Real Income Per Capita v. Health Insurance Coverage

BY:
Aaron Coleman

Health insurance is an economic variable that is extremely significant when examining different demographics across areas of population. This characteristic is a critical indicator of well-being, access to healthcare, and other long-term economic aspects. The purpose behind this study is to analyze the relationship between health insurance coverage and real income per capita on a county level to test for any correlation. Higher income per capita and health insurance coverage has been seen in other studies to have a positive correlation to each other. Because of this, I have separated this data into three different political subgroups that are mutually exclusive to each other to further analysis. These groups are predominantly republican, predominantly democratic, and politically mixed counties. This is to test whether public policy and political affiliation will influence the level and variability of health insurance coverage across populations. The basis of this data is that political affiliation is associated with public policy which can be associated with real GDP income within counties across the country. Higher GDP across counties creates a higher level of insurance coverage which creates higher well being and economic production in the population.

The three hypotheses created before the research was that first, real income per capita is positively correlated with health insurance coverage (already studied and proven). Second, republican, democratic, and mixed political counties differ in health insurance coverage. Lastly, the difference in variance between these correlations differ across counties with different political affiliation. To help support these hypotheses, I have researched literature similar to this study and found two different sources that help support my conclusions. The first study was the paper, “The ACA and Medicaid Expansion: Diverging Trends” written by Katherine Swartz and John Graves (Source 1). Within this paper, it goes into data about income and variables that stem off of it. It was found that there was a strong correlation between income and health insurance coverage. The second source was the paper, “Public Insurance and Mortality: Evidence from Medicaid Implementation” written by Andrew Goodman-Bacon (Source 2). This paper goes into the depths of health insurance coverage and the different aspects of it and how it relates to public policy. A big finding from this paper is that red states (republican) generally have lower coverage rates than blue states (democratic) due to public policy standards in those areas. Both of these sources have helped me formulate the study regarding the relationship between health insurance and income.

The data that I used is very important to this study to formulate its conclusions. To start off, I took the presidential vote statistics from the 2020 U.S. census data. This is data of all the people who voted from every county and which party their vote affiliated with. With this data, I tallied up all of the affiliated votes with each county and then tallied up the total amount of votes. From here, I created a percentage off of each county for each party affiliation there was. As an example, let's say there are 10 total votes in a selected county and 7 of them were republican and 3 of them were democratic, the percentage of that county would be 70% republican and 30% democrat. I did this for each county and then created a test to determine if the county was primarily democrat, republican, or overall mixed. I did this by indicating if a county was over 60% leaning towards a party, it would be considered predominantly that party shown. Within the previous example shown, that selected county would be predominantly republican. If the county showed that neither party was 60% or more prevalent, it would be considered a mixed party. After dissecting that information from the census data, I put each county into one of the three exclusive subgroups. Group 1 is a predominantly republican county. Group 2 is a predominantly democratic county. Group 3 is a mixed county. The second part of the specific data I needed was taken from the census data of individuals who do not have health insurance across counties in the

United States taken in 2022. To find the variable I needed, I first off added up all of the total males and females who did not have health insurance within every county. After this, I took the population of each county from the 2022 census data of county population and created a ratio. This ratio was the number of individuals who did not have health insurance divided by the total number of individuals in that population. From here, I created a percentage of individuals who did not have health insurance in each county and subtracted that number from (1) to get the percentage of individuals who did have health insurance from each county in 2022. This was considered my “Criterion” variable. The last part of retrieving the data I needed was taken from the census data on real gdp per capita in each county from the year 2021. I understand that this data is from a different year but proportions are very likely to be similar. This served as my “Predictor” variable. Using these two variables and the separation of groups, this will allow me to come to a conclusion on the relationship between real income per capita and health insurance coverage across the United States.

From here, I calculated descriptive statistics of my criterion variable. I calculated the sample size, minimum, mean, median, maximum, standard deviation, and correlation coefficient for the overall data and for each different subgroup. The results indicated the following. Republican counties had the highest sample size. Democratic counties had the highest minimum. Mixed counties had the highest mean. Mixed counties had the highest median. Republican counties had the highest maximum. Republican counties had the highest standard deviation. Lastly, both republican and mixed counties were barely negatively correlated based on the predictor variable data while democratic counties were positively correlated. To dive deeper into some of the more relevant variables, it first off seemed that there were far more republican counties in the United States at this time compared to other affiliated counties. Next, it seemed as though the average percentile of people with health insurance increased as party affiliation went from republican to democratic (which confirms hypothesis). Another aspect that I wanted to cover was the frequency distribution of the criterion data found. With this, I created a table of percentiles and another table for total amounts that each percentile of health insurance coverage covered. The table was set up for each group and the total overall and was separated into increments of (5%) starting from (50%) to (100%). As expected, there were few outliers sitting around (50%) to (75%) and then the numbers started to pick up from (75%) to (100%) where most of the data lied. This frequency table shows that most counties in the United States have at least (75%) of individuals within the population have health insurance.

Criterion Descriptive Variables

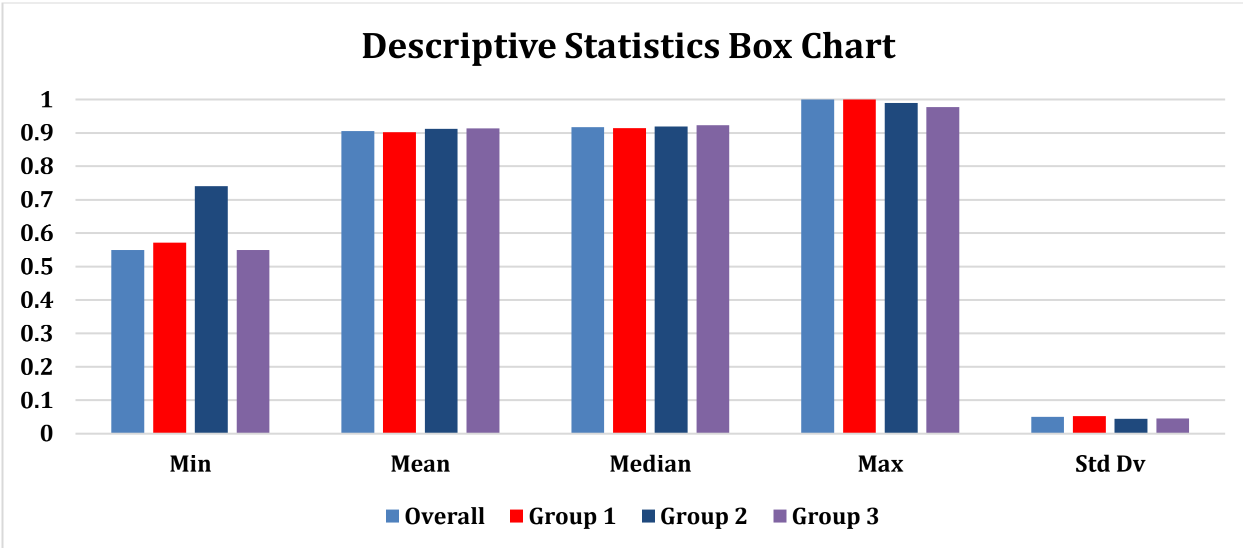
Group	Sample Size	Min	Mean	Median	Max	Std Dv	Correlation
Overall	3084	0.54949379	0.905408079	0.917119406	1.00000000	0.05028865	-0.03526754
Group 1	2134	0.57174933	0.902010236	0.914521869	1.00000000	0.05196677	-0.03906519
Group 2	254	0.74042567	0.912469632	0.919557517	0.98993573	0.04483631	0.08803662
Group 3	696	0.54949379	0.913249116	0.923254042	0.97716147	0.04564149	-0.10973618

1 - Descriptive Statistics – Criterion Variable (Overall, Group 1/2/3)

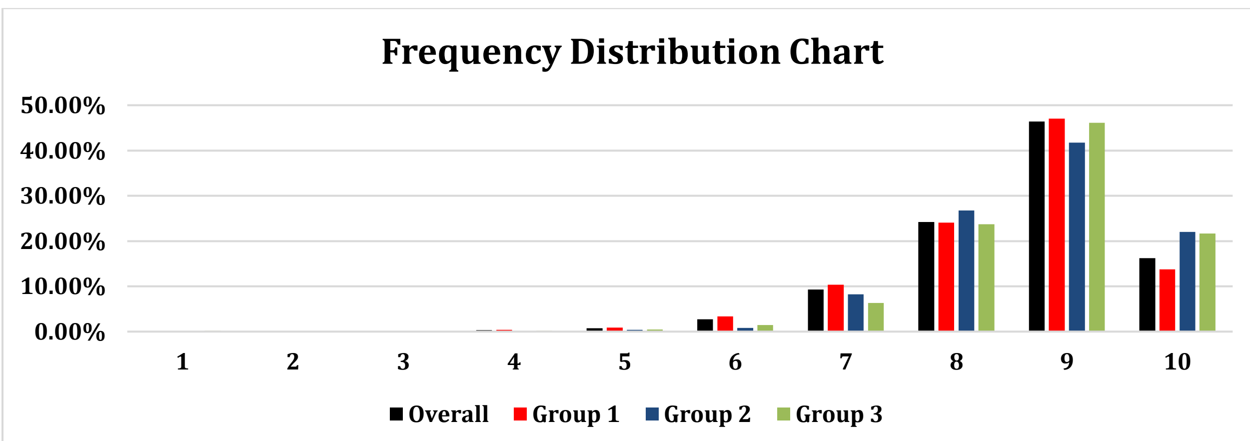
Frequency Percentile

Class	Overall	Group 1	Group 2	Group 3
0.50-0.55	0.03%	0.00%	0.00%	0.14%
0.55-0.60	0.06%	0.09%	0.00%	0.00%
0.60-0.65	0.03%	0.05%	0.00%	0.00%
0.65-0.70	0.29%	0.37%	0.00%	0.14%
0.70-0.75	0.75%	0.89%	0.39%	0.43%
0.75-0.80	2.69%	3.33%	0.79%	1.44%
0.80-0.85	9.27%	10.36%	8.27%	6.32%
0.85-0.90	24.19%	24.04%	26.77%	23.71%
0.90-0.95	46.40%	47.05%	41.73%	46.12%
0.95-1.00	16.25%	13.78%	22.05%	21.70%

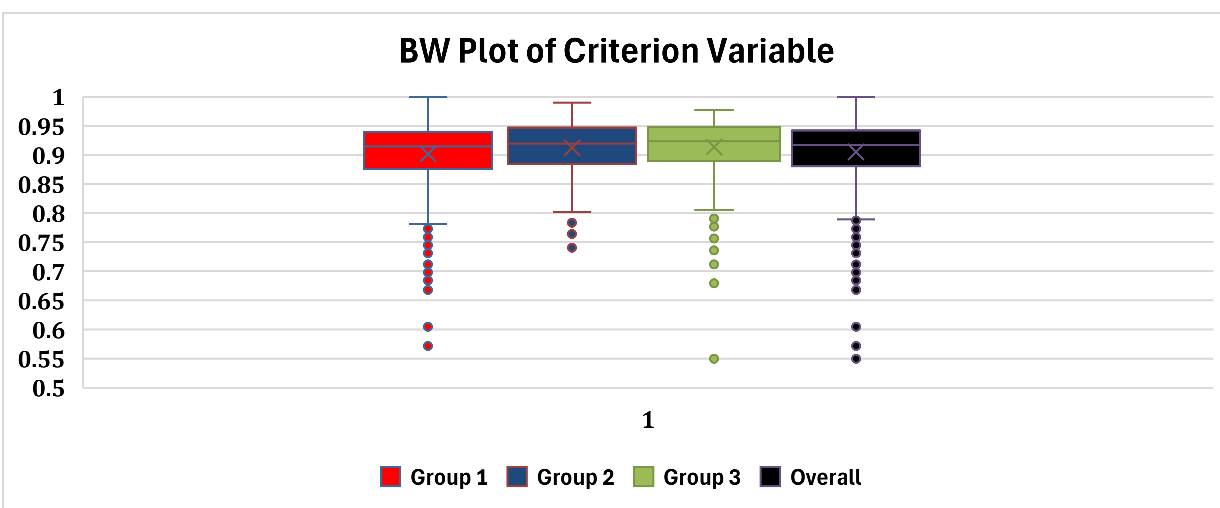
2 - Frequency Percentile Table – Criterion Variable (Overall, Group 1/2/3)



3 - Descriptive Statistics Box Chart



4 - Frequency Distribution Box Chart



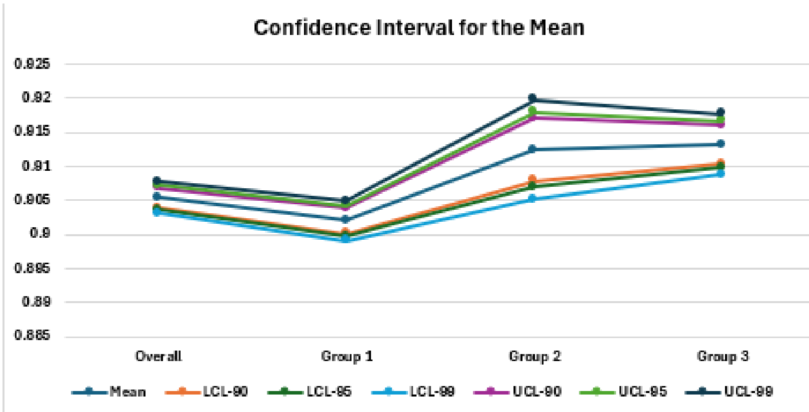
5 - Box and Whiskers Plot - Criterion Variable

This data is further supported with confidence intervals created. To start off, a confidence interval represents a range of values that could come from a population parameter. An example of this would be a 95% confidence interval that represents that if we repeated a study over and over again, approximately 95% of parameters created would include the true value. I first off created a confidence interval table for our mean. I took the mean from each group and total overall and created intervals at 90, 95, and 100 percent confidence. Before calculating these, I had to find the margin of error associated with each confidence level. To find the margin of error, I had to find the critical value for t-distributions of each alpha. Using that value, the standard deviation, and the sample size, I was able to calculate the margin of error for each confidence interval in each group (and overall). After finding this margin of error variable, I created the lower level intervals by subtracting the margin of error from the mean and upper level intervals by adding the margin of error to the mean. The findings were these as follows. Many of the intervals were above 90%. As confidence intervals went up (ex. 99%), the intervals became wider as the margin of error increased. After this, we created confidence intervals for the variance. To start off, we had to find the left tailed critical value that belonged to all three levels of confidence for each group. Doing this, we used the alpha and sample size and calculated each value. After finding this critical value, we calculated the confidence intervals by using the sample size, variance, and critical value found at each interval for each group. The results indicated the following. First off, Group 2 has the narrowest intervals indicating there is more consistent coverage rates and lower variance. Second, Groups 1 and 2 confidence intervals do not overlap very much indicating meaningful differences in average health insurance coverage across the counties.

Confidence Interval For Mean

Group	Mean	LCL-90	LCL-95	LCL-99	UCL-90	UCL-95	UCL-99
Overall	0.905408079	0.90391813	0.903632535	0.90307409	0.90689803	0.90718362	0.90774207
Group 1	0.902010236	0.90015907	0.899804147	0.899109994	0.9038614	0.90421633	0.90491048
Group 2	0.912469632	0.90782519	0.906929201	0.905168041	0.91711407	0.91801006	0.91977122
Group 3	0.913249116	0.91039966	0.909852392	0.908780568	0.91609857	0.91664584	0.91771766

6 - Confidence Interval Statistics – Mean

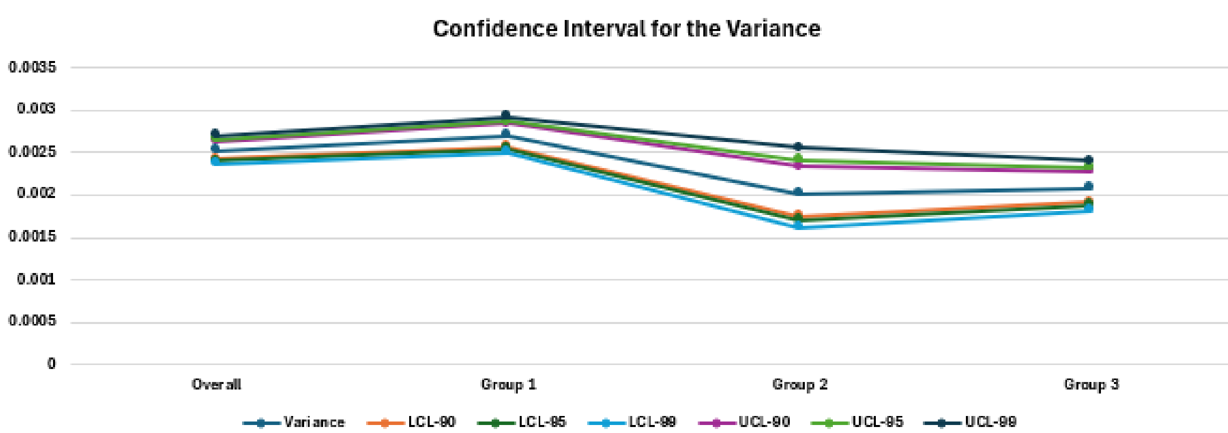


7 - Confidence Interval Line Chat – Mean

Confidence Interval For Variance

Group	Variance	LCL-90	LCL-95	LCL-99	UCL-90	UCL-95	UCL-99
Overall	0.002528948	0.00242641	0.002407303	0.002370539	0.00263851	0.0026601	0.00270299
Group 1	0.002700545	0.00256976	0.002545524	0.002499036	0.00284217	0.00287024	0.00292619
Group 2	0.002010295	0.00174717	0.001701297	0.001616204	0.00234195	0.00241233	0.00255817
Group 3	0.002083146	0.00191142	0.001880368	0.001821604	0.00228058	0.00232077	0.00240207

8 - Confidence Interval Statistics – Variance



9 - Confidence Interval Line Chat - Variance

Hypothesis testing allows us to reach a conclusion based on the data we found. To start off, I created a single sample of hypothesis tests for means. These are two tailed tests. To do this, I used the mean and then calculated a T-statistic. I also calculated a critical T-Statistic for each confidence interval. To do so, I needed to use the mean, sample size, and standard deviation of each group and aligned it for each confidence interval. With this being said, after calculating each value, I evaluated whether to reject my hypothesis or fail to reject it. If my T-statistic is higher than my critical T-value, I would reject my conclusion. The results indicated the following. For these tests, every conclusion resulted in rejecting the hypothesis except for the (99%) confidence interval created for Group 2. This means that for Group 2, there is not enough evidence to conclude that the sample is different from the true value. After this, I created a single sample hypothesis testing for variances. These are also two-tailed tests. To start off, I had to use the overall variance and sample sizes for each group. Using these variables, I created lower and upper chi-statistic confidence intervals and an overall chi-statistic along with the variance to create another set of conclusions for each group. The results indicate the following. Every hypothesis conclusion ended up being rejected. This was because the value of the chi-statistic was not in the interval created for each level of confidence. This means that the subgroup variance is different from the overall variance and that the overall variance is outside the level of confidence needed to accept the null hypothesis.

		1-a/2	0.95		0.975		0.995	
Single Sample of Hypothesis Tests for Means: Two Tailed Tests								
Group	Mean	T-Stat	T-Crit 90	Concl. - 90	T-Crit 95	Concl. - 95	T-Crit 99	Concl. - 99
Group 1	0.902010236	-3.02047178	1.645568318	Reject	1.96107678	Reject	2.57813624	Reject
Group 2	0.912469632	2.51007803	1.650898678	Reject	1.9693848	Reject	2.59540107	FTR
Group 3	0.913249116	4.53229648	1.647049044	Reject	1.96338318	Reject	2.5829218	Reject

Single Sample Hypothesis Tests for Variances: Two Tailed Test

Group	Variance	Chi-Stat	Chi-L 90	Chi-U 90	Concl. - 90	Chi-L 95	Chi-U 95	Concl. - 95	Chi-L 99	Chi-U 99	Concl. - 99
Group 1	0.002700545	3292.19044	2026.715992	2241.55795	Reject	2006.8904	2262.89796	Reject	1968.5185	2304.9939	Reject
Group 2	0.002010295	1695.54995	217.1713459	291.1017369	Reject	210.835457	298.950996	Reject	198.81606	314.69078	Reject
Group 3	0.002083146	208.401194	634.8333087	757.440395	Reject	623.839596	769.948231	Reject	602.72433	794.78655	Reject

10/11 – Single Sample Two-Tailed Hypothesis Test Statistics

Next, we can move on to the pair-wise hypothesis tests that I conducted. The data values in these hypothesis testing came from the “XLMiner Analysis Toolpak” tool. The specific testing done was two sample t-tests assuming unequal variances. After plugging in each group's criterion variable data, the tool found a variety of descriptive statistics such as degrees of freedom (df), t-test values, p-values, and more. The first part of it was doing hypothesis testing for equal variances. The null hypothesis was that the variances between the groups were equal while the alternative hypothesis was that they were not equal. These tests were based on an alpha level of (.05). When testing between group one and two, we discovered that we would reject the null hypothesis. I also did the same between groups one and three. However, we found that we would end up failing to reject the null hypothesis between groups two and three because the p-value being found was in between (.05) and (.95) being the measured interval. This proved that the variances between the group pairs (1/2) and (1/3) were not equal while the group pair (2/3) was equal. Next we did something similar but instead of variances, we conducted testing with differences of means. I found similar results. Between group pairs of (1/2) and (1/3), we rejected the null hypothesis. In the group pair (2/3), we failed to reject the null hypothesis as the p-value was higher than (.05). The interpretation of these findings is that group two’s mean is significantly higher than group one and group three’s mean is also significantly higher than group one. However, group two and three have no statistically significant difference in means. To conclude these results, this means that when comparing group one to the other groups, it tends to be different while groups two and three tend to be very similar to each other and have common tendencies.

T Test: Two-Sample Assuming Unequal Variances		
Measure	**Group 1**	**Group 2**
Mean	0.902010236	0.912469632
Variance	0.002700545	0.002010295
Observations	2134	254
Hypothesized Mean Difference	0	
df	339	
t Stat	-3.452109204	
P(T<=t) one-tail	0.000313314	
t Critical one-tail	1.649360844	
P(T<=t) two-tail	0.000626627	
t Critical two-tail	1.966986392	
ME	0.005959687	
LCL	-0.016419082	
UCL	-0.004499709	

12 - *T-Test "XLMiner Analysis Toolpak" Data – Groups 1/2*

T Test: Two-Sample Assuming Unequal Variances		
Measure	**Group 1**	**Group 3**
Mean	0.902010236	0.913249116
Variance	0.002700545	0.002083146
Observations	2134	696
Hypothesized Mean Difference	0	
df	1329	
t Stat	-5.446207413	
P(T<=t) one-tail	3.06161E-08	
t Critical one-tail	1.646000924	
P(T<=t) two-tail	6.12323E-08	
t Critical two-tail	1.961750541	
ME	0.0040483	
LCL	-0.015287179	
UCL	-0.00719058	

13 - *T-Test "XLMiner Analysis Toolpak" Data – Groups 1/3*

T Test: Two-Sample Assuming Unequal Variances

Measure	Group 2	Group 3
Mean	0.912469632	0.913249116
Variance	0.002010295	0.002083146
Observations	254	696
Hypothesized Mean Difference	0	
df	456	
t Stat	-0.236017058	
P(T<=t) one-tail	0.406762718	
t Critical one-tail	1.648202006	
P(T<=t) two-tail	0.813525436	
t Critical two-tail	1.965179854	
ME	0.006490323	
LCL	-0.007269808	
UCL	0.005710839	

14 - T-Test "XLMiner Analysis Toolpak" Data – Groups 2/3

Sample Variances For Criterion Variable

Group	Variance	Sample Size
Group 1	0.002700545	2134
Group 2	0.002010295	254
Group 3	0.002083146	696

15 - Sample Variances For Criterion Variable

Variance Test F-Calc

Group	Group 1	Group 2	Group 3
Group 2	1.34335777	N/A	N/A
Group 3	1.29637827	0.9650283	N/A

16 - Variance Test F-Calculation Statistics

P-Values			
Group	Group 1	Group 2	Group 3
Group 2	0.00137592	N/A	N/A
Group 3	0.00002096	0.372396169	N/A

17 - P-Value Statistics – Groups 1/2/3

Conclusion: Reject if P-Value is less than .05			
Group	Group 1	Group 2	Group 3
Group 2	Reject	N/A	N/A
Group 3	Reject	F.T.R	N/A

18 - P-Value Conclusions – Groups 1/2/3

95% Confidence Intervals				
Group	CI	Group 1	Group 2	Group 3
Group 2	UCL	-0.004	N/A	N/A
	LCL	-0.016	N/A	N/A
Group 3	UCL	-0.007	0.006	N/A
	LCL	-0.015	-0.007	N/A

19 - 95% Confidence Intervals – Groups 1/2/3

Pair-Wise Hypothesis Tests for Differences in Means			
T-Statistics			
Group	Group 1	Group 2	Group 3
Group 2	-3.452	N/A	N/A
Group 3	-5.446	-0.236	N/A

20 - Pair-Wise Hypothesis Tests for Differences in Means – Groups 1/2/3

P-Values			
Group	Group 1	Group 2	Group 3
Group 2	0.001	N/A	N/A
Group 3	0.000	0.814	N/A

21 - P-Value Statistics – Group 1/2/3

Conclusions: Reject if P-Value is Less than 5%			
Group	Group 1	Group 2	Group 3
Group 2	Reject	N/A	N/A
Group 3	Reject	F.T.R.	N/A

22 - P-Value Conclusions – Group 1/2/3

After this hypothesis testing, we went on to create an ANOVA Single Factor test. To do this, we went into the same "XLMiner Analysis Toolpak" tool used for the hypothesis testing mentioned previously and created the test. I input the criterion variable data from each group and it gave us some statistics such as the f-statistic, p-value, critical value; and similarities within and between groups. The null hypothesis of this test is that the means between these three groups are generally equal. The result from this test is that we are to reject the null hypothesis due to the f-statistic being greater than the critical value and p-value being less than the alpha value of (.05). This means that the ANOVA test provides evidence that not all subgroup means are generally equal to each other. To compare this test to the findings in the pair-wise tests, the result can be concluded that group one is different from the other two groups.

SUMMARY				
Groups	Count	Sum	Average	Variance
Group 1	2134	1924.889844	0.902010236	0.002700545
Group 2	254	231.7672865	0.912469632	0.002010295
Group 3	696	635.6213849	0.913249116	0.002083146

23 - ANOVA Test Summary Statistics – Groups 1/2/3

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.080094968	2	0.040047484	15.98961339	0.000000123478	2.998646987
Within Groups	7.716652964	3081	0.002504594			
Total	7.796747932	3083				

24 - ANOVA Test Statistics

After these two tests, we created a correlational analysis and correlational significance tests for the different subgroups. To start off, we found the different values of r, r^2, zr, and also took the sample size we had from before to create the analysis we needed for the testing. For the test, we then found the t-statistic values for each group and then came to a conclusion based on the alpha of (.05). The null hypothesis is that there is no significance in correlation between the criterion and predictor variables. The results are that for the overall, group one, and group two samples; we failed to reject the null hypothesis. However, for group three, we rejected the null hypothesis as the t-calculated statistic was greater than the t-critical statistic. After the correlation tests, we conducted another set of pair-wise tests except these being differences in correlations. I calculated the z-values for each comparison of groups and then came to a conclusion based on the alpha of (.05). The results were that for pair groups (1/2) and (1/3), we failed to reject the null hypothesis. However, in the pair group (2/3), we rejected the null hypothesis because the z-calculated value was greater than the z-critical value. This means that the correlation between the criterion and predictor variables differ significantly between groups two and three. The last test we did was a joint multi-group correlation test. The null hypothesis of this test is that all subgroup correlations are jointly equal. For this test, we calculated variables such as (zr), (nj-3), and some calculations between the two. This allowed us to further calculate important values for the test such as the chi-squared calculated value and chi-squared critical value. This allowed us to come to a conclusion based on the alpha of (.05). The results of this test is that we rejected the null hypothesis. This was because the calculated value was greater than the critical value. This means that the subgroup correlations are not jointly equal to each other.

Overall and Group Correlations				
Group	**Correlation**	**R-Squared**	**Sample Size**	**zr**
Overall	-0.035	0.001	3084	
Group 1	-0.039	0.002	2134	-0.039
Group 2	0.088	0.008	254	0.088
Group 3	-0.110	0.012	696	-0.110

25 - Overall and Groups 1/2/3 Correlation Statistics

Tests of Individual Correlation Significance H0: ρ=0			
Two-Tailed Tests			
Group	**t-Calc**	**t-Critical**	**Conclusion**
Overall	-1.959	1.961	F.T.R
Group 1	-1.805	1.961	F.T.R
Group 2	1.403	1.969	F.T.R
Group 3	-2.908	1.963	Reject

26 - Individual Correlation Significance Test Statistics/Conclusions

Pair-Wise Correlation Tests H0: $\rho_i = \rho_j$			
Z-Calc			
Group	**Group 1**	**Group 2**	**Group 3**
Group 2	-1.912	N/A	N/A
Group 3	1.627	2.698	N/A
Two-Tailed Test, a =	0.05		
Z-Critical Value =	1.96		

27 - Pair-Wise Correlation Test (Z) Statistics

Conclusions			
Group	**Group 1**	**Group 2**	**Group 3**
Group 2	F.T.R.	N/A	N/A
Group 3	F.T.R.	Reject	N/A

28 - Pair-Wise Correlation Test (Z) Conclusions

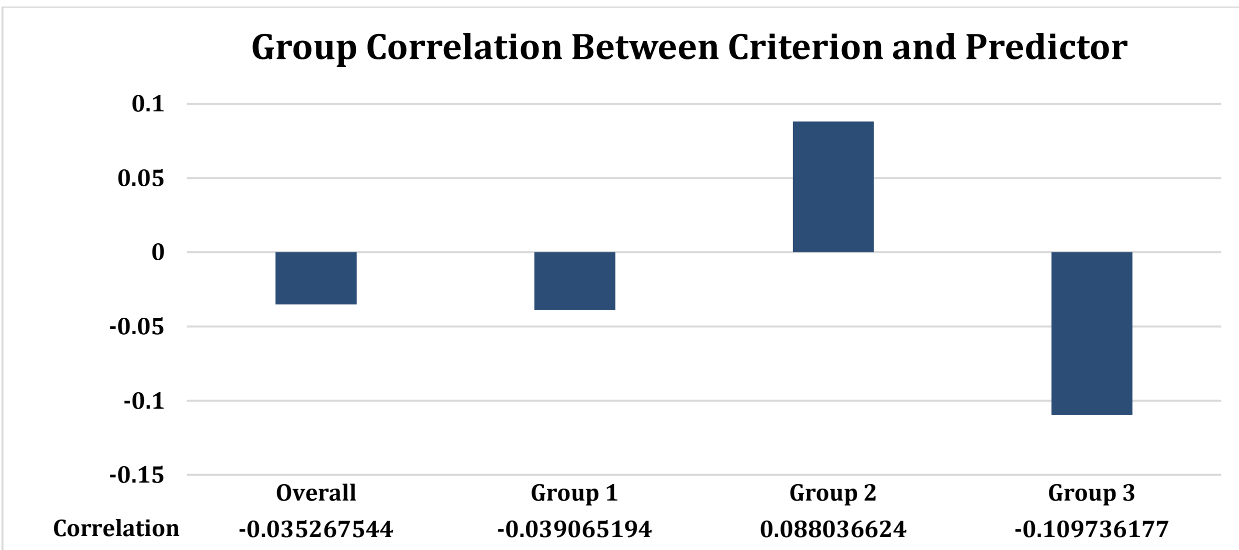
Joint Multi-Group Correlation Test, alpha = 0.05

Group	Sample Size	Correlation	zr trans.	nj-3	(nj-3)*zr^2	(nj-3)*zr
Group 1	2134	-0.035	-0.035	2131	2.653	-75.186
Group 2	254	-0.039	-0.039	251	0.383	-9.810
Group 3	696	0.088	0.088	693	5.399	61.168
Sums				3075	8.435	-23.829
Sum Squared						567.818

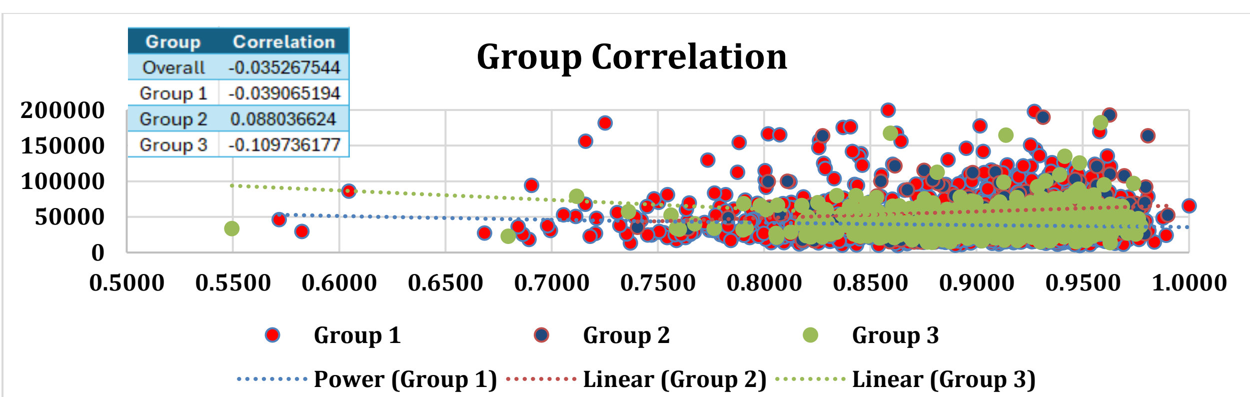
29 - Joint Multi-Group Correlation Test Statistics

Chi-Sq Calc	8.250
Chi-Sq Crit	7.815
Conclusion	Reject

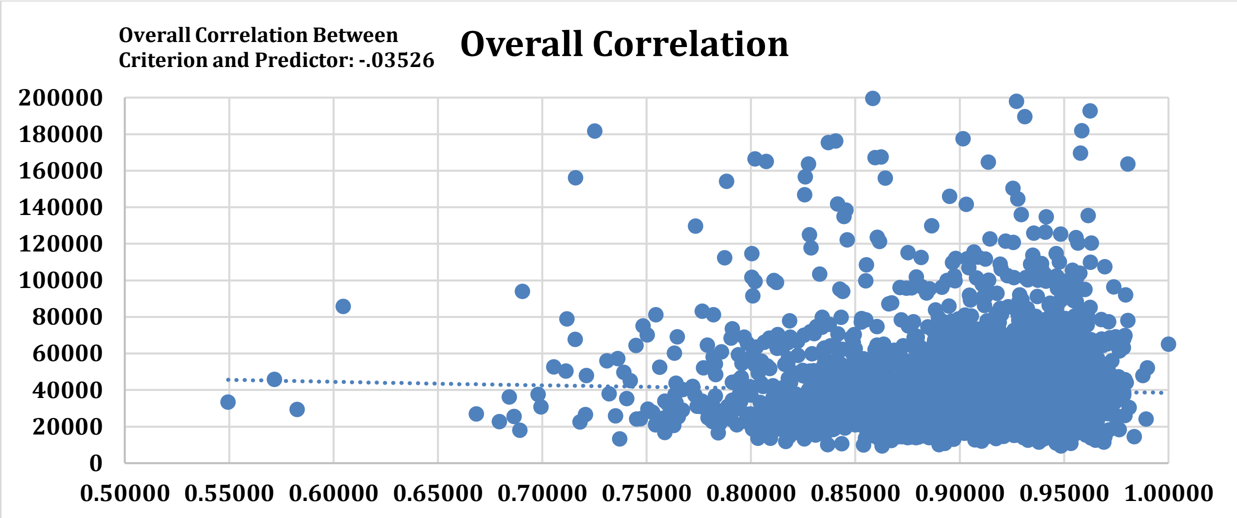
30 - Chi-Square Calculations/Conclusion



31 - Bar Chart – Group Correlation Between Criterion/Predictor



32 - Scatterplot Chart – Group Correlation



33 - Scatterplot Chart – Overall Correlation

With this being said, I can conclude that real income per capita does have a positive correlation with health insurance coverage. This can be seen not only in the descriptive variable data but also the confidence interval and hypothesis testing for each subgroup with their variances and means. This data is economically significant as if we are able to identify correlation between health insurance and income while relating that to public policy, we can increase economic production and well-being across the country.

Works Cited

Guth, Madeline, Rachel Garfield, and Robin Rudowitz. “The Effects of Medicaid Expansion under the ACA: Studies from January 2014 to January 2020.” Kaiser Family Foundation, 17 Mar. 2020, (Source 1)

Goodman-Bacon, Andrew. “Public Insurance and Mortality: Evidence from Medicaid Implementation.” Journal of Political Economy, vol. 126, no. 1, Feb. 2018, pp. 216-262. DOI: 10.1086/695528. (Source 2)

Coleman, Aaron. ECMT 461 Project Final. Microsoft Excel file, 9 Dec. 2025. (Source 3-33)