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PQHS 500
Project Abstract
2020-04-29

Background

People who live in rural communities have been believed to have lower access to care because of multiple different factors. These are such as longer commutes, less physicians, lower income, and etc. This has been known for around 20 years, but since the medicaid expansion it isn't known how much of an access to care gap currently exists between urban and rural communities. There are also multiple different variables used to understand access to care and which ones rural communities are at the highest risk of isn't completely understood. The objective is to learn about the largest access to care effect on rural communities two different outcome variables will be studied. These variables are the percent of the population that is uninsured and the rate of primary care physicians per 100,000 population. Specifically is the probability of uninsured lower in urban counties compared to rural counties in the United States? And is the rate of primary care physicians per 100,000 population higher in urban counties compared to rural counties in the United States?

Methods

The County Health Rankings Data in 2019 was used to best evaluate how access to care affects the population at the county level. An exposure variable was made defining urban as a county with a population greater than or equal to 50,000 people and rural as any county lower than that. This exposure variable was used with the urban category being the treated group and the rural category being the control group. This exposure variable was used along with 13 other covariates to define propensity scores for the two outcome variables. These propensity scores were used to do 1:1 greedy matching without replacement, with replacement, and ATT weighting. Once the propensity score methods were done, outcome analysis was done with mixed modeling techniques for continuous outcomes. These mixed modeling techniques used matching methods as the random variable in the model.

Results

The 987 total urban counties were matched against rural counties for every propensity score method that was done. The rubin's rules were not good for every type of propensity score method except for 1:1 greedy matching with replacement. This is also the same for the love plots that were created to show the distribution of the standardized differences. The outcome analysis showed a large effect for the outcome of primary care physicians. For the greedy matching with replacement an estimate of 14.66 95% CI: (11.23, 18.09). This method for the outcome uninsured showed a point estimate of -0.01 95% CI: (-0.02, -0.01). These were the main

outcomes that were focused on since greedy matching with replacement showed decent matching between the urban and rural categories.

Conclusions

The results for the greedy matching with replacement were interesting because the uninsured outcome had a much smaller effect than expected. The other propensity score methods didn't look to successfully match between the two groups. The ATT weighting approach showed poor results for rubin rules, love plots, and estimates. The weighting approach even made the original unadjusted results nonsignificant. This is most likely because some rural counties were much higher weighted than urban counties. The propensity score doesn't fit this analysis as well as expected with how extremely different the majority of rural and urban counties appeared. Further analysis will need to be done using subgroups to determine severity of rurality against a baseline urban category.

Do Urban US Counties have Better Access to Care than Rural Counties?



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2020-04-30

Background

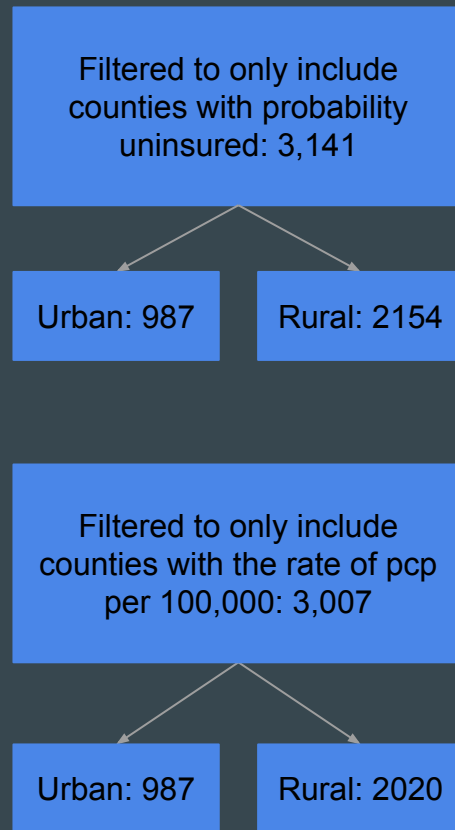
- Rural communities
 - Have been considered to have less quality healthcare access than urban areas
 - One study says that only 9% of the nations physicians practice in rural areas
 - The uninsured rate has also been estimated to be significantly different in rural communities compared to urban areas
 - This also differs a lot between counties
 - Most of these studies are fairly old
 - Unknown how large the effect size currently is since medicaid expansion

Research Question

- Objective
 - To understand access to care in urban compared to rural US counties using the percent uninsured and the rate of primary care physicians per 100,000 population.
- Is the probability of uninsured lower in urban counties compared to rural counties in the United States?
- Is the rate of primary care physicians per 100,000 population higher in urban counties compared to rural counties in the United States?

Data Source, Exposure, and Outcome

- County Health Rankings in 2019
 - Collects data on all the counties in the United States
- Exposure:
 - Urban (population $\geq 50,000$)
 - Rural (population $< 50,000$)
- Outcome 1:
 - Probability of US county uninsured (continuous outcome)
- Outcome 2:
 - Rate of PCP per 100,000 population (continuous outcome)



Covariates

- Demographics and socioeconomic
 - % of high school graduation, % of population that's white, median income, % of the population that is unemployed
- Health outcomes
 - % of population that self-reports as poor or fair health, age-adjusted mortality per 100,000 for people under 75, % of the population that has low birth weight
- Health behaviors
 - % of the population that doesn't have access to reliable food, % of adults smoking, % of adults that have obesity, % of the population that is inactive, % of the population that excessively drinks, % of teen births

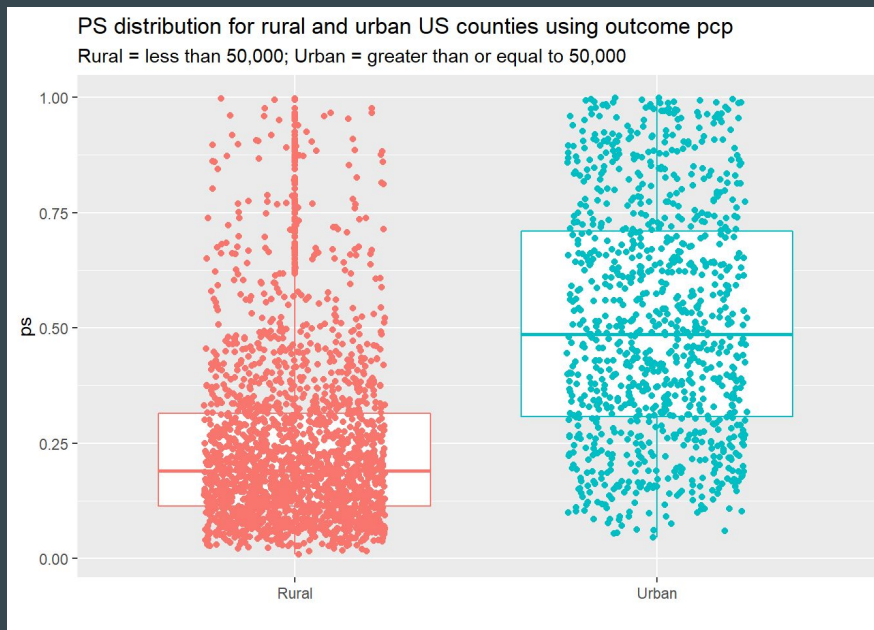
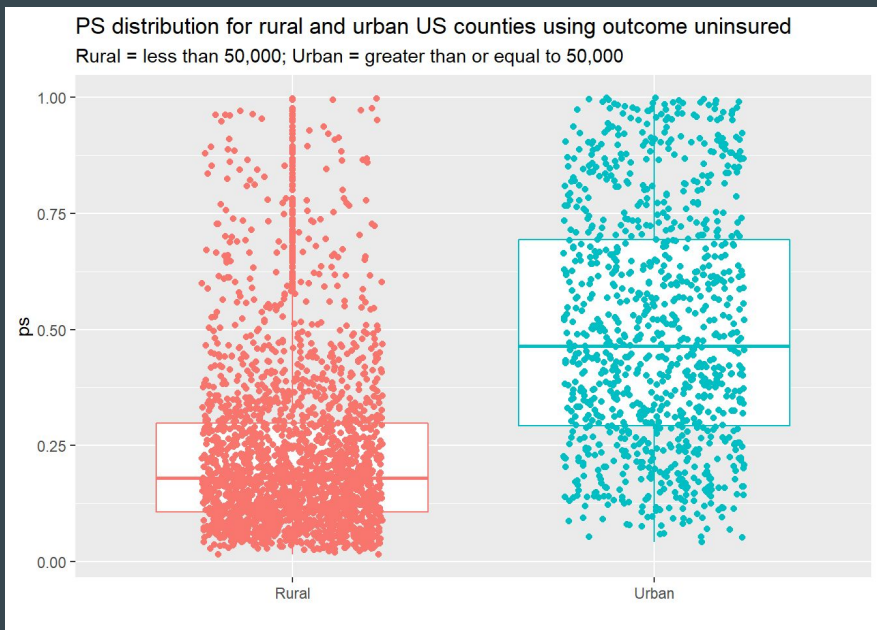
Table One

	Stratified by urban_area_f			Stratified by urban_area_f	
	Rural		Urban	p	test
n	2155	n	987		
hs_grad (mean (SD))	0.89 (0.08)	hs_grad (mean (SD))	0.87 (0.06)	<0.001	
white (mean (SD))	0.78 (0.20)	white (mean (SD))	0.72 (0.19)	<0.001	
unemployment (mean (SD))	0.05 (0.02)	unemployment (mean (SD))	0.04 (0.01)	0.003	
median_income (mean (SD))	47425.47 (10664.36)	median_income (mean (SD))	59089.06 (15443.29)	<0.001	
poor_health (mean (SD))	0.18 (0.05)	poor_health (mean (SD))	0.16 (0.04)	<0.001	
age_adjust_mortality (mean (SD))	426.07 (118.68)	age_adjust_mortality (mean (SD))	366.44 (88.68)	<0.001	
lbw (mean (SD))	0.08 (0.02)	lbw (mean (SD))	0.08 (0.01)	0.011	
food_insecurity (mean (SD))	0.14 (0.04)	food_insecurity (mean (SD))	0.13 (0.04)	<0.001	
smoking (mean (SD))	0.18 (0.04)	smoking (mean (SD))	0.17 (0.03)	<0.001	
obesity (mean (SD))	0.33 (0.04)	obesity (mean (SD))	0.31 (0.05)	<0.001	
inactivity (mean (SD))	0.27 (0.05)	inactivity (mean (SD))	0.24 (0.05)	<0.001	
drinking (mean (SD))	0.17 (0.03)	drinking (mean (SD))	0.19 (0.03)	<0.001	
teen_births (mean (SD))	35.06 (15.53)	teen_births (mean (SD))	26.07 (12.23)	<0.001	

Propensity score distribution

PCP: min = 0.046, max = 0.998

Uninsured: min = 0.042, max = 0.999



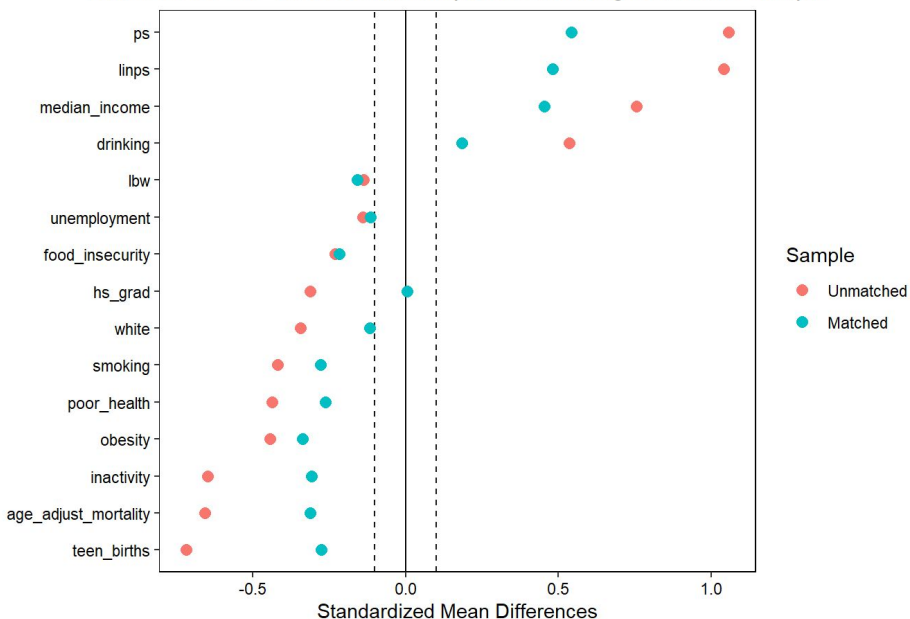
1:1 Greedy Matching without Replacement

Using the sample with uninsured outcome		
Rubin's Rules	Unmatched	Matched
Rule #1	108.1	54.54
Rule #2	1.8	2.23

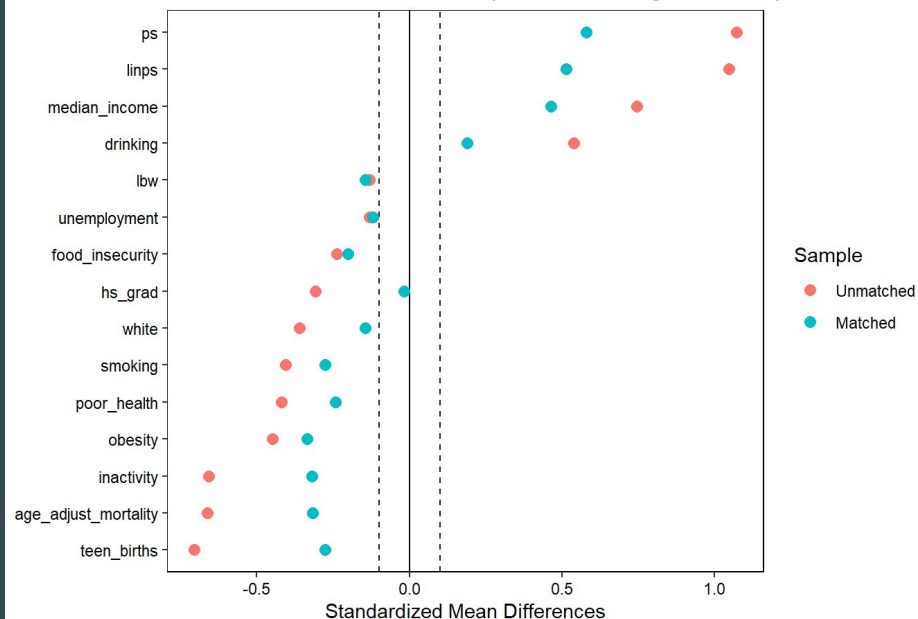
Using the sample with PCP outcome		
Rubin's Rules	Unmatched	Matched
Rule #1	107.2	57.8
Rule #2	1.75	2.23

1:1 Greedy Matching without Replacement

Love Plot for our 1:1 Match w/o Replacement using Uninsured Sample



Love Plot for our 1:1 Match w/o Replacement using PCP Sample



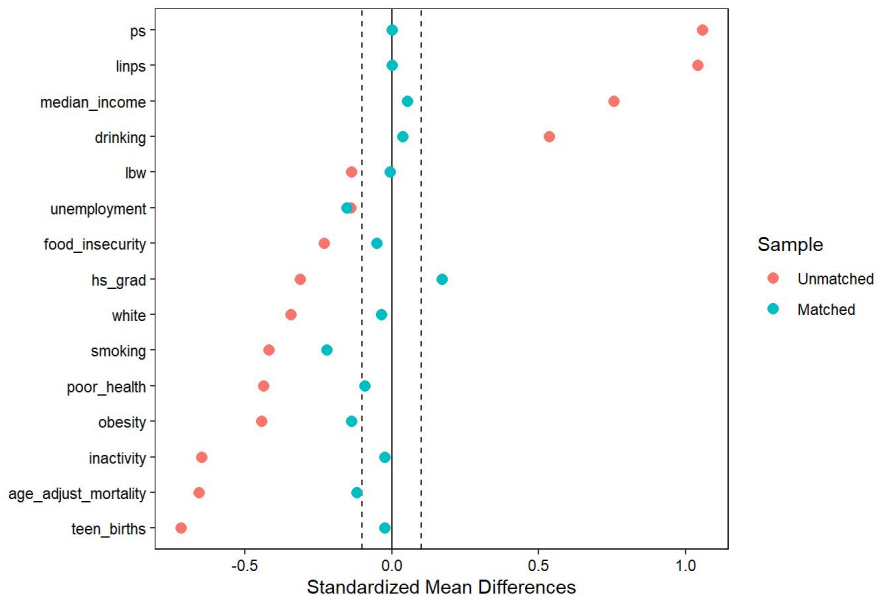
1:1 Greedy Matching with Replacement

Using the sample with uninsured outcome		
Rubin's Rules	Unmatched	Matched
Rule #1	108.1	0.2
Rule #2	1.8	1.01

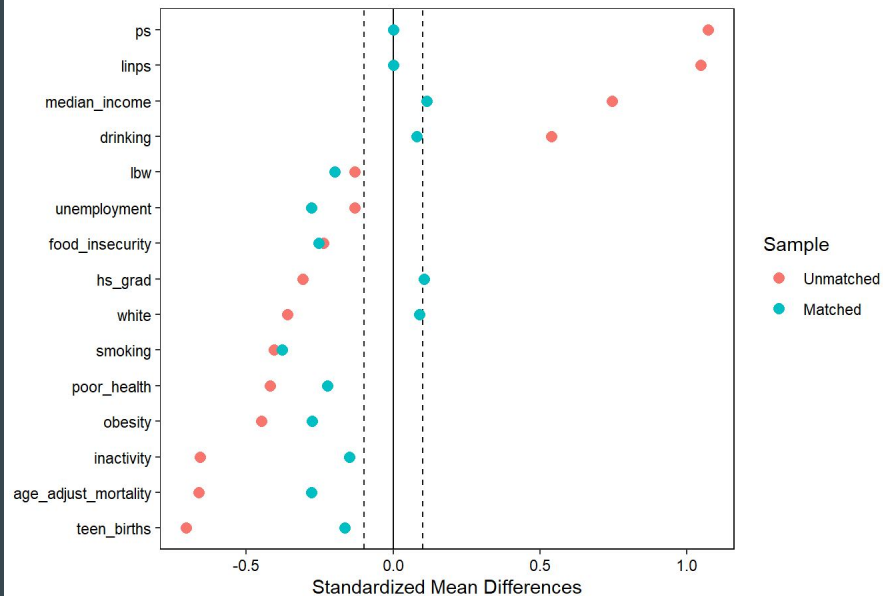
Using the sample with PCP outcome		
Rubin's Rules	Unmatched	Matched
Rule #1	107.2	0.1
Rule #2	1.75	1.00

1:1 Greedy Matching with Replacement

Love Plot for our 1:1 Match with Replacement using Uninsured Sample



Love Plot for our 1:1 Match with Replacement using PCP Sample

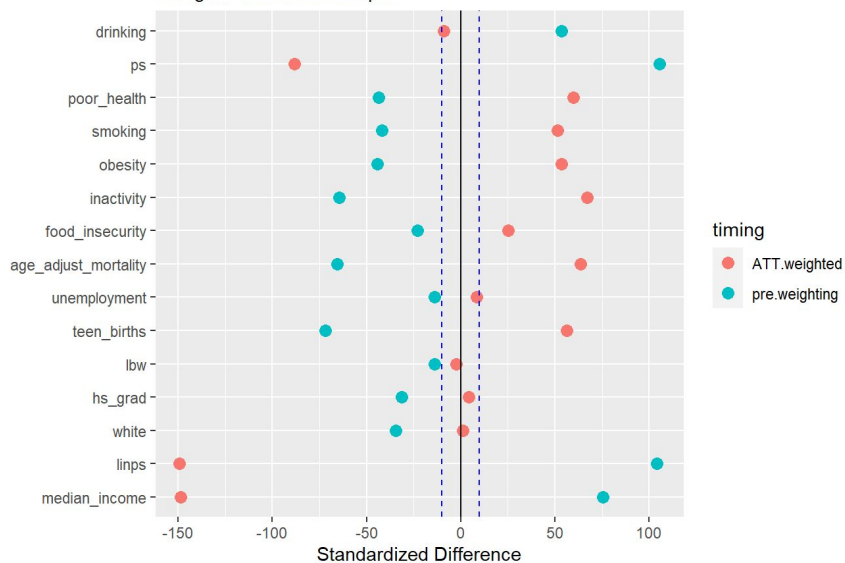


Results after matching

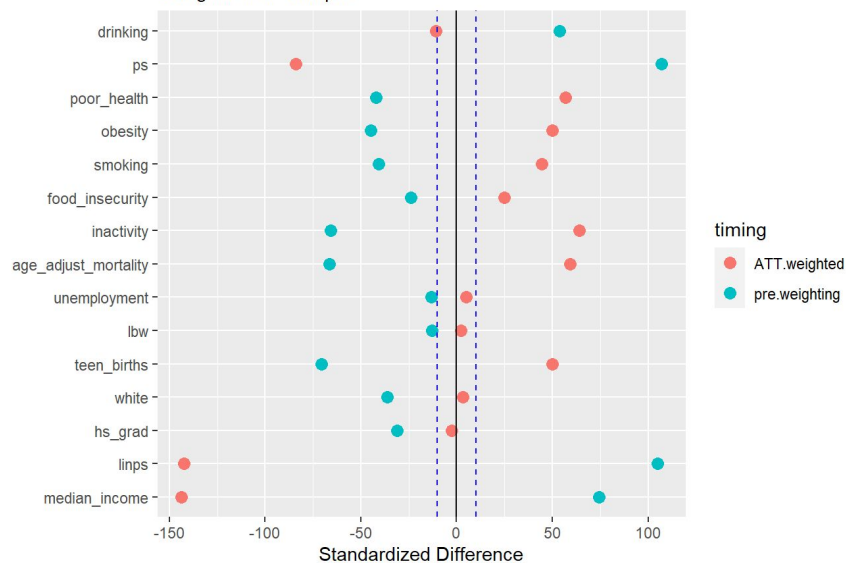
Model	Estimate	95% CI
unadjusted using uninsured	-0.02	(-0.02, -0.02)
unadjusted using pcpr	21.68	(19.1, 24.25)
1:1 greedy w/o repl using uninsured	-0.02	(-0.02, -0.01)
1:1 greedy w/o repl using pcpr	19.43	(16.51, 22.34)
1:1 greedy w/ repl using uninsured	-0.01	(-0.02, -0.01)
1:1 greedy w/ repl using pcpr	14.66	(11.23, 18.09)

ATT Weighting using inverse PS

Standardized Difference before and after ATT Weighting
Using the uninsured sample



Standardized Difference before and after ATT Weighting
Using the PCP sample



Sensitivity Analysis

Outcome: Uninsured

Gamma	Lower bound	Upper bound
1.0	0	0.0000
1.1	0	0.0001
1.2	0	0.0070
1.3	0	0.0834
1.4	0	0.3482
1.5	0	0.7030
1.6	0	0.9189
1.7	0	0.9865
1.8	0	0.9986
1.9	0	0.9999
2.0	0	1.0000

Outcome: PCP

Gamma	Lower bound	Upper bound
1.0	0	0.0000
1.1	0	0.0000
1.2	0	0.0000
1.3	0	0.0000
1.4	0	0.0000
1.5	0	0.0000
1.6	0	0.0000
1.7	0	0.0000
1.8	0	0.0001
1.9	0	0.0012
2.0	0	0.0081
2.1	0	0.0361
2.2	0	0.1109
2.3	0	0.2510
2.4	0	0.4425
2.5	0	0.6407

Conclusions

- PCP Outcome
 - Larger amount of pcsp per 100,000 population in urban areas
- Uninsured Outcome
 - Small effect size was seen
- Weighting
 - Didn't show good results, possibly because of the large weights on some rural counties
- Limitations
 - Had to lose a lot of variables because ps was too separated

Model	Estimate	95% CI
unadjusted using uninsured	-0.02	(-0.02, -0.02)
unadjusted using pcsp	21.68	(19.1, 24.25)
1:1 greedy w/o repl using uninsured	-0.02	(-0.02, -0.01)
1:1 greedy w/o repl using pcsp	19.43	(16.51, 22.34)
1:1 greedy w/ repl using uninsured	-0.01	(-0.02, -0.01)
1:1 greedy w/ repl using pcsp	14.66	(11.23, 18.09)
ATT weighting using uninsured	0.00	(-0.02, 0.03)
ATT weighting using pcsp	-32.03	(-78.99, 14.93)

- Future considerations
 - Look at doing a subgroup analysis
 - Using the % rural variable for the counties