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 to the workforce to determine the effects of local labor markets on selection into teaching. I find that local labor market conditions are countercyclical with selection into teaching. I also show that 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 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. As such, increasing the economic standing of teachers and highlighting stability of the profession have potential to improve the future supply of teachers.

JEL: E32, H75, I20, J24, J45

Keywords: teachers, occupational choice, college major, local labor markets

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1 Introduction

Recent interest in teachers' working conditions resulting from the Covid-19 pandemic has highlighted two persistent issues plaguing the teaching profession. First, certain subjects (math) and localities (poor urban) have difficulty in filling vacancies (Cowan et al., 2016). Further, the rigid structure of teacher pay has potentially pushed high ability individuals away from teaching (Hoxby and Leigh, 2004; Bacolod, 2007; Britton and Propper, 2016; Fraenkel, 2018; Nagler et al., 2020). Crucial to maintaining a large and effective workforce of primary and secondary teachers is understanding how individuals select into the teaching profession both in terms of quantity and quality. However, studying selection into teaching is difficult because individuals form expectations over careers well before they begin working. Further, previous research has typically studied teacher quality using employed teachers. However, employed teachers are a function of changes in demand (hiring) and supply (selection), making it difficult to conclude effects are the result of selection alone (Nagler et al., 2020).

To overcome these issues, I use administrative data from the state of Texas to track individuals from adolescence along the pipeline of becoming a teacher. I ask whether local labor conditions during adolescence affect selection into the teaching profession. Economic conditions matter because teaching is a stable career, and thus recessions may increase the perceived desirability of teaching relative to other professions (Nagler et al., 2020). Further, the desirability of teaching relative to other occupations in the local area may be particularly important because many teachers work close to home (Reininger, 2012). I join the Texas administrative data with variation in local business cycles across commuting zones (CZs) in a fixed effects design to identify an effect of unemployment rates (URs) on interest in teaching and associated quality. I find that worse local labor market conditions increase the number of individuals interested in teaching, and that the effects of local labor market conditions experienced during or prior to high school graduation have the largest effect on future career decisions. Finally, I show that individuals induced into teaching due to poor local labor market conditions have higher math ability and higher math value-added than the typical individual selecting into teaching.

Specifically, I begin by creating a longitudinal dataset that follows individuals from high school through college and into teaching careers for the entire state of Texas. I start with 2.6 million students who graduated from Texas public schools from 1996 through 2010 who have math and reading standardized test scores. I connect these graduates to their college enrollment and college graduation outcomes. This allows me to view both the extensive margin of educational attainment as well as the intensive margin - whether they show interest in teaching as measured by college majors. I further match these data with the universe of teacher certificates which contain information on whether and when an individual took teacher certification exams and how they scored. Finally, I track these individuals into realized employment outcomes. I see whether they gain employment in Texas public schools (TPS) and, for some, calculate value-added, a well-validated productivity measure of teachers (Chetty et al., 2014a). The data comprise a long panel structure and produce insights into decisions made along several junctures well before individuals begin their job search. This is a particularly valuable contribution given the time span between selecting a career path and entering the labor force (Freeman, 1975; Bettinger, 2010).

To measure the strength of the local economy, I utilize unemployment rates at the commuting zone-level. Unemployment rates represent a salient measure of the local economy and are likely to be felt and understood with fairly little information seeking. I define the relevant CZ as the one in which the individuals graduated from high school. I focus on CZs because of the propensity to return to local areas post-graduation, especially among teachers (Boyd et al., 2005; Reininger, 2012). 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.[1] Combining these data, I use naturally occurring variation in local business cycles across CZs in a fixed effects design to identify an effect of URs on interest in teaching. My empirical strategy is akin to a natural experiment comparing individuals who incur better or worse local economic conditions due to factors such

[1] 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, approximately 38 percent had their modal county-of-business from UI data 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.

as differential impacts of macroeconomic shocks, local factories closing, or fracking booms (Nagler et al., 2020; Weinstein, 2020; Acton, 2021). Causality under this empirical strategy requires that changes in URs over time are plausibly exogenous with respect to individuals' future career paths conditional on a rich set of controls including location and time fixed effects.

I find higher local URs that occur during high school increase interest in teaching. This result is consistent across several definitions of interest in teaching including future enrollment in an education major, future receipt of a bachelor's 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 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. This suggests movement into at least one shortage subject. Finally, I do not find evidence that these teachers are more likely to leave the profession within a six year period which suggests these are long-term shifts in career paths.

During depressed local labor markets, those who express interest in teaching have higher ability as measured by math standardized exam scores. Further, employed teachers who matured during 1 percentage point higher URs improve their students' standardized math scores by approximately .005 standard deviations. This means that the effects on teacher ability translate to realized gains for next generation students. Consistent with earlier results, I find that local labor market conditions are most relevant the years before potential teachers graduate college and enter the teaching labor market.

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. Balance tests do not detect differences in demographic composition of 10th graders, high school graduates, college enrollees, or on-time college graduates during my sample period. Further, my results are robust to different definitions of local labor market conditions, alternatively defined outcome variables, and constant linear trends 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).

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. For instance, there is suggestive evidence of a decline in college graduation, albeit statistically insignificant. This decline 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.

There are several mechanisms through which local labor markets could assert influence over major or career choice. Two likely candidates are changes in expected risk or employment probabilities and changes to expected earnings. As discussed in more detail in Section 7, I do not find that local labor market wages are significantly associated with selection into the labor market. This means that I do not find evidence of a direct wage mechanism at play but cannot necessarily rule it out. My results are entirely consistent with a risk channel or updated beliefs over employment probabilities. While relatively modest, the results suggest scope for policy makers to attract more and better able individuals into the teaching profession by increasing economic standing and by promoting the relative stability of the profession (Nagler et al., 2020; Kraft et al., 2020). Finding effects pre-college suggests that grow-your-own programs may be successful in attracting quality candidates into teaching.

Previous research linking economic conditions to selection into the teaching profession has exclusively focused on individuals who ultimately accepted teaching positions (Figlio, 2002; Hoxby and Leigh, 2004; Bacolod, 2007; Fraenkel, 2018; Nagler et al., 2020).[2] In other

[2]One exception is Leigh (2012) who studies selection in Australia using pre-employment data and teacher wages instead of employment. Australia's process for becoming a teacher and social/financial context for teachers is different from the US. Further, I have improved quality measures and use different methodologies. Further Leigh (2012) again just considers one point on the pipeline instead of the whole process.

words, researchers have related labor market conditions with *employed* teachers' corresponding ability/quality. Given that changes in labor market conditions can potentially influence teacher hiring decisions, studying employed teachers does not definitively convey information on selection both in terms of quantity or quality. Also, in previous work such as Bacolod (2007), (relative) pay and teacher quality may be endogenous. Teachers may sort *within* a labor market such that higher quality teachers are employed in areas with higher (relative) teacher pay.

My contribution to this literature is in reasonably isolating the supply side effects of labor market conditions by tracking individuals *before* they participate in the labor market and through perturbing shocks to their expectations over careers *prior* to any changes that occur during the labor market in which they participate. Further, I track individuals along the pipeline of becoming a teacher instead of at one point in time such as employment. The dataset I construct contributes to the understanding of the potential supply of teachers, their alternatives including at the extensive margin (i.e. completing college), and quality in a way that uniquely defines how local labor markets influence selection. I also explore shortage areas and heterogeneity across demographics. Finally, I study sub-state labor markets which is particularly valuable given the need for teachers in every community, and the locality of the teacher labor markets in general.

In addition to the work on selection into teaching, I also contribute to a burgeoning literature on the effects of business cycle fluctuations on college major choice. Blom et al. (2021), Ersoy (2020), Liu et al. (2019), and Bradley (2012) analyze macroeconomic effects over cohorts on a wide variety of four-year degrees.[3] Generally, they find individuals sort towards higher paying or more stable jobs during recessionary periods, though there are differences in some specific college majors across the Great Recession versus previous economic downturns. These studies rely on the assumptions that college major unobservables do not change over a given time span or they place specific functional forms on the way college major unobservables may trend over time. Contrastingly, my empirical approach using time fixed effects is less restrictive and allows the utility of teaching relative to non-teaching careers

[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)

to flexibly change in each year. Furthermore, I study the effects of local labor markets as opposed to U.S. or state-level employment conditions. Additionally, I study how this affects selection by ability, not just changes in composition of college majors.

Other work has studied the importance of local factors in influencing degree choice, but for other types of majors and labor markets. Focusing on geology, business, and computer science degrees, Weinstein (2020) studies macro-industry shocks (i.e. 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. I track individuals beyond initial college enrollment by observing college graduation and post-graduate occupation.

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.

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).[4] Until 2019, there was no defined education major, meaning 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.[5] The process for traditional teacher certification begins with enrollment in an education preparation program affiliated with a university. During enrollment, students concurrently make progress towards their bachelor's degree and the requirements of the education preparation program. Despite the lack of a uniform major regulated by the Texas State Board for Educator Certification, many colleges have specified majors - often categorized under interdisciplinary studies. Table A16 and A17 list the most common majors among employed teachers.

Starting in 1999, the Texas State Board for Educator Certification relaxed standards for alternative certification programs in order to attract individuals from non-traditional paths into teaching (Templeton et al., 2020). Similar to traditional programs, alternative certification programs require passing the education preparation program requirements and license exams conditional on having a bachelor's degree. Given the lack of a unified "education" major in Texas, the alternative education preparation program is similar in spirit to the traditional pathway but is targeted towards post-baccalaureate individuals. Alternative certification programs are becoming more popular across all states, and they are quite popular in Texas.[6] Just from the 2010-11 to 2017-18 school year, the percent of teachers certified through traditional routes declined from 89 percent to 74 percent based on national statistics (Education, 2021). In my sample, described in Section 3, about 29 percent and 68 percent of students become certified through alternative programs and traditional programs, respectively.

Overall, the number of college students pursuing teaching as a *share* of total bachelor's earned has declined, and these declines are not recent (Altonji et al., 2016; Bacolod, 2007). In fact, the share of women choosing teaching has steadily declined since the 1970s when women started to enter college at much higher rates (Hoxby and Leigh, 2004; Bacolod, 2007)

[4] For the complete list of information, see Appendix E.

[5] For change in 2019 see HB 3217, SB 1731 amending Section 21.050.

[6] See Title 2 data on enrollment in education preparation program on this website for more recent years: https://title2.ed.gov/Public/Home.aspx

- see Figure A2. This pattern is present in Texas as well.

2.2 Conceptual Framework

Teacher employment tends to be *relatively* more stable than private sector jobs (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. As such, it is not unreasonable to suppose that business cycles would bring attention to the relative stability of the teaching profession.

However, teachers are not immune to economic shocks even if they have on average more stable employment levels. In particular, much of school districts' revenue is derived from sources that may fluctuate with changes in economic conditions. What would happen to the average quality of teachers under reduced demand? If school districts can ascertain the quality of a candidate, they would always choose the highest quality candidate willing to teach in their schools. Holding fixed the supply of teachers, reduced demand would consequently lead to higher quality newly-hired teachers on average.

Thus with many moving parts, particularly during times of economic fluctuations, it is difficult to ascertain whether hiring (demand) or selection into teaching (supply) is a stronger influence on changes in quality. Without further assumptions or better data, we cannot delineate the two. Motivated by the difficulties to disentangle equilibrium observed number of teachers employed and their relative quality, as opposed to the *flow* of potential teachers and *their* quality, I study individuals during a crucial period in which they are finalizing a decision that affects their career trajectory, but before they enter the labor market.

Students for whom college attendance (and completion) has been decided face similar educational costs across major fields of study.[7] Still, there are many components that enter into their choice of what to study and do post-college graduation. These include non-

[7] Of course, field of study can be related to either of these, i.e. some fields may induce more dropouts than others. I also study the full set of HS graduates in some specifications. In other words, enrollment or graduation may not be realized. How changes in differential pricing may affect students' major choice depends in part on the institutional aid and context (Stange, 2012; Andrews and Stange, 2019)

pecuniary factors such as interest in the subject, perceived work environment, warm-glow, and pecuniary factors such as expected earnings and opportunities for advancement.

Here, I concentrate on one aspect of major/career choice: experiencing local labor market fluctuations at the approximate time of decision (i.e. for college graduates, pre-college graduation). 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). Consequently, 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 affects their subjective expected earnings and, under the assumption that expected earnings matter, has the possibility of tipping the subjective expected utility of one major over another. Furthermore, experiencing a negative shock may make individuals more cautious (Malmendier and Nagel, 2011; Giuliano and Spilimbergo, 2014; 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.

Because employment in teaching and other government sectors remains relatively stable even during recessionary periods, individuals experiencing a negative shock may be more receptive to the teaching profession for any of the reasons above. I model the health of the local labor market using an unemployment rate as it represents a salient and easily understood measure 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. Commuting zones are county clusters defined to represent where people tend to live and work, and as such define narrow but naturally occurring labor markets. With these two 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 below.

3 Data

I use administrative data from Texas connected at the individual level to determine interest in teaching outcomes. Specifically, linked data from the Texas Education Agency (TEA), Texas Higher Education Coordinating Board (THECB), and Texas State Board for Educator Certification (SBEC) housed at the Texas Education Resource Center allow tracking of individuals from where and when they graduated high school, whether and when they enrolled in college (and what major they chose to study), whether or not they took a license exam to become a teacher, and finally whether they received employment as a teacher in a Texas public school. I merge the student files with employment conditions using unemployment rates from the Bureau of Labor Statistics, population estimates from Census Population and Housing Units and, in robustness, alternative employment measures from the Quarterly Census of Employment and Wages (QCEW). These are all aggregated to a geographical unit, commuting zone (CZ), using United States Department of Agriculture's definition. CZs include clusters of counties that are characterized by strong commuting ties within a CZ but weak commuting ties across other CZs.

3.1 Data Construction

Starting with the high school graduate files as a baseline serves two purposes. First, the district where potential teachers graduated high school provides a location to which I can assign a commuting zone (CZ). Second, it creates a common cohort – defined as the year a potential teacher graduated high school. These files capture all students who graduated from a public or charter school in Texas. Variables included in this dataset are the district from which each student graduated, their ethnicity, and sex for high school graduation years 1993-2010.[8] Henceforth, cohort refers to the spring year of the academic year in which a

[8] 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.

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

Practically, 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 high school graduate file leaving over 3.1 million high school graduates. I further drop about 15 percent of remaining high school graduates who do not have both a reading and math 10th grade exam score leaving almost 2.7 million high school graduates.[9] This includes all in graduating cohorts 1993-1995 who have no scores available. Thus, my final sample ranges from high school graduating years 1996 to 2010. The 10th grade exam scores are standardized across all test takers, not just high school graduates, in the test subject – academic year of exam. The reading and math scores are used as proxy ability measures in related subjects.[10] From the test file, I also obtain an economic disadvantage indicator.

Next, I link college enrollment and graduation files to the high school graduation files via a unique identifier. THECB reports enrollment in each semester and year and degrees earned across all Texas Public Universities, Texas Community, Technical and State Colleges, and Texas Health-Related Institutions for years 1992 to 2018. They additionally report enrollment and degrees earned for Texas Independent Colleges and Universities from 2003 to 2018. THECB reports information on college majors. College majors are defined by the nationally representative CIP codes maintained by the National Center for Education Statistics. I harmonize college majors to the 2020 CIP codes to be consistent across years.[11] Education major is defined as a CIP code for interdisciplinary studies (general) and two digit categories for parks, recreation, leisure and fitness and two digit education (though technically not allowed for undergraduates). See Appendix B for more details.

I define "graduated with a bachelor's degree", henceforth college graduate or on-time

[9] My results are robust to the inclusion of individuals with imputed exam scores.

[10] 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.

[11] 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.

college graduate, as whether the student appeared in the college graduation file, excluding independent colleges, within six years of graduating high school with a degree conferred at the bachelor's level.[12] Similarly, I define "ever enroll in college" as one if an individual shows up in a non-independent college pursing 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 does not change the results.

My preferred measure of interest in the teaching profession is whether an individual took a Pedagogy and Professional Responsibilities (PPR) exam. Teacher licenses and certification test files from the SBEC report PPR exams taken from 1990 to 2018. Practically, I define interest in being a teacher as one if the person takes their first PPR exam within eight academic years of graduating from high school. This gives students approximately two years following their college graduation (within six years of graduating high school) to take the PPR exam. However, I explore other indicators of interest in education. I create an "ever enrolled in an education major" and "graduated with a bachelor's in education" within six years as alternative measures of interest in teaching. Finally, I map employment data from the TEA back to the high school graduate file to create a variable for employment in TPS within eight years of high school graduation.

Furthermore, I use the PPR standardized exam score from the first-ever attempt of a PPR exam to serve as a proxy quality variable in addition to 10th grade standardized 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.

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

[12] 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.

conditions in calendar year 2002, and so on). Employment conditions include unemployment rate which I calculate from Texas Labor Market Information data of BLS LAUS for Texas counties.[13] I 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. I also include QCEW employment data aggregated from counties to CZs, and I 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.

3.1.1 Additional data cleaning restrictions:

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.

3.2 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 (82,177) - see Tables 1 and A1 for more descriptive details.

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

My data does not capture students who attend college outside the state of Texas. However, previous research studies have concluded that less than 5 percent of high school graduates study outside of Texas using National Student Clearinghouse data (Mountjoy and Hickman, 2020).[14] Further, it is possible that other individuals leave the state entirely. However, only about 1.7 percent of Texas residents leave the state each year, so outmigration is not a common occurrence (White et al., 2016; Mountjoy and Hickman, 2020; Ballis and Heath, 2021).

4 Empirical Specification and Identification

Do worse (better) economic conditions increase (decrease) the potential supply of teachers? This is akin to asking whether the probability of interest in teaching increases (decreases) when local economic conditions are poor (worse). To answer this question, I relate a range of unemployment rates with multiple outcomes representing interest in teaching along the progressive pipeline by estimating the following linear probability model:

$$\text{Teach}_{izc} = \alpha + \beta \text{UR}_{zc} + \gamma_z + \eta_c + \theta X_{izc} + \epsilon_{izc} \tag{1}$$

where z indexes CZs, c represents high school graduating cohort, and i references individuals. Standard errors are clustered at the CZ-level (Cameron and Miller, 2015). The outcomes, 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 as Texas does not have a clearly defined education major - see Section 3 or Appendix B for more details.

My primary independent variable of interest is UR_{zc}, representing the unemployment rate in the individual's CZ of high school graduation. In separate specifications, I allow UR_{zc} to

[14] This is calculated for the 2008 and 2009 graduating cohorts and this statistic is pulled from Mountjoy and Hickman (2020) who also use the Texas administrative data.

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 given the high amount of correlation between unemployment rates year-over-year.

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

To isolate the effect of economic conditions on teacher supply, I add several additional demographic controls though I report estimates without them. The demographic 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, 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 represents possible bias in interpreting $\hat{\beta}$ as causal effect of local labor market effects alone.

The variation in URs that identifies β stems from two main sources. The first of which is 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 β towards a positive relationship.

Figure 3 illustrates this type of variation in URs. For instance, in Figure 3, 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/9-11 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 substantial 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 β. Figure A1 provides another visualization of over time differences in unemployment rates across select CZs.

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 β. The underlying relationship identified by $\hat{\beta}$ is causal under the assumption that CZ-year URs are plausibly exogenous with respect to individuals' future decision to become a teacher. 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-level 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.[15] However, it is unlikely any of these factors move in relationship with local changes in economic conditions unless they work as a mediator. For instance, it is possible URs influence an individual's expectations and their expectations influence career choice. Here, expectations act as a mechanism instead of a potential confounder.

[15] See Patnaik et al. (2020) for a thorough literature review on college major choice.

One possible exception is changes to demographics. As discussed above, I include both demographic CZ- and individual-level controls in the primary specification. For further balance tests, 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 1 with 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.

Finding a significant relationship between total count or demographic outcomes and URs informs the extent to which the high school graduate and on-time college graduate samples are changing in response to labor market conditions. This becomes important in interpreting the relationship between career choice and URs. For instance, it is possible that depressed local labor markets influence an individual to graduate college on-time and these marginal college graduates have a propensity to select into teaching. This is a different interpretation from the case where students' propensity to graduate college does not change but more students select into teaching and out of alternative career paths. Additionally, any existing relationships between compositional demographic changes and URs leaves open the possibility that CZs-cohorts do not represent accurate counterfactuals for one another, or that they are trending too differently to be comparable. This would call into question the use of equation 1 as a plausible natural experiment.

Table 2 presents the results from these regressions. Beginning with overall total changes in the number of individuals in each sample, the estimates imply that when URs are higher, there are increases in the number of 10th graders and high school graduates. These estimates are not statistically significant, but are in line with papers that show individuals increase their consumption of education when opportunity costs are reduced (Black et al., 2005; Betts and McFarland, 1995; Foote and Grosz, 2020). Less is known about whether students who experience downturns have increased probabilities of completing college on-time. The point estimate on log college graduates, though not statistically significant, suggests students are less likely to complete a four-year degree. In terms of demographic compositional changes across all samples, there are few statistically significant relationships with respect to URs, which would be expected after controlling for CZ-level demographics. One exception is a decrease in the share of economically disadvantaged students among the on-time college enrollees and graduates. Though it is beyond the scope of this paper, it is not unreasonable to speculate that disadvantaged students who experienced economic hardship in their local communities may have to take on responsibilities to support family members or may have entered college less prepared, for instance. Any of these reasons could make it difficult to complete college. Regardless, this finding would downward bias estimates for probability of selecting teaching as economically disadvantaged are more likely to select into teaching conditional on graduating college. Overall, the results from balance tests suggest limited changes in demographics and a modest role for changes in the shares of high school graduates and on-time college graduates in response to changes in employment opportunities. Regardless, my specification ultimately uncovers the net effects conditional on all the movements occurring.

Finally, assuming $\hat{\beta}$ recovers a parameter of interest such as an average causal response[16] requires a version of strong parallel trends, homogeneous treatment effects, and SUTVA/no anticipation conditions. While some of these assumptions are plausible, I will not argue that $\hat{\beta}$ perfectly identifies an average causal response. However, given the robustness of my estimates to alternative empirical strategies that do not rely on some of these assumptions, I suggest my estimates provide accurate direction and benchmark the approximate magnitude of underlying causal parameters. See Section 6 for more details on the robustness of my empirical strategy to functional form, variable choice, and sample selection. See Appendix C for more details regarding identification assumptions for the average causal response.

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

5.1 Supply

To make use of the multiple measures of interest in teaching as well as the long panel structure of the Texas administrative data, I first relate the URs in years relative to an individuals'

[16] $ACR(UR) = \frac{\partial E[Y(UR)]}{\partial UR}$

high school graduation year to various indicators of interest in teaching. Figure 4 graphs point estimates and 95 percent confidence intervals of alternatively timed URs from equation 1 for each teacher outcome. The point estimate is representative of URs assigned to a student relative to their high school graduation year. For instance, -1 is the point estimate for UR occurring in a student's CZ z during the year before graduating high school (i.e. when they were a junior in high school). Outcomes include the probability of ever enrolling in an education major conditional on ever enrolling in college, the probability of graduating with a bachelor's degree in an education major conditional on completing college, the probability of taking the PPR license exam conditional on graduating college, and the probability of ever being observed teaching in TPS within eight years among all high school graduates. The point estimates and confidence intervals in Figure 4 are rescaled by the mean to be comparable across outcomes and samples.

Figure 4 makes clear that the outcomes and their respective samples all paint a similar picture. The URs that occur prior to an individual graduating high school have a positive and statistically significant relationship while local URs in students' assigned CZ post-high school graduation are small and insignificant. In other words, local labor markets have the potential to shift the future potential supply of teachers, and these effects are concentrated earlier on.

Intuitively, finding effects pre-college graduation makes sense for at least a few reasons. First, even though major switching is certainly possible, it becomes both psychologically and practically more taxing to change the further into a bachelor's degree individuals advance (Patterson et al., 2019). This is likely to be more binding for the sample of individuals who graduate college on-time.[17] Second, recall the CZs are assigned based on students' high school graduation location. Assuming that this is the location students would like to return to, this is the optimal definition of the 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.

[17] 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.

To obtain a singular point estimate, I use a three-year moving average of URs across junior year of high school through one year post-high school graduation. Conditional on being a college graduate within six years of high school graduation, the probability of taking a PPR exam is positively related to moving average URs. With a 1 percentage point 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 (pval = .01) - see Table 3. This translates to approximately 3-7 percent increase over the mean.

Figure 6 illustrates the point estimates and confidence intervals for moving average UR and whether an individual takes the PPR exam conditional on graduating college for each subgroup on the y-axis (male, female, Black, etc). These are run separately for each category, so the equations compare PPR completion for students with a given characteristic to other students with the same characteristic but who face differential local labor market conditions. Students living in rural CZs seem to respond more to local affects than students in urban CZs.[18] Females tend to be more affected by URs than males and non-economically disadvantaged students are affected more than lower income students.[19] 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.

Finally, I explore 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 candidates (U.S. Department of Education, 2017).[20] 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. Within the set of individuals with a content exam, I then estimate equation 1, with the outcome variable being a binary for content type. This is effectively comparing the propensity of potential teachers to take certain subject content exams over

[18]Definitions for rural listed in Appendix B.

[19]The sample size for economic disadvantage is much smaller which could contribute to its insignificance.

[20]Those who were specifically trained in the subject are qualified.

others during times of different local labor market conditions.

I present the coefficients and confidence intervals of these estimates in Figure 7. There is a weak decline in probability of studying elementary subjects and an increased probability of taking a bilingual/English as a second language. 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 delineate these or other explanations.

How do these relate to the total number of PPR completions over time? Without the inclusion of demographic controls, log PPR count, inverse hyperbolic sine and a Poisson model all point to evidence of an increased number of teachers in CZ-cohorts that experience elevated levels of UR on the order of a 3 percent increase - Table A5. However, controlling for CZ-cohort demographics renders the estimates insignificant.

It may be worrisome if the individuals who sort into teaching due to depressed labor markets just 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 5, 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 as such statistically insignificant relationship should be interpreted as suggestive evidence of no effect. The probabilities on staying at least two years seems to increase during higher unemployment rates occurring closer to college graduation. Given the persistence in unemployment rates over time, it is is possible that these individuals face a difficult labor market during college graduation and stay in teaching for longer.

5.2 Quality

Now that there is an established relationship between proclivity to become a teacher and local labor market conditions around college entry, I turn to the question of whether these individuals are more effective instructors.

5.3 Measures of Quality

I employ several proxies for quality 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 8 shows the mean 10th grade test score difference between PPR test takers and non-PPR test takers by college major. Recall that up until 2019, there was no required education major in Texas providing an opportunity for traditional students to have a variety of background training. Individuals with lower mathematical skills in a given major are more likely to sort into teaching. Reading skills are more 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. This overall fits with other work that claims lower skilled individuals sort into occupations with more compressed wages (Hoxby and Leigh, 2004; Bacolod, 2007).

However, standardized test scores have the major drawback that they do not necessarily represent a person's innate teaching ability.[21] In addition to the standardized test scores, I also calculate value-added for the subset of potential teachers who gain employment in Texas Public Schools and work in grades 4-8 instructing math or reading. Value-added is a well-validated measure of teacher effectiveness of raising test scores - one dimension of quality teaching (Kane and Staiger, 2008; Chetty et al., 2014a,b; Koedel et al., 2015). Furthermore, Chetty et al. (2014b) has shown that test score value-added is predictive of long-run outcomes including educational attainment. Of course, test score value-added does not predict other ways in which teachers influence students such as through soft skills (Jackson, 2018). Another

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

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 set of potential teachers or even across occupations. In any case, it is an informative measure of productivity that has been shown to predict important outcomes.

5.3.1 Calculating Value-Added

Using data on more than 3.5 million students grades 3-8 in math and reading, I link students and teachers via a classroom ID available for academic years 2012-2019.[22] To obtain an estimate of value-added for math or reading for a given teacher, I estimate the following model for each subject *sub* (math or reading):

$$A^{sub}_{ijkgst} = \alpha_1 A^{sub}_{it-1} + \alpha_2 A^{-sub}_{it-1} + \gamma X_{it} + \lambda C_{kgst} + \nu_{gt} + \zeta S_{st} + \mu^{sub}_j + \epsilon_{ikgst} \tag{2}$$

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

5.4 Effects of Local Unemployment Rates on the Quality of Teachers

If an increase (decrease) in potential teacher supply is among higher (lower) quality individuals, then a draw at random will provide school districts with, on average, higher (lower)

[22]For further details on data construction, see Appendix B

quality candidates. Thus, the ideal experiment compares the average quality of potential teachers as the set of potential teachers changes with local labor markets. I consider local labor market conditions that occur leading up to entry into active participation in the labor market. In essence, I adapt equation 1 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).

As in supply results, Figure 9 maps point estimates and (95 percent) confidence intervals of URs at 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 in earlier years. 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 described above with three year moving average URs. When there is a 1 percentage point increase in the CZ-cohort moving average UR, the average ability of potential teachers (those who took the PPR exam) is about a .01 standard deviation higher on math exams (pval = .2). Recall that the estimates for value-added describe the test score change expected for a randomly assigned student. The set of teachers who experience a 1 percentage point increase in their URs improve their students' math scores by approximately .005 of a standard deviation (pval = .03). Another way of thinking about value-added is how teachers rank in comparison to each other. In Table A2, 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 teachers sorting during times of 1 percentage point higher URs are .02 standard deviations (pval = .03) better at affecting student test scores. Due to the 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 A18.

6 Robustness

In addition to the balance tests, my results are impervious to different definitions of local labor market conditions, constant linear trends, 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. However, my results are not robust with respect to group-specific linear trends. In general, I find quality results to be more sensitive to deviations from my primary specifications. This may be explained by the fact that quality measures are estimated on a much smaller sample.

6.1 Alternative methods

Finding a positive association between UR and taking the PPR exam is not limited to a linear probability model.[23] Qualitatively, I find large increases in the log odds using logistic regression. Similarly, OLS of equation 1 with outcome being (log) share of PPR takers over 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) - see Table A5.

Statewide Estimates: Qualitatively, I find a positive relationship between URs and taking the PPR conditional on graduating college estimated at the statewide level with linear and quadratic trends.[24] The estimates are slightly attenuated - see Table A4 - 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, though also statistically insignificant. The statewide estimates of quality measures largely support the CZ findings.

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

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

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

However, the math value-added estimates lose their significance and the point estimate is negative in contrast to the primary specification.

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. When there are no exact stayers (CZs that do not change moving average URs over the year), estimating WAMPOS requires the selection of an ϵ value such that when the absolute value in year-over-year change in moving average UR is less than ϵ, the observation defines a stayer. Specifics on the estimation are provided in Appendix D.

Table A6 presents the estimates of WAMPOS for different values of ϵ, which were chosen based on the mean difference between moving average URs. 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.

Testing for linear trends: In addition to providing estimates using the statewide specification, I probe how sensitive the CZ specification is to additional controls and different functional forms for the time trend. Table A7, panel A shows the outcomes for PPR. The first two columns in this panel benchmark the main results presented in Table 3. The next two columns include CZ-specific linear trends in addition to the CZ fixed effects and the final columns use a common linear trend including CZ fixed effects. The estimates with CZ-specific linear trends are small and not statistically significant. However, CZ demographic controls are mostly linear (linear increases in Hispanic individuals over time for many CZs), thus doubling up on the linear trends so to speak may reduce identifying variation. The point estimate in the final column which allows for linear trends is nearly identical in size as my primary specification.

Removing comparisons between consecutive cohorts: 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. Reassuringly, the three separate panels report similar point estimates across PPR exams - see Table A8. They are qualitatively the same across 10th grade math exams and math value-added as in the primary specification.

6.2 Sample selection and variable choices

Alternative employment measures: Unemployment rates are a natural choice for measuring the health of a labor market because they are salient. However, I test the robustness of the results to other forms of local labor market conditions. 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 probability and quality are qualitatively consistent with estimates using URs (point estimates on *employment* are mostly 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 (pval = .03) and an increase of 0.09 standard deviations in 10th grade math scores among PPR takers (pval = .07). Math value-added is insignificant for this measure of employment.

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 benchmark. For an increase (of any level) in the UR, the estimates suggests 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 A11. The effect of moving average URs on student math exam scores is nearly identical to the one estimated under equation 2. This is unsurprising 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 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 A12 lays out the primary estimates using a definition for college graduate including independent colleges.

7 Discussion

7.1 Mechanisms

While my setting does not allow for strong tests of mechanisms, supporting evidence implies that some mechanisms are more plausible. The results presented here are consistent with a mechanism that updates students' risk preferences or subjective expectations over job security. There is less support that students are motivated by naturally occurring changes in wages or that the results are driven by compositional changes in college enrollment or graduation due to changes in the business cycle.

One mechanism includes risk preferences or changes to subjective expected probability of finding employment. While these two are not the same, I include them together because the way they work in changing behavior is observably similar in this context. In terms of college major choice, Saks and Shore (2005) find that students with predicted levels of higher risk aversion sort into safer careers. Insomuch as it is believable that experiencing labor shocks can update risk preferences, this is a straightforward link. Recent research demonstrates that emotions can play a strong role in people's risk preferences over time. For instance, Meier (2022) finds that fear causes people to become more risk averse while anger and happy emotions are associated with increases in risk taking. To the extent that a booming labor market can induce positive outlooks (even if only temporarily) or that weak labor markets can induce fear, this line of research supports the findings in this paper. Similarly, Malmendier and Nagel (2011) show that recently experiencing a recession decreases risk taking and optimism with respect to investments. As potential supporting evidence, my results imply an increased share of shortage-area certifications during higher URs which points to an employment security channel.

In thinking about whether a wage channel exists, it is important to note there are at least two interpretations of wage effects. First, subjective expected earnings change with changes to expected employment changes. Second, it is possible that actual wages or subjective expected wages change. I can make progress on one of these: whether actual wages affect interest in teaching. I first begin by relating teacher and non-teacher wages with interest in teaching in similar specifications as before. I do not find wages to be significant predictors of taking a PPR exam conditional on graduating college – see Table A13 columns 4-7. In the models where both wages and URs are present, UR always maintains its significance. However, finding a null effect on wages could be due to a lack of variation given that wages tend to be sticky (Grigsby et al., 2021; Grigsby, 2022). 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.

I further explore how changes in college graduation rates affect the interpretation of my findings. Given the (insignificant) decline in college graduates and the lack of (significant) increases in total PPR takers, it is possible that there was a differential decline in college graduation among non-teaching careers. Under this scenario, those dropping out of college would be disproportionately more likely to be non-teachers. To explore this possibility, it is useful to see who are the most likely to drop out of college when experiencing local labor market conditions that precede college enrollment. As already stated, I find that economically disadvantaged students are more likely to leave college prior to graduation - see the Table 2. This would potentially work against the findings here as economically disadvantaged students are more likely to be enrolled in education majors than their peers. However, a decline in economic disadvantage could be a plausible explanation for the increase in quality.

Additionally, a general decline in college graduation rates could inflate estimates in a positive direction. However, this is not strongly supported in the data. Table A14 shows equation 1 with alternative college major categories as outcomes. For instance, STEM majors have a negative relationship with URs. While this may seem counterintuitive given high demand and associated stability for STEM occupations, recall that my sample happens squarely around the dot-com bubble which particularly hurt Texas (FED, 2005).[25] Thus,

[25]Weinstein (2020) finds that dot-com bubble affected enrollment in STEM-related majors as well.

employment prospects in STEM would have seemed particularly bleak. If anything, this is a further example of a risk or employment security channel at work.

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.

Comment on the Roy Model:

Previous work has suggested a simplified Roy model could explain a decrease in teacher quality when relative wages for teachers are worse or more compressed (Roy, 1951; Hoxby and Leigh, 2004; Leigh, 2012; Bacolod, 2007; Nagler et al., 2020). Bacolod (2007) and Nagler et al. (2020) both find that increased relative economic conditions improve average ability among employed teachers. I confirm these findings in an entirely new context. I also provide evidence of an increase in potential teacher supply with worse local economic conditions (presumably better *relative* economic conditions for teachers).[26] The evidence presented here is not in disagreement with a simple Roy model such as the one put forth by Nagler et al. (2020). However, the lack of evidence supporting a wage channel, as posited by a simplified Roy model, warrants a more sophisticated model. For instance, Cubas and Silos (2017) combine risk aversion (simplified Roy models assume risk neutrality) and Roy model selection through occupational-specific ability to study compensating differentials for riskier professions. While beyond the scope of this paper, it is certainly possible to expand upon both of these models to further study selection into the teaching profession integrating both risk and selection.

[26] Bacolod (2007) looks at quantity but during a time when women increased their college-going substantially. This makes it difficult to ascertain sorting between fields versus changes to the composition of college-graduates.

7.2 Policy Implications

In terms of external validity, this study focuses on a particular type of student - one who 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. That is to say that this paper does not speak to attracting alternatively trained teachers who are shifting careers. This is non-trivial given the increasing share of alternatively certified individuals, especially in Texas.

Regardless, 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. This could 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 this is consistent with the results here.[27]

Finally, the finding that effects are more concentrated before students leave for college implies that targeted programs during high school may be effective. This is not an entirely new concept. 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, 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.[28] The idea behind them is motivated in part by

[27] They also find one measure of quality - selectivity of colleges - to increase; however, college selectivity is only weakly correlated with other measures of teacher quality (Kraft et al., 2020). Thus it's difficult to tell how their results on quality relate back to the ability measures here.

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

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.

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 of teaching and non-teaching careers 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.

My estimates better represent the supply of teachers as they capture indicators for interest in teaching besides employment in teaching. My results are ultimately consistent with previous work that finds women of higher ability are likely to sort towards non-teaching professions as the wages and opportunities decline in teaching (Bacolod, 2007) and that macroeconomic conditions affect non-traditional sorting into teaching among individuals with higher productivity (Nagler et al., 2020). Overall, the collection of work and this paper together paint a clearer picture of the challenges the teaching profession faces in losing quality candidates to non-teaching professions.

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9 Tables

Table 1: Descriptive Statistics

Samples:	HS Grads mean/sd	Ever Enroll mean/sd	College Graduates mean/sd	PPR Takers mean/sd
Took PPR	0.03	0.04	0.16	1.00
	(0.17)	(0.20)	(0.37)	(0.00)
Male	0.48	0.46	0.41	0.18
	(0.50)	(0.50)	(0.49)	(0.39)
Economic Disadvantage	0.31	0.27	0.15	0.18
	(0.46)	(0.44)	(0.36)	(0.39)
White	0.52	0.54	0.65	0.66
	(0.50)	(0.50)	(0.48)	(0.47)
Black	0.12	0.12	0.08	0.07
	(0.33)	(0.32)	(0.27)	(0.26)
Hispanic	0.32	0.30	0.20	0.25
	(0.47)	(0.46)	(0.40)	(0.43)
Asian	0.03	0.04	0.07	0.02
	(0.18)	(0.19)	(0.25)	(0.13)
10th Grade Reading	0.17	0.29	0.61	0.57
STD Test Score	(0.84)	(0.74)	(0.49)	(0.49)
10th Grade Reading	0.17	0.29	0.73	0.60
STD Test Score	(0.91)	(0.85)	(0.64)	(0.64)
Reading Value-Added				0.00
				(0.16)
Math Value-Added				0.00
				(0.23)
Experience Years in				7.26
Teaching (if VA Score)				(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: Balance Tests: Probability of Racial, Ethnic, Sex, and Economic Disadvantage and Local Unemployment Rates Across the Set of 10th Graders, High School Graduates, and College Graduates

	All 10th Graders	All High School Graduates	Enrolled in College	College Graduates
Outcomes - dependent variable				
Black	-0.106*	-0.050	-0.010	0.010
	(0.062)	(0.097)	(0.118)	(0.115)
Hispanic	0.021	-0.084	-0.173	-0.393
	(0.163)	(0.157)	(0.183)	(0.239)
White	0.083	0.158	0.232	0.506
	(0.192)	(0.215)	(0.251)	(0.311)
Econ Disadvantage	-0.442	-0.501	-0.711*	-0.994***
	(0.429)	(0.405)	(0.365)	(0.273)
Male	0.049	-0.012	-0.038	0.010
	(0.037)	(0.044)	(0.068)	(0.135)
Tot Obs	4,570,200	3,340,867	2,413,398	661,782
Log total count				
MA UR	0.935	0.859	-0.045	-1.562
	(0.580)	(0.857)	(0.892)	(1.175)
Tot Obs (cells)	952	952	952	952
Outcome Mean	9.41	9.03	8.70	7.38

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 1. 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. These data are run for high school graduating or assigned cohorts 1996-2013. *Logs* - this specification collapses the total log number of individuals in each of the czone-cohort cells (where cohort for the 10th grade sample is defined as above). The regressions are weighted by the total number of high school graduates in 1996. The regressions are run on high school graduating cohorts 1997-2013. 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.

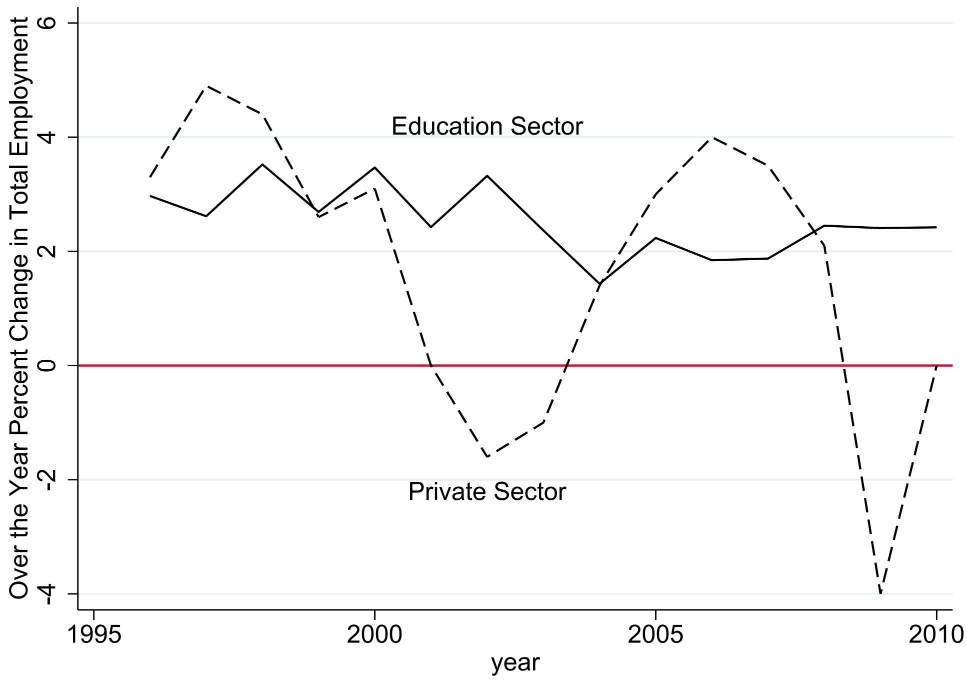
Table 3: Probability of Taking PPR Exam, Quality of PPR Test Completers, and Local Unemployment Rates

	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 1. MA UR refers to the three year moving average UR as defined in text. Columns represent the outcome. Takes the PPR exam 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

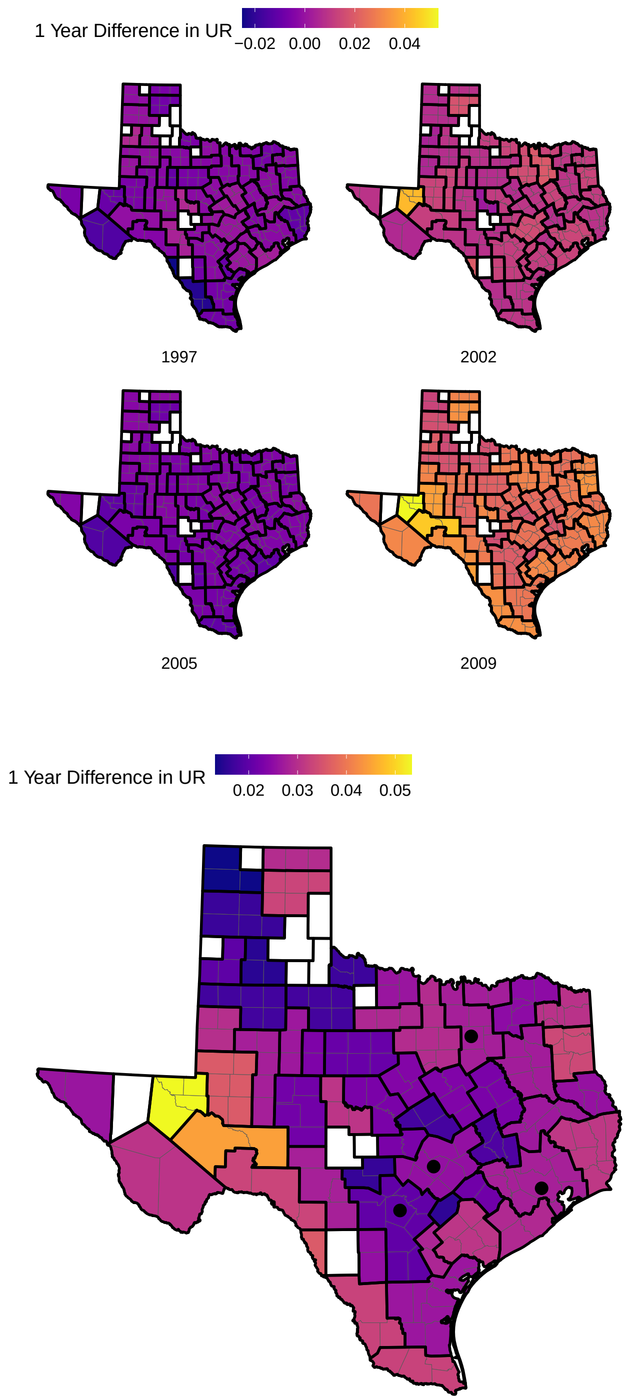


Note: Annual average of total Texas private employment plotted as a one-year percentage change. Education sector is industry NAICS 61 total employment across private, state government or local government, plotted as a one year percentage change. Data from the QCEW for calendar years 1996-2013.

Figure 2: Count of Newly Hired Teachers in Texas by Calendar Year of Career Start

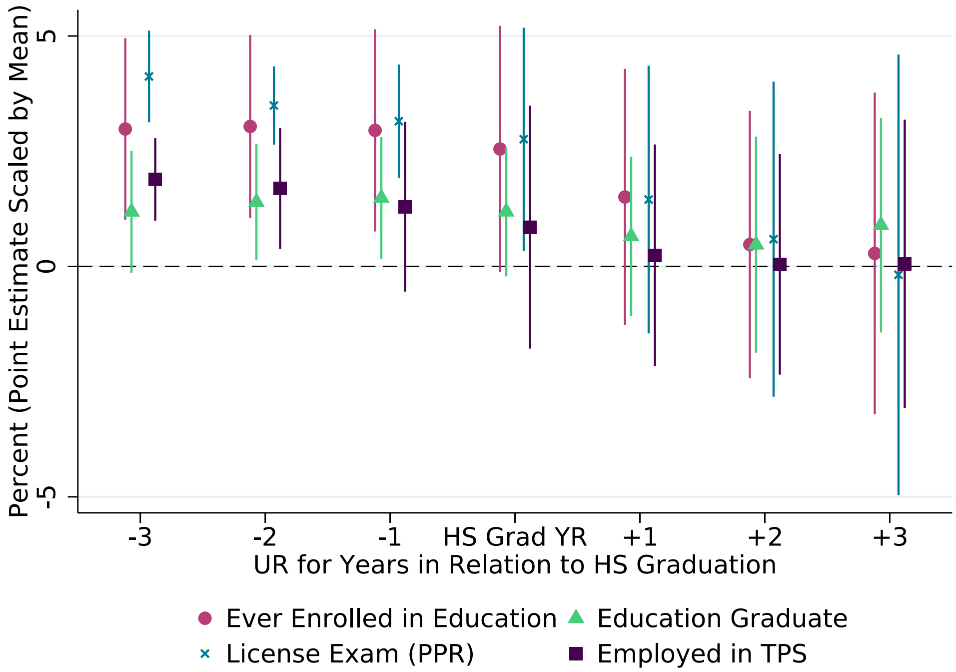
Note: Plots the total count of newly hired individuals in Texas public schools. Newly hired year is defined as the first year a teacher would have taught given their experience level. Calendar year refers to the year in which they would have started. For example, if a teacher started in 2001-02 school year, they are counted as newly hired in 2001 calendar year. Data: TEA. See Table A22 for regression output of newly hired and current employment conditions.

Figure 3: One Year Difference in Unemployment Rates by Commuting Zones for Years 1997, 2002, 2005, and 2009



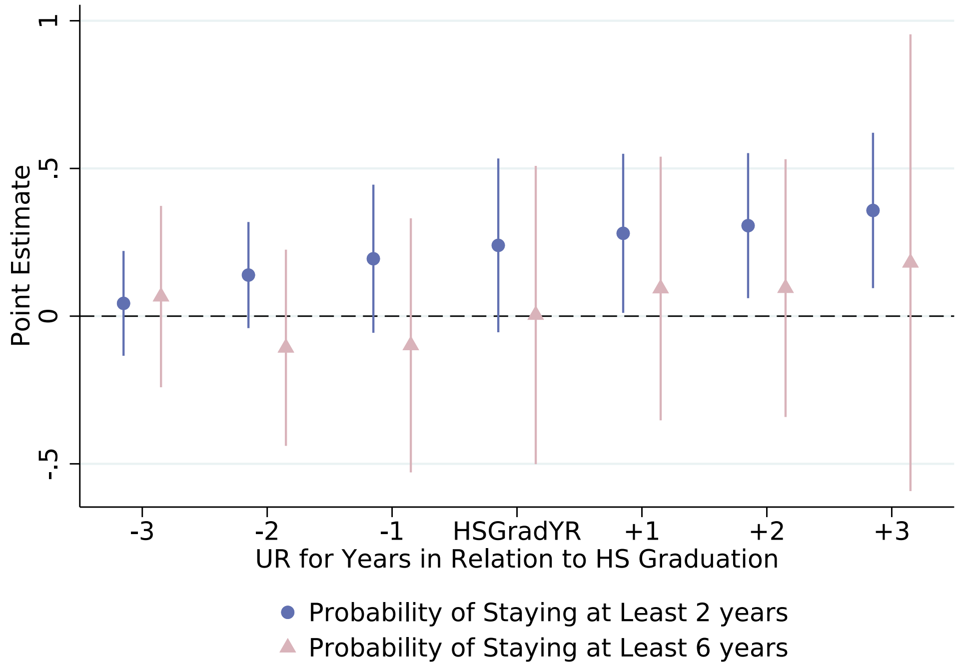
Note: One year differences in URs at the CZ level. White counties represent ones excluded from the sample, grey lines denote counties, and black lines trace CZs. Black cities denote Dallas, Austin, Houston, and San Antonio. Data sources: BLS.

Figure 4: Effect of a One Percentage Point Increase in Local Unemployment on Likelihood of Becoming a Teacher



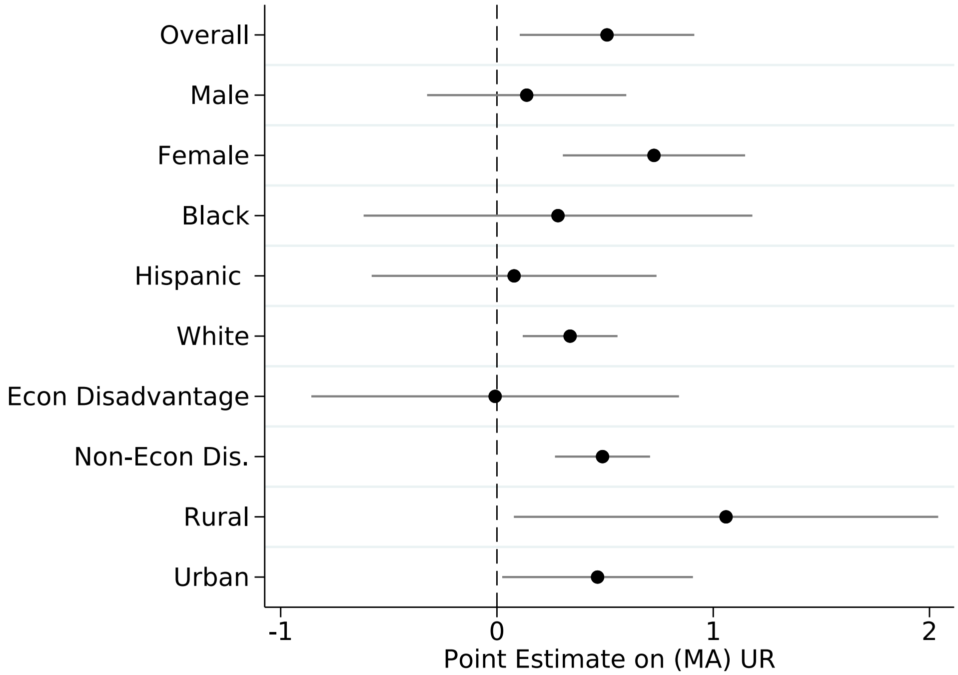
Note: Each point and bar are the point estimate on UR and confidence interval, respectively, *re-scaled* by the mean of the outcome so as to be comparable across outcomes. Each point estimate is a unique regression using equation 1 whereby the UR is assigned in a year relative to an individual's high 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 A19 reports regression output. Data: TEA, THECB, SBEC, Census.

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



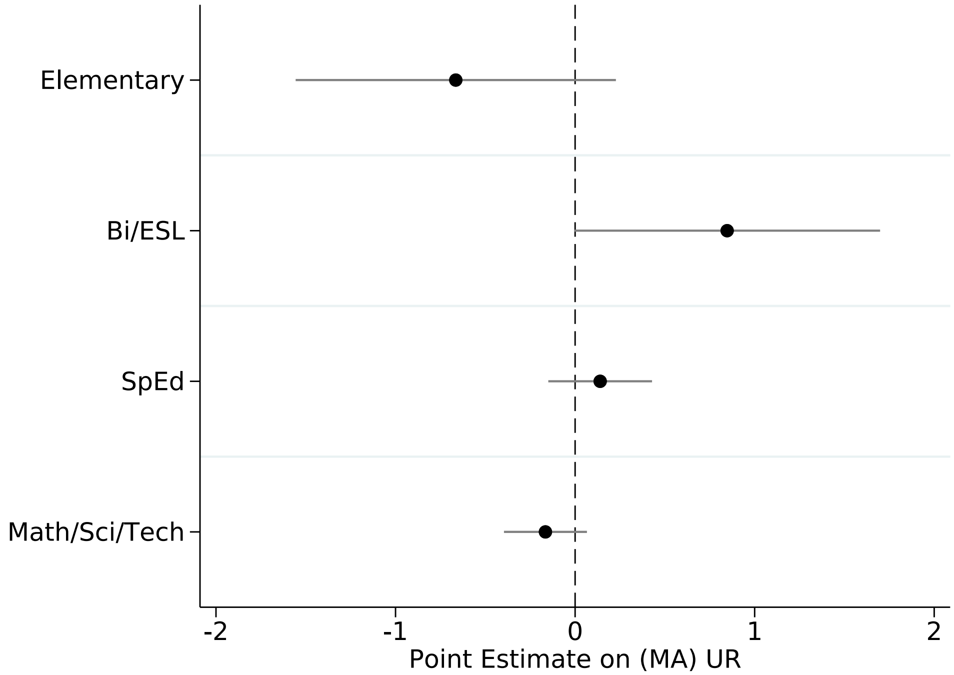
Note: These are point estimates and confidence intervals for unemployment rates in different calendar years with respect to high school graduation year from equation 1 where outcomes have been replaced. Outcomes are binary - 1 if an individual reported having at least two or six years of experience and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

Figure 6: Probability of Taking PPR and Unemployment Rates by Individual Demographic Characteristics Conditional on Graduating College On-time



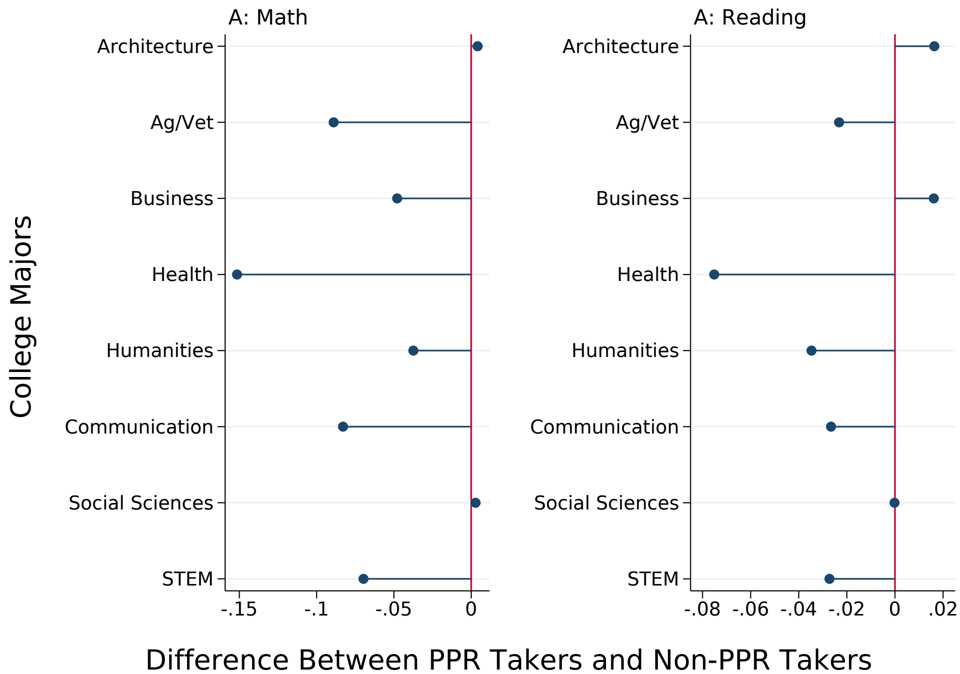
Note: Regression output, point estimates and confidence intervals, of whether an individual takes a PPR using equation 1 by different individual characteristics. These are estimated conditional on graduating college on time. Controls include CZ demographics but not individual demographics. See Table A18 and associated footnote for the regression output in more detail. Data sources: TEA, THECB, SBEC, BLS, Census.

Figure 7: Probability of Taking Different Subject Content Exams and Local Unemployment Rates Conditional on Taking the PPR



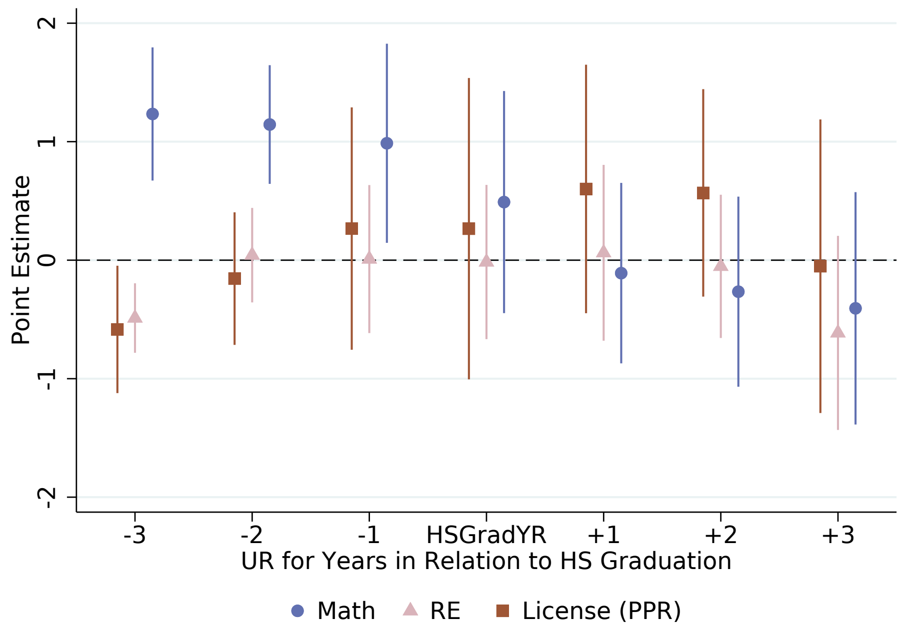
Note: Regression output, point estimates and confidence intervals, on my sample of PPR exam takers within 8 years of high school graduation date who also had a corresponding content exam in the SBEC. Outcomes include whether the content exam was for elementary, bilingual/ESL, math/science/technology, or special education subjects. Outcomes are formatted (0/1). See Table A21 and footnote for the regression output in more detail. Data sources: TEA, SBEC, THECB, BLS, Census.

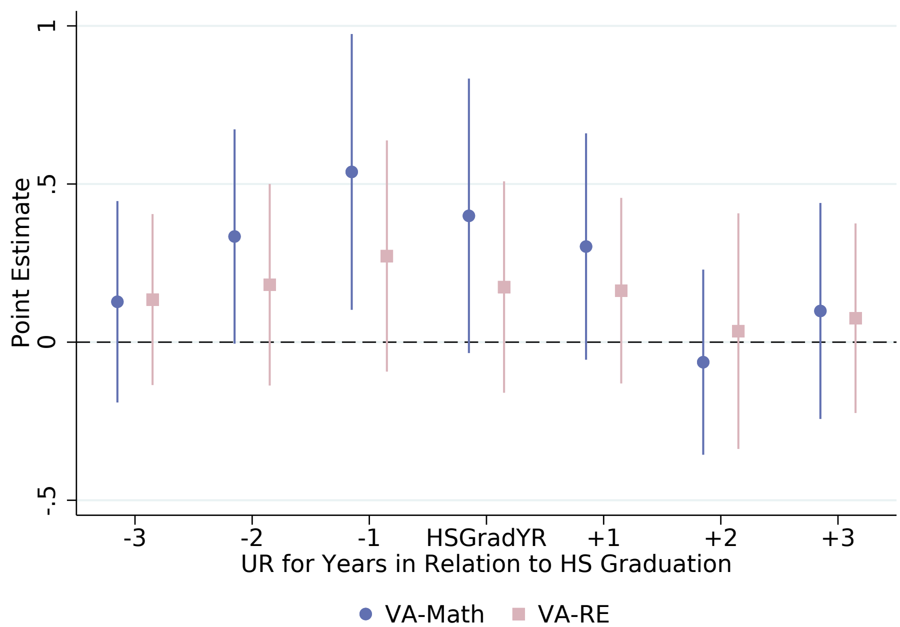
Figure 8: Difference in Math and Reading Standardized Exams Between PPR Takers and Non-PPR Takers by College Major



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 A16 and A17 for information on the major-to-teaching mapping in Texas. Total observations: 519,016. Data sources: TEA, SBEC, THECB.

Figure 9: Local Unemployment Rates and Quality Measures for Individuals who Completed the PPR Exam





Note: Each point and bar is the point estimate and confidence interval of separate regressions of equation 1. These are conditional on having taken the PPR exam. The outcomes are 10th grade standardized math and reading exams, standardized PPR exam scores and math and reading value-added as described in text. 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 A20 reports regression output. Data: TEA, THECB, SBEC, Census.

Appendices

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: Standardized Value-Added Estimates and Local Unemployment Rates for PPR Exam Takers

	STD VA-M		STD VA-R	
MA UR - statewide	1.427	-0.686	-0.320	0.391
	(0.834)	(1.127)	(1.040)	(1.241)
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 1 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. *Statewide:* Outcomes are the standardized VA for math and standardized VA for reading conditional on taking PPR regressed (OLS) on statewide URs with linear and quadratic trends in time. 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 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 A3: Value-Added Summary Statistics

	mean/sd	count
VA Math	-0.01	79,614
	0.24	
VA Reading	0.00	85,949
	0.17	
Standardized VA 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 2 for years 2013-2019. Data: TEA. For more description on the sample construction see Appendix B.

Table A4: Probability of Taking PPR and Corresponding Quality Measures 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)
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 $\mathrm{Y}_{ic} = \alpha + \beta \mathrm{MAUR}_c + c + c^2 + \theta X_{ic} + \epsilon_{ic}$ if i is a College Graduate, where Y is an indicator for takes PPR exam. MA UR refers to the three year averaged *statewide* UR. 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 having taken 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 A5: Probability of Taking the PPR Exam and Local Unemployment Rates Under Alternative Functional Forms

	OLS-PPR		Logit-PPR		LnSharePPR		SharePPR		LnPPR		Poisson		Inverse Hyp. Sine	
MA UR	1.124***	0.509**	5.202***	1.956	3.767***	1.928*	1.096***	0.633***	2.915*	-0.171	2.264**	-1.437	2.911*	-0.181
	(0.095)	(0.201)	(0.386)	(1.424)	(0.336)	(1.074)	(0.081)	(0.199)	(1.734)	(1.265)	(1.015)	(1.218)	(1.731)	(1.263)
Controls?	no	yes	no	yes	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	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	464.84	464.84	6.20	6.20

Notes: Regressions first to last: OLS on whether an individual took pedagogy and professional responsibilities (PPR) exam (0/1) conditional on being a college graduate, logit on whether an individual took the PPR exam (0/1) conditional on being a college graduate, OLS with 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, Poisson on the count of PPR takers, and OLS with the inverse hyperbolic sine on the 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 A6: Point Estimates of WAMPOS

Epsilon	Point Est	Std Err	Years
.001	1.288293	-	1999,2000,2001
.002	4.430816	-	1999,2000,2001
.004	1.853741	-	1999,2000,2001
.006	-	-	-

Notes: WAMPOS estimates as described in detail in Appendix D. Epsilon value of .006 did not have sufficient numbers of increasers, decreasers and stayers. Data sources: TEA, THECB, SBEC, BLS, Census.

Table A7: Probability of Enrollment in Education, Graduation in Education, and PPR Completion for Local Unemployment Rates Across Different Controls

	Fixed Effects		Group Specific Linear Trends		Linear Trends	
Panel A - PPR						
MA UR	1.124***	0.509**	-0.017	0.057	0.678***	0.441***
	(0.095)	(0.201)	(0.129)	(0.120)	(0.136)	(0.051)
Controls	no	yes	no	yes	no	yes
Tot Obs	519,016	519,016	519,016	519,016	519,016	519,016
Outcome Mean	0.16	0.16	0.16	0.16	0.16	0.16
Panel B - Educ Grad						
MA UR	0.554***	0.182**	0.008	0.011	0.244***	0.097**
	(0.080)	(0.076)	(0.086)	(0.073)	(0.078)	(0.046)
Controls	no	yes	no	yes	no	yes
Tot Obs	661,782	661,782	661,782	661,782	661,782	661,782
Outcome Mean	0.13	0.13	0.13	0.13	0.13	0.13
Panel C - Educ Enroll						
MA UR	0.592**	0.526*	-0.160***	-0.086	0.318**	0.106
	(0.235)	(0.264)	(0.045)	(0.081)	(0.125)	(0.113)
Controls	no	yes	no	yes	no	yes
Tot Obs	1,915,488	1,915,488	1,915,488	1,915,488	1,915,488	1,915,488
Outcome Mean	0.17	0.17	0.17	0.17	0.17	0.17

Notes: Panels represent outcome variables: PPR - took the PPR, graduated with an education major, enrolled in an education major. Columns represent different controls. The first two columns repeat the results from Table 3 of equation 1. The next two columns, "GS Linear Trends", replace cohort fixed effects with CZ-group specific linear trends ($\gamma_z * cohort$), "Linear" trends replaces fixed effects with a linear trend, common to all CZs. 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. PPR and graduation major are conditional on being a college graduate. First enrolled is conditional on enrollment in college within six years. MA UR refers to the three year moving average UR described in the text. Standard errors are clustered at the CZ-level and * denotes significance at 0.10; ** at 0.05; and *** at 0.01. Education Graduate and Education Enrolled within six years additionally use cohorts 2012 and 2013. Data sources: TEA, THECB, SBEC, BLS, Census. B.

Table A8: Probability of Taking PPR and Corresponding Quality Measures with Local Unemployment Rates: Non-Overlapping Cohorts

	PPR		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 1 for cohorts 1996, 1999, 2002, 2005, and 2008. Panel B reports outcomes of equation 1 for cohorts 1997, 2000, 2003, 2006, and 2009. Panel C reports outcomes of equation 1 for cohorts 1998, 2001, 2004, 2007, and 2010. The column names represent the outcomes. The PPR is whether individuals take 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 A9: Probability of Taking PPR Exam and Quality of PPR Test Takers by Alternative Local Employment Statistics

	Takes PPR Exam (0/1)		10 Grade Math Math		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)
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 1 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 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 A10: Probability of Taking 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)
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 1 where UR_{zc} has been replaced with a binary variable for UR increasing from c-1 to c. 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 A11: 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 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 A12: Probability of Taking 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 - Statewide	0.467**	0.214	0.705	2.431**	-0.312	3.083***	1.882***	2.713***	0.445***	0.106	-0.012	0.055
	(0.194)	(0.134)	(0.827)	(0.969)	(1.114)	(1.009)	(0.455)	(0.837)	(0.139)	(0.193)	(0.154)	(0.237)
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	13,635	13,635
Outcome Mean	0.16	0.16	0.61	0.61	0.58	0.58	0.03	0.03	0.01	0.01	0.01	0.01

Notes: CZ panel- OLS regression output of equation 1 under an alternative definition of “college graduate”. These repeat results of Tables 3 and A4 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. Statewide panel includes linear and quadratic controls for cohorts instead of cohort and CZ fixed effects. Statewide 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. 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 A13: Local Unemployment Rates Affect on Log Wages and Probability of Taking PPR with Employment and Wages

	Log Average Salary for Newly Hired Teachers	Log Average Salary For All Teachers	Log Non-teacher Average Salary	Takes 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 column reports point estimates from equation 1, 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. 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.

Table A14: Local Unemployment Rates and Probability of Majoring in Various Field Categories

	Educ	SocSci	Comm	Hum	Health	Bus	Math	STEM	Econ	Other
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)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
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

Notes: OLS estimates of equation 1, where outcome is probability (0/1) of graduating with a bachelor's in the major in the columns. For descriptions of the major categories and their corresponding CIP codes see Table A15. 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 A15: 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 A16: Major Categories for (Matched) Employed Teachers

	Count	Percent
Interdisciplinary	139,349	37
Parks/Leisure/Fitness	27,953	7
English	21,768	6
Business	21,371	6
Arts	19,890	5
Psychology	14,763	4
History	13,925	4
Health	12,856	3
Social Sci	12,718	3
Biology	11,987	3
Education	11,961	3
Communication	9,775	3
Foreign Lang	9,513	3
Liberal Arts	8,894	2
Math/Stat	8,796	2
Family Studies	8,415	2
Ag/Vet	6,643	2
Other	5,585	1
Physical Sci	2,389	1
Public Admin	2,354	1
Engineering	1,806	0
Nat Resources	935	0
Computer Sci	871	0
Engineering Tech	810	0
Architecture	720	0
Philosophy	581	0
Ethnic Studies	477	0
Religious Stud	329	0
Communication Tech	70	0
Total	377,504	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. Sources include: THECB and TEA.

Table A17: 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 A18: 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 1 are represented in the columns and point estimates are from the three-year moving average UR. The panel variables (male, female) refer to the sample the regressions are run on. For instance, column one row one presents the point estimate of equation 1 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

Table A19: Probability of Ever Enrolling in Education Major, Ever Graduating with Education Major, Taking the PPR Exam, and Ever Working in TPS and Local Unemployment Rates Over Time

	Ever Enrolled in Education Major	Graduated with Education Major	Took 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 4 from equation 1. 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. Graduate with education major and takes the PPR 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 A20: Quality Measures Conditional on Taking PPR Exam and Local Unemployment Rates over Time

	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 9 from equation 1. 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 math 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 A21: Probability of Taking a Content Test in Elementary Education, Bilingual/English as a Second Language, Special Education or Math/Science/Technology with Local Labor Market URs Conditional on Having Taken the PPR

	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

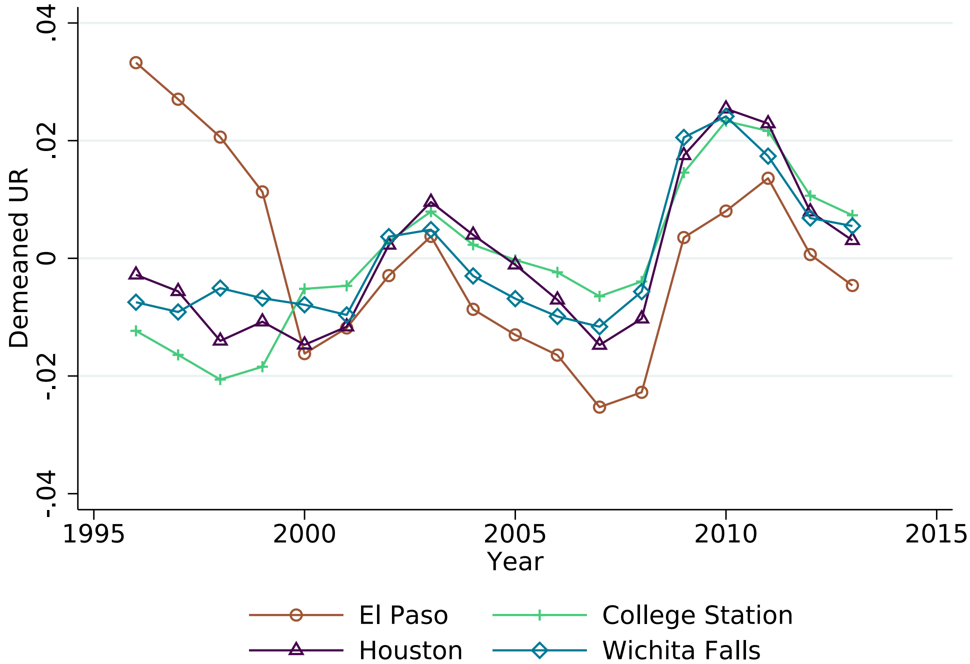
Notes: This is the regression output as illustrated in Figure 7. OLS regression output from equation 1 on the sample of PPR exam takers who additionally had a corresponding content exam. Outcomes include whether the content exam was for elementary, bilingual/ESL, Math/Science/Technology, or Special Ed 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 A22: 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
Panel B - CZ		
UR - CZ	1,993	-0.721
	(1,871.901)	(1.026)
Tot Obs	952	952
Outcome Mean	2,377	7.137

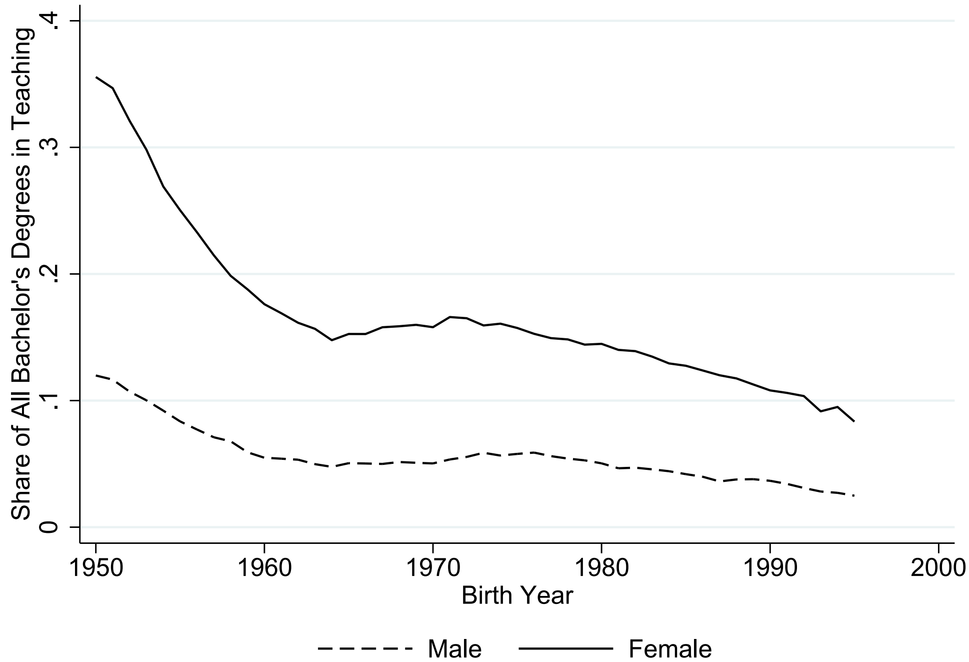
Note: Columns are outcomes including count of newly hired teachers and log count of newly hired teachers. Newly hired is defined as an individual and year in which the individual had 0 experience years. Career start year is the calendar year in which the teacher started. URs are the prevailing unemployment rate during the calendar year of the career start year. Panel A regresses the outcomes on linear and quadratic trends for career start year. Panel B regresses outcomes on CZ unemployment rates with CZ and career start fixed effects, and weighted by total working population in each CZ. CZ is the district in which the newly hired works. No additional controls. Both run on career start years 1997-2013.

Figure A1: De-meaned Unemployment Rates for Four Commuting Zones from 1996-2010



Note: 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 A2: Share of Individuals Reporting an Education Bachelor's Degree by Birth Cohort for U.S. - American Community Survey



Note: Calculated from pooled of American Community Surveys 2009-2019. Share is calculated among those who report any bachelor's degree within each sex.

B Data Details

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,[29] 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 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

[29]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).

pass exit level exams in math, reading and writing administered during 10th grade under the TAAS test taking regime (Digest, 2019).[30] 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.[31] 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. TEA defines other economic disadvantage as including: 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.

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

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

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

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 students for VA estimation. In practice these test scores were 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.

"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 A16, the most common majors for those who appear in the enrollment file 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 A17 shows the percentage of each two digit major that is observed in the teacher employment file.

First College Enrollment: THECB reports enrollment in each semester and year for all Texas Public Universities, Texas Community, Technical and State Colleges, and Texas Health-Related Institutions for years 1992- present. They additionally report enrollment and degrees for Texas Independent Colleges and Universities from 2003 to present. To create enrollment identifiers and first enrolled major, I select the most recent observation within 6 years of high school graduation date for each high school graduate who appears in the college enrollment files and is earning at least some credit hours except for Independent colleges which started reporting in later years. Specifically, I select the most recent observation relative to the student's high school graduation date that is explicitly not dual credit earning (it should not be if it is post-high school), prioritizing the designation of first time enrolled by THECB (first time enrolled in a Texas college or university since graduating high school). I assign the institution and major corresponding of this particular observation as the first time/first enrollment location and major. I harmonized the CIP codes to the 2020 specification.

Unemployment Rates - LAUS/BLS: I download from Texas Labor Market Information BLS LAUS data for Texas counties.[32] 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.

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

QCEW: I obtain county-level public Quarterly Census of Employment and Wages (QCEW) program data from 1990-2019. From these, I aggregate total (private and government) annual employment and annual wages up to the commuting zone-year and commuting zone-industry-year level.[33] The QCEW publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs.[34] 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: To create the labor demand shocks, 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:

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

[33]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.

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

where $\text{Share}^{Ind}_{z,c-5}$ represents the share of NAICS industry Ind in CZ z during time c-5.[35] The choice of updating the industry share overtime is to make the instrument more predictive. The $gr^{Ind}_{-z,c}$ term represents industry-specific employment change over 5 years that is calculated by using total growth rate from each state-industry excluding Texas entirely.

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

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

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

The basic intuition is that the ratio of non-Texas employment in a industry is a predicted value of how much employment in Texas in that industry should change over a 5 year period. This multiplied by the original employment in CZ z generates a predicted employment level. 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."[36] Using counties results in data

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

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

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

Definition of Rural CZ: I pick 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.

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

C Identifying an ACR with TWFE

The following outlines a case in which a TWFE can identify an average causal response (ACR) and what assumptions are required empirically. I do not take a stance on whether the assumptions are plausible for any given setting.

C.1 Definitions

Let's establish the following definitions based on Callaway et al. (2021) for average causal response and average treatment effect. Leaving out individual subscripts i, for all time t, and for any value d,d' (that can be continuous and is in the set of possible treatments) let:

$$ACR_t(d) = \frac{\partial E[Y_t(d)]}{\partial d} \tag{5}$$

$$\begin{aligned} ATE_t(d) &= E[Y_t(d) - Y_t(0)] \\ ATE_t(d) - ATE_t(d') &= E[Y_t(d) - Y_t(d')] \end{aligned} \tag{6}$$

Where $Y_t(d)$ is the potential outcomes in time t for treatment d. The second equality in 2 follows directly from the first. Let D_t represent the realized level of (continuous) treatment in time t.

C.2 Assumptions

Let the following assumptions be true:

1. Sample is IID

2. SUTVA and no anticipation

   $Y_t = Y_t(D_t)$

   $Y_{t-1}(D_t = x, D_{t-1} = c) = Y_{t-1}(D_t = y, D_{t-1} = c)$, for any x,y, and c

3. Strong parallel trends:

$$E[Y_t(d) - Y_{t-1}(c)] = E[Y_t(d) - Y_{t-1}(c)|D_t = d, D_{t-1} = c] \ \forall d, c$$

4. Technical - we can take derivatives

C.3 Proving ACR

We first want to establish a DID-style estimate is equivalent to ACR for strong parallel trends. Under the assumptions above, we can show

$$\frac{\partial E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c]}{\partial d} = ACR_t(d)$$

Proof: First we begin by proving the following relationship $ATE_t(d) = E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c] - E[Y_t - Y_{t-1}|D_t = 0, D_{t-1} = c]$:

$$\begin{aligned}
&ATE_t(d) = E[Y_t(d) - Y_t(0)] \\
&= E[Y_t(d) - Y_{t-1}(c)] - E[Y_t(0) - Y_{t-1}(c)] \\
&= E[Y_t(d) - Y_{t-1}(c)|D_t = d, D_{t-1} = c] - E[Y_t(0) - Y_{t-1}(c)|D_t = d, D_{t-1} = c] \\
&= E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c] - E[Y_t - Y_{t-1}|D_t = 0, D_{t-1} = c]
\end{aligned} \tag{7}$$

Where the second equality holds by adding/subtracting $Y_{t-1}(c)$, third is through parallel trends and the final based on the SUTVA/no anticipation - ie that the observed value $(Y_t|D_t = d)$ is the potential value $(Y_t(d))$.

Next, we can use the outcome above to prove what we're interested in (assuming derivatives exist):

$$\begin{aligned}
&\frac{\partial E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c]}{\partial d} \\
&= \lim_{h \to 0} \frac{E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c] - E[Y_t - Y_{t-1}|D_t = d + h, D_{t-1} = c]}{h} \\
&= \lim_{h \to 0} \frac{E[Y_t - Y_{t-1}|D_t = d, D_{t-1} = c] - E[Y_t - Y_{t-1}|D_t = 0, D_{t-1} = c]}{h} \\
&- \frac{E[Y_t - Y_{t-1}|D_t = d + h, D_{t-1} = c] - E[Y_t - Y_{t-1}|D_t = 0, D_{t-1} = c]}{h} \\
&= \lim_{h \to 0} \frac{ATE_t(d) - ATE_t(d + h)}{h} \\
&= \lim_{h \to 0} \frac{E[Y_t(d) - Y_t(d + h)]}{h} \\
&= ACR_t(d)
\end{aligned} \tag{8}$$

Where the first equality holds by definition, the second adds/subtracts $E[Y_t - Y_{t-1}|D_t = 0, D_{t-1} = c]$, the third holds by the first proof above, the fourth holds by definition, and the final also holds by definition.

C.4 Connecting to TWFE models

Now all we need to do is show that a two-way-fixed effect parameter with homogeneous (linear) treatment effects identifies the ACR function. Suppose the following set up (adding back i's):

$$Y_{it} = \gamma_i + \theta_t + \alpha * D_{it} + \epsilon_{it}, \text{ where } E(\epsilon_{it} = 0) \tag{9}$$

By definition:

$$E[Y_{it} - Y_{it-1} | D_{it} = d, D_{it-1} = c] = \theta_t - \theta_{t-1} + \alpha d - \alpha c$$

Taking the derivative:

$$ACR_t(d) = \frac{\partial E[Y_{it} - Y_{it-1} | D_{it} = d, D_{it-1} = c]}{\partial d} = \alpha$$

Or that a one unit change in D_{it} corresponds to an increase in α, and this corresponds to the average causal response under the assumptions listed above (and linear, homogeneous treatment effects).

D 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 δ_i's and the time specific δ_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.

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.

D.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. Based on TWFE models, this would likely increase the size of the effect relative to a weighted version. I begin with a balanced panel.

Given that δ_{it} and δ_{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 $\epsilon = .001$, ϵ 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 ϵ such that the absolute value of any movement less than ϵ is considered a stayer, or that:

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

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

I let ϵ be .001, .002, .004 and .006.

D.2 Calculating δ_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.
    $\rightarrow$ They do not explicitly state what to do about other covariates. I calculate this with my additional demographic controls.

The final step is to create a weighted average these individual δ_{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.

D.3 Calculating δ_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 δ_{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).

    $\rightarrow$ 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 δ_{dt}.

What remains in the estimation of δ_d is the weighted average as above and the denominator in the δ_{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 of 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 $\hat{\delta}_d$

D.4 Final Estimate

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

D.5 Inference

–to come

E 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). Practically speaking, I include Post-Baccalaurate as ACP.[38]

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

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

- Student must be recommended through program

5. Apply for a Standard Certificate

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

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

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