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Consequences of America’s Health Insurance System & Poverty on Child and Teen Deaths

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Abstract. Access to health care and wealth inequality continue to be central topics in American politics. This research aims to examine the true cost of these concerns by analyzing their effect on a severe societal issue: children and teen deaths.

1 INTRODUCTION

Many researchers have agreed that America’s successful future is depending on the raising generation of healthy and educated children, however, there is growing of evidence showing that this future is threatened by problems begin in early childhood such as poverty, maltreatment, health issues and so on. [1] The main focus question of this study is how access to health insurance and poverty levels impact child and teen deaths in the United States. This research shows alarming trends of child and teen death rates in the United States since 2010. With the current discussions related to health care and “Medicare for All” I have conducted a timely study to determine the connection access to health insurance and poverty have to this serious issue. In the hypothesis, I predict that lack of health insurance for children is associated with higher child and teen deaths in the United States. I also hypothesize that higher levels of poverty are associated with higher child and teen deaths in the United States.

2 Data

The dataset used was collected and constructed from 12 data sources, including governmental reports and nonprofit organizations. See Appendix 1 for a list of the sources. The data includes all fifty United States (often including D.C. and Puerto Rico as well) either over eight years (2010-2017) or over fewer years for some. I am using child and teen deaths per 100,000 as the dependent variable and percent of children without health insurance and percent of population in poverty as the two core independent variables. And I include fourteen additional control variables relevant to the study.

In Table 1, I show the mean, median, maximum, minimum, and interquartile ranges for these variables within the 50 states from 2010-2017. Data on Washington D.C. and Puerto Rico have been omitted from these statistics as this information was not available for the dependent variable. The adult health variables (percent of low self-reported health, overweight/obese, diabetes, obstructive pulmonary disease, and asthma) only had 300 observations available in the dataset. As such, I calculated the mean of these observations and used this statistic to fill in the missing data for each variable, so each had a total of 400 observations in the final data set. Although this missing data represents 25% of the necessary observations, I did not omit these variables as they are theoretically important to this study. Also, to calculate the number of people per hospital, I divided the total state population by the number of hospitals per state. This explains the large absolute values of the observations for this variable.

	Mean	Median	Max	Min	IQR
Child and Teen deaths per 100,000	26.95	26	52	15	9
% of Children <18 without Health Insurance	5.875	5	17	1	3
% of Population in Poverty	14.46	14.1	24.2	7.3	5
Unemployment rate	6.31	6	13.5	2.4	3.15
% of Babies with low birth weight	8.02	8.1	12.1	5.7	1.8
# of People per 1 Hospital	60,491.74	56,941.98	136,009.28	15,257.3	43,320.7
Teen Births per 1,000	26.08	25	55	8	13
% Non-white	22.69	21.3	75.4	4.4	17
% Not a U.S. citizen	4.86	3.87	14.77	.66	4.55
% Hispanic or Latino	11.25	8.8	48.8	1.1	8.7
% > 25 years Without H.S. Degree	11.68	11.1	19.3	6.4	5
% of Labor Force in Union	11.66	11.4	26.1	2.6	8.35
% Adults Low Self-Reported Health	17.21	17.21	26.3	11.7	3.05
% Adults Overweight or Obese	64.43	64.43	71.3	55.4	2.6
% Adults w/ Diabetes	9.99	9.99	15	6.5	1.45
% Adults w/ Obstructive Pulmonary Disease	9.71	9.71	19.3	4.8	2
% Adults w/ Asthma	9.16	9.16	12.2	6.2	1.15

N = 400

Fig. 1. Summary Statistics for Variables in Models Relating Child and Teen Death Rates to Economic and Demographic Resident Characteristics in the 50 U.S. States, 2010-2017

Sources Used for Data Set: American Community Survey; Bureau of Economic Analysis; Bureau of Labor Statistics; Chronic Disease Indicators Database; U.S. Energy Information Administration; Federal Bureau of Investigation; Annie E. Casey Kids Count; Kaiser Family Foundation; Digest of Education Statistics; Standard Education Data Archive; Tax Policy Center; Wikipedia.

Appendix 2 shows the maximum and minimum values for the dependent variable and the two core independent

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variables. For child and teen deaths per 100,000, Alaska had the highest value, 52 in 2012. Alaska also was one of the two highest rates of youth suicide, and suicide was the second leading cause of death of Alaska youth. [2] Connecticut (2014-15) , Massachusetts (2012) and Rhode Island (2011, 2014, 2016) all had the lowest value 15 throughout the years. Secondly, for percent of children under 18 without health insurance, Nevada had the highest value at 17% in 2010 and 2012, and Massachusetts (2012, 2015-7) and Vermont (2017) had the lowest value at 1%. Thirdly, for percent of population in poverty, Mississippi had the maximum value 24.2% in 2012 and New Hampshire had the lowest value 7.3% in 2016.

3 Model and empirical strategy

The main objective of the model is to examine the relationship between the death rates among children and teens in relation to demographic and economic characteristics in the 50 United States. To estimate this model, my study estimates an OLS regression. After considering all conditions that may affect the death rates of children and teens, the equation for the preferred regression model is: *Yit = β0 + β1Xit + β2Zit + Tt + ai + εit* where Yit is the child and teen deaths per 100,000 people for the 50 U.S. states i in time t, Xit is the percent of population in poverty and percent of people uninsured for the 50 U.S. states i in time t, Zit is a set of control variables for the 50 U.S. states i in time t, Tt is a set of year effects, ai is a state fixed effect, and εit is an error term. The specific model with variable labels is as follows:

*Child&TeenDeathsit= β0 + β1ChildUninsuredit+ β2ChildUninsured*Non-Whiteitit+ β3ChildUninsured*Non-Citizenit+ β4PovertyRateit + β5Ln(PeoplePerHospital)it + β6UnemploymentRateit+ β7LowBirthWeightit+β8TeenBirthsit+β9NonWhiteit+ β10Non-Citizenit + β11Hispanicit + β12NoHSDegreeit - β13Unionit + β14LowSelfReportedHealthit + β15Overweight/Obeseit + β16Diabetesit+ β17COPDit+ β18Asthmait+ ai+Tt+ εit*

This study examines the relationship between child mortality and the percent of population in poverty and the percent of children without health insurance while controlling for other socioeconomic, health, and demographic population characteristics such as race, child and adult health data, and citizenship. Therefore, the preferred model achieves this goal by holding constant other theoretical determinants of child and teen mortality to isolate the impact of the independent variables of interest, while applying fixed state and year effects.

In order to evaluate the relationship between dependent variable and the two main independent variables, I constructed four different OLS regression models to compare the differences after adding control variables and controlling for the time and state effects. I first constructed a simple base model including only the dependent variable and the two main independent variables with time effects. Second, I added the fourteen control variables to this equation. In the third regression model I generated two interaction variables: 1) an interaction between percent of children without health insurance and percent of the population who are a minority, and 2) an interaction between percent of children without health insurance and percent of the population who are not U.S. citizens. I also replaced the control variable “number of people per 1 hospital” with the log of this variable to reduce the large range. In the fourth and preferred model, I included fixed effects for the states.

Finally, I ran several diagnostic tests on the models to determine if there were any specification errors with my models. When I ran a White Test to test for heteroskedasticity after my third model, I received a P-Value of 0.02, meaning there is less than 5% chance of homoskedasticity in my model. I applied robust standard errors to all regression models to treat the detected heteroskedasticity. When conducting the variance inflation factor (VIF) to test for multicollinearity, my average VIF score was 5.49. However, no action was taken due to the theoretical significance of all included variables.

4 Result

The results of the four regression models examining the impact of health insurance and poverty levels on child and teen deaths rates can be found in Table 2. Column 1 shows the first base model regressing only my dependent variable with the two main independent variables of this study: percent of children without health insurance and percent of the population in poverty, including time effects for 2010-2017. Both my dependent variables are statistically significant at the 1% level and the model explains 34% of the variation in child and teen deaths per 100,000. For each percentage point increase in the percentage of children without health insurance, child and teen deaths increase by 0.678 per 100,000 - or 6.78 deaths per 1 million people. For each percentage point increase in the percentage of population in poverty, child and teen deaths increases by 0.917 deaths per 100,000 - or 9.17 deaths per 1 million people.

Sources Used for Data Set: American Community Survey；Bureau of Economic Analysis；Bureau of Labor Statistics；Chronic Disease Indicators Database；U.S. Energy Information Administration；Federal Bureau of Investigation；Annie E. Casey Kids Count；Kaiser Family Foundation；Digest of Education Statistics；Standard Education Data Archive；Tax Policy Center；Wikipedia.

Column 2 presents my second model adding in my fourteen control variables. The percent of children without health insurance remains statistically significant at the 1% level, but its impact has decreased slightly which is indicative of omitted variable bias in the first regression model. In this second model, each percentage point increase in the percent of children without health insurance is associated with an increase of 0.443 child and teen deaths per 100,000 - or 4.43 deaths per 1 million people. The association between percent of population in poverty with child and teen deaths is no longer statistically significant. Four control variables are also statistically significant at the 1% level of significance, but only two in the direction I originally predicted. For each percentage point increase in percent non-citizen, child and teen deaths decrease by 1.227 deaths per 100,000 people - or 12.27 deaths per 1 million people. For each percentage point increase in percent of adults with asthma, child and teen deaths decrease by 0.926 per 100,000 people - or 9.26 per 1 million people. The direction of both of these relationships opposes my hypothesis. Of my five adult health control variables indicated with the "^" symbol, only one was statistically significant. However, when testing for joint statistical significance, the F test indicated these variables were jointly significant at the 1% level. The second model explains 75.3% of the variation in child and teen deaths per 100,000.

Column 3 displays my third regression model including my two generated interaction variables and number of people per one hospital control variable in the logged form. My main independent variable percent of children without health insurance remained statistically significant at the 1% level. At the average percent of population who are non-white and average percent of population who are non-citizens, a one percentage point increase in the percent of children uninsured is associated with a 0.51 increase in child and teen deaths per 100,000 - or 5.1 deaths per 1 million people. As the percent of population who are non-white increases and the percent of population who are non-citizens decreases, the effect of an increase in percent of children uninsured on child and teen deaths increases. For example, at the maximum percent of population who are non-white and the minimum percent of population who are non-citizen, a one percentage point increase in the percent of children who are uninsured is associated with a 1.38 increase in child and teen deaths per 100,000. This compares to a decrease of 0.14 deaths per 100,000 for each additional percentage point increase in percent of children uninsured at the minimum percent of population who are non-white and the maximum percent of population who are non-citizens. Please see Appendix 4 for more interpretations of these interactions. The log of the number of people per one hospital is also statistically significant, but the relationship is unexpected. A one percentage point increase in the number of people per hospital is associated with a 0.03 decrease in child and teen deaths per 100,000. The F tests show that the adult health coefficients remain jointly significant, and the interaction variables are also jointly significant. This third specification explains 77.1% of the variation in child and teen deaths per 100,000.

Finally, Column 4 presents the fourth regression model accounting for fixed state effects. In this model, the interaction variables are no longer jointly significant. Neither of my main independent variables are significant. Three control variables are statistically significant at the 10% level of significance or higher: percent of labor force in a union, percent of adults who are obese or overweight, and percent of adults with Chronic Obstructive Pulmonary Disease. For each additional percentage point in percent of the labor force in a union, child and teen deaths decrease by 0.342 per 100,000 deaths - or 3.42 deaths per 1 million people. In addition, the adult health variables remain jointly statistically significant. This fourth and final specification model explains 86.6% of the variation in child and teen deaths per 100,000. The F tests of joint significance show time effects are significant at the 1% level of significance in all four models.

5 Conclusion

To understand what this research says about the child and teen death rate, we have to look at both Model 3 and Model 4. Model 4 is the most sophisticated model because it controls for unobserved state characteristics. However, when using fixed effects, most of the prior significant variables fall out of significance. One possible reason might be low variation within the states, especially on the dependent variable. The standard deviation for the child and teen death rate is 6.49 overall, but only 2.42 within states. There simply isn't a lot of variation for the model to try to explain in the fixed effects model. Given this low variation, the fact that there are still significant variables shows the powerful effect of those variables. Further research is needed on those variables (labor force participation in a union, percent of adults who are overweight or obese, and percent of adults with COPD) especially when the relationship was unexpected.

I believe Model 3, although it does not control for unobserved state characteristics, still has valuable information, since there is much more variation overall than within states. Future research, with more data from more years, is needed to more accurately understand the effects of significant variables. One possible research design could be studying state data over more years, where there might be more variation in the variables. With more data, future research could look at the effects of specific policies around poverty and children's health insurance to better understand possible effects. I believe many of the significant variables in Model 3 could have an effect on child and teen death rates if states created policies that caused larger variations in them (e.g., state enacted child health insurance programs that cause the number of uninsured children to significantly change). Although I cannot conclude with certainty they would have an effect regardless of the individual circumstances of each state, I think policies that affect the significant variables should still be strongly considered because it is possible that they could show an effect with larger variation.

I focus here on the variables most relevant to my hypotheses and the ones with the most surprising results in Model 3 and Model 4. Based on Model 3, my research shows there is a positive association between the percent of children uninsured and the child and teen death rate. The American Council of Life Insurance in 1997 showed that 57% of children under 15 years old had insurance coverage. [3] The percent of non-citizens modified the effect of children without health insurance significantly, but not in the direction I predicted. I predicted it would increase the effect of no insurance under the assumption that non-citizens may not be eligible for some government programs to help uninsured children. In addition, I thought they may be more hesitant to use some programs due to possible negative effects on their immigration cases. However, there are also many possible reasons why it had a positive effect. I believe that it could be due to the close-knit nature of many immigrant communities which may have communal systems to help support families and their children when they do not have health insurance for the children.

The percent of the population in poverty only had a significant effect in Model 1, without any control variables. I believe this could signal that many of the effects of poverty actually come from variables associated with poverty rather than poverty itself. Child poverty is related to the social structure of the community, and also influenced by demographic, socioeconomic and some other family factors. [4]

Other unexpected results include that having more people per hospital decreases the child and teen death rate. I predicted it would increase it, because hospitals may be overwhelmed and unable to provide proper care. One possible reason that it would decrease is if hospitals treat more patients, they are better able to recognize common ailments and learn the best way to address them. In addition, being larger may make them eligible for more funding, which could allow them to provide better care. More research is needed to fully understand these effects.

There are some important limitations. As discussed above, the limited variance within states limits what there is for Model 4 to analyze. In addition, this data was collected before the global pandemic started. Future research should carefully incorporate data from during the pandemic to understand what has and has not changed. Also, the health variables only had 75% of the observations originally, so the 25% missing were replaced with averages. Since the missing variables were often from the same year, it was not possible to replace with an average for that year, so they were replaced with the overall average for that variable. Finally, there was no data on children's health conditions, so adult health variables were used as the closest proxy.

I recommend that future research includes data from during the pandemic. In addition, it would be illuminating to study more specific policies that affect poverty and health insurance rates. There are many new polices being launched after the Covid-19 pandemic on helping children's health problems, such as the Child Protective Services who played important role in supporting children and families during and after the pandemic. [5]

I believe that this research provides valuable insight into potential policies that policymakers could use to save the lives of children and teens. Union-friendly policies that increase labor force participation rates in unions and programs to prevent COPD (Chronic obstructive pulmonary disease) could significantly decrease the death rate. In addition, I think that policymakers should also consider policies that would affect some of the significant variables in Model 3. Policies that increase health insurance for children and decrease teen birth rates could also significantly decrease the death rate. Although further research is needed to fully understand the possible effects of these policies, I believe this research identifies some areas for potential interventions and for future research.

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