The Effect of Medicaid Expansion on the Medicare Population

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Abstract

While the Affordable Care Act of 2010 expanded health care access to millions of Americans, it is unclear how specifically the expansion of Medicaid has affected preventative health outcomes in the United States. We aim to investigate through regression techniques if there are significant associations between expanding Medicaid and preventative health outcomes, particularly in the population aging into Medicare. Using regression techniques on publicly available Medicare data, we have found that states with Medicaid expansion have significantly lower rates of preventable hospital admissions, HCC scores, emergency room usage, and higher rates of outpatient visits among the Medicare beneficiary population, controlling for a selection of demographic factors.

Introduction

Since 2010, several states in the United States have expanded eligibility for Medicaid to extend access to affordable healthcare to millions of Americans. There have been numerous studies examining the effect of Medicaid expansion on access and quality of care, in addition to potential economic gains. While much of our literature review included research on the effects of Medicaid expansion, we did not find much that pertained specifically to the effect of Medicaid expansion on the Medicare population. Miller et al found in a landmark study linking the American Community Survey data and administrative death data that Medicaid expansion is associated with a 0.132 percentage point decrease in annual mortality in adults aged 55 to 64 during the study period from 2014 - 2017[1]. They attribute this reduction in premature deaths to better screening access and earlier diagnoses of diseases. We would like to better understand whether these gains continue to be present as older adults age into the following decade of their lives and become eligible for Medicare.

Methods

Study Population: We obtained annual health care service utilization and health outcome data in the Medicare population (individuals aged 65 or older & select individuals under 65 with certain disabilities) from 3,196 (n = 3,046 after dropping records with missing covariates) U.S. counties across the 50 states, DC, and U.S. territories spanning the years 2007-2018. The population includes all beneficiaries enrolled in the fee-for-service program, as well as those enrolled in the Medicare Advantage program. The data came from the Medicare Geographic Variation Public Use file (GVPUF), which has data both at the county and hospital referral region (HRR) level. [2] While the HRR dataset is smaller, it is representative of the county level information[3].

Missing Data: To evaluate the missing data in the GVPUF file, we determined that it is likely that some counties report metrics more frequently or more consistently than other counties, which accounts for

[1] https://www.nber.org/papers/w26081
[2] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/GV_PUF
[3] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/Downloads/Geo_Var_PUF_Methods_Paper.pdf

missingness at random (MAR) across our response variables and covariates. Additionally, CMS has suppressed data for counties with insufficient number of users for specific services, which is more common in sparsely populated counties. To handle this, we evaluated the missingness in our covariates and outcomes for each dataset and used that information to perform complete case analyses in our models when missing records were a small fraction of our total dataset.

Medicaid Expansion Dates[4]:We used the information on when each state expanded Medicaid to create four categories of expansion, and all counties within a state were labeled with the same expansion status:

- 1 - Expanded Medicaid before 2014
- 2 - Expanded Medicaid in 2014
- 3 - Expanded Medicaid after 2014
- 4 - Not yet expanded Medicaid as of 2018

Key Health Outcomes

The following metrics are used as outcomes in our model to quantify differences in *overall quality of health* and types of *health care services utilized* in the Medicare population:

Aggregate Health Scores

HCC Score: The hierarchical condition category (HCC) score is a model developed by CMS to assign risk scores for patients based on health conditions.[6] The risk score accounts for factors such as hospital admissions for acute and chronic issues, as well as the severity of diseases and conditions the patient is diagnosed with. The average national score serves as the reference value and is equal to 1. Patients in poorer health than the average beneficiary would have a score greater than 1, whereas a patient with better health would have a score closer to 0. This metric can serve as a proxy to broadly quantify the average individual health of a community since several dimensions of health are considered in this score.

PQI: Prevention quality indicators are metrics designed by the Agency for Healthcare Research and Quality which identify hospital admissions that could be avoided by having access to high quality outpatient care, and can provide information on the quality of health services in a community.[7]

Health Services Utilization

Emergency department visits: To evaluate how Medicare health care services are impacted by Medicaid expansion status, we looked at county-level emergency department visits per 1,000 beneficiaries. score. Patients often seek care in emergency departments for non-emergent issues when they do not have regular access to care, or when preventable conditions escalate to critical states.

Outpatient visits: To evaluate how Medicare outpatient utilization is impacted by Medicaid expansion status, we looked at county-level outpatient visits per 1,000 beneficiaries.

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[4] https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/?activeTab=map&currentTimeframe=0&selectedDistributions=status-of-medicaid-expansion-decision&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

[6] https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/Downloads/2015-RiskAdj-FactSheet.pdf

[7] https://www.qualityindicators.ahrq.gov/Modules/pqi_resources.aspx

Other Covariates of Interest

We selected our additional covariates from the demographics fields, based on informative predictors in similar analyses we saw in literature[8]:

Table 1. Summary of Demographic Covariates

Field	Description
Average age	Average age of the Medicare population in the county
Percent male	Percent of the Medicare population in the county identified as male
Percent non-Hispanic white	Percent of the Medicare population in the county identified as non-Hispanic white
Percent African American	Percent of the Medicare population in the county identified as African American
Percent Hispanic	Percent of the Medicare population in the county identified as Hispanic
Percent eligible for Medicaid	Percent of the Medicare population in the county who are dually eligible for Medicaid

We evaluated these variables for missingness and found that the race-related demographics were missing for ~42% of the observations in the county data and for ~0.6% of records in the HRR level data. We also evaluated these covariates for collinearity and took the results into account when selecting each of our models (see Appendix). The table below summarizes the number of complete records we had available for analysis at each expansion status.

Table 2. Data Summary

Expansion Status	Number of Counties with Complete Data for all Outcomes & Potential Covariates in 2018 Dataset (total=3,096)
1	209
2	865
3	380
4	1,592

Statistical Analysis

We used a series of regression techniques including multinomial regression, logistic regression, and Poisson regression to determine the effect of Medicaid expansion. Please refer to the appendices for more details about the model fitting process, along with supplemental figures.

Analysis of Aggregate Health Scores

HCC score: To determine whether Medicaid expansion improved the average HCC score of Medicare beneficiaries, we fit two models: (1) a multivariable linear regression model examining HCC scores in 2018 across U.S. counties and (2) a multivariable linear model comparing each county's 2010 HCC

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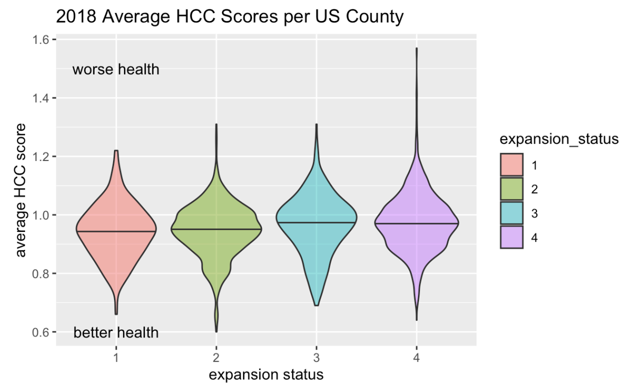
[8] https://www.annualreviews.org/doi/pdf/10.1146/annurev-publhealth-040617-013517

score before the Affordable Care Act was enacted to its score in 2018 in order to estimate the potential long term effects on quality of health.

Model 1: 2018 HCC Scores - We first assessed the normality of the outcome (average individual HCC scores in each county), and found that the scores were fairly normally distributed with a slight right skew (Appendix Section I: Figure 1). Performing a log transform provided a modest decrease in skewness (Appendix Section I: Figure 2). Initially, a reduced linear regression model was fit to examine the association between county-level HCC scores and the expansion statuses of the state the counties reside in. The expansions statuses were modeled with indicator variables, using Expansion Status 1 as the reference category.



This initial model had an extremely low Adjusted R-Squared value (0.02), and so additional covariates were considered in the model. Data exploration indicated that percent eligible for Medicaid had a strong positive correlation with average HCC scores, and so the linear and quadratic terms for this covariate were added to the model. Average age and percent male were also negatively correlated with average HCC scores, and so both covariates were included. From analyzing the diagnostic plots, we saw that this updated model violated both linearity and normality assumptions (Appendix Section I: Figure 3). Thus, we considered higher order terms and potential effect modification. Higher order terms for average age and percent male were not statistically significant, and the interaction term for expansion status and percent eligible for Medicaid proved to be insignificant as well. However, we did find that there is a significant interaction effect between average age and percent male, and the inclusion of this interaction term improved the linearity of the model based on the residual versus fitted values diagnostic scatter plot (Appendix Section I: Figure 4). This final model was considered our full model, and F-tests concluded that this full model explained more variance in the data than all reduced models considered ($p<0.05$).

Because the assumption of normality was still violated in this final model, the robust sandwich estimator method was employed to calculate the standard errors of the coefficients and the associated confidence intervals. The final model for the 2018 average HCC scores is:

$$\begin{aligned} E(average\ 2018\ HCC\ score) &= -3.54 - 0.001 * I(State\ Expanded\ Medicaid\ in\ 2014) - 0.015 * I(State\ Expanded\ Medicaid\ after\ 2014) \\ &+ 0.035 * I(State\ has\ not\ Expanded\ Medicaid) + 0.049 * (average\ age) + 14.31 * (percent\ male) - 7.58 \\ &* (perecent\ male)^2 + 0.82 * (\%\ eligible\ for\ Medicaid) - 0.45 * (\%\ eligible\ for\ Medicaid)^2 - 0.13 \\ &* (average\ age * percent\ male) \end{aligned}$$

Summary Model Statistics: AIC = -7614.53 | Multiple R-squared: 0.5096, Adjusted R-squared: 0.5081 |F-statistic: 96.54 on 6 and 3111 DF, p-value: < 2.2e-16

Model 2: 2018 vs 2010 HCC Scores - In order to understand how health care outcomes have changed overtime as a result of Medicaid expansion, we compared average HCC scores from 2010 before the Affordable Care Act was enacted to HCC scores in 2018, after several states had increased coverage. We calculated both the ratio and difference of 2018 versus 2010 HCC scores, and saw that the distribution of score differences had less extreme tails than the ratio of the scores (Appendix Section II: Figures 1 & 2). The difference also seemed more intuitive and facilitated fairer comparisons, whereas the ratio would vary depending on a county's 2010 baseline score (i.e. counties with lower baseline HCC scores would show greater changes than counties with higher baseline HCC scores).

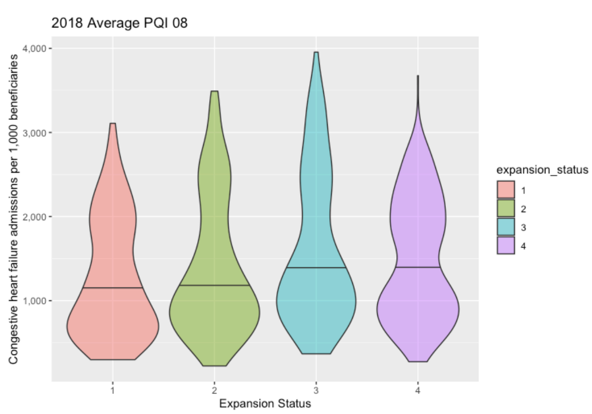
After deciding on using HCC score differences as the outcome, we compared a reduced model (expansion status as only covariate) with an expanded model that includes the percent change in Medicaid eligibility, percent change in average age, and percent change in the male population from 2010 to 2018. The adjusted model had a substantially higher adjusted-R squared value (0.155 versus 0.01), but the expanded model violated the linearity assumptions based on the residual diagnostic scatter plot (Appendix Section II: Figure 3). Thus, we also considered a quadratic term for the percent eligible for Medicaid ($p < 0.05$), and the inclusion of this term improved the linear fit of the model (Appendix Section II: Figure 4). An F-test comparing this full model to the reduced model was statistically significant ($p<0.05$), indicating that the additional covariates were needed to explain the variation in the data.

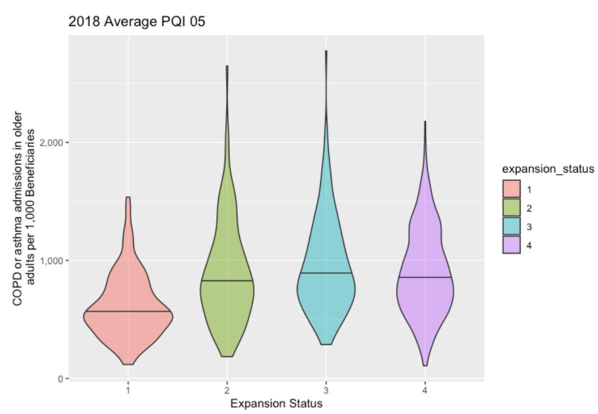
Based on the QQ-plots of the residuals, the final model violated the assumption of normality, and so, the robust sandwich estimator method was employed to calculate the standard errors of the coefficients and the associated confidence intervals. The final model for the difference in average HCC scores between 2018 and 2010 was:

$$\begin{aligned} E(2018\ HCC\ score\ -\ 2010\ HCC\ score) \\ &= 0.27 - 0.0098 * I(State\ Expanded\ Medicaid\ in\ 2014) - 0.01 * I(State\ Expanded\ Medicaid\ after\ 2014) \\ &+ 0.011 * I(State\ has\ not\ Expanded\ Medicaid) + 1.0136 * (\%\ change\ in\ average\ age) + 0.0866 \\ &* (\%\ change\ in\ percent\ male) + 0.136 * (\%\ change\ in\ Medicaid\ eligibility) - 0.054 \\ &* (\%change\ in\ Medicaid\ eligibility)^2 \end{aligned}$$

Summary Model Statistics: AIC = -9924.365 | Multiple R-squared: 0.1614, Adjusted R-squared: 0.1596 | F-statistic: 96.54 on 6 and 3111 DF, p-value: < 2.2e-16

PQIs: In order to determine which PQI outcomes to model with Medicaid expansion status, we evaluated the missingess in the GVPUF-HRR dataset, across PQI 05 - COPD or asthma in older adults admissions rate, PQI07 - hypertension admissions rate, and PQI08 - congestive heart failure admissions rate. These PQI values are stratified by age category (under 65 years, 65-75 years, and 75+ years). Since the actual selection of PQIs is somewhat arbitrary for our research intent, we chose two metrics with the least amount of missingness, PQI05 and PQI08, as proxies for the quality of care for Medicare beneficiaries across the various hospital referral regions.





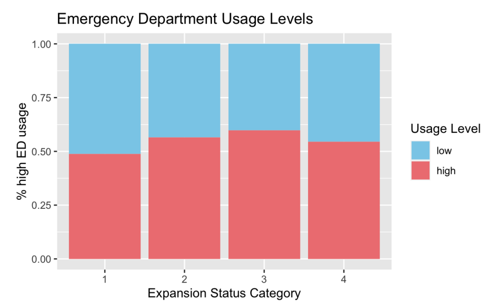
The distributions of PQI 05 and PQI 08 showed evidence of overdispersion and a somewhat right skewed distribution, so we fit a negative binomial models for each PQI, using our categorical Medicaid expansion status variable. We adjusted these models for percent male, percent African American, percent Hispanic, linear and quadratic terms for percent eligible for Medicaid, age category, and interaction between percent eligible for Medicaid and expansion status one covariate at a time using likelihood ratio tests in order to improve our model fit, since we did not identify any of these potential covariates as confounders on the relationship between Medicaid expansion status and the PQI outcomes.

We checked the overdispersion of this model by considering the goodness of fit of a Poisson complement. The ratios of deviance and Pearson χ^2 statistic with their respective degrees of freedom are above 1 (PQI 05:178.17 and 79.36, PQI 08: 90.85 and 90.84), which confirms overdispersion and that the negative binomial model is more appropriate for both outcomes. Our final model statements for PQI05 and PQI08 were:

$$E(log(PQI\ 05)) = 1.974 + 0.392I(Expansion\ status = 2) + 0.354I(Expansion\ status = 3) + 0.419I(Expansion\ status = 4) - 7.791 Percent\ Male + 0.133 Percent\ African\ American - 0.689 Percent\ Hispanic - 0.689I(Age\ category = 65-74) - 0.284I(Age\ category = 75+) + 4.793 Percent\ eligible\ for\ Medicaid - 6.014 Percent\ eligible\ for\ Medicaid^2$$

$$E(log(PQI08)) = 1.205 + 0.149I(Expansion\ status = 2) + 0.187I(Expansion\ status = 3) + 0.160I(Expansion\ status = 4) - 5.328 Percent\ Male + 1.558 Percent\ African\ American - 0.387 Percent\ Hispanic - 0.453I(Age\ category = 65-74) + 0.641I(Age\ category = 75+) + 3.26 Percent\ eligible\ for\ Medicaid - 4.946 Percent\ eligible\ for\ Medicaid^2$$

Analysis of Health Services Utilization



Emergency Department visit rates: A logistic regression model was used to explore whether the odds of high emergency department usage differed between counties in states that had expanded care compared to states that had not expanded Medicaid coverage. We categorized counties that exceeded the national average usage rate of 670 emergency department visits per 1,000 beneficiaries as ‘high’ usage and counties below this threshold as ‘low/normal’ usage. Using this binary outcome, we fit a logistic model using similar covariates as our models above, and achieved an AIC score of 3,050.8. We also considered modeling expansion status as a continuous variable instead of a categorical variable, and saw that this reduced model performed comparably to the expanded model (Likelihood Ratio Test statistic was not statistically significant, p > 0.05 for χ^2distribution with 2 degrees of freedom; AIC = 3,051.2). Thus, we elected to model expansion status as a continuous covariate.

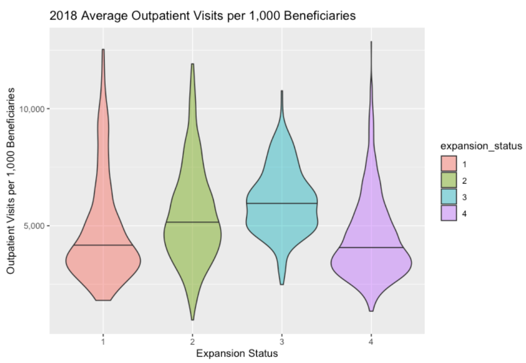
To check goodness of fit, we conducted a Hosmer-Lemeshow test with 10 groups, and determined that the candidate model was well calibrated (p>0.05). Additionally, we fit a ROC curve (AUC = 0.834) and determined the model adequately discriminated between counties with high and low emergency department usage (Appendix Section III: Figure 1).

Our final model statement for the emergency department usage level was:

$$logit(p(high\ ED\ usage)) = 29.4 + 0.13 * (expansion\ status) - 0.322 * (average\ age) - 24.56 * (percent\ male) + 34.67 * (\%\ eligible\ for\ Medicaid) - 44.32 * (\%\ eligible\ for\ Medicaid)^2$$

Summary Model Statistics: AIC = 3051.2 | AUC = 0.834 | Hosmer-Lemeshow Test Statistic (p>0.05)

Outpatient Visits: We model the outpatient visit rates across counties in 2018 on Medicaid expansion status to determine if expansion significantly impacts outpatient utilization. We would expect that health quality and the outpatient visit rate would be positively associated, although we see that states who expanded Medicaid early and states that did not expand Medicaid as of 2018 have similar outpatient visit rates.



A distribution of the outpatient visit rates for all counties in 2018 looked pretty normal but also showed some potential overdispersion (see Appendix Section 5), so we fit a negative binomial regression model to model the relationship between outpatient visit rates and Medicaid expansion status. We adjusted this model for additional covariates one at a time using likelihood ratio tests in order to improve our model fit, since we did not identify any of our potential covariates as confounders on the relationship between Medicaid expansion status and outpatient visit rates.

We checked the overdispersion in the model by checking the goodness of fit of the Poisson version of the model. The ratios of the Pearson χ^2 statistic and deviance to their respective degrees of freedom were well above 1 (730.89 and 710.54 respectively), which provides evidence that the negative binomial is the better fit.

Our final model statement for the outpatient visits rate was:

$$\begin{aligned} E(log(Outpatient)) = {} & -5.474 - 0.176I(Expansion\ Status = 2) - 0.024\mathrm{I}(\text{Expansion Status} \\ & = 3) - 0.180\mathrm{I}(\text{Expansion Status} \\ & = 4) + 1.1076\text{Percent Eligible for Medicaid} + 0.914\text{Percent Male} + 0.0833\text{Average Age} \\ & - 1.653\text{Percent Eligible for Medicaid}^2 + 0.827\mathrm{I}(\text{Expansion Status} \\ & = 2) * \text{Percent Eligible for Medicaid} + 0.547\mathrm{I}(\text{Expansion Status} \\ & = 3) * \text{Percent Eligible for Medicaid} + 0.123\mathrm{I}(\text{Expansion Status} \end{aligned}$$

Results

Aggregate Health Scores

HCC: The estimated change in average individual HCC scores in 2018 for counties associated with the different Medicaid expansion categories as compared to counties who expanded Medicaid before 2014 (reference group), holding all other covariates constant are as follows:

Table 3: Average HCC Score (2018): Summary of Beta Coefficients

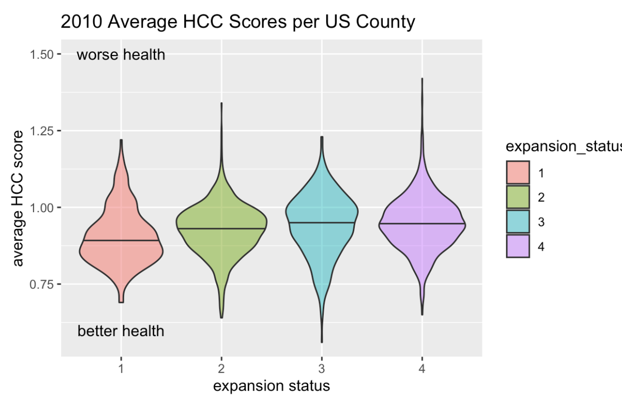
Medicaid Expansion Category	Estimates of Effect on 2018 average individual HCC score	95% Confidence Interval	P-value
2	0.001	(-0.001, 0.113)	>0.05
3	0.015	(0.003, 0.026)	<0.05
4	0.035	(0.024, 0.045)	<0.05

Based on these estimates, we can conclude that by 2018, a county that expanded Medicaid coverage in 2014 had comparable HCC scores to counties that expanded prior to 2014, adjusting for all other factors. That is, over the course of 4 years, the counties that delayed sightly to expand Medicaid access seem to have caught up in this health quality measure. However, counties that expanded after 2014 have on average, HCC scores that are 0.015 (95% CI: 0.003, 0.026) units higher than counties that expanded prior to 2014, holding all other covariates constant (note, the national average HCC score is 1, and county averages range in value from 0.6-1.57, with 0.6 implying county residents are, on average, in a better health state than the national average and 1.57 indicating county residents experience worse health than the national average). After adjusting for all other factors in the model, we see that counties that have elected *not* to expand Medicaid coverage as of 2018 have on average, HCC scores that are 0.035 (95% CI: 0.024 - 0.045) units higher than counties that expanded prior to 2014, indicating residents may have worse health states in these geographic locations.

To understand the long-term changes in average HCC scores, we also calculated the difference in each county's average individual HCC score in 2018 compared to its score in 2010. The estimated difference between average 2018 HCC score and 2010 HCC score for the expansion categories compared to counties that expanded coverage prior to 2014 (reference group) are summarized below:

Table 4: Difference in Average HCC Scores (2018 vs 2010): Summary of Beta Coefficients

Medicaid Expansion Category	Estimates of Effect on Difference in HCC scores (2018 vs 2010)	95% Confidence Interval	P-value
2	-0.0098	(-0.018, -0.002)	<0.05
3	-0.01	(-0.019, -0.002)	<0.05
4	0.011	(0.003, 0.018)	<0.01



Compared to counties who were among the earliest to expand coverage, counties that expanded in 2014 have experienced an average *decrease* of 0.0098 more units (95% CI: -0.018, -0.002) in their HCC scores from 2010 to 2018 after adjusting for all other covariates. Similar improvements are seen in counties that delayed expanding until after 2014, where an average *decrease* of 0.01 more units (95% CI: -0.019, -0.002) is observed in HCC scores compared to counties that expanded prior to 2014, holding all other factors constant. This unexpected finding could be because states who were the first to expand already had a greater commitment to improving health outcomes, and thus had a lower baseline HCC score with less room for improvement than states who expanded later as illustrated in the figure above. Counties that have not expanded Medicaid coverage as of 2018 have seen their average HCC scores *increase* by an average of 0.01 units (95% CI: 0.003, 0.018) from 2010 to 2018 after adjusting for all other factors, indicating declining health for these counties' residents compared to those who live in counties that expanded coverage prior to 2014.

PQI: The average estimated incidence rate ratios of the COPD or asthma admissions in older adults in the counties with the different Medicaid expansion categories as compared to counties who expanded Medicaid before 2014 (reference group), holding all other covariates constant are as follows:

Table 5: PQI 05 (2018): Summary of Incidence Rate Ratios

Medicaid Expansion Category	Incidence Rate Ratio of COPD/Asthma Admissions in Older Adults Per 100,000 Beneficiaries	95% Confidence Interval	P-value
2	1.479	(1.383, 1.582)	< 2e-16
3	1.425	(1.323, 1.535)	< 2e-16
4	1.520	(1.423, 1.624)	< 2e-16

On average, the estimated incidence rate of COPD or asthma admissions in older adults in states that expanded Medicaid in or after 2014 is about 1.4-1.5 times higher than the rate in states that expanded before 2014, holding all of the other covariates in the model constant. There is not a significant difference between the incidence rate ratios for expansion status 2 vs 1, expansion status 3 vs 1 and expansion status 4 vs 1, holding all other covariates constant, which indicates that there is not strong evidence having Medicaid expansion alone decreases COPD and asthma admissions, but possibly that a state needs to have Medicaid expansion for a number of years before seeing an improvement.

The average estimated incidence rate ratios of congestive heart failure hospital admissions in the counties with the different Medicaid expansion categories as compared to counties who expanded Medicaid before 2014 (reference group), holding all other covariates constant are as follows:

Table 6: PQI 08 (2018): Summary of Incidence Rate Ratios

Medicaid Expansion Category	Incidence Rate Ratio of Congestive Heart Failure Per 100,000 Beneficiaries	95% Confidence Interval	P-value
2	1.161	(1.096, 1.229)	3.33e-07
3	1.206	(1.131, 1.284)	7e-09
4	1.174	(1.109, 1.242)	2.56e-08

On average, the estimated incidence rate of congestive heart failure admissions in states that expanded Medicaid in or after 2014 is about 1.1-1.2 times higher than the rate in states that expanded before 2014, holding all of the other covariates in the model constant. Similar to PQI 05, there isn't a significant difference in the incidence rate ratios.

Health Services Utilization

Emergency Department Visit Rates: The odds of a county having high levels of emergency department usage in 2018 is 1.14 times greater (95% CI: 1.046, 1.24) with each subsequent expansion status category. For examples, after adjusting for all covariates in the model, counties that expanded coverage in 2014 have on average, 1.14 times greater odds of high levels of emergency department usage than counties that expanded coverage prior to 2014. Also, the odds of high levels of emergency department usage in counties that have not expanded coverage as of 2018 are 1.48 times greater than the odds of high levels of usage in counties that expanded prior to 2014.

Table 7: High Emergency Department Usage (2018): Summary of Odds Ratios

Covariate	Odds Ratio High Emergency Department Usage	95% Confidence Interval	P-value
Expansion status (continuous - 1, 2, 3, 4)	1.14	(1.046, 1.24)	<0.05

Outpatient Visits Rates: The estimated average incidence rate ratios of the outpatient visits in the counties with the different Medicaid expansion categories as compared to counties who expanded Medicaid before 2014 (reference group), all other covariates constant are as follows:

Table 8: Outpatient Visit Rate (2018): Summary of Incidence Rate Ratios

Medicaid Expansion Category	Incidence Rate Ratio of Outpatient Visits Per 1,000 Beneficiaries	95% Confidence Interval	P-values
2	1.919	(1.362, 2.70)	0.028, 0.016
3	1.687	(1.099, 2.588)	0.788, 0.153
4	0.944	(0.688, 1.296)	0.0185, 0.7092

These estimated incidence rate ratios include the interaction between expansion status and percent eligible for Medicaid, while holding all covariates including percent eligible for Medicaid constant. On average, states with Medicaid expansion have higher rates of outpatient visits than states that do not have Medicaid expansion at all, holding all other covariates in the model constant.

Discussion

Our analyses demonstrate that counties in states that expanded early, either prior to 2014 or in 2014, have better average individual HCC scores and PQI metrics. Outpatient visits are more frequent, and emergency departments are used less often in these areas to receive health care.

Counties that elected not to expand or delayed expanding Medicaid coverage until after 2014 have worse average HCC scores compared to counties that expanded prior to 2014, and counties that have not expanded Medicaid coverage have seen their average HCC scores *increase* by an average of 0.01 units from 2010 to 2018 after adjusting for other demographic factors, indicating declining health for these counties' residents compared to those who live in counties that expanded coverage prior to 2014. Counties in states that did not expand Medicaid or expanded Medicaid in 2014 or after had significantly higher rates of hospital admissions for COPD or asthma in older adults and congestive heart failure, indicating that quality outpatient care is lacking in states that did not expand Medicaid before 2014. As we did not find a significant difference in the PQI rate ratios, it is possible that while Medicaid expansion increases access to affordable health care, it may not improve the quality of such health care, but further research is necessary to determine this.

The odds of high levels of emergency department usage in counties that have not expanded coverage as of 2018 are 1.48 times greater than the odds of high levels of usage in counties that expanded prior to 2014. States that have Medicaid expansion have higher rates of outpatient visits than states that do not, however, we did not find very significant results supporting this as many of our regression coefficients were insignificant once we adjusted for all of our other covariates.

The direct effects of Medicaid expansion could be better examined if we could focus our analysis on the Medicaid population and could analyze individual level health outcomes as patients enter and exit the program, however we were limited by the lack of publicly available Medicaid data. In the absence of such data, the publicly available Medicare data used in this analysis serves as an adequate proxy since there is information about patients who are dually enrolled in both Medicaid and Medicare in each county, although our results are not generalizable to other age groups.

Conclusion

Our models provided significant evidence that expanding Medicaid improves the health of the Medicare population over time. Our analysis showed that various health metrics in 2018 looked better for states that expanded Medicaid before 2014 than states that expanded Medicaid in 2014, and they look better for states that expanded Medicaid in 2014 than states that expanded Medicaid after 2014. From this we can see that as expected, it takes a few years for the effects of Medicaid expansion to impact the Medicare community, but there is evidence that the impact is significant and positive.

To encourage state policy makers to adopt Medicaid expansion, a better understanding of the associated costs could provide guidance. Future research should consider whether decreased costs from treating less acute conditions due to better preventative care is balanced by the increased coverage costs, particularly because improved life expectancy in a larger beneficiary population would require long-term management of chronic illnesses. Research should be conducted to better understand the cost effectiveness of the components of Medicaid coverage, which could help policy makers in states that have yet to expand coverage prioritize adoption of elements of Medicaid that they feel would most improve the health outcome of their constituents.