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1 Appendix: Additional Information about Data and Descriptive Analyses

1.1 Vacancy Data

I now provide additional information about the vacancy posting data. While the main variables used in the analysis are SOC code, location, number of skills, and employer name, the data also contain information on industry, education requirements, experience requirements, job title, and salary, though much of this information is missing for many observations. For example, only about 10 percent of vacancies post any salary information. Many vacancies lack detailed North American Industry Classification System (NAICS) codes, but 78 percent of vacancies for health care workers are for the broad health care and social assistance sector (NAICS codes of 62).

As discussed in the main text, 57 percent of the vacancy postings contain the employer's name, and many of the postings that do not have the employer's name are posted by recruiters or staffing agencies that do not list the name of the employer where the worker will work. BGT does not provide the name of the staffing agency or recruiter. BGT cleans the employer name, and I take additional steps to ensure that similar employer names have the same fixed effect by standardizing punctuation (e.g., removing periods and replacing ampersands with the word *and*) and removing words that might often be considered optional parts of names (e.g., article adjectives). For example, vacancies in the same CZ with employer names of "Providence Health & Services", "Providence Health and Services", and "The Providence Health & Services" would all have the same employer fixed effect.

In Section 4, I consider the effect of Medicaid eligibility on various types of skill requirements. I classify skills as being cognitive skills, health skills, organizational skills, or social skills based on the words in the skill requirements. Skills are classified as cognitive skills if they contain the following words and phrases: *Problem Solving, Research, Analytical, Critical Thinking, Math,* or *Statistics*. Skills are classified as health skills if they contain the word *Health*.[1] Skills are classified as organizational skills if they contain the following words and phrases: *Organization, Detail-Oriented, Meeting Deadlines, Multi-Tasking,* or *Time Management*. Skills are classified as social skills if they contain the following words and phrases: *Communication, Team Work, Collaboration, Negotiation Skills, Presentation Skills,* or *Energetic*. Deming and Kahn (2018) use a similar classification, though our classifications are not identical since we consider different sets of occupations.

1.2 Quarterly Workforce Indicators

I now provide additional information about the QWI. The QWI is produced by the U.S. Census Bureau and provides quarterly industry-level information on various outcomes related to employment. The QWI is aggregated from Longitudinal Employer-Household Dynamics data, which comes from unemployment insurance records and covers 96 percent of wage and salary civilian jobs in the United States. The names of the variables that I use are *hira*, which is the total number of new hires and recalls in a quarter, and *emptotal*, which is the number of people employed in a firm at any time during the quarter. I focus on the NAICS code of 62.

The QWI data provide unique advantages for studying the relationship between Medicaid and employment. Relative to individual-level survey data like the Current Population Survey or even the ACS, the QWI covers many more jobs. As the data come from administrative records, the QWI is also likely highly accurate. In contrast to the Quarterly Census of Employment and Wages, the QWI contains information on jobs flows, which allows for considering hiring. Refer to Abowd et al. (2009) for more information about the QWI.

[1] In addition to harmonizing the names of various skills, BGT also clusters some of the skills into broader skill groups. I classify a skill as being health-related if the skill's name includes the word *Health* or if its broader skill cluster includes the word *Health* (e.g., *Public Health and Disease Prevention*), which means that skills that contain words and phrases like *Group Therapy, Behavioral Health,* and *Triage* are also classified as health skills. This approach misses many health skills but results in few false positives.

1.3 Descriptive Statistics and Analysis

For counties identifiable in the 2010 to 2012 ACS, Figure 1.1 demonstrates the relationships among Medicaid coverage, registered nurses' mean years of education, and income relative to the FPL at the county level calculated from the 2010 to 2012 ACS. Graph A of Figure 1.1 plots the relationship between the share of people with Medicaid coverage and the mean years of education for registered nurses and demonstrates that higher Medicaid coverage is associated with registered nurses having fewer years of education on average. However, Graphs B and C of Figure 1.1 show that the relationship between Medicaid and income is potentially a confounding factor in interpreting the relationship between Medicaid and registered nurses' years of education as being causal. In addition to the possibility that areas with lower average incomes may have less money to afford more-educated registered nurses, the relationship between Medicaid and registered nurses' years of education might reflect that less-educated registered nurses earn lower incomes, which leads to them living in counties with lower incomes.

Studying variation in Medicaid eligibility from the ACA's changes in Medicaid eligibility rules allows for assessing the effect of Medicaid apart from the effect of poverty. The vacancy data provide broader measures of skills than are available in most data sets and allow for basing the analysis on the location of jobs rather than on where workers live. The vacancy data are also a flow measure, which is important since stocks of workers evolve slowly over time.

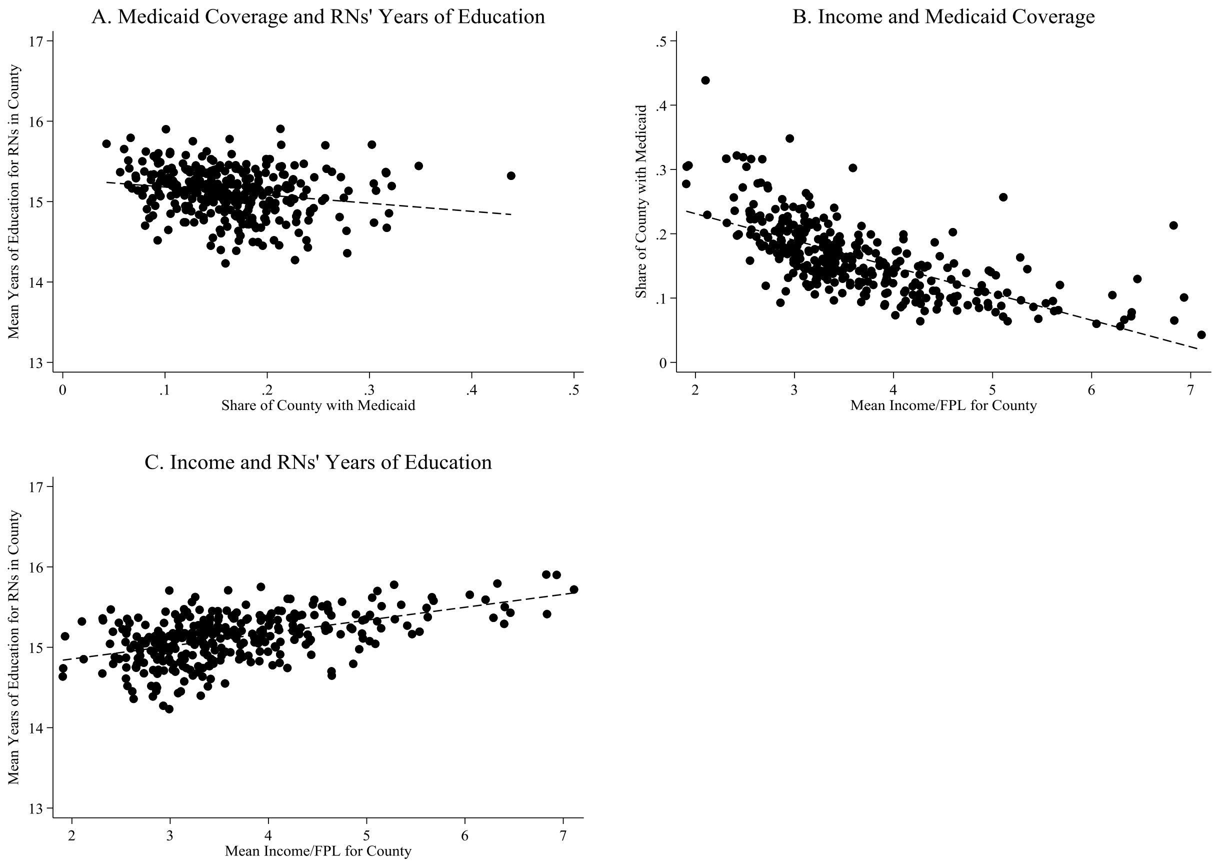

Figure 1.1: **Relationships among Medicaid Coverage, Registered Nurses' Years of Education, and Income at the County Level.** The data come from the 2010 to 2012 ACS.

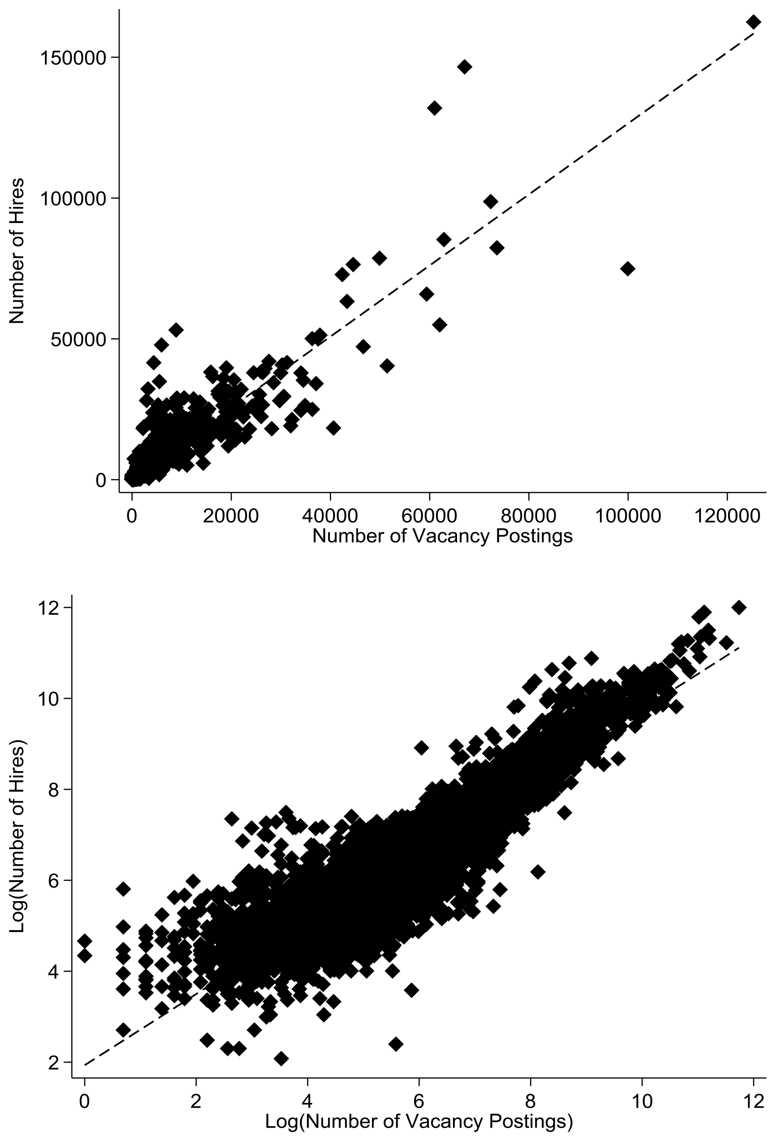

Figure 1.2: **Relationship Between Annual Vacancy Postings and Annual Hires for Health Care Industry.** The data come from vacancies posted online from 2013 to 2015 and from the 2013 to 2015 QWI.

Table 1.1: Unweighted Descriptive Statistics

	Mean	St. Dev.
Panel A. ACS Data		
Fraction Eligible for Medicaid	0.26	0.10
Fraction with Medicaid	0.19	0.06
Fraction with Employer-Sponsored Health Insurance	0.51	0.07
Fraction with Privately Purchased Health Insurance	0.15	0.04
Fraction with Any Private Insurance	0.65	0.08
Fraction with Any Health Insurance	0.87	0.05
Panel B. Vacancy Data		
Mean Number of Vacancy Postings per CZ	2,810	7,879
Mean Skills Required	5.5	6.2
Panel C. QWI Data		
Hires	3,533	9,219
Employment	31,958	84,193

Notes: **Panel A:** The data come from the 2010 to 2016 ACS. The unit of observation is the year-CZ combination. The sample contains a total of 5,082 observations from 726 CZs. **Panel B:** The data come from job vacancies posted online from 2010 to 2016. The unit of observation is a vacancy posting. The sample contains 14,278,072 postings. **Panel C:** The data come from the 2013 to 2015 QWI. The unit of observation is the year-quarter-CZ combination. The sample contains a total of 7,404 observations from 617 CZs.

Table 1.2: 20 Most Commonly Requested Skills

Skill Name	% of Vacancy Postings That Request Skill
Patient Care	19
Communication Skills	14
Treatment Planning	11
Cardiopulmonary Resuscitation (CPR)	10
Planning	7
Team Work/Collaboration	7
Advanced Cardiac Life Support (ACLS)	7
Supervisory Skills	7
Writing	7
Physical Therapy	7
Computer Skills	6
Therapy	6
Acute Care	6
Teaching	5
Patient/Family Education and Instruction	5
Occupational Therapy	5
Organizational Skills	5
Research	5
Home Health	5
English	5

Notes: The data come from job vacancies posted online from 2010 to 2016. The unit of observation is a vacancy posting. The sample contains 14,278,072 postings.

Table 1.3: 20 Most Commonly Requested Occupations at 5-Digit SOC Level

SOC Name	% of Vacancy Postings
Registered Nurses	38.2
Therapists	15.0
Physicians and Surgeons	10.1
Licensed Practical and Licensed Vocational Nurses	5.6
Medical Records and Health Information Technicians	4.1
Clinical Laboratory Technologists and Technicians	4.1
Health Practitioner Support Technologists and Technicians	3.8
Nurse Practitioners	3.8
Diagnostic Related Technologists and Technicians	3.1
Pharmacists	2.6
Miscellaneous Health Technologists and Technicians	2.3
Physician Assistants	2.0
Emergency Medical Technicians and Paramedics	1.2
Occupational Health and Safety Specialists and Technicians	0.9
Dietitians and Nutritionists	0.9
Dentists	0.8
Miscellaneous Health Diagnosing and Treating Practitioners	0.3
Dental Hygienists	0.3
Miscellaneous Health Practitioners and Technical Workers	0.2

Notes: The data come from job vacancies posted online from 2010 to 2016. The unit of observation is a vacancy posting. The sample contains 14,278,072 postings.

2 Appendix: Supplemental Analysis

This appendix includes supplemental analysis that is discussed in the main text of the paper. I display tables and figures for the analysis in this appendix and provide more details on the analysis when necessary.

Figures 2.1 and 2.2 consider the timing of the effects for several key outcomes by examining the relationship between a CZ's increase in Medicaid eligibility from 2010 to 2016 and its changes in the outcomes each year. Specifically, I estimate Equations (1) and (2) with OLS but replace $SHARE\_ELIG$ with interactions of each CZ's percentage-point change in the share of people eligible for Medicaid and year indicator variables for 2010 to 2012 and 2014 to 2016. This approach shows how the difference in outcomes between CZs that experienced large increases in Medicaid eligibility and other CZs changes each year relative to the difference in 2013. The estimates in Figure 2.1 and 2.2 show the relationship between an additional percentage point increase in Medicaid eligibility and the outcome variables. The individual estimates are often imprecise, but the results suggest that the timing of the changes in outcomes aligns across outcomes and with the timing of the Medicaid expansion.

Table 2.1 incorporates information about Medicaid's reimbursement rates. Incorporating information about Medicaid's reimbursement rates is not straightforward because states have different reimbursement rates for different services. Even within states, payments for the same service vary considerably (Medicaid and CHIP Payment and Access Commission 2017). Capturing and summarizing these differences is difficult. Furthermore, many Medicaid enrollees are in Medicaid Managed Care, which pays physicians a per-patient fee, rather than a fee for each service performed, which further adds to the complexity of summarizing Medicaid's reimbursement rates. The summary measure of reimbursement rates that I use for the analysis presented in this appendix is the Urban Institute's compilation of state-level Medicaid-to-Medicare reimbursement ratios for primary care. For CZs that span multiple states, I compute a population-weighted average of CZs' different Medicaid-to-Medicare reimbursement ratios.

Most states' Medicaid reimbursement rates had been relatively flat leading up to the ACA, but the ACA temporarily set national minimum Medicaid reimbursement rates that states could pay primary care providers equal to Medicare's reimbursement rates for 2013 and 2014. As reimbursement rates differed across states prior to 2013, states experienced differential rate increases for these years. While the federal government provided funding for the increased reimbursement rates in 2013 and 2014, states had to pay for the increased reimbursements themselves thereafter if they wanted to maintain them and many chose not to maintain the rate increases. The primary care services included in the rate hike were evaluation and management services and vaccine administration provided by physicians in family medicine, general internal medicine, and pediatric medicine.[2]

Although the increased reimbursement rates only cover a small subset of total services, one might be concerned that a possible correlation between the size of the fee increases and the size of the increases in Medicaid eligibility could confound the analysis if health care employers' demand for workers changes in response to these temporary reimbursement hikes. To consider how correlated the two measures are, Figure 2.3 graphs each CZ's change in Medicaid eligibility from 2010 to 2016 calculated from the ACS along with the change in its Medicaid-to-Medicare reimbursement ratios generated by the ACA's primary care rate hike. Figure 2.3 suggests that the two measures are not strongly correlated, which provides supportive evidence that the rate hikes do not confound the analysis.

As another way to verify that the rate hikes do not confound the analysis, panel A of Table 2.1 replicates the analysis shown in panel A of Table 4 but supplements Equation (2) with a control for the Medicaid-to-Medicare reimbursement ratio, which is one or greater in 2013 and 2014 but can be lower in other years. The estimates changing dramatically with this new control added would raise concerns that changes to Medicaid's reimbursement rates confound the analysis. Reassuringly, though, the estimates shown in panel A of Table 2.1 are very similar to the baseline estimates.

Aside from the possibility that changes to the reimbursement rates confound the analysis,

[2]Refer to Alexander and Schnell (2019) for an excellent discussion of Medicaid reimbursement rates and how the ACA changed those rates. For Tennessee, which only has Medicaid Managed Care, I use the reimbursement rates imputed by Alexander and Schnell for the analysis that follows.

Medicaid's reimbursement rates have the potential to be an important source of heterogeneity for the impact of Medicaid eligibility. In particular, higher-quality providers may increase hiring in response to increased demand when reimbursement rates are higher, so increased Medicaid eligibility may not have negative effects on average skills in areas with higher Medicaid reimbursement rates.

Panel B of Table 2.1 tests for separate effects of increased Medicaid eligibility for CZs with 2012 Medicaid-to-Medicare reimbursement ratios above the median and for CZs with 2012 Medicaid-to-Medicare reimbursement ratios below the median. To obtain separate estimates of the impact of Medicaid eligibility for the two sets of CZs, I create one variable that is equal to the share of people in a CZ eligible for Medicaid interacted with an indicator for being a high-reimbursement CZ and another variable that is equal to the share of people in a CZ eligible for Medicaid interacted with an indicator for being a low-reimbursement CZ. To obtain two instruments, I create one instrument that is equal to simulated eligibility for high-reimbursement CZs and zero for low-reimbursement CZs and another instrument that is equal to simulated eligibility for low-reimbursement CZs and zero for high-reimbursement CZs.

In addition to showing the estimated effects of Medicaid eligibility for the different reimbursement rates, Table 2.1 also shows p-values from tests of the null hypothesis that the coefficients on Medicaid eligibility are the same for high- and low-reimbursement CZs. As discussed in Section 4, the results are consistent with higher-quality providers posting more vacancies in response to increased Medicaid eligibility when Medicaid's reimbursement rates are higher, though the analysis cannot conclusively rule out that the effect of increased Medicaid eligibility is the same for places with high and low reimbursement rates for primary care.

Next, I consider the possibility that Medicaid expansions have spillover effects on the health care labor markets of non-expansion CZs, which could happen if CZs with increased Medicaid eligibility attract workers from other CZs. There are a number of reasons that these types of spillovers may be small in this environment. One is that migration rates are currently low relative to migration rates in previous decades (Molloy, Smith, and Wozniak 2011). Another is the previous research that has found that economic shocks induce workers to shift across sectors much more than across space (Autor et al. 2014). A third reason is that while the employment changes calculated in the main analysis are meaningful, they are not so large that they would require major shifts in the geographic distribution of the health care workforce. The employment increases documented in the main analysis could come from decreases in health care unemployment or from delayed retirements.

Still, it is possible that employers that experience increased demand from Medicaid expansions increase recruiting efforts in places that did not experience increases in Medicaid eligibility. As research shows that most of the people who move to a place experiencing an economic boon come from nearby places (Wilson 2020) and that people in general are more willing to move across shorter distances (Molloy, Smith, and Wozniak 2011), I next test for possible spillover effects of Medicaid expansions on CZs close to expansion states versus those that are farther from expansion states by implementing a difference-in-differences design. I define the treated CZs as CZs in states that did not expand Medicaid but that border expansion states. I define control CZs as CZs in states that do not border expansion states, which means the control states come from the South. I estimate equations of the following form:

$$y_{ct} = \gamma_c + \delta_t + \beta X_{ct} + \alpha Post\_Expan_t * Border\_Expan_c + \epsilon_{ct}, \tag{3}$$

where $Post\_Expan$ is an indicator equal to one in 2014 or later, $Border\_Expan$ is an indicator for a non-expansion CZ being in a state that borders an expansion state, and all other variables are defined as before. The sample only includes CZs that are entirely in non-expansion states.

Table 2.3 and 2.4 display estimates of the effect of the Medicaid expansion on CZs near expansion CZs from various regressions of Equation (3). None of the coefficients are statistically different from zero. This analysis provides no evidence that Medicaid expansions have spillover effects on nearby non-expansion CZs.

Finally, Table 2.5 shows estimates of the effect of Medicaid eligibility on the sample of vacancies for the broad health care sector (two-digit NAICs code of 62). The specifications in columns 2 and 4 of Table 2.5 also include controls for industry fixed effects for the 56 percent of vacancies with finer industry codes available. The results do not change dramatically when industry fixed effects are included and thus suggest that industrial shifts in vacancy postings are not responsible for Medicaid's negative impact on skill requirements.

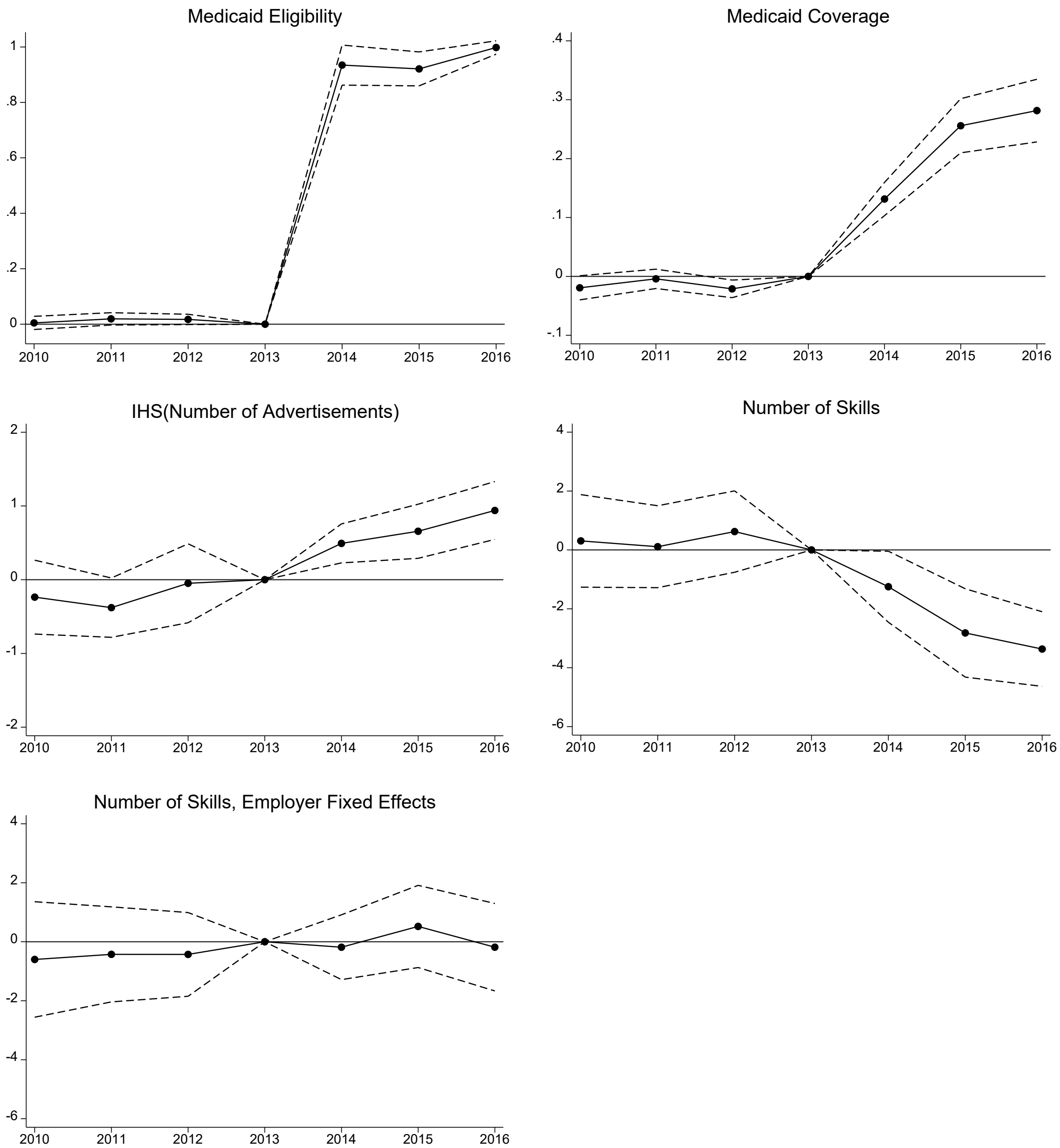

Figure 2.1: **Event Study Graphs for Selected Outcomes.** The graphs show coefficients on the interaction of CZs' percentage-point change in Medicaid eligibility from 2010 to 2016 and year, excluding 2013. Regressions for the first three graphs include year fixed effects and CZ fixed effects. Regressions for the last two graphs include occupation-by-CZ fixed effects and occupation-by-year fixed effects. The regression for the last graph also includes employer fixed effects. All regressions include the annual CZ-level covariates described in the text. The dashed lines indicate the 95-percent confident intervals constructed from standard errors clustered at the CZ level.

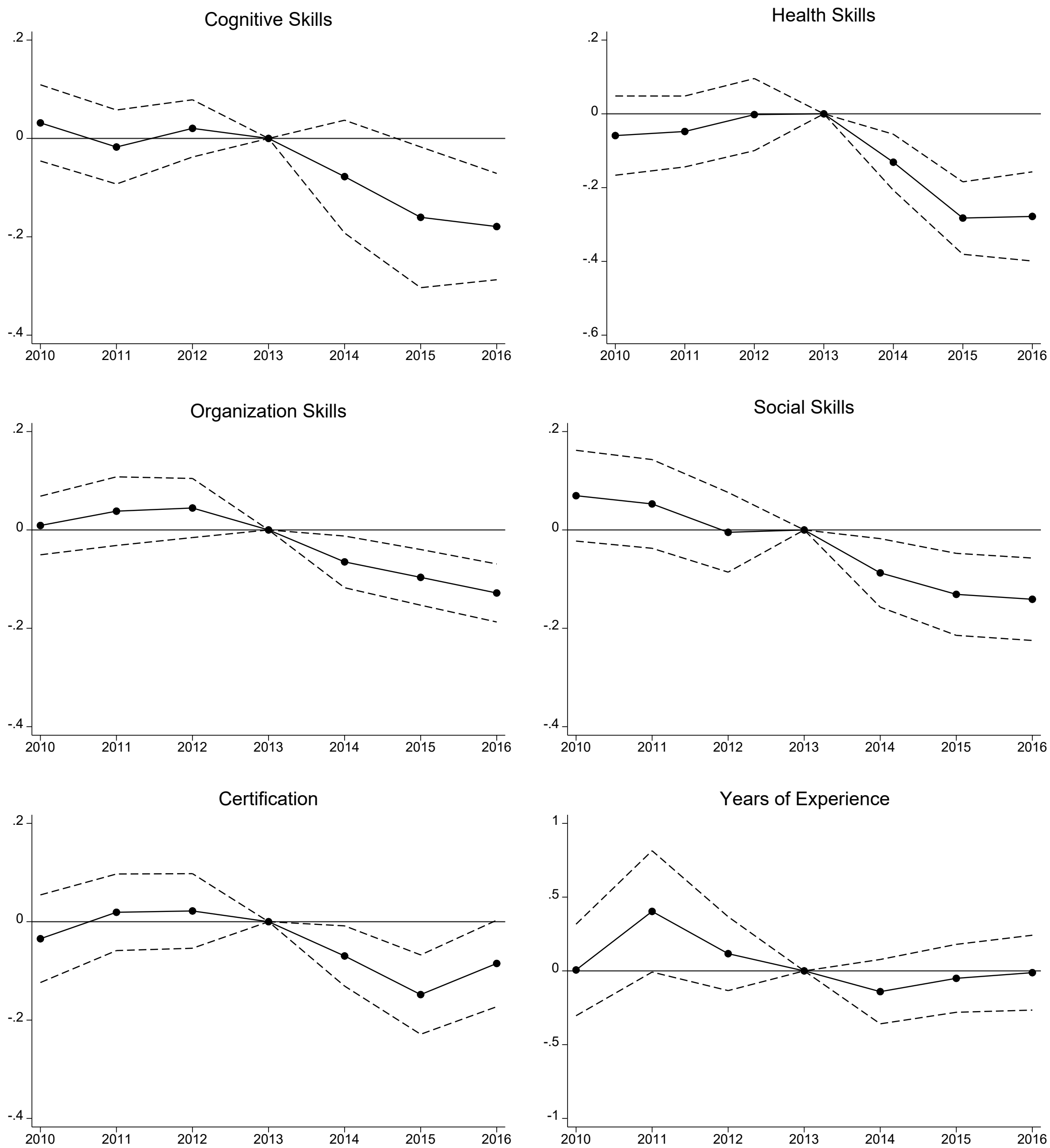

Figure 2.2: **Event Study Graphs for Alternative Skill Measures.** The graphs show coefficients on the interaction of CZs' percentage-point change in Medicaid eligibility from 2010 to 2016 and year, excluding 2013. All regressions include occupation-by-CZ fixed effects, occupation-by-year fixed effects, and the annual CZ-level covariates described in the text. The dashed lines indicate the 95-percent confident intervals constructed from standard errors clustered at the CZ level.

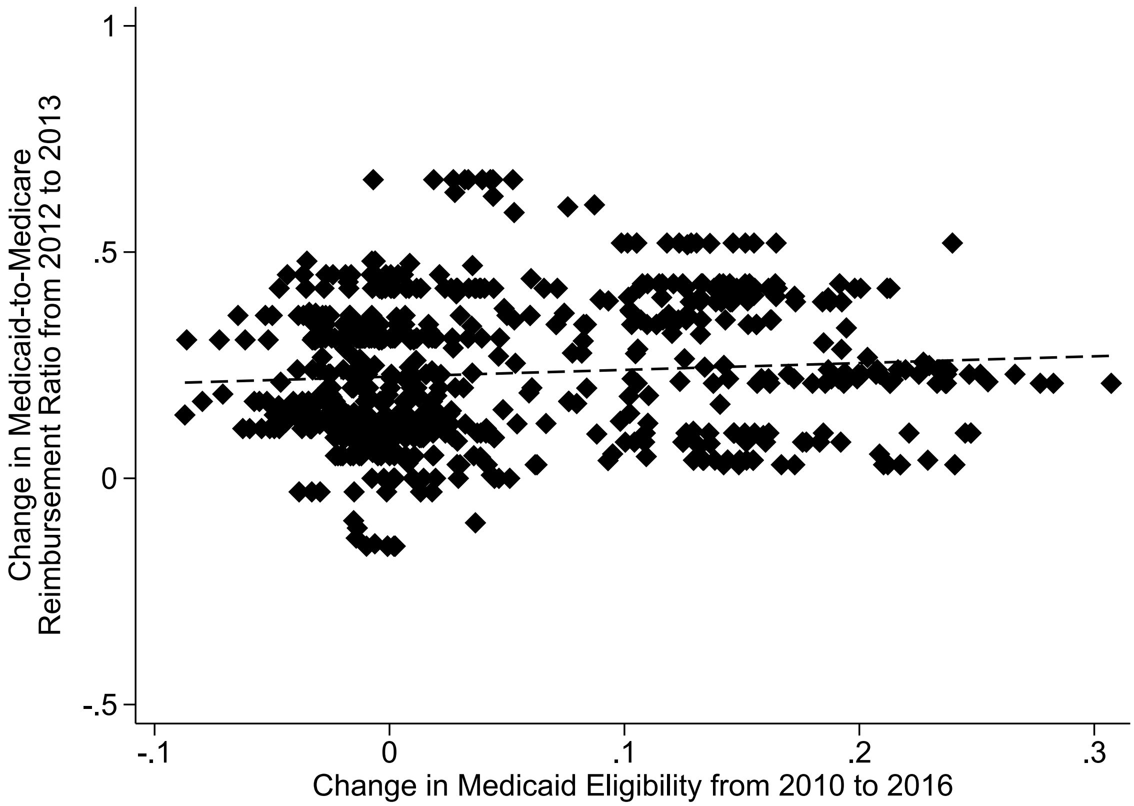

Figure 2.3: **Relationship Between CZs' Change in 2010 to 2016 Medicaid Eligibility and 2012 to 2013 Change in the Primary Care Medicaid-to-Medicare Reimbursement Ratio.**

Table 2.1: The Effect of Medicaid Eligibility on Skill Requirements, Robustness to and Heterogeneity by Medicaid Reimbursement Levels

	OLS	2SLS
Panel A. Robustness to Controlling for Medicaid-to-Medicare Reimbursement Ratio		
Medicaid Eligibility	-2.107***	-2.348***
	(0.548)	(0.573)
Panel B. Heterogeneity by Medicaid-to-Medicare Reimbursement Ratio		
Medicaid Eligibility * High Reimbursement	-1.444**	-1.479**
	(0.651)	(0.637)
Medicaid Eligibility * Low Reimbursement	-2.318***	-2.456***
	(0.639)	(0.595)
p-value of t-test of difference	0.265	0.192
Fixed Effects	CZ*occ year*occ	CZ*occ year*occ

Notes: The data come from job vacancies posted online from 2010 to 2016. The unit of observation is a vacancy posting. The sample contains 14,278,072 postings. Each cell is the effect of Medicaid eligibility from separate regressions of Equation (2). All regressions include the annual CZ-level covariates described in the text and CZs' population-weighted Medicaid-to-Medicare reimbursement ratio in addition to the fixed effects described in the table. Standard errors are clustered at the CZ level and are shown in parentheses below the estimates.

Table 2.2: The Effect of Medicaid Eligibility on Capacity Measures

	OLS	2SLS
Log(Number of Hospital Beds)	0.028	0.041
	(0.041)	(0.045)
Log(Number of Skilled Nursing Facility Beds)	0.036	0.042
	(0.037)	(0.040)

Notes: The data come from the 2010 to 2016 Area Health Resource File. The unit of observation is the year-CZ combination. The sample contains a total of 5,082 observations from 726 CZs. Each cell is the effect of Medicaid eligibility from separate regressions of Equation (1). All regressions include year fixed effects, CZ fixed effects, and the annual CZ-level covariates described in the text. Regressions are weighted by population. Standard errors are clustered at the CZ level and are shown in parentheses below the estimates.

Table 2.3: The Effect of Being near an Expansion State on Vacancy Postings, Hiring, and Employment for Health Care Jobs

IHS (Number of Vacancy Postings)	-0.045
	(0.037)
IHS (Hires)	0.001
	(0.014)
IHS (Employment)	-0.005
	(0.006)

Notes: The data come from job vacancies posted online from 2010 to 2016 and from the 2013 to 2015 QWI. The unit of observation is the year-CZ combination for the first row and the year-quarter-CZ combination for the second and third rows. The sample in the first row contains a total of 5,082 observations from 726 CZs, while the sample in rows 2 and 3 contain a total of 7,404 observations from 617 CZs. Each cell is the effect of the Medicaid expansion on non-expansion CZs that are near expansion CZs from separate regressions of Equation (3). The regression for row 1 includes year fixed effects, CZ fixed effects, and the annual CZ-level covariates described in the text. Regressions for rows 2 and 3 include year-quarter fixed effects, CZ fixed effects, and the annual CZ-level covariates described in the text. Regressions are weighted by population. Standard errors are clustered at the CZ level and are shown in parentheses below the estimates.

Table 2.4: The Effect of Being near an Expansion State on Skill Requirements

Panel A. Full Sample		
	0.161 (0.147)	0.113 (0.144)
Fixed Effects:	CZ year	CZ*occ year*occ
Panel B. Sample with Employer Name		
	0.228 (0.190)	0.240 (0.207)
Fixed Effects:	CZ*occ year*occ emp	emp*occ occ*year

Notes: The data come from job vacancies posted online from 2010 to 2016. The unit of observation is a vacancy posting. The sample in panel A contains 5,032,723 postings, while the sample in panel B contains the 3,058,988 vacancies with non-missing employer names. Each cell is the effect of the Medicaid expansion on non-expansion CZs that are near expansion CZs from separate regressions of Equation (3). All regressions include the annual CZ-level covariates described in the text in addition to the fixed effects described in the table. Standard errors are clustered at the CZ level and are shown in parentheses below the estimates.

Table 2.5: 2SLS Estimates of the Effect of Medicaid Eligibility on Different Measures of Skills for Health Care Sector

	Mean of Dependent Variable					
Number of Skills	4.530	-2.270***	-2.028***	-1.853**	-1.827**	0.496
		(0.630)	(0.579)	(0.862)	(0.838)	(0.901)
Number of Cognitive Skills	0.0669	-0.081	-0.067	-0.099	-0.090	0.024
		(0.066)	(0.065)	(0.102)	(0.100)	(0.118)
Number of Health Skills	0.289	-0.217***	-0.195***	-0.230***	-0.205***	-0.064
		(0.043)	(0.043)	(0.056)	(0.055)	(0.044)
Number of Organizational Skills	0.0828	-0.103***	-0.099***	-0.105**	-0.109**	-0.096
		(0.032)	(0.032)	(0.042)	(0.043)	(0.067)
Number of Social Skills	0.0944	-0.082**	-0.065*	-0.025	-0.018	0.021
		(0.042)	(0.037)	(0.055)	(0.053)	(0.050)
Certification	0.263	-0.081**	-0.062**	-0.068	-0.062	-0.050
		(0.033)	(0.029)	(0.044)	(0.039)	(0.041)
Years of Experience	0.691	-0.108	-0.100	-0.170*	-0.161*	-0.082
		(0.109)	(0.107)	(0.098)	(0.098)	(0.102)
Number of Vacancies:		11,144,399	11,144,399	6,216,915	6,216,915	6,216,915
Fixed Effects:		CZ*occ year*occ	CZ*occ year*occ industry	CZ*occ year*occ	CZ*occ year*occ industry	employer*occ year*occ
All Vacancies:		x	x			
Only Vacancies with Firm Name:				x	x	x

Notes: The data come from job vacancies posted online for two-digit NAICs code of 62 from 2010 to 2016. The unit of observation is a vacancy posting. Each cell is the effect of Medicaid eligibility from separate 2SLS regressions of Equation (2) that include controls for CZs' annual demographic and economic characteristics as described in the text in addition to the fixed effects described in the table. Standard errors are clustered at the CZ level and are shown in parentheses below the estimates.

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