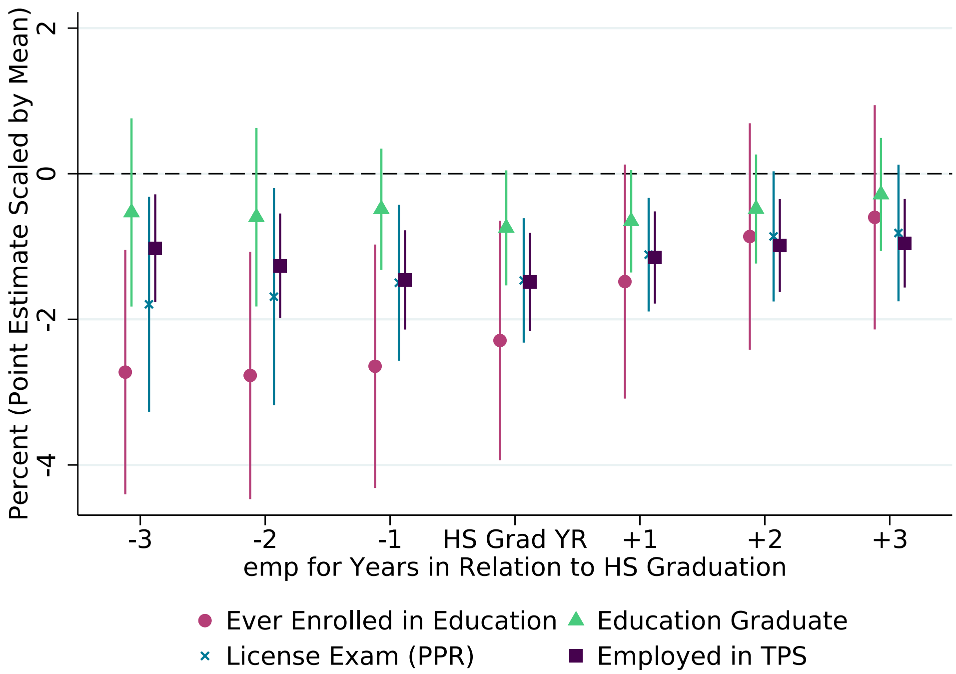

*Note*: Scatters of the standardized 10th grade math scores and math value-added (top) as well as for reading (bottom). Data: Data: TEA, THECB, SBEC.

Figure A5: UR Cross-sectional Variation Affect on PPR Exams



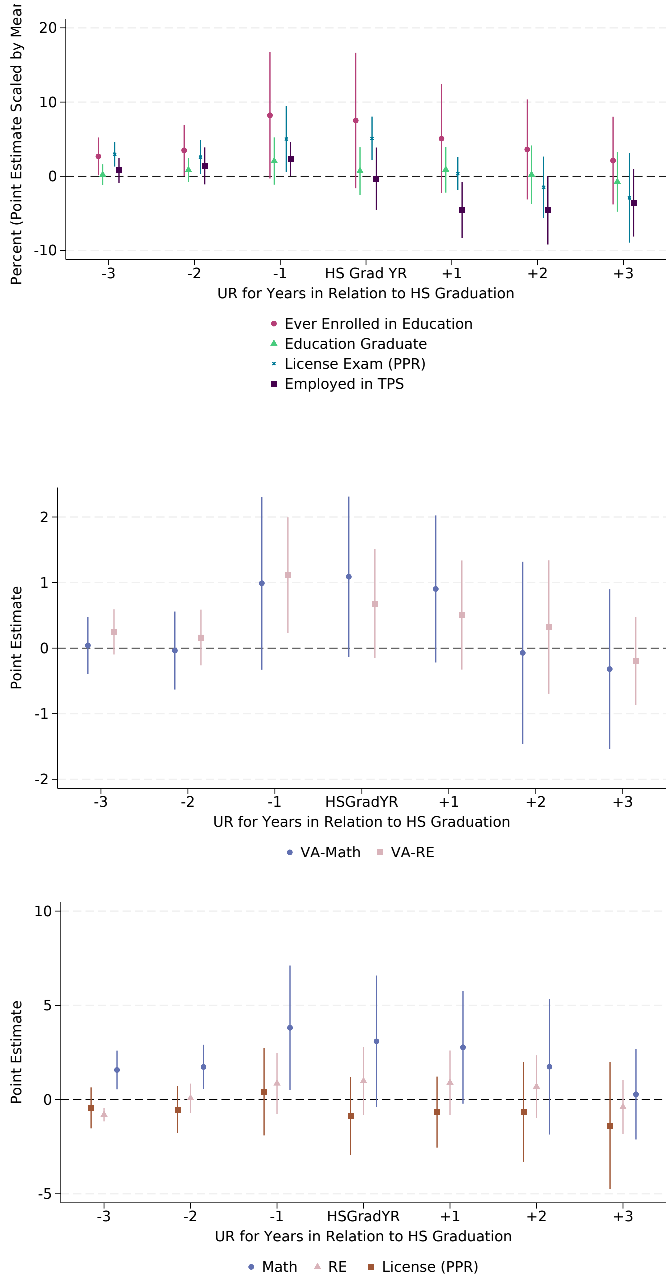

*Note*: Each point and bar are the point estimate on UR and 95 % confidence interval. Each point estimate is a unique regression using only cross-sectional variation in UR within the cohort-year. All regressions control for the variables in the text. Data: Data: TEA, THECB, SBEC, BLS, Census.

Figure A6: 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. Ever enrolled is a dummy variable for ever enrolled in an education major within 6 years of high school graduation and is run conditional on ever enrolling in college within 6 years. Graduated with education major and takes the PPR are conditional on having graduated college. Finally, employed in Texas public schools is estimated on the *whole* sample of high school graduates - there is no further conditioning on whether they graduated college or enrolled in college. All regressions control for the variables in the text. Data: Data: TEA, THECB, SBEC, BLS, Census.

Figure A7: Main Results for students who attended their HS for 4 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

**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,[36] 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, 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

[36] 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).

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).[37] 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.[38] 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 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

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

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

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 A19, 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 A20 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.[39] 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 employ-

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

ment and annual wages up to the commuting zone-year and commuting zone-industry-year level.[40] The QCEW publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs.[41] 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 employment 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.[42] 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

[40] 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.

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

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

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. 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."[43] 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.[44] I download the 1990-2015 data from https://www.nber.org/research/data/us-intercensal-county- 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).

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

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

**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 counties 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 Calculating WAMPOS from de Chaisemartin et al. (2022)

de Chaisemartin et al. (2022) propose a heterogeneous robust estimator, referred to as the weighted average movers' potential outcome slope (WAMPOS). This estimator is useful in the case of two-way fixed effects models where the treatment is continuous.

de Chaisemartin et al. (2022) define:

$$\delta_{it} := \frac{E(Y_t(D_t) - Y_t(D_{t-1})|M_{i,t} = 1)}{E(D_t - D_{t-1}|M_{i,t=1})}$$

$$\delta_{dt} := \frac{E(Y_t(D_{t-1}) - Y_t(D_t)|M_{d,t} = 1)}{E(D_{t-1} - D_t|M_{d,t=1})}$$

Where $M_{i,t}$ is an indicator for treatment strictly increasing over time t-1 to t and $M_{d,t}$ is an indicator for treatment strictly decreasing over time t-1 to t. Finally, $Y_t(D_t)$ is the potential outcome at time t for level of treatment $D_t$. Under their assumptions A7, 2-3 of A8 (listed below) the overall WAMPOS is equivalent to:

$$= \sum_{t=2}^{T} \frac{P(M_{i,t} = 1)}{\sum_{k=2}^{T} P(M_k = 1)} \delta_{it} + \sum_{t=2}^{T} \frac{P(M_{d,t} = 1)}{\sum_{k=2}^{T} P(M_k = 1)} \delta_{dt}$$

Or that the overall estimate for WAMPOS is a weighted average of the time specific $\delta_i$'s and the time specific $\delta_d$'s with weights corresponding to roughly how likely it is that the treatment is increasing in time t or decreasing in time t given the probability to change in any direction, $P(M_k)$.

Assumptions:

- (de Chaisemartin et al. (2022)'s A7) Parallel trends - for every period and for all potential levels of the continuous treatment, the mean differences over time would have been the same without any change in treatment status
- (de Chaisemartin et al. (2022)'s Pt 1 and 2 of A9) some stayers- for each group of increasers and decreasers, there is some comparison group to which you can compare for each t-1 to t $\rightarrow$ Applied straight forwardly in the case of no exact stayers.

### C.1 Practical implementation and data decisions

I collapse down to the CZ-cohort level and use share of PPR takers per college graduates per cohort as the outcome. In this specification, I do *not* weight for relative size of the CZ-cohort. I begin with a balanced panel.

Given that $\delta_{it}$ and $\delta_{dt}$ are calculated for each t-1,t, or consecutive two period iterations in the full sample, this requires at least some stayers and some increasers/decreasers for each t-1,t period. However, this may not be possible for each t-1,t period. In my case, I have to eliminate several years, and make the choice to only include a consecuetive two year period if it includes increasing units AND decreasing units. (For instance, t = 1999, 2000, and 2001 when $\epsilon = .002$, $\epsilon$ described below.) In what follows, I only include this subset of years in the calculation of any sample estimates. For my purposes, I label

$$\sum_{t=2}^{T} \frac{P(M_{i,t} = 1)}{\sum_{k=2}^{T} P(M_k = 1)} \delta_{it} = \delta_i$$

$$\sum_{t=2}^{T} \frac{P(M_{d,t} = 1)}{\sum_{k=2}^{T} P(M_k = 1)} \delta_{dt} = \delta_d$$

And its sample estimate denoted with a hat. **Note:** because in my sample I have no organic stayers (i.e. I never experience a difference in moving average unemployment rates from t-1 to t to be exactly zero), I must assume some small $\epsilon$ such that the absolute value of any movement less than $\epsilon$ is considered a stayer, or that:

$$M_{it} = (MAUR_t - MAUR_{t-1} > \epsilon)$$

$$M_{dt} = (MAUR_t - MAUR_{t-1} < -\epsilon)$$

I let $\epsilon$ be .001, .002, and .004.

### C.2 Calculating $\delta_i$

There are two components needed to calculate $\hat{\delta}_i$. First is an estimate of each $\hat{\delta}_{it}$. This is straight forward using the `fuzzydid` program in Stata with guide de Chaisemartin et al. (2019). Let:

- `Y` - is equivalent to the outcome variable, in this case share of PPR takers out of all college graduates.
- `G(s)` - Because it is the two period case for each `t`, only one value needs to be defined here, this is the treatment-*group*. Since we're calculating an estimate of the increasers versus stayers, this is an indicator for whether the period t-1 to t (continuous) treatment increases for each CZ, or in de Chaisemartin et al. (2022) the period t-1 to t $M_{it}$
- `T` -the time variable. Here it is cohort.

- `D` - the treatment variable. Here it is the continuous treatment, or moving average unemployment rate.

- `Options`

  - Select `did` which computes the Wald DID X given that we specify control variables.

  - `continuous()` as is **necessary**, I include the lagged value of the continuous treatment variable as required by de Chaisemartin et al. (2022), or the t-1 moving average unemployment rate for each CZ.
    → de Chaisemartin et al. (2022) do not explicitly state what to do about other covariates. I add my additional demographic covariates here.

Additionally, I choose to keep only units that are defined as increasers or stayers for the `fuzzydid`. In general, including the decreasers (as stayers) reduces the estimates but is qualitatively in line with estimates without them (still positive). The final step is to create a weighted average these individual $\delta_{it}$. The weights correspond to $\frac{P(M_{i,t}=1)}{\sum_{t=2}^{T} P(M_k=1)}$, or approximately how likely in period t it is to have increasing unemployment rates from t-1 over the total probability that unemployment rates will change in any direction in any period. Practically, I calculate the sample estimate of $\sum_{t=2}^{T} P(M_k = 1)$ as the mean value of an indicator with movement in any direction in each year (cohort) and then added together. Similarly, I calculate the sample estimates of $P(M_{i,t} = 1)$ as the mean value of an indicator for increasing in period t.

### C.3 Calculating $\delta_d$

As suggested in de Chaisemartin et al. (2022), part of each $\hat{\delta}_{dt}$ is calculated via the `absdid` command with help guide Houngbedji (2016). As stated, `absdid` calculates an estimate the numerator of the $\delta_{dt}$, or $E(Y_t(D_{t-1}) - Y_t(D_t)|M_{d,t} = 1)$ (de Chaisemartin et al., 2022). For now, I'll call it $-\hat{\delta}_{dt}^{Num}$. I calculate this following in the `absdid` program (Houngbedji, 2016):

- `depvar` - this is the *difference* in the outcome variable from time t-1 to t. Here, this corresponds to the difference from t-1 to t in share of PPR takers per total college graduates.

- `Options`:

  - `tvar` - an indicator for whether the moving average unemployment rate decreased from period t-1 to t, or $M_{dt}$ (de Chaisemartin et al., 2022).

– `xvar` - the lagged (continuous) treatment variable, or moving average unemployment rate in t-1 (de Chaisemartin et al., 2022).

  → As above, there's no explicit statement for what to do with additional controls. I add demographic controls here.

- Note: We do not include the (continuous) treatment variable here because it is used in calculating the denominator of $\delta_{dt}$.

Like above, I include only decreasers and stayers for these estimates. What remains in the estimation of $\delta_d$ is the weighted average as above and the denominator in the $\delta_{dt}$. Technically for each time t, we still need to calculate:

$$\sum_{t=2}^{T} \frac{P(M_{d,t}=1)}{\sum_{k=2}^{T} P(M_k=1)} \frac{-\delta_{dt}^{Num}}{E(D_{t-1}-D_t|M_{dt}=1)}$$

I replace each component with their sample estimates. Practically, I calculate the $\sum_{k=2}^{T} P(M_k = 1)$ as the mean value of an indicator with movement in any direction for each year and added together. The estimate of $P(M_{d,t} = 1)$ is the mean of an indicator for decreasing continuous treatment in period t ($M_{dt}$). Finally, the average in the (negative) change in treatment from t-1 to t conditional on having a negative change in that two-period set of years is the estimate for $E(D_{t-1} - D_t|M_{dt} = 1)$. All together and over time, this leaves $\hat{\delta}_d$

### C.4 Final Estimate

WAMPOS $= \hat{\delta}_i + \hat{\delta}_d$

### C.5 Inference

At the time of this draft, de Chaisemartin et al. (2022) have not provided guidance on calculating standard errors. To get bounds on the point estimates, I calculate bootstrap standard errors (1,000 reps). Specifically, I sample with replacement units while keeping the time horizon fixed. Two caveats are of note. First, I am not weighing by size of CZ and these estimates are calculated on the shares. This inherently means small CZs may be over sampled (equal probability of being chosen in each sampling of the dataset). Second, due to some of the data restrictions outlined above, some iterations may sample CZs such that fewer years are used in the making of the point estimate or that the estimate cannot be calculated at all.[45] Both of these are likely to inflate standard errors and it is difficult to say how informative the bootstrap errors are.

[45]For instance, epsilon = .001, results in 14 out of 1,000 fails in estimation.

## D 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).[46]

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
    - Student must be recommended through program
5. Apply for a Standard Certificate

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

[46] 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."

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.