An Empirical Evaluation On The Effectiveness Of Medicaid Expansion Across 49 States [*][†]

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Abstract

In 2014 the Patient Protection and Affordable Care Act (ACA) introduced the expansion of Medicaid where states can opt to expand the eligibility for those in need of free health insurance. In this paper we attempt to assess the effectiveness of Medicaid expansion on health outcomes of state populations using Difference-in-Difference (DD) regressions to seek for causal impacts of expanding Medicaid on health outcomes in 49 states. We find that in the time frame of 2013 to 2016, Medicaid expansion seems to have had no significant impact on the health outcomes of states that have chosen to expand.

1 Introduction

The Patient Protection and Affordable Care Act (ACA) more commonly known as Obamacare is one of the largest reformations of the U.S. healthcare system. One of the main features of the ACA is the revised expansion of Medicaid eligibility in 2014. The Medicaid program has been providing and funding medical assistances to American citizens since its introduction in 1965. As of 2018, it has been responsible for providing free health insurance to 68 million people (Medicaid.gov, 2018). The Medicaid Expansion under the ACA allows individuals and households to qualify for Medicaid based on income alone with respect to the Federal Poverty Level (FPL). Under the current law, individual states have the choice on whether or not to participate in the ACA. Since its introduction, the ACA has sparked controversy within various fields ranging from politics, businesses and the general population, particularly people in the lower income groups. This is understandable from an economic viewpoint as it is easy to see the costs of providing free health insurance for millions. This brings us to the question of whether the costs of such policies can be justified by the benefits.

To see the relevance of Medicaid, we look at the following observations. Over the years, it has been observed that healthcare costs have been experiencing a steady price inflation.[1]

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[*]Including Washington DC. Montana and Louisiana have been omitted from the study as they expanded Medicaid during 2016 together with the lack of data for 2017.

[†]ECON 4274 Final Project, HKUST Spring Semester 2018

[1]see Appendix A

Wilson (n.d.) suggests that this is essentially a demand-pull inflation where he narrows down to two main causes. The first being that people are getting richer over time (as shown by the steady increase in real GDP per capita) which leads to an income effect of increased healthcare consumption. The second being that people are valuing personal health more and more (Spogárd & James, 1999) hence leading to increased healthcare consumption.[2] However, despite the increasing GDP per capita, the income gap has been observed to be widening since the 1980s.[3] This is wherein lies the relevance of Medicaid, to provide healthcare to the lower income groups who are gradually leaving the healthcare market due to inflating prices.

Boudreaux, Golberstein, & McAlpine (2016) finds that exposure to Medicaid in early child-hood is associated with improvements in adult health which was specific to the treatment group having participated in Medicaid. Thompson (2017) finds similar results "an additional year of public health insurance eligibility during childhood improves the summary index of adult health." So it should be safe to say that Medicaid has been shown to have a positive effect on health outcomes. From this, intuition would tell us that by extension, Medicaid expansion would also have a positive effect on health outcomes.

As discussed by Wilson (n.d.), there are many impacts (both budgetary and non-budgetary) brought about as a result. One of the most discussed non-budgetary concerns is the crowding out of the health insurance market, although according to Yazici & Kaestner (2000) "Medicaid expansions resulted in relatively little crowd out of private insurance." So in order to settle the controversy around policies such as Medicaid and by extension the ACA, government officials and the general public have to be convinced that the overall benefits of the program are significant enough to justify the costs (both budgetary and non-budgetary). In this paper, we will attempt to evaluate whether Medicaid expansion has a significant impact on health outcomes by seeing whether states that have chosen to expand Medicaid experience significant differences in health status. Because this topic is of great interest to a great number of parties, this paper attempts to shed light on the apparent effectiveness of the ACA's main objective of promoting health status of the states. We will do this by using Difference-in-Difference (DD) regressions to seek a causal relationship of having expanded Medicaid on health outcomes of the states.

2 Data

The data used in this study come from a variety of sources, primarily from the U.S. Census Bureau, The State Health Access Data Assistance Center (SHADAC) and the Henry J. Kaiser Family Foundation (KFF). The structure of the dataset is in panel data. Most of the data (control variables) are in terms of either percentages or rates per n people to control for population sizes. Most control variables are time-variant whilst two are time-invariant due to the lack of data.[4] For HDI, we assume that there is little to no fluctuation. This can be justified from the general observation that High Income Countries (HIC) tend to have stable measures of quality of life. This is shown by Konya & Guisan (2008) where they conclude that more developed

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[2]see Appendix B

[3]see Appendix C

[4]The two time-invariant controls being Human Development Index (HDI) and CO_2 emissions.

countries tend to converge rather slowly with respect to HDI. As for CO_2 emissions, we take a fifteen year average from 2000 to 2015.

The time periods of the dataset go from 2013 to 2016 where the data is annual. Some controls that are expressed as a percentage of population use annual estimates of population by the U.S. Census Bureau using 2010 as an estimate base.[5] The controls are chosen with considerations of how important they are as determinants of health status. Almost all controls are proxies or measures of the Social Determinants of Health recognized by the World Health Organization (WHO), (National Center for Health Statistics and others, 2016).

Table 1: Statistic Definitions

Statistic	Definition
treat.1	Dummy (= 1) for states that expanded Medicaid during 2014[1]
treat.2	Dummy (= 1) for states that expanded Medicaid during 2015[1]
D.14	Time dummy for 2014
D.15	Time dummy for 2015
D.16	Time dummy for 2016
HDI	Human Development index (HDI)[2]
co2	Mean CO_2 emissions from 2000-2015 in million metric tons[3]
rGDP.cap	Real GDP per capita in chained 2009 dollars[4]
disability	Percent of adults who report having a disability[5]
Y1	Health Outcome: Prevalence of Diabetes, CVD and Asthma in adults[6]
Y2	Health Outcome: Percent of adults with fair or poor health status[6]
hos.days	Hospital inpatient days per 1000 population[1]
pov.perc	Percentage in poverty[5][7]
HS.perc	Percentage that have attained High School education or higher[5]
uni.perc	Percentage that have attained Bachelor's education or higher[5]
SSI.perc	Percentage participating in the Supplemental Security Income program[8]
UE	Unemployment rate[9]
age	Median age[5]
fat	Prevalence of obesity (BMI $\geq$ 30) among adults[6]
crime	Violent crime rate per 100,000[10]
hosps	Number of hospitals per 100,000[1]
insured	Percentage of health insured[6]
exercise	Percentage of adults participating in any physical activity or exercise[5]
death	Health Outcome: Deaths per 100,000[5]

[1] The Henry J. Kaiser Family Foundation (2018)
[2] Social Science Research Council (2015)
[3] U.S. Energy Information Administration (2015)
[4] Bureau of Economic Analysis (2018)
[5] U.S. Census Bureau (2016); The definition of disability follows from the American Community Survey (ACS)
[6] State Health Access Data Assistance Center (SHADAC) (2018)
[7] As defined and measured by the U.S. Census Bureau
[8] Bureau of Labor Statistics, U.S. Department of Labor (2017)
[9] Social Security Administration (2017)
[10] Federal Bureau of Investigation, Uniform Crime Reporting (2016)

Table 1 lists all the variables and controls used in the study together with their definitions and Table 2 shows the summary statistics. National Center for Health Statistics and others

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[5] Number of hospitals per 100,000, Death rate and Number of violent crimes uses the annual population estimates from the U.S. Census Bureau.

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
treat.1	196	0.531	0.500	0	1
treat.2	196	0.061	0.240	0	1
D.14	196	0.250	0.434	0	1
D.15	196	0.250	0.434	0	1
D.16	196	0.250	0.434	0	1
HDI	196	6.794	1.546	2.900	9.600
co2	196	91.017	39.027	37.101	283.607
rGDP.cap	196	50,494.340	18,072.080	31,635	159,530
disability	196	0.131	0.022	0.095	0.202
Y1	196	0.231	0.026	0.180	0.319
Y2	196	0.144	0.033	0.090	0.273
hos.days	196	600.730	186.877	336	1,464
pov.perc	196	0.133	0.036	0.055	0.258
HS.perc	196	0.881	0.030	0.812	0.926
uni.perc	196	0.294	0.060	0.183	0.554
SSI.perc	196	0.024	0.008	0.010	0.043
UE	196	5.571	1.488	2.700	9.600
age	196	37.792	2.399	29.600	44.000
fat	196	0.292	0.035	0.202	0.377
crime	196	374.424	184.164	99.300	1,300.300
hosps	196	2.071	1.219	0.735	6.409
insured	196	0.900	0.040	0.781	0.975
exercise	196	0.755	0.043	0.619	0.843
death	196	8.426	1.224	5.129	12.293

(2016) lists a number of social determinants of health including economic stability, education, health and healthcare, neighbourhood and built environment. The variables listed in Table 1 attempt to control for the determination of these variables on health outcomes.

3 Empirical Analysis

3.1 Empirical Strategy

To attempt to find a causal relationship between health outcomes of the states and Medicaid expansion status, the potential endogeneity surrounding whether a state chooses to expand Medicaid or not should be addressed as this makes for essentially non-random treatment. As mentioned earlier, to tackle this endogeneity problem we will be using DD regression. In addition, among the 49 states in our study, most states which have expanded Medicaid did so during the year 2014 whilst three states expanded during 2015 and two states expanded during 2016 (which have been omitted in this study). To attempt capture the effect of Medicaid expansion across all 49 states, we will be using two treatment periods in our DD regression (2014 and 2015). For the DD estimators to be valid in the face of endogeneity we need to make two identification assumptions.

Assumption 1 (No anticipation)**.** *Given a treatment group of individuals $i = 1, 2, .., n$ and control group of individuals $j = 1, 2, ..., m$ and time periods $t = 0, 1$ with outcome Y, and treatment dummy T,*

$$\mathbb{E}(Y_i | t = 0, T = 1) = \mathbb{E}(Y_i | t = 0, T = 0) \tag{1}$$

Meaning that the outcome of the treatment group at $t = 0$ is independent of their status of being in the treatment group.

Assumption 2 (Parallel Trend)**.** *The treatment group would have followed the same trend as the control group given that the treatment was absent.*

i.e.

$$\mathbb{E}(Y_i | t = 1, T = 0) - \mathbb{E}(Y_i | t = 0, T = 0) = \mathbb{E}(Y_j | t = 1, T = 0) - \mathbb{E}(Y_j | t = 0, T = 0) \tag{2}$$

Since the treatment in our study has an indirect effect on health status in the sense that it is a vehicle to health care (which has a direct impact on health) access through Medicaid, the validity of assumption 1 is transferred over to the anticipation of healthcare on health outcomes. In other words, an individual's anticipation of being in a state with Medicaid expansion should not affect his/her health outcome directly. Medicaid expansion is merely a vehicle to healthcare access which itself is a vehicle to healthcare which has a direct impact on health outcomes. Therefore any anticipation of enjoying Medicaid expansion or not should not directly affect an individual's health outcome.

For assumption 2, we need to show that both groups would have followed the same trend given neither were treated. To test this assumption, we ran a Welch two sample t-test to test if there were significant differences between $\Delta_{T_1=1} = \mathbb{E}(Y_i, t = 2014, T_1 = 1) - \mathbb{E}(Y_i, t = 2013, T_1 = 1)$ and $\Delta_{T_1=0} = \mathbb{E}(Y_j, t = 2014, T_1 = 0) - \mathbb{E}(Y_j, t = 2013, T_1 = 0)$.[6] Although this is not a perfect test in that despite during the year 2013 none of the groups were treated, the first treatment group expanded Medicaid during 2014, meaning that the difference between health outcomes from 2013 and 2014 is not entirely the case where both groups were untreated (did not enjoy Medicaid expansion). However it could also be argued that the benefits of Medicaid expansion on health outcomes are not immediately observable.

After performing the Welch t-test on all three health outcomes, we observe that for Y_1 the p-value $= 0.2761$ and for *death* p-value$= 0.8477$ whilst for Y_2 the p-value $= 0.003114$. We can see from this that the validity of assumption 2 can be somewhat justified as the p-values for Y_1 and *death* allow us to accept the null of the health trends being statistically similar. However we should be wary of the output of the DD regression on Y_2 as assumption 2 does not seem to hold in this case.

Other than the potential endogeneity surrounding whether a state chooses to expand or not, we will assume for our study that all controls are exogenous for the sake of simplification.

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[6]In this case $T_1 = 0$ implies control group.

3.2 Econometric Model

The DD regression model will take the following form.

$$Health = \alpha + \delta_1 D_{14} + \delta_2 D_{15} + \delta_3 D_{16} + \delta_4 T_1 + \delta_5(D_{14} \times T_1) + \delta_6(D_{15} \times T_1) + \delta_7(D_{16} \times T_1)$$

$$+\delta_8 T_2 + \delta_9(D_{14} \times T_2) + \delta_{10}(D_{15} \times T_2) + \delta_{11}(D_{16} \times T_2) + X\beta + \epsilon \tag{3}$$

Where X is the matrix of controls.

To interpret the results from the DD regression, we will be comparing the health outcomes of the control group with states that expanded during 2014 and states that expanded during 2015 at the year 2016. This change would be represented by $\delta_4 + \delta_7$ for states that expanded during 2014 and for states that expanded during 2015, $\delta_8 + \delta_{11}$.

As listed in Table 1 we have three measures of health outcomes. We will run DD regressions on all three outcomes and compare the results.

3.3 Empirical Results

3.3.1 Y_1: Prevalence of Diabetes, Cardiovascular Diseases and Asthma in Adults

Table 4 shows the DD regressions for the health outcome Y_1 with heteroskedastic robust standard errors. We can see that none of the DD coefficients are significant at any level and are also very small in magnitude as well as occasionally having non-intuitive signs. The controls across the six specifications are shown to be very significant as well as most of them having signs that are consistent with intuition.[7] Further to the right of Table 4, controls that have been shown to be insignificant are dropped and those significant are kept. We see that for the controls that are kept that their coefficients are relatively stable across specifications. The R^2 values are also very high for specifications (2) to (6) and the F-statistics are shown to be highly significant for all specifications.

After reviewing the results from Table 4 it seems apparent that expanding Medicaid in either 2014 or 2015 has not shown any significant changes in the prevalence of Diabetes, CVD and Asthma in Adults after having incorporated controls derived from the social determinants of health which are shown to be highly significant and relevant.

3.3.2 Y_2: Percentage of Adults with fair or poor health status

Looking at Table 5, we actually see $(D_{14} \times T_1)$ to be significant at the 5% level but with a positive sign for specifications (4), (5) and (6) whilst all the other DD coefficients are insignificant as with Y_1. The controls also seem relatively stable, although $HS.perc$ changes from specification (3) to (4) but stays stable up to (6). The R^2 values are relatively high as you go towards the

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[7]Though for some controls such as hos.days, there may be some reverse causality that explains their signs (having CVD, Asthma or diabetes would lead to one staying at the hospital longer.)

right of Table 5 with specification (6) with $\bar{R}^2 = 0.788$. The F-statistics are also shown to be highly significant for all specifications.

As mentioned in section 3.1, we could not validate assumption 2 for Y_2. Reviewing the results in table 5, Medicaid expansion seems to have had an adverse effect on the reported health status of adults. Although this result seems counter-intuitive, it is possible that this is a result of an omitted factor from our model. There is also the possibility of reverse causality, but further study is required to affirm whether Medicaid expansion does lead to higher counts of fair or poor health status amongst adults. This may of be some interest as positive signs on the DD coefficients are observed throughout all specifications for $(D_{14} \times T_1)$, $(D_{15} \times T_1)$, $(D_{16} \times T_1)$, $(D_{14} \times T_2)$ and $(D_{16} \times T_2)$.

3.3.3 Death Rate

The use of death rate as a measure of health status is commonly discouraged as there are a multitude of factors that go into the determination of the figure. Because of this, it is very easy to run into omitted variable bias (OVB) and endogeneity problems in estimation when using death rate as an outcome. In this paper, we will be running two sets of regressions on death rate. In the U.S., over 50% of deaths are caused by heard diseases (Center of Disease Control and Prevention, 2013). As such, we will be running one set of regressions using Y_1 as a control and in another we will omit Y_1 from the regressions. By including Y_1 in the regression it is apparent that the model will suffer from some form of endogeneity as we have been using it as an outcome variable itself; and therefore lead to the estimates to be biased and inconsistent. However in exchange, the regression models should have a much better fit with the data due to the correlation and relevance of Y_1 on $death$.

For the second set of regressions, the presence of the problem of inconsistent and biased estimates depend on whether Y_1 is correlated with treatment. If Y_1 is correlated with our variables of interest then by omitting it we run into OVB. However if there is no correlation then the estimates will be free of bias (from lack of correlation) and inconsistency (from omission of endogenous control). Table 3 shows the Point-Biserial correlation between $death$ and the DD variables. We can see that all of them have relatively low values of r_{pb}, so it is possible that by omitting Y_1, the DD coefficients will be unbiased and consistent.

Table 3: Biserial correlation

Death rate	DD variable	r_{pb}
$death$	T_1	-5.2×10^-7
$death$	T_2	0.0324
$death$	$D_{14} \times T_1$	0.0232
$death$	$D_{14} \times T_2$	0.0216
$death$	$D_{15} \times T_1$	0.0115
$death$	$D_{15} \times T_2$	0.0193
$death$	$D_{16} \times T_1$	-0.0957
$death$	$D_{16} \times T_2$	-0.0133

We can see from table 6 that Y_1 is highly significant across all specifications as well as having coefficients of high magnitude. We see some significance for the time dummy coefficients for 2014 and 2015. Looking at specifications (3), (4) and (5) we find that $(D_{14} \times T_1)$ is shown to be significant as well as having a negative sign. Specification (3) also shows $(D_{14} \times T_1)$, $(D_{15} \times T_1)$ and $(D_{16} \times T_1)$ to be significant at the 10% level. The highly significant controls also seem to have reasonable signs on their coefficients with the exception of *insured* which may be subject to reverse causality[8]. We also see very high goodness of fits with all five specifications having $\bar{R}^2$ values between 0.8 and 0.9 together with high joint significance shown by the F-statistics.

Although the results from table 6 seem very intuitive, it should be noted that these estimates are known suffer from endogeneity meaning we cannot draw any causal conclusions. At best, the specifications in table 6 show the correlation between the covariates.

Table 7 shows the second set of regressions where we omit Y_1 as a control. With these specifications we are more convinced the estimates are free of bias and inconsistency. Similar with previous cases, none of the DD coefficients are shown to be significant at any level, although the signs are more intuitive this time. The controls are also relatively stable and unchanging which convinces us that specification (6) may be accurate. In theory, by including Y_1 as a control in the regressions in table 6, we run the trade-off of increasing goodness of fit at the cost of consistent and unbiased estimates when compared to the regressions on table 7. However, the $\bar{R}^2$ values are surprisingly high and not so different from the regressions from table 6.

4   Conclusion

After reviewing the results of the regressions on all three health outcomes: Prevalence of Diabetes, CVD and Asthma (Y_1), adults with fair or poor health status (Y_2) and Death rate it seems apparent that Medicaid expansion by the ACA has not had any significant effect on the mentioned health outcomes in the time frame of 2013 to 2016. Although the set of regressions for death rate that included Y_1 as a control showed intuitive and reasonable results for states that expanded Medicaid in 2014, the concerned estimates suffer from endogeneity and no causal interpretation can be drawn.

It should be noted that this study may not be the best reflection on the effectiveness of Medicaid Expansion on health outcomes as the time frame of this study is relatively short when compared to other studies that have attempted to study the effectiveness of Medicaid.[9] This may suggest that if Medicaid expansion does indeed have a significant impact on health outcomes, that the effects are not immediately observable and require a study of a longer time frame. In terms of a short-term evaluation on the effectiveness of Medicaid expansion, it may be more effective to evaluate the impact on healthcare usage as to health outcomes, as healthcare usage is more immediately observable as compared to health outcomes. Thus, in order to have a better grasp of this issue this study may have to be revisited in a few years time.

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[8]Residents of states with high death rates may tend to buy insurance more than states with lower death rates.
[9]The studies provided by Boudreaux et al. (2016), Thompson (2017), Sohn (2017) and many others who have studied the effectiveness of Medicaid have studied a much larger time frame.

Table 4: Y_1: Prevalence of Diabetes, CVD and Asthma in Adults

	Dependent variable:					
	Y1					
	(1)	(2)	(3)	(4)	(5)	(6)
D.14	−0.001	−0.001	−0.002	−0.001	0.002	0.001
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
D.15	−0.005	−0.003	−0.004	−0.003	−0.002	−0.006*
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
D.16	−0.001	0.001	−0.001	0.001	0.003	−0.0002
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
treat.1	−0.0001	0.002	0.0001	0.002	0.002	0.001
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
treat.2	−0.006	−0.0004	−0.004	−0.0002	−0.001	−0.001
	(0.007)	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)
fat	0.446***	0.163***	0.277***	0.223***	0.183***	0.180***
	(0.044)	(0.040)	(0.034)	(0.032)	(0.039)	(0.036)
age	0.005***	0.002***	0.002***	0.001***	0.002***	0.001***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
disability		0.766***	0.752***	0.678***	0.695***	0.728***
		(0.064)	(0.057)	(0.055)	(0.055)	(0.055)
rGDP.cap			0.00000***	−0.00000**		
			(0.00000)	(0.00000)		
hosps			−0.005***	−0.008***	−0.006***	−0.006***
			(0.001)	(0.001)	(0.001)	(0.001)
hos.days				0.00004***	0.00003***	0.00002***
				(0.00001)	(0.00000)	(0.00001)
exercise					−0.078**	−0.101***
					(0.031)	(0.032)

insured						0.098***
						(0.031)
D.14:treat.1	0.002	0.003	0.002	0.003	0.002	0.0004
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
D.15:treat.1	0.002	0.001	0.001	0.001	0.0002	−0.002
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
D.16:treat.1	0.002	0.002	0.002	0.003	0.002	−0.0001
	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
D.14:treat.2	−0.001	−0.001	−0.001	−0.001	−0.0005	0.0001
	(0.013)	(0.013)	(0.011)	(0.008)	(0.008)	(0.007)
D.15:treat.2	0.011	0.007	0.008	0.008	0.007	0.006
	(0.012)	(0.011)	(0.010)	(0.008)	(0.007)	(0.006)
D.16:treat.2	0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.015)	(0.014)	(0.013)	(0.010)	(0.010)	(0.008)
Constant	−0.080***	0.001	−0.028	0.019	0.074**	0.030
	(0.023)	(0.018)	(0.017)	(0.017)	(0.034)	(0.034)
Observations	196	196	196	196	196	196
R^2	0.590	0.770	0.826	0.856	0.858	0.865
Adjusted R^2	0.561	0.752	0.811	0.843	0.844	0.852
Residual Std. Error	0.017	0.013	0.011	0.010	0.010	0.010
F Statistic	20.173***	43.220***	53.256***	62.479***	63.196***	63.182***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Y_2: Percentage of adults with fair or poor health status

	Dependent variable:					
	Y2					
	(1)	(2)	(3)	(4)	(5)	(6)
D.14	−0.008	−0.005	−0.012***	−0.004	−0.003	−0.004
	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
D.15	0.005	0.009	−0.004	−0.0005	0.003	−0.0001
	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
D.16	0.004	0.010	−0.007	0.001	0.005	0.001
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
treat.1	−0.005	−0.009	−0.005	−0.002	−0.003	−0.002
	(0.009)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)
treat.2	0.014	0.005	0.011**	0.008	0.007	0.008
	(0.009)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
rGDP.cap	−0.00000***					
	(0.00000)					
pov.perc	0.504***	0.199**	−0.057			
	(0.085)	(0.081)	(0.069)			
co2	0.00000					
	(0.0001)					
HDI	0.003**					
	(0.001)					
age		0.004***	−0.001**	−0.001***	−0.002***	−0.001***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UE		0.004*	−0.0002	0.001	0.003**	0.001
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
hosps		0.003				
		(0.002)				

disability			1.133***	0.969***	0.995***	0.993***
			(0.096)	(0.085)	(0.082)	(0.082)
HS.perc		−0.349***	−0.394***	−0.177**	−0.184***	−0.194***
		(0.086)	(0.059)	(0.073)	(0.062)	(0.065)
uni.perc		−0.207***				
		(0.032)				
SSI.perc				0.159		
				(0.247)		
exercise				−0.191***	−0.192***	−0.191***
				(0.043)	(0.042)	(0.042)
crime					−0.00002***	
					(0.00001)	
D.14:treat.1	0.010	0.013	0.014**	0.012**	0.012**	0.012**
	(0.010)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
D.15:treat.1	0.002	0.005	0.005	0.003	0.004	0.003
	(0.012)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
D.16:treat.1	0.004	0.005	0.004	0.002	0.003	0.003
	(0.010)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
D.14:treat.2	0.009	0.014	0.015	0.015	0.015	0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
D.15:treat.2	−0.011	−0.007	−0.009	−0.009	−0.009	−0.009
	(0.011)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)
D.16:treat.2	−0.004	0.001	−0.001	0.0004	0.001	0.0004
	(0.012)	(0.008)	(0.005)	(0.006)	(0.006)	(0.006)
Constant	0.096***	0.319***	0.401***	0.362***	0.383***	0.374***
	(0.012)	(0.080)	(0.063)	(0.059)	(0.052)	(0.053)

Observations	196	196	196	196	196	196
R^2	0.550	0.687	0.782	0.806	0.814	0.806
Adjusted R^2	0.513	0.657	0.762	0.788	0.796	0.788
Residual Std. Error	0.023	0.019	0.016	0.015	0.015	0.015
F Statistic	14.683***	22.947***	40.106***	43.578***	45.764***	46.399***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Death per 100,100 (with Y_1 control)

	Dependent variable:				
	death				
	(1)	(2)	(3)	(4)	(5)
D.14	0.073	0.333***	0.256***	0.265***	0.201*
	(0.117)	(0.123)	(0.098)	(0.099)	(0.107)
D.15	0.094	0.150	−0.113	−0.032	−0.095
	(0.124)	(0.119)	(0.114)	(0.105)	(0.115)
D.16	0.244*	0.512***	0.273**	0.329***	0.241*
	(0.135)	(0.145)	(0.125)	(0.116)	(0.132)
treat.1	−0.132	−0.017	−0.063	0.020	0.013
	(0.139)	(0.117)	(0.105)	(0.099)	(0.101)
treat.2	−0.042	−0.025	0.041	0.087	0.027
	(0.441)	(0.455)	(0.366)	(0.338)	(0.340)
Y1	24.193***	15.217***	8.438***	9.924***	8.326***
	(2.674)	(2.795)	(2.582)	(2.319)	(2.564)
age	0.191***	0.219***	0.195***	0.185***	0.202***
	(0.020)	(0.016)	(0.017)	(0.016)	(0.017)
disability	12.467***	13.156***	19.341***	20.053***	17.507***
	(3.063)	(2.697)	(2.940)	(2.642)	(2.927)

co2	0.003***	0.004***	0.003***		
	(0.001)	(0.001)	(0.001)		
HDI	−0.087***	−0.097***	−0.031		
	(0.031)	(0.024)	(0.027)		
exercise		−7.183***	−9.515***	−8.039***	−6.736***
		(1.068)	(0.978)	(0.875)	(1.178)
pov.perc			4.876***	3.797***	3.829***
			(1.376)	(1.227)	(1.319)
insured			9.783***	6.874***	7.165***
			(1.429)	(1.364)	(1.725)
SSI.perc			−15.747**	−20.739***	−15.729**
			(6.376)	(4.943)	(6.400)
hos.days				0.001***	0.001***
				(0.0001)	(0.0002)
fat					3.730***
					(1.348)
crime					0.0002
					(0.0002)
HS.perc					0.113
					(2.148)
D.14:treat.1	−0.085	−0.121	−0.285**	−0.233*	−0.230*
	(0.181)	(0.161)	(0.145)	(0.139)	(0.138)
D.15:treat.1	0.019	−0.050	−0.259*	−0.188	−0.156
	(0.192)	(0.165)	(0.147)	(0.140)	(0.141)
D.16:treat.1	−0.048	−0.107	−0.283*	−0.214	−0.203
	(0.201)	(0.180)	(0.155)	(0.146)	(0.145)
D.14:treat.2	0.020	0.032	0.032	0.026	0.014
	(0.523)	(0.563)	(0.444)	(0.415)	(0.428)

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	(1)	(2)	(3)	(4)	(5)
D.15:treat.2	−0.159	−0.141	−0.180	−0.157	−0.109
	(0.591)	(0.587)	(0.432)	(0.413)	(0.428)
D.16:treat.2	−0.039	0.003	−0.085	−0.061	−0.073
	(0.554)	(0.595)	(0.491)	(0.457)	(0.487)
Constant	−5.734***	0.430	−5.332***	−4.327***	−6.734***
	(0.601)	(1.203)	(1.205)	(1.109)	(1.390)
Observations	196	196	196	196	196
R^2	0.859	0.888	0.918	0.928	0.931
Adjusted R^2	0.846	0.877	0.909	0.920	0.922
Residual Std. Error	0.480	0.429	0.370	0.346	0.341
F Statistic	68.059***	82.804***	98.077***	118.922***	106.107***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Death per 100,000 (without Y_1 control)

	Dependent variable:				
	death				
	(1)	(2)	(3)	(4)	(5)
D.14	−0.073	−0.070	0.181	0.198*	0.231*
	(0.147)	(0.149)	(0.115)	(0.112)	(0.119)
D.15	−0.173	−0.169	−0.250**	−0.153	−0.109
	(0.164)	(0.187)	(0.120)	(0.114)	(0.117)
D.16	0.016	0.020	0.131	0.222*	0.285**
	(0.166)	(0.210)	(0.132)	(0.126)	(0.129)
treat.1	−0.244	−0.249	−0.087	−0.005	0.020
	(0.158)	(0.160)	(0.114)	(0.110)	(0.113)
treat.2	−0.043	−0.102	−0.148	−0.063	−0.010

	(0.446)	(0.485)	(0.374)	(0.351)	(0.349)
age	0.173***	0.194***	0.208***	0.205***	0.198***
	(0.025)	(0.024)	(0.016)	(0.016)	(0.016)
disability	38.119***	37.073***	22.441***	22.890***	23.716***
	(1.854)	(1.886)	(2.498)	(1.814)	(1.798)
insured	6.994***	6.908***	9.375***	6.682***	6.185***
	(1.312)	(1.333)	(1.253)	(1.288)	(1.314)
UE		0.003			
		(0.079)			
co2		0.003***			
		(0.001)			
HDI		0.004			
		(0.065)			
fat			5.694***	5.678***	4.358***
			(1.458)	(1.457)	(1.196)
SSI.perc			0.264		
			(5.327)		
crime			0.001***	0.0003	
			(0.0002)	(0.0002)	
exercise			−8.516***	−7.195***	−7.667***
			(1.203)	(1.112)	(1.043)
hosps				−0.029	
				(0.035)	
hos.days				0.001***	0.001***
				(0.0003)	(0.0001)
D.14:treat.1	−0.097	−0.096	−0.217	−0.177	−0.174
	(0.219)	(0.209)	(0.150)	(0.147)	(0.151)

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D.15:treat.1	−0.109	−0.106	−0.179	−0.124	−0.132
	(0.228)	(0.226)	(0.152)	(0.146)	(0.152)
D.16:treat.1	−0.108	−0.104	−0.242	−0.178	−0.177
	(0.226)	(0.227)	(0.159)	(0.151)	(0.155)
D.14:treat.2	0.057	0.060	0.070	0.052	0.052
	(0.589)	(0.643)	(0.505)	(0.477)	(0.471)
D.15:treat.2	−0.057	−0.050	−0.056	−0.021	−0.029
	(0.616)	(0.674)	(0.511)	(0.479)	(0.466)
D.16:treat.2	−0.117	−0.110	−0.074	−0.041	−0.025
	(0.639)	(0.691)	(0.581)	(0.541)	(0.521)
Constant	−9.188***	−10.098***	−6.252***	−5.198***	−3.899***
	(1.297)	(1.275)	(1.335)	(1.248)	(1.296)
Observations	196	196	196	196	196
R^2	0.807	0.818	0.912	0.921	0.918
Adjusted R^2	0.792	0.800	0.904	0.912	0.910
Residual Std. Error	0.558	0.547	0.380	0.362	0.366
F Statistic	54.143***	46.916***	102.545***	107.843***	117.493***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A   Health care prices

Cumulative percent change since December 2007 in health care prices and GDP deflator

■ GDP deflator   ■ Health care price

Source: Altarum analysis of monthly BLS price data and monthly GDPD data published by Macroeconomic Adviser • Get the data • PNG
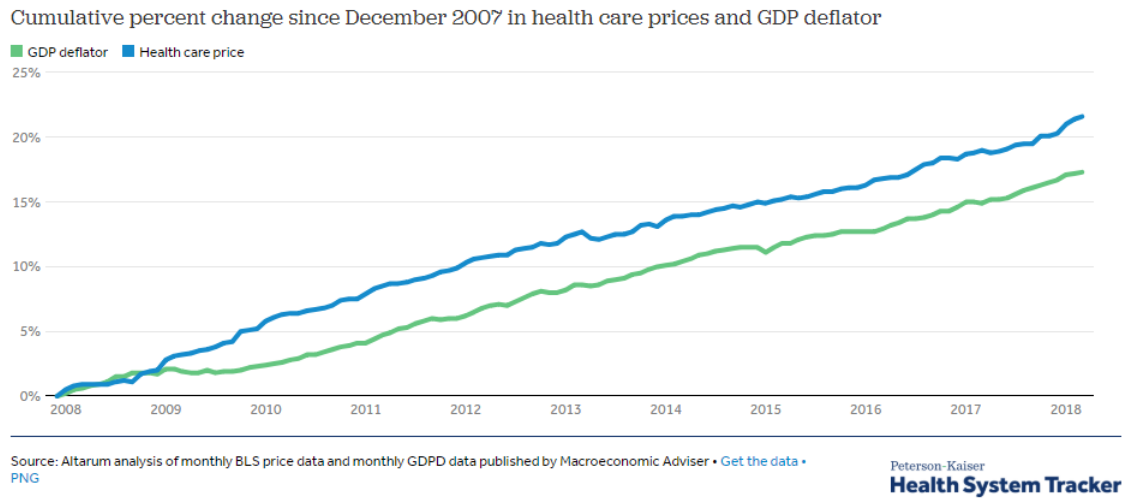
Peterson-Kaiser
Health System Tracker

Figure 1

B   Real Personal Consumption Expenditures: Services: Health-care
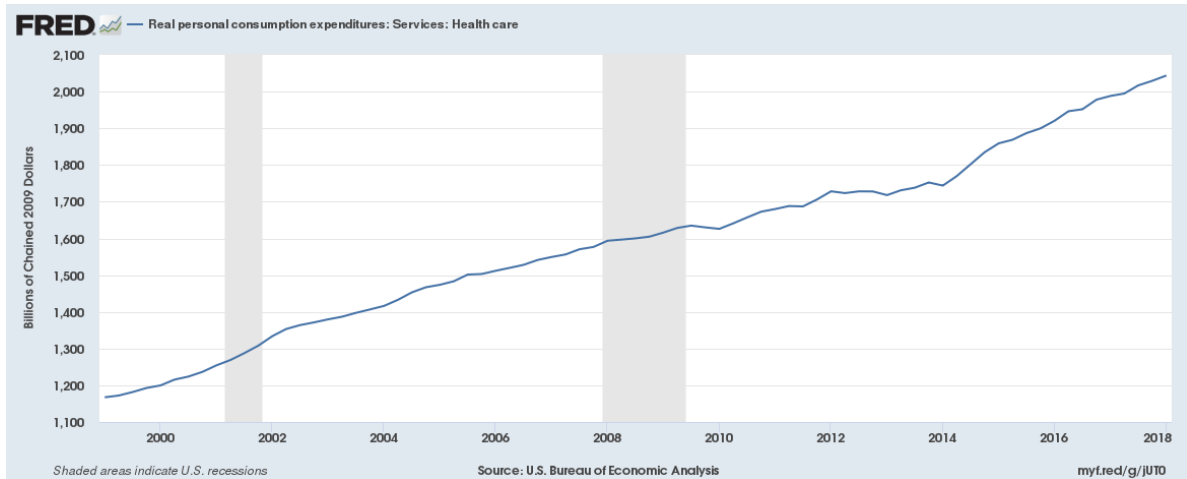
Figure 2

(U. S. Bureau of Economic Analysis, 2018)

C   Income Gap

Income Gains Widely Shared in Early Postwar Decades — But Not Since Then

Real family income between 1947 and 2016, as a percentage of 1973 level

95th percentile

Median

20th percentile

180%
160
140
120
100
80
60
40
20
0

1950   1960   1970   1980   1990   2000   2010
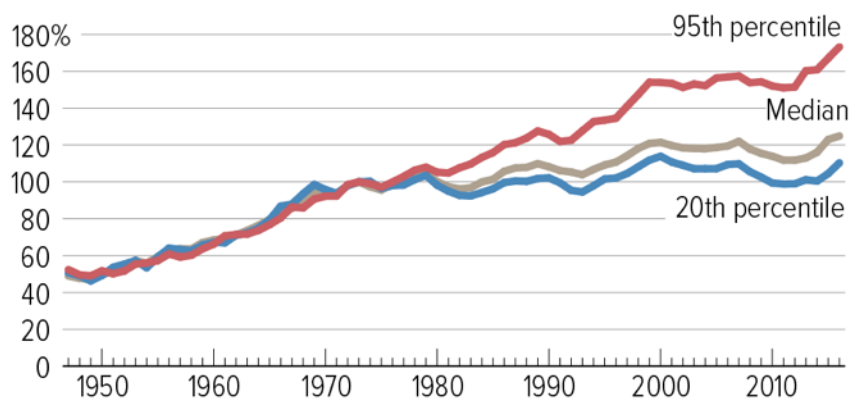
Note: In 2014 Census split its sample of survey respondents into two groups to test a set of redesigned income questions. In 2015 (reporting on 2014 income using the new questions), Census released two estimates of 2013 incomes, one based on the old questions and one on the new. The chart uses the estimate based on the old questions, based on CBPP's judgment that, due in part to sample size, it is likely more accurate for 2013.

Source: CBPP calculations based on U.S. Census Bureau Data

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Figure 3

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