DOES THE VALUE ADDED TO GDP FROM NONPROFIT INSTITUTIONS DECREASE MEDICAID PAYOUTS?

by

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A thesis submitted to the faculty of
The University of North Carolina at Charlotte
In partial fulfillment of the requirements
For the degree of Master of Science in
Economics

Charlotte

2019

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ABSTRACT

BRIAN PAUL SULLIVAN. Does the value added to GDP from nonprofit institutions decrease Medicaid payouts? (Under the direction of DR. CRAIG A. DEPKEN II)

This paper investigates the impact of nonprofit activities, measured by their total contribution to gross domestic product, on poverty, measured by Medicaid payouts. Additional control variables include: the value of the housing stock, the employment level, the unemployment rate, outstanding securitized consumer credit, and the level of the stock market. The analysis might prove fruitful for the numbers-oriented individual who prefers to know how far a dollar will go before choosing an amount to donate to a charity or foundation; especially those interested in donating to health-oriented nonprofits. The empirical method used for analysis is ordinary least squares regression, and the independent variable of focus on is the gross value added to GDP from nonprofit institutions. The conclusion is that a one percent change in the value added to GDP from nonprofit institutions does not statistically influence the percentage change in Medicaid payouts if the population data is considered; however, eliminating structural breaks in the data (and analyzing a sample of the data instead of the population) changes the outcome so that a one percent change in the value added to GDP from nonprofit institutions does statistically influence the percentage change in Medicaid payouts.

ACKNOWLEDGMENTS

Thank you Dr. Depken for the great amount of effort that you have provided me with guiding me through the process of writing my paper, and thank you Dr. Gaggl and Dr. Schorno for taking time to evaluate my paper. This paper would not have been possible without the help from all three of you; I am very grateful to all three of you!

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PART I: INTRODUCTION

The passage of the 16th amendment on July 2, 1909 to establish a Federal Income Tax (Library of Congress, 2018) permanently changed the American economy; a few years later, the Revenue Act of 1913 created the first federal tax exemption legislation following the 16th amendment (Arnsberger, Ludlum, Riley, Stanton, 2008), and in 1943, certain organizations exempt from federal taxes were mandated to begin filing Form 990 with the IRS, creating easy public access to the financial activity of nonprofits.

The dependent variable in this paper was selected as a proxy for the number of those in poverty (in the form of a rate) as a measure of the effectiveness of nonprofit organizations. Any organization categorized under sections 501 or 527 of the Internal Revenue Service Code, or any federal, state, or local government is exempt from federal taxes and is referred to as a “nonprofit” (IRS, 2019). Many of these organizations frequently have some type of mission statement that [at least partially] suggests they seek to help fight poverty. A few examples are: Goodwill (Goodwill Industries International Inc., 2019), United Way (United Way, 2019), The Salvation Army (The Salvation Army, 2019), and Compassion International (Compassion, 2019).

These organizations frequently advocate that donations and other funding services are the driving force behind their compassionate efforts. Developing an objective understanding of how effective nonprofits are at alleviating poverty could help guide future donor decisions and possibly the organizational behavior of nonprofits. With this in mind, this paper provides a comprehensive analysis of how nonprofits impact poverty in America as reflected by Medicaid payouts.

PART II: LITERATURE REVIEW

The premise of this paper is to see if the value added to GDP from nonprofit institutions decreases Medicaid payouts; there are numerous topics written by others that could be investigated that might yield insight to this question. This section will focus on reviewing a few topics that may provide benefit.

Firstly, why use a proxy variable at all? As the literature review reveals, this particular proxy is representative of the most widely used welfare program in the United States, making it a viable metric to showcase poverty (those in poverty will probably seek government assistance); specifically, this metric is dollars paid by Medicaid. Table 1 reports the distribution of the population relative to the Federal Poverty Level (FPL):

Table 1: Distribution of the Nonelderly with Medicaid by the Federal Poverty Level[1]

Year	Under 100% FPL	100-199% FPL	0-199% FPL	200-399% FPL	400%+ FPL
2017	32%	34%	66%	25%	10%
2016	33%	33%	66%	24%	10%
2015	36%	34%	70%	22%	9%
2014	39%	33%	72%	21%	7%
2013	41%	33%	74%	20%	7%
2012	42%	33%	75%	19%	6%
2011	42%	33%	75%	19%	6%
2010	41%	33%	74%	20%	7%
2009	40%	33%	73%	20%	7%
2008	40%	33%	73%	20%	7%

[1]chart sourced from: https://www.kff.org/medicaid/state-indicator/distribution-by-fpl-4/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

As shown in Table 1, the Henry J Kaiser Family Foundation (KFF) shows that over one-third of individuals receiving Medicaid benefits from 2008 to 2017 were below the Federal Poverty Level, and roughly two-thirds are still within what many might think of as “poor”. Table 1 demonstrates the quality of the proxy used in this paper, Medicaid payouts.

Economists might not expect an explicit relationship between Medicaid payments and nonprofit activity. While most nonprofits do not pay the medical bills of their customers, many nonprofits help their customers find employment, learn a new trade, obtain housing, or other activities to help alleviate financial burdens or become capable of producing more personal income. To the extent that they are successful, nonprofit actions that lead to higher personal income would eventually disqualify an individual for Medicaid, unless they otherwise qualify for Medicaid through disability, old age, or acting as a caretaker, as shown in figure 1.

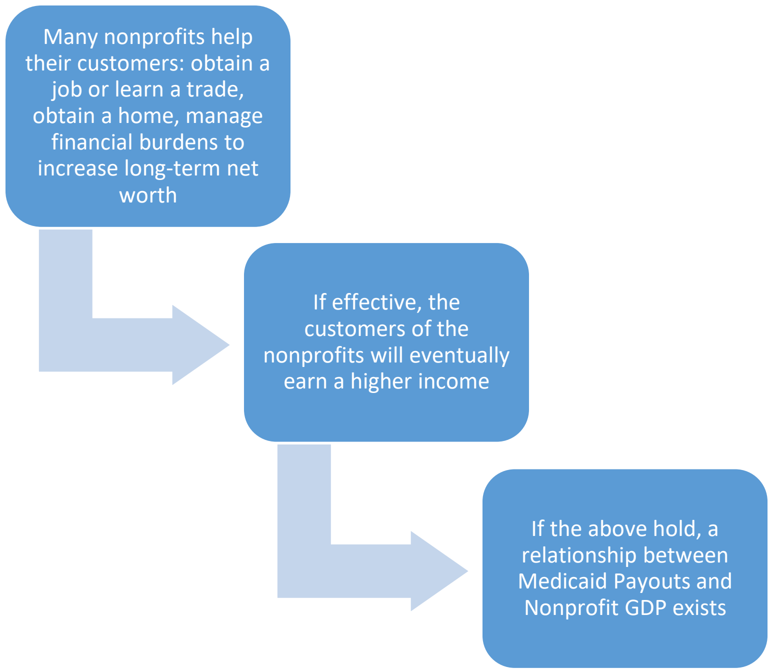

Figure 1: Logic behind using Medicaid Payouts as a proxy for Poverty

On a broader level, to decrease Medicaid payouts, one might conjecture that overall wealth would need to increase in society; this focus will be considered (how wealth increases as a whole in society) along with the research question posed in this paper. After all, "wealthy" by definition excludes the population in poverty (creating a case to review literature about wealth creation, rather than exclusively literature about escaping poverty). This logic will be used to guide the literature review, which will ultimately help the process of variable selection.

The Bureau of Economic Analysis defines GDP as "the value of the goods and services produced in the United States" (2018). This paper will focus on the Gross Value Added to GDP for Nonprofit Institutions Serving Households as the independent variable of focus since this is a measurement of the realized value of nonprofits, and omits intermediary output (BEA, 2018).

According to Benhabib, Bisin, Luo, (2015), three factors contribute to becoming wealthy: a skewed and persistent distribution of earnings, differential saving and bequest rates across wealth levels, and capital income risk. The later analysis includes a variable representative of the stock market to demonstrate capital income risk (funds invested in the stock market inherently experience risk).

Many consider a house to be the largest asset that many Americans own, and therefore a potentially useful wealth-building tool. Herbert, McCue, and Sanchez-Moyano, (2013) conclude "that homeownership continues to represent an important opportunity for individuals and families of limited means to accumulate wealth". Later analysis includes a variable that is a measurement of home ownership because it is a viable tool to building wealth.

Lastly, the reason for the inclusion of the variable that represents outstanding consumer credit is inspired by Deaton (2015):

"If the income process is positively autocorrelated, but stationary, assets are still used to buffer consumption, but do so less effectively, and at a greater cost in terms of foregone consumption. In the limit, when labor income is a random walk, it is optimal for impatient liquidity constrained consumers simply to consume their incomes. As a consequence, a liquidity constrained representative agent cannot generate aggregate U.S. saving behavior if that agent receives aggregate labor income. Either there is no saving, when income is a random walk, or saving is contracyclical over the business cycle, when income changes are positively autocorrelated."

PART III: INSPIRATION FOR CHOOSING THIS TOPIC AND THE FUNDAMENTAL THEORY

The logic of this paper is that charities will have greater potential to accomplish their missions as their *share* of GDP increases. They have greater potential to accomplish their missions since their relative financial resources would be increasing as their share of GDP increases, and that Medicaid payouts will decrease as fewer people are in poverty. The eventual results of this paper are not significant (at least not with respect to the independent variable under scrutiny, $Nonprofit_t$), and the dependent variable $Medicaid_t$ might be more influenced by politics than economics. According to Fichtner (2014):

"The Congressional Budget Office (CBO) estimates that by 2024, 20 million new people will be added to Medicaid (and the Children's Health Insurance Program) under the Patient Protection and Affordable Care Act (ACA)—an increase of nearly 30 percent. Further, according to the CBO, federal spending on Medicaid is already projected to rapidly increase under the ACA, from $265 billion in fiscal year (FY) 2013 to $574 billion in FY2024. Additionally, because Medicaid is actually run by each individual state with major funding assistance from federal cost-sharing dollars, state costs devoted to Medicaid are also expected to become much more burdensome. In terms of total state expenditures, Medicaid is the largest item in states' budgets—and will only get larger."

This quote reveals the potential for a lack of statistically significant relationship between $Nonprofit_t$ and $Medicaid_t$.

PART IV: DATA AND BASIC RELATIONSHIP

Table 2: Descriptive Statistics of the Sample[1]

Variable	Observations, n	Earliest Observation	Latest Observation	Min Value	Max Value	Mean	Std. Dev.
$Medicaid$	211	4/1/1966	10/1/2018	-7.85	20.36	2.94	4.01
$Nonprofit$	211	4/1/1966	10/1/2018	20.41	1,138.70	398.63	337.29
$Housing$	211	4/1/1966	10/1/2018	-2.50	12.10	2.68	2.00
$Credit$	211	4/1/1966	10/1/2018	99.30	4,000.62	1,313.95	1,142.98
$Priv\,Jobs$	211	4/1/1966	10/1/2018	52,926.00	127,574.00	90,983.27	21,929.20
$Govt\,Jobs$	211	4/1/1966	10/1/2018	10,827.33	22,768.33	18,291.97	3,447.09
$Unemploy$	211	4/1/1966	10/1/2018	2,696.33	15,223.00	7,616.78	2,632.59
$Market$	211	4/1/1966	10/1/2018	5.91	196.88	61.98	56.33

The variable that this paper studies is a measure of dollars paid to recipients by Medicaid. This series ranges in values from -7.85 to 20.36, with a standard deviation of 4.01 and a mean of 2.94 (all values for dollars paid to recipients by Medicaid are displayed as billions of dollars). This measurement is from the St. Louis Federal Reserve's series *W729RC1Q027SBEA, Personal current transfer receipts: Government social benefits to persons: Medicaid*. The regression variable used is adjusted from billions of dollars to percentage change from the previous period (quarterly), and is referred to as $Medicaid_t$ in this paper.

Medicaid is not exclusively offered to those in poverty (Medicaid, 2019), but is also offered to those with specific disabilities, and other exceptions, including:

"States have the option to establish a "medically needy program" for individuals with significant health needs whose income is too high to otherwise qualify for Medicaid under other eligibility groups. Medically needy individuals can still become eligible by "spending down" the amount of income that is above a state's medically needy income standard. Individuals spend down by incurring expenses for medical and remedial care for which they do not have health insurance. Once an individual's incurred expenses exceed the difference between the individual's income and the state's medically needy income level (the "spenddown" amount), the person can be eligible for Medicaid."

And also under this exception:

"States have additional options for coverage and may choose to cover other groups, such as individuals receiving home and community-based services and children in foster care who are not otherwise eligible."

[1] All values shown in Table 2 are displayed in unadjusted units. Specific unit types are discussed in the body of Part IV. All of the variables shown in Part IV are converted to percentage change (period-over-period) before regressing.

Using Medicaid payouts as a proxy for poverty gives this later analysis a distinct advantage (over using poverty itself) with respect to simplifying the models used. Firstly, the Poverty Rate (as measured by the U.S. Census) is a poor variable of choice to use in a time series analysis. The dollar thresholds for the FPL rely on more than just income, complicating any regression models. In addition, the information required to determine the FPL status is adjusted for inflation each September using the CPI-U measurement, which is the consumer price index for all urban consumers[2]. From the perspective of an econometrician, poverty itself is a poor regression variable because it is relatively stable over time.

All of the variables in this paper are shown on a quarterly basis, from the end of quarter two in 1966 to the end of quarter three in 2018. Because the sample period spans years that exhibit vastly different inflation levels, all of the variables that were captured in nominal dollars have been adjusted to real reflect dollars in the first quarter of year 2000, by using the PCE index. The specific PCE dataset used is series *PCEC* from the St. Louis Federal Reserve. The PCE has been selected to use (instead of the CPI) because PCE "includes more comprehensive coverage of goods and services, and historical PCE data can be revised (more than for seasonal factors only)" (Bullard, 2013). Although the CPI is generally used for adjusting government benefits, all of the other variables used in this paper are not a measurement of some given government benefit, making PCE more appropriate to use with respect to all of the variables.

The main independent variable in this paper is *Gross value added: GDP: Households and institutions: Nonprofit institutions serving households*, series *B702RC1Q027SBEA* (FRED, 2019), and is referred to as $Nonprofit_t$ in this paper. The unadjusted version of this variable exhibits an exponential slope and is relatively smooth, even during recessions and business cycles. The values of this series range from 20.41 to 1,138.70, with a standard deviation of 337.29 and a mean of 398.63 (as billions of dollars).

[2]Produced by the Bureau of Labor Statistics, this analysis covers about 88% of all Americans, and follows the prices of items including, but not limited to: food, clothing, shelter, and medical services (BLS, 2018)

Common macroeconomic variables are included as control variables, and the first of these control variables is *Real Gross Housing Value Added*, series *A2009L1Q225SBEA*. This variable is referred to as $Housing_t$ in this paper (FRED, 2019). Real estate is frequently the largest asset in a given individual's possession and the aggregate value of these assets could be influential to the rate of poverty. Its values range from -2.50 to 12.10, with a standard deviation of 2.00 and a mean of 2.68 (all measurements for this variable are displayed as a percentage change from the preceding period).

The next variable utilized in this paper was originally produced by the Federal Reserve, and is referred to as *Total Consumer Credit Owned and Securitized, Outstanding*, series *TOTALSL*, shown in dollars in this paper, and is referred to as $Credit_t$. According to Deaton (1989):

> *"Limited borrowing opportunities may also help to explain the observed patterns of household wealth holdings as well as the fact that consumption appears to track household income quite closely over the life-cycle."*

Deaton (1989) demonstrates the relationship between wealth and consumption, and liquidity and consumption; thus there is an implicit relationship between liquidity and wealth. Deaton goes on to suggest that decreased liquidity could be a cause for reduced wealth. If this logic holds, then $Credit_t$ should be inversely related to $Medicaid_t$, ceteris paribus. The values of series *TOTALSL* range from 99.30 to 4,000.62, with a standard deviation of 1,142.98 and a mean of 1,313.95 (all measurements for this variable are displayed as billions of dollars).

The FRED variables *All Employees: Total Private Industries* (series *USPRIV*) and *All Employees: Government* (series *USGOVT*) included in the paper were both sourced from the U.S. Bureau of Labor Statistics, and are well-known key macroeconomic indicators. The separation between private employment and government employment was included simply for the purpose of adding extra detail. They are respectively referred to as $Priv\ Jobs_t$ and $Govt\ Jobs_t$ in this paper. The values of series *USPRIV* range from 52,926.00 to 127,574.00 (the largest nominal range of any of the variables), with a standard deviation of 21,929.20 and a mean of 90,983.27

(all measurements for this variable are in thousands of persons). The values of series *USGOVT* range from 10,827.33 to 22,768.33, with a standard deviation of 3,447.09 and a mean of 18,291.97 (all measurements for this variable are displayed as thousands of persons).

The FRED variable *Unemployment Level* (series *UNEMPLOY*) has also been retrieved from the U.S. Bureau of Labor Statistics by FRED; this macroeconomic indicator is commonly used in econometric regressions. The argument that unemployment can be influential on the poverty level follows from the U.S. Census including unemployment compensation, but not the unemployment rate, is a component of poverty status (U.S. Census Bureau, 2019). The unemployment rate will be referred to as $Unemploy_t$ in this paper. The values of series *UNEMPLOY* range from 2,696.33 to 15,223.00, with a standard deviation of 2,632.59 and a mean of 7,616.78 (all measurements for this variable are displayed as thousands of persons).

The stock market is a unique measurement of the financial markets' confidence, business investment performance, and the economy (Hu, 2018). In addition to being an important measurement for the performance of the American economy, equities also represent a sizable portion of individuals' wealth (Bertaut, 2002). The variable analyzed in this paper, $Market_t$, is a broad representation of the stock market, retrieved from FRED. The data shown in FRED was originally sourced from the Organization for Economic Co-operation and Development. This variable is generally increasing over time, but with significantly greater volatility than the other variables included in this analysis, and particularly sensitive to recessions (FRED, 2019). This series has a range from 5.91 to 196.88, with a standard deviation of 56.33 and a mean of 61.98 (all measurements for this variable are indexed to Jan 2000=100)

The sample period for the dataset is from April 1966 to October 2018. Before analysis is conducted on the data, the variables will be transformed to meaningful and comparable units (all variables will be analyzed as units of percentage change).

PART V: DATA MODELING

5.1: First Model

Equation 1

$$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}} = \beta_0 + \beta_1 \frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} + \beta_2 \frac{Housing_t - Housing_{t-1}}{Housing_{t-1}} + \beta_3 \frac{Credit_t - Credit_{t-1}}{Credit_{t-1}} +$$

$$\beta_4 \frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}} + \beta_5 \frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}} + \beta_6 \frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}} + \beta_7 \frac{Market_t - Market_{t-1}}{Market_{t-1}} + \varepsilon_t$$

Table 3: Summary statistics for Equation 1

Variable	Observations, *n*	Earliest Date	Latest Date	Min Value	Max Value	Mean	Std. Dev.
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	210	4/1/1966	10/1/2018	-0.0889	0.1645	0.0121	0.0371
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	210	4/1/1966	10/1/2018	-0.0359	0.0649	0.0030	0.0103
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	210	4/1/1966	10/1/2018	-50.0000	39.0000	-0.6419	6.0762
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	210	4/1/1966	10/1/2018	-0.0370	0.03152	0.0015	0.0119
$\frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}}$	210	4/1/1966	10/1/2018	-0.0222	0.0199	0.0042	0.0061
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	210	4/1/1966	10/1/2018	-0.0157	0.0173	0.0035	0.0047
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	210	4/1/1966	10/1/2018	-0.0869	0.2568	0.0049	0.0523
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	210	4/1/1966	10/1/2018	-0.2871	0.1716	0.0009	0.0608

Note that the observations column uses 211 observations in other units, then is adjusted to percentage change to obtain 210 observations.
The percentage change in $Housing_t$ has outliers in the early 1980's

Table 4: Equation 1 results

Regression Variable	Coefficient
$Intercept_t$	0.0115** *SE: 0.0043*
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	0.1592 *SE: 0.2741*
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	0.0005 *SE: 0.0004*
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	-0.2436 *SE: 0.2347*
$\frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}}$	-0.7917 *SE: 0.7844*
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	1.1460^^ *SE: 0.6027*
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	0.0277 *SE: 0.0892*
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	0.0032 *SE: 0.0447*

***designates a 99.0% significance level,*
^^ designates a 90.0% significance level

The model specified as “Equation 1” suggests that the most influential (and the only statistically significant) variable on the percentage change of $Medicaid_t$ is the percentage change of $Govt\ Jobs_t$, suggesting that the hypothesis of this paper should be rejected. The direction of the coefficient of the percent change in $Govt\ Jobs_t$ is logical; one supporting conjecture is that the more revenue the federal government has, the more it has historically expanded its programs (not exclusive to Medicaid). The more programs it has, the more staffers it might need.

Perhaps the most surprising aspect of this result is not the result of the two primary variables of interest in this paper, but that unemployment was not identified as a statistically significant variable. This could be due to numerous factors; but one conjecture might be the exclusion of certain groups in the calculation of the unemployment rate. Specifically, the recent phenomenon of “under employment,” in part due to the “gig economy” might be to blame for the insignificance of the impact of the percent change of $Unemploy_t$ on the percent change on $Medicaid_t$ (Smith, 2018).

The rejection of the statistical significance of the percent change in the variable $Housing_t$ is not as surprising as the rejection of the percent change of $Unemploy_t$, but the sign of the coefficient for the percent change of $Housing_t$ is a little surprising; one might speculate that as the value of Real Gross Housing Added increases, the percent change in $Medicaid_t$ might decrease since one might conclude that more housing value would indicate more wealth among the sample population. This result could perhaps be due to easier qualifiers to obtain Medicaid coverage, the potential for total wealth polarization in America, potential rising healthcare costs that surpass the realized growth in $Housing_t$, or something else.

The sign of the coefficients of the percent change in $Credit_t$, $Priv\ Jobs_t$, and $Market_t$ are as expected, although none of them exhibit statistical significance. One might speculate that the liquidity of consumers, represented by $Credit_t$ would impact the ability of people to escape poverty. One potential reason why this variable might be statistically insignificant is the possibility that it excludes that portion of consumer credit that is not securitized which represents a significant pool of consumer credit. The potential for the percent change in $Priv\ Jobs_t$ to be a significant variable is fairly simple logic; an employed person might have a greater potential to have access to private healthcare insurance or to become disqualified for Medicaid. Lastly, the percent change in the variable $Market_t$ has traditionally composed many classic economic indicators into its valuation (it incorporates interest rates, inflation, intrinsic value of its underlying assets), it has also been known to price in illogical components as well, much of which would fall under “behavioral finance” (Thaler and Barberis, 2003).

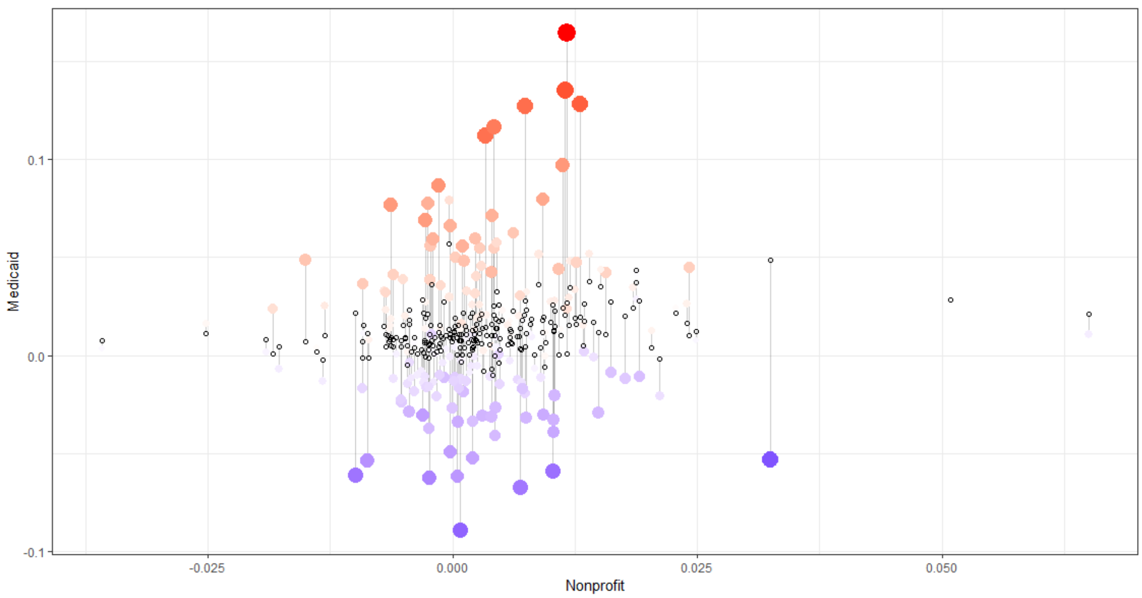

Figure 2: Linear regression results of the percent change in $Medicaid_t$ and $Nonprofit_t$ for Equation 1

Figure 2 is a visual representation of the linear regression of Equation 1. Hollow points indicate predicted values and solid points indicate actual values; larger points indicate values further from the predicated values. All of the variables have been adjusted to percentage change since last period (after adjusting dollar variables for PCE), eliminating the unit root, which might have been the most severe problem with the data. To confirm that the unit root has been eliminated, the Augmented Dickey Fuller test has been used to analyze the variables (and it indeed confirms the stationarity of the data); the p-value is significant for each variable used (with 99% significance), rejecting the null hypothesis of a unit root in each of the variables.

Table 5: VIF and ADF values for Equation 1

Regression Variable	VIF	ADF & P-value of ADF
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	NA	-15.951, 0.01
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	1.2621	-15.193, 0.01
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	1.0394	-14.164, 0.01
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	1.2280	-6.6133, 0.01
$\frac{Priv\,Jobs_t - Priv\,Jobs_{t-1}}{Priv\,Jobs_{t-1}}$	3.6694	-4.652, 0.01
$\frac{Govt\,Jobs_t - Govt\,Jobs_{t-1}}{Govt\,Jobs_{t-1}}$	1.2592	-10.155, 0.01
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	3.4572	-6.7612, 0.01
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	1.1712	-10.571, 0.01

The variables used in Equation 1 demonstrate low multicollinearity, as shown by the Variance Inflation Factors. High degrees of multicollinearity will not affect the model as a whole, but certainly can affect the output from a single isolated predictor (The Pennsylvania State University, 2018). All of the variables fall close to 1, the "best" possible value that a given variable can produce with respect to the VIF test (The Pennsylvania State University, 2018).

The Durban-Watson test has been performed to ensure that the data do not exhibit autocorrelation, with a resulting DW value of 2.333 (a relatively good result, close to 2), and a p-value of 0.98 (unable to reject the null that autocorrelation does not exist).

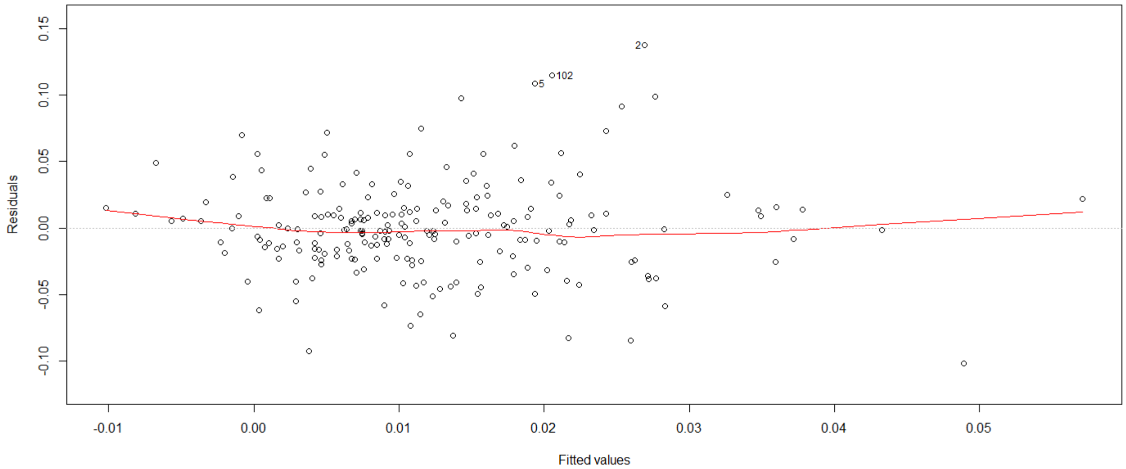

Figure 3: Residuals vs. Fitted values for Equation 1

The residuals shown in Figure 3 are random in appearance, further suggesting that the results of this regression are reliable and adhere to good practice. A normal Q-Q plot is available to further show the goodness of fit in Appendix A (Equation 1 Standardized Residuals vs. Theoretical Quartiles).

5.2: Second Model

Equation 2

$$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}} = \beta_0 + \beta_1 \frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} + \beta_2 \frac{Govt\,Jobs_t - Govt\,Jobs_{t-1}}{Govt\,Jobs_{t-1}} + \varepsilon_t$$

Table 6: Summary statistics for Equation 2

Variable	Observations, n	Earliest Date	Latest Date	Min Value	Max Value	Mean	Std. Dev.
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	210	4/1/1966	10/1/2018	-0.0889	0.1645	0.0121	0.0371
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	210	4/1/1966	10/1/2018	-0.0359	0.0649	0.0030	0.0103
$\frac{Govt\,Jobs_t - Govt\,Jobs_{t-1}}{Govt\,Jobs_{t-1}}$	210	4/1/1966	10/1/2018	-0.0157	0.0173	0.0035	0.0047

Note that the observations column uses 211 observations in other units, then is adjusted to percentage change to obtain 210 observations.
The percentage change in $Housing_t$ has outliers in the early 1980's

Table 7: Equation 2 results

Regression Variable	Coefficient
$Intercept_t$	0.0074* *SE: 0.0032*
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	0.2673 *SE: 0.2511*
$\frac{Govt\,Jobs_t - Govt\,Jobs_{t-1}}{Govt\,Jobs_{t-1}}$	1.1195* *SE: 0.5527*

** designates a 95.0% significance level*

This particular model (Equation 2) excludes all variables that are not significant, but includes the two variables that are of particular interest and the single significant explanatory variable. Like the earlier model, the percent change in $Govt\,Jobs_t$ is once again the only statistically significant independent variable. Also like the earlier model, the percent change in $Nonprofit_t$ is not statistically significant. At this point, one might begin to speculate if there are additional external factors that might influence the dependent variable. Given the qualifications to apply for Medicaid, an external factor not included here is the decision to apply (and subsequently request a payout) to Medicaid.

With respect to the summary statistics of the data used in Equation 2, there were no significant outliers, the same amount of observations as in Equation 1, and a lower count of independent variables.

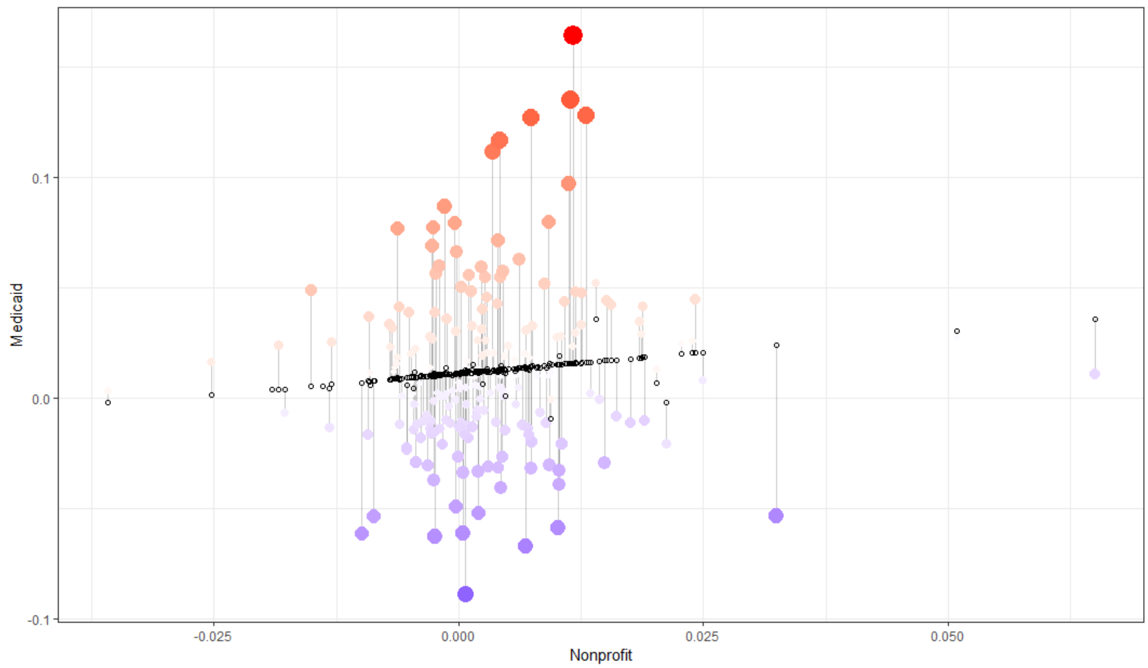

Figure 4: Linear regression results of the percent change in $Medicaid_t$ and $Nonprofit_t$ for Equation 2

Figure 4 is a visual representation of the two variables of interest for the linear regression specified as Equation 2. The hollow points in Figure 4 are the predicted values and the solid points are actual values; larger solid points indicate a more severe under or over prediction than smaller solid points. Figure 5, below, is a visual representation of the full linear model (residuals versus fitted values, with a red regression line).

Table 8: VIF and ADF values for Equation 2

Regression Variable	VIF	ADF & P-value of ADF
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	NA	-15.951, 0.01
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	1.0358	-15.193, 0.01
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	1.0358	-10.155, 0.01

With respect to the quality of the data regressed in this model, one can see from Table 8 that the VIF and ADF tests produced acceptable results. The adjusted coefficient of correlation is the weakest for this model out of all of the models; although this technically does not mean anything from the perspective of an academic, it might be suggestive evidence that the percent change in $Nonprofit_t$ has little effect on the percent change in $Medicaid_t$ to the non-academic. From the perspective of an academic, the variable percent change in $Nonprofit_t$ is once again not significant.

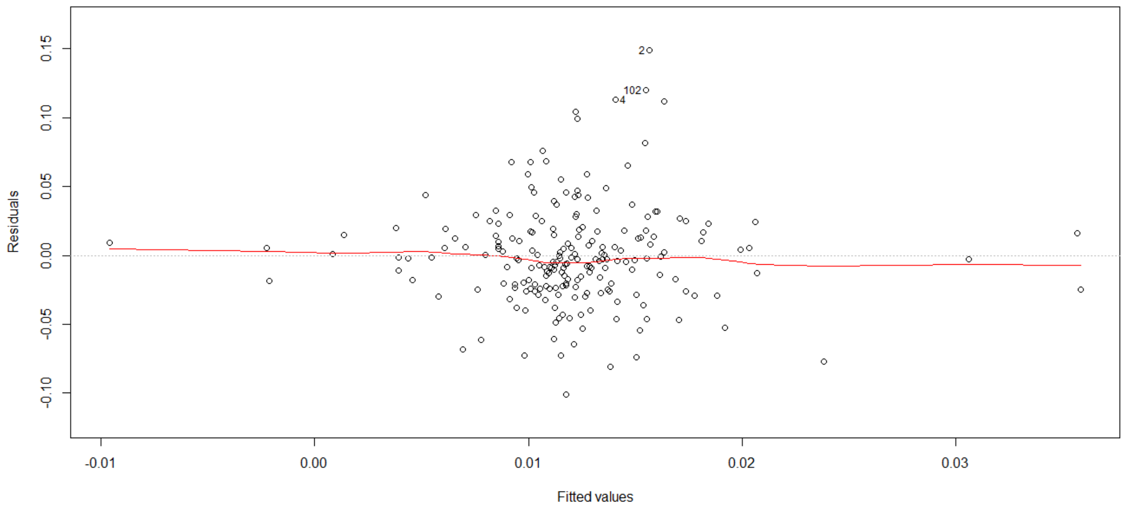

Figure 5: Residuals vs. Fitted values for Equation 2

Although Figure 5 demonstrates that the model is reliable, the output of the model indicates that the independent variables do not do a good job of explaining the percent change of $Medicaid_t$. A normal Q-Q plot is available to further show the goodness of fit in Appendix A (Equation 2 Standardized Residuals vs. Theoretical Quartiles).

Third Model

Equation 3

$$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}} = \beta_0 + \beta_1 \frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} + \beta_2 \frac{Housing_t - Housing_{t-1}}{Housing_{t-1}} + \beta_3 \frac{Credit_t - Credit_{t-1}}{Credit_{t-1}} +$$

$$\beta_4 \frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}} + \beta_5 \frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}} + \beta_6 \frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}} + \beta_7 \frac{Market_t - Market_{t-1}}{Market_{t-1}} + \varepsilon_t$$

Table 9: Summary statistics for Equation 3

Variable	Observations, n	Earliest Date	Latest Date	Min Value	Max Value	Mean	Std. Dev.
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	102	7/1/1993	10/1/2018	-0.0889	0.1166	0.0045	0.0324
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	102	7/1/1993	10/1/2018	-0.0252	0.0509	0.0006	0.0085
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	102	7/1/1993	10/1/2018	-3.4286	8.1667	0.0499	1.5556
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	102	7/1/1993	10/1/2018	-0.0229	0.03152	0.0041	0.0098
$\frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}}$	102	7/1/1993	10/1/2018	-0.0201	0.0102	0.0033	0.0052
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	102	7/1/1993	10/1/2018	-0.0157	0.0151	0.0017	0.0036
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	102	7/1/1993	10/1/2018	-0.0157	0.0151	0.0017	0.0036
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	102	7/1/1993	10/1/2018	-0.2871	0.1214	0.0055	0.0582

Table 10: Equation 3 results

Regression Variable	Coefficient
$Intercept_t$	0.00778 *SE: 0.0048*
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	-0.8821* *SE: 0.4682*
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	-0.0009 *SE: 0.0022*
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	0.1170 *SE: 0.3546*
$\frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}}$	-0.7561 *SE: 1.2154*
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	0.0566 *SE: 0.8995*
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	0.1261 *SE: 0.1307*
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	-0.0665 *SE: 0.0631*

** designates a 95.0% significance level*

Equation 3 differs from the first two equations because it uses data only from the second quarter of year 1993 to the third quarter of 2018 to isolate a sample of the data that does not experience a structural break. The Chow Test is a test commonly used to determine if a structural break exists, but is flawed because it relies on the assumption that the econometrician has to help identify when the break occurs, likely by visual analysis. To overcome this limitation, a lesser-used test that is based on the Bellman Principle, developed by Bai and Perron (1998) is utilized. The test produces the following results (shown in Figure 6):

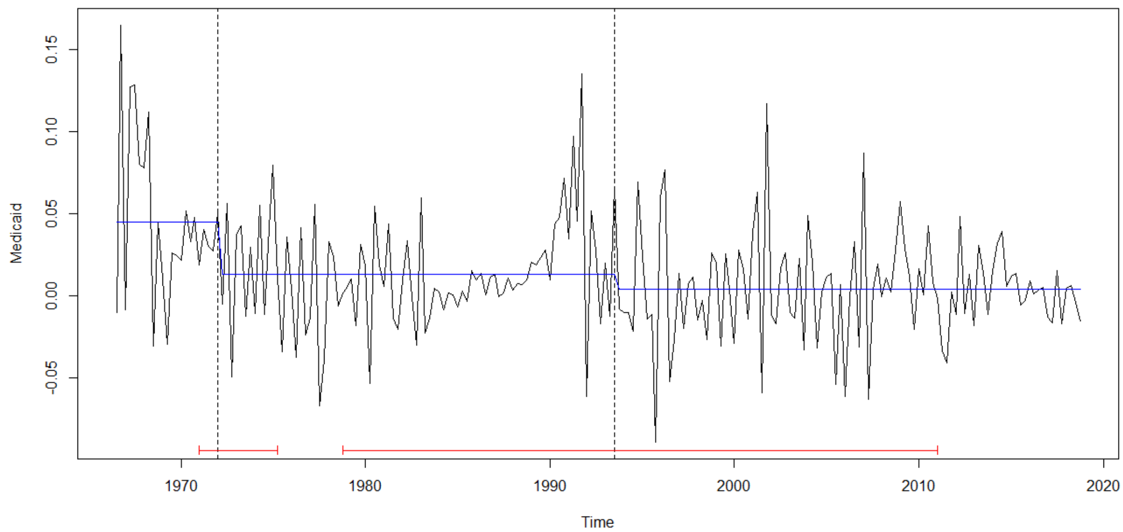

Figure 6: The Change in $Medicaid_t$ *with Structural Breaks and Confidence Intervals*

The first structural break occurs in the first quarter of 1972 and a second structural break occurs in the third quarter of 1993. The confidence intervals shown as the lines on the bottom part of Figure 6 are shown with 80% confidence. Even though the structural break that occurs in 1972 has a smaller confidence interval than the confidence interval for the structural break in 1993, Equation 3's regression focuses on the years 1993-2018 simply because these are more recent years (and have more relevance today).

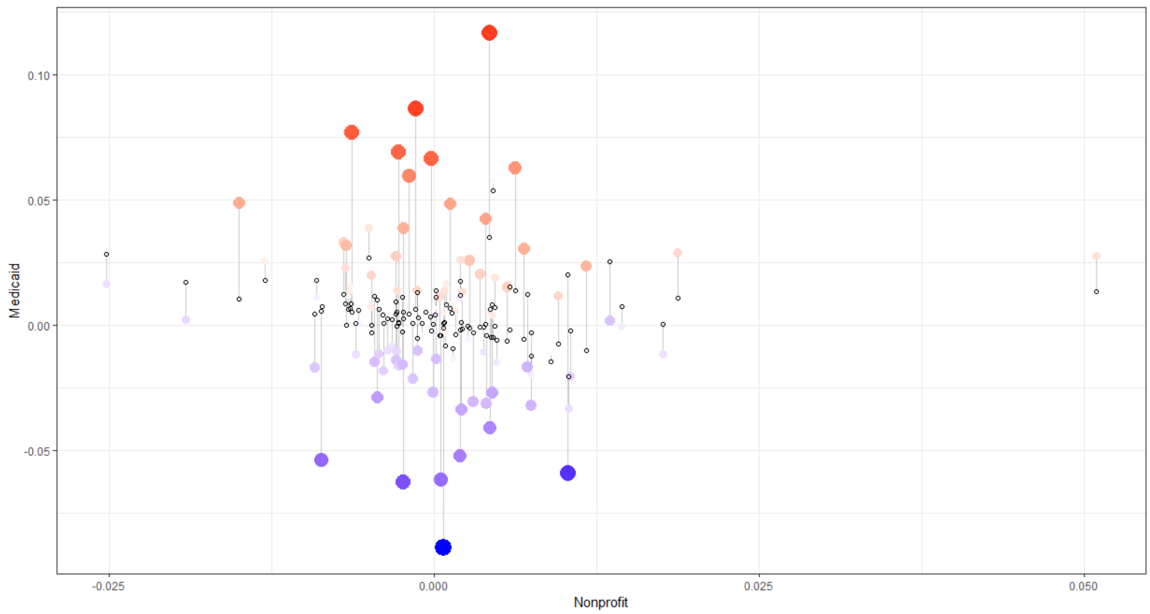

Figure 7: Linear regression results of the percent change in $Medicaid_t$ *and* $Nonprofit_t$ *for Equation 3*

Equation 3 shows markedly different results than the first two regressions; the only significant variable is the percent change of $Nonprofit_t$. Although this regression does not precisely indicate what occurred to cause the structural breaks, the structural breaks do indicate that something occurred that caused a change in the relationship between the change in $Medicaid_t$ and the change in $Nonprofit_t$.

Table 11: VIF and ADF values for Equation 3

Regression Variable	VIF	ADF & P-value of ADF
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	NA	-12.9020, 0.01
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	1.5631	-9.4383, 0.01
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	1.1197	-9.5605, 0.01
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	1.2040	-5.6168, 0.01
$\frac{Priv\,Jobs_t - Priv\,Jobs_{t-1}}{Priv\,Jobs_{t-1}}$	3.9695	-2.1603, 0.01
$\frac{Govt\,Jobs_t - Govt\,Jobs_{t-1}}{Govt\,Jobs_{t-1}}$	1.0511	-8.4131, 0.01
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	3.6939	-4.5665, 0.01
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	1.3411	-6.7848, 0.01

Table 11 shows the ADF test results and VIF test results. All of the ADF values are acceptable, but there is a slightly higher level of multicollinearity than in the previous regressions, as shown by the VIF test results; but not at a problematic level.

The residuals shown in Figure 8 are random in appearance, suggesting that the results of this regression are reliable. Appendix A contains a normal Q-Q plot to further show detail of the goodness of fit (Equation 3 Standardized Residuals vs. Theoretical Quartiles).

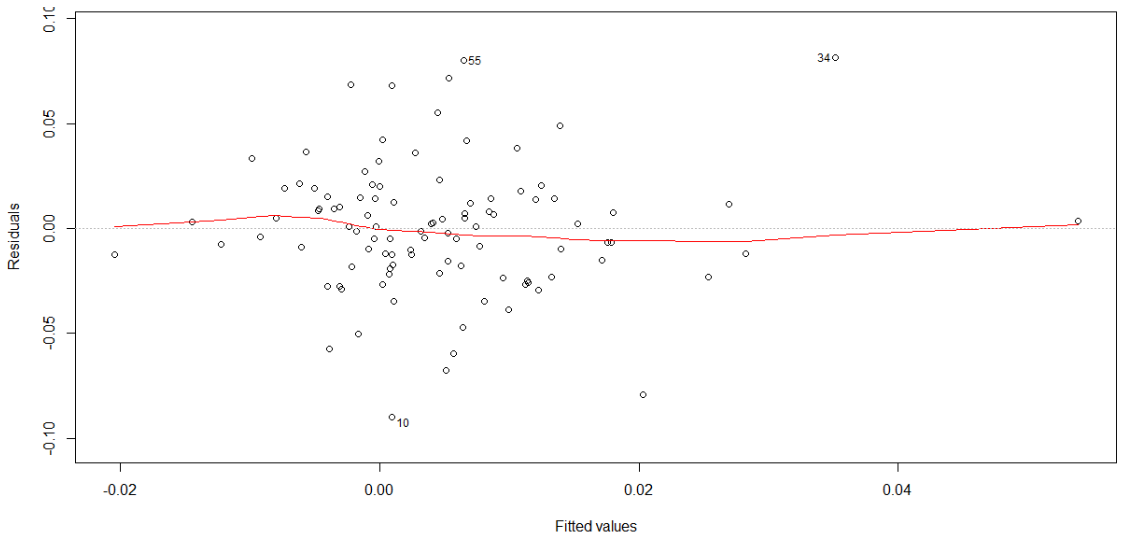

Figure 8: Residuals vs. Fitted values for Equation 3

5.4: Fourth Model

Equation 4

$$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}} = \beta_0 + \beta_1 \frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} + \beta_2 \frac{Housing_t - Housing_{t-1}}{Housing_{t-1}} + \beta_3 \frac{Credit_t - Credit_{t-1}}{Credit_{t-1}} +$$

$$\beta_4 \frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}} + \beta_5 \frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}} + \beta_6 \frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}} + \beta_7 \frac{Market_t - Market_{t-1}}{Market_{t-1}} +$$

$$\beta_8 \left(\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} * \frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}\right) + \beta_9(Recession_t) + \varepsilon_t$$

Table 12: Summary statistics for Equation 4

Variable	Observations, n	Earliest Date	Latest Date	Min Value	Max Value	Mean	Std. Dev.
$\frac{Medicaid_t - Medicaid_{t-1}}{Medicaid_{t-1}}$	210	4/1/1966	10/1/2018	-0.0889	0.1166	0.0045	0.0324
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}}$	210	4/1/1966	10/1/2018	-0.0252	0.0509	0.0006	0.0085
$\frac{Housing_t - Housing_{t-1}}{Housing_{t-1}}$	210	4/1/1966	10/1/2018	-3.4286	8.1667	0.0499	1.5556
$\frac{Credit_t - Credit_{t-1}}{Credit_{t-1}}$	210	4/1/1966	10/1/2018	-0.0229	0.03152	0.0041	0.0098
$\frac{Priv\ Jobs_t - Priv\ Jobs_{t-1}}{Priv\ Jobs_{t-1}}$	210	4/1/1966	10/1/2018	-0.0201	0.0102	0.0033	0.0052
$\frac{Govt\ Jobs_t - Govt\ Jobs_{t-1}}{Govt\ Jobs_{t-1}}$	210	4/1/1966	10/1/2018	-0.0157	0.0151	0.0017	0.0036
$\frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	210	4/1/1966	10/1/2018	-0.0157	0.0151	0.0017	0.0036
$\frac{Market_t - Market_{t-1}}{Market_{t-1}}$	210	4/1/1966	10/1/2018	-0.2871	0.1214	0.0055	0.0582
$\frac{Nonprofit_t - Nonprofit_{t-1}}{Nonprofit_{t-1}} * \frac{Unemploy_t - Unemploy_{t-1}}{Unemploy_{t-1}}$	210	4/1/1966	10/1/2018	-0.0013	0.0074	0.0002	0.0008
$Recession_t$	210	4/1/1966	10/1/2018	0	1	0.1286	0.3355

Table 13: Equation 4 results

Regression Variable	Coefficient
$\boldsymbol{Intercept_t}$	0.0127** *SE 0.0048*
$\frac{\boldsymbol{Nonprofit_t - Nonprofit_{t-1}}}{\boldsymbol{Nonprofit_{t-1}}}$	-0.2079 *SE: 0.2786*
$\frac{\boldsymbol{Housing_t - Housing_{t-1}}}{\boldsymbol{Housing_{t-1}}}$	-0.0004 *SE: 0.0004*
$\frac{\boldsymbol{Credit_t - Credit_{t-1}}}{\boldsymbol{Credit_{t-1}}}$	-0.2169 *SE: 0.2365*
$\frac{\boldsymbol{Priv\,Jobs_t - Priv\,Jobs_{t-1}}}{\boldsymbol{Priv\,Jobs_{t-1}}}$	-0.9363 *SE: 0.8082*
$\frac{\boldsymbol{Govt\,Jobs_t - Govt\,Jobs_{t-1}}}{\boldsymbol{Govt\,Jobs_{t-1}}}$	1.1498^^ *SE: 0.6040*
$\frac{\boldsymbol{Unemploy_t - Unemploy_{t-1}}}{\boldsymbol{Unemploy_{t-1}}}$	0.0522 *SE: 0.0995*
$\frac{\boldsymbol{Market_t - Market_{t-1}}}{\boldsymbol{Market_{t-1}}}$	-0.0066 *SE: 0.0463*
$\frac{\boldsymbol{Nonprofit_t - Nonprofit_{t-1}}}{\boldsymbol{Nonprofit_{t-1}}} * \frac{\boldsymbol{Unemploy_t - Unemploy_{t-1}}}{\boldsymbol{Unemploy_{t-1}}}$	-4.2118 *SE: 4.0238*
$\boldsymbol{Recession_t}$	-0.0018 *SE: 0.0124*

***designates a 99.0% significance level,*
^^ designates a 90.0% significance level

Building on the discovery made after analyzing the structural breaks in the data, this section [about Equation 4] attempts to explain why the change in $Nonprofit_t$ became significant after isolating the data from structural breaks. The two structural breaks shown in Figure 6 occur between roughly one-to-two years after a recession has ended (FRED, 2019). Since the change in $Nonprofit_t$ occurred after isolating the structural breaks, and because the structural breaks might have an association with past recessions, a new binary variable, $Recession_t$, has been introduced. This variable uses data from FRED (originally produced by the NBER) that indicates recessions (the variable will equal one if an observation is in a recession, and zero otherwise).

A second new variable has been introduced as well that represents the product of the change in $Nonprofit_t$ and the change in $Unemploy_t$, called $\frac{\boldsymbol{Nonprofit_t - Nonprofit_{t-1}}}{\boldsymbol{Nonprofit_{t-1}}} * \frac{\boldsymbol{Unemploy_t - Unemploy_{t-1}}}{\boldsymbol{Unemploy_{t-1}}}$. This variable allows for a more thorough investigation if the relationship between the change in $Nonprofit_t$ and the change in $Medicaid_t$ is conditional upon a given state in the business cycle. After regressing Equation 4, we once again find that the change in $Nonprofit_t$ is not statistically significant.

Business cycles could still have an effect on the change in $Medicaid_t$ (particularly troughs), however they do not appear to be as influential as some other force(s) on the change in $Medicaid_t$. Because of this, one could speculate that not business cycles, but policy changes to the program might be influential on the observations. For example, the first structural break (in 1973) shown in Figure 6 occurs the year after almost every state begins to participate in the program (Arizona was the only state that was not participating in 1973) (Henry J Kaiser Family Foundation, 2019). The second structural break in Figure 6 occurs just a few years after the Omnibus Budget Reconciliation Act of 1990 mandated coverage of children ages 6-18 in families with incomes at or below 100% of the FPL, and right as section 1115 waivers to states began being approved (which enabled states to expand Medicaid programs for experimental, pilot, or demonstration projects). Nonetheless, the behavior in the change in $Medicaid_t$ over the past decade is distinct from that of decades prior.

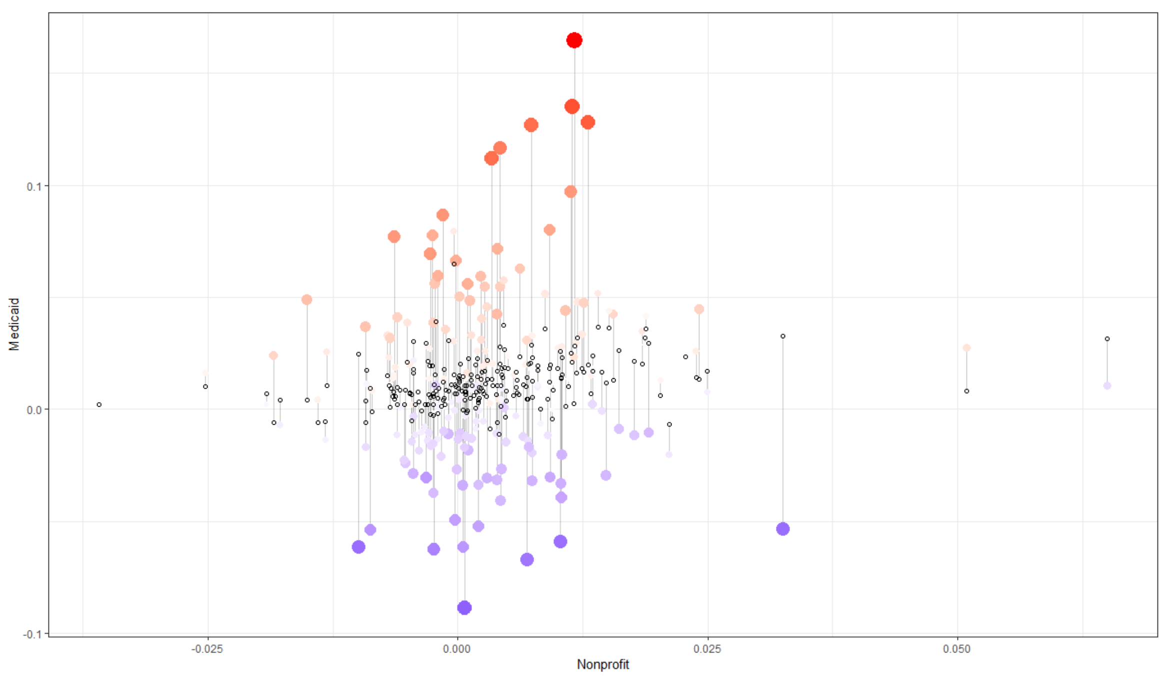

Figure 9: Linear regression results of the percent change in $Medicaid_t$ and $Nonprofit_t$ for Equation 4

Figure 9 displays a few outliers, but likely not enough to be significant. Figure 10 shows the residuals, which are random in appearance and suggest that the results of this regression are reliable. Appendix A contains a normal Q-Q plot that displays detail of the goodness of fit (Equation 4 Standardized Residuals vs. Theoretical Quartiles).

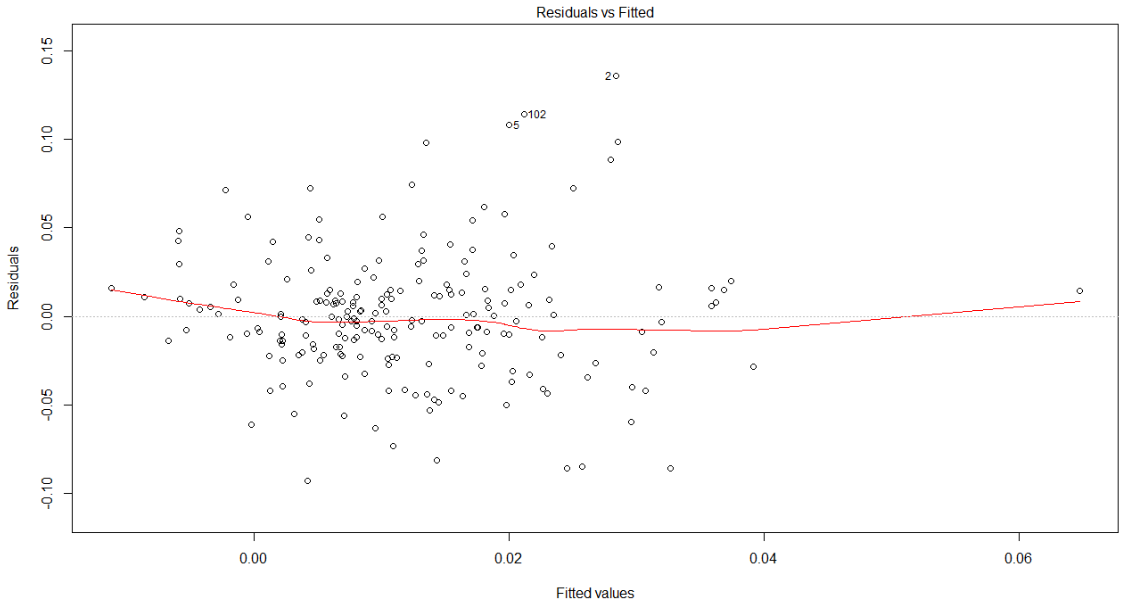

Figure 10: Residuals vs. Fitted values for Equation 4

PART VI: CONCLUSION

The premise of this paper was to answer to the research question "does the value added to GDP from nonprofit institutions decrease Medicaid payouts?" with the intention of using the measurement of Medicaid payouts as a proxy for the rate of poverty.

A robust literature review of papers authored by credible economists (many of which are from the NBER) lead to the variable selection in this paper. In addition to the literature review, the independent variables chosen for analysis are typical of many economic models, and the variables themselves have been retrieved from credible sources. They were adjusted to meaningful units that are simple to understand, and regressed with parsimony in mind. Because ordinary least squares regression is an inherently simple methodology, it allowed for a straightforward analysis of the output, making it in some regard superior to more complex methods. From a "traditional" econometrics approach, using the data described in this paper, it is statistically safe to say that the value added to GDP from nonprofit institutions does not influence Medicaid payouts (and to continue using the proxy: does not affect poverty) if evaluating the population data, or if controlling for recessions in the population data. Upon closer inspection and controlling for structural breaks, nonprofits become statistically relevant to reducing Medicaid payouts and affecting poverty.

Regardless of the results, many individuals continue to demonstrate the dearness that nonprofit organizations have in their hearts, shown through their ever-increasing donations. Because these organizations are so important to some individuals (and because individuals continue to donate so much money), these organizations might benefit from the conclusion in this paper; nonprofit organizations could possibly benefit from measuring and determining how to improve the performance of donated dollars, and researchers of nonprofits could investigate other metrics that nonprofits are excelling at. With individual organization improvement, the aggregate indicators would eventually change too.

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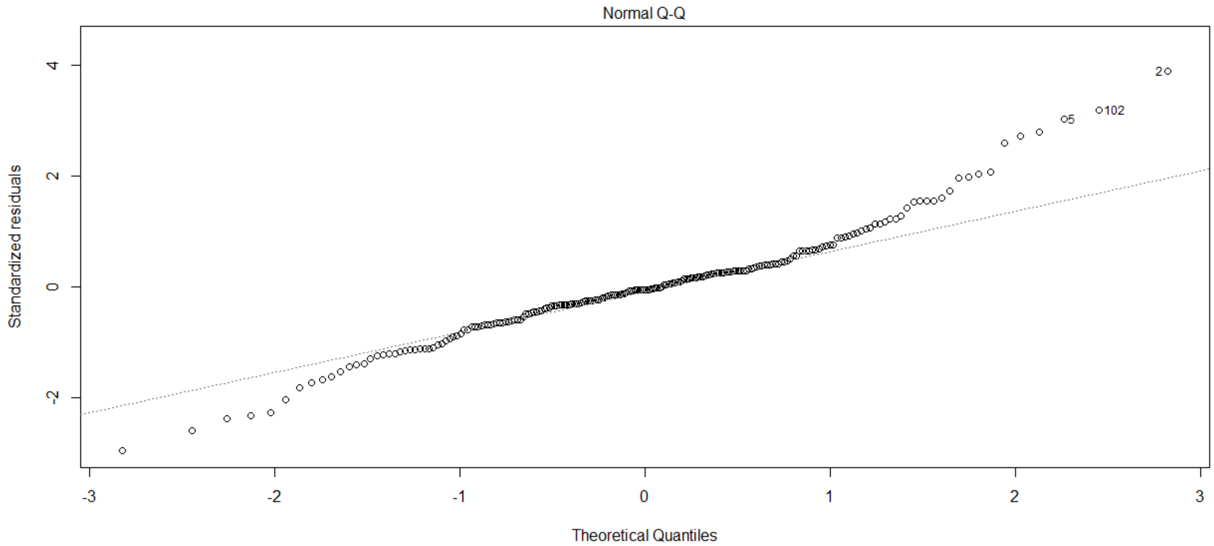
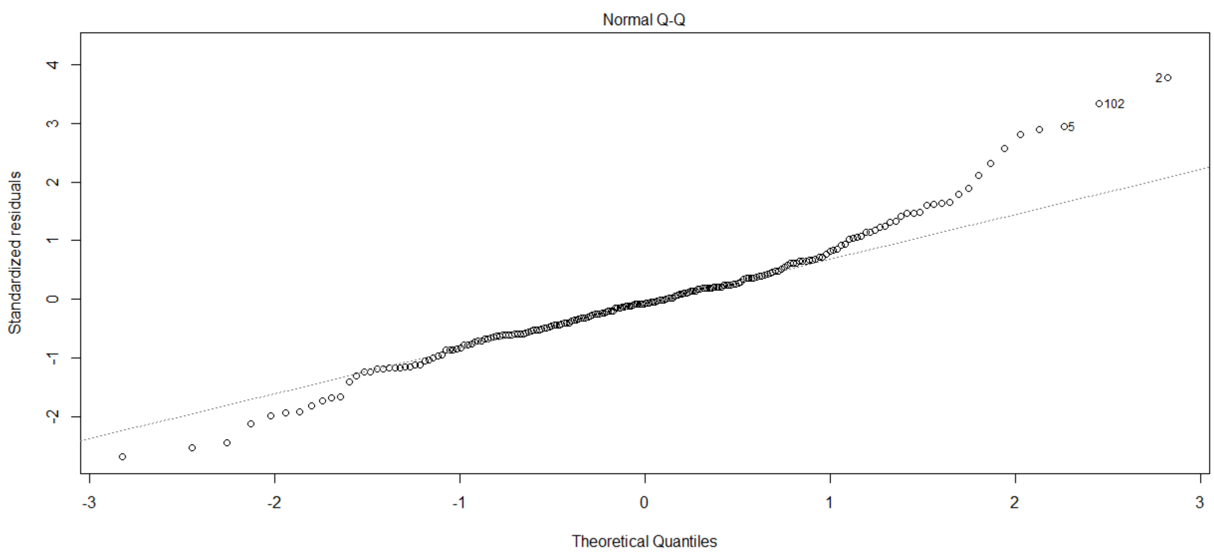
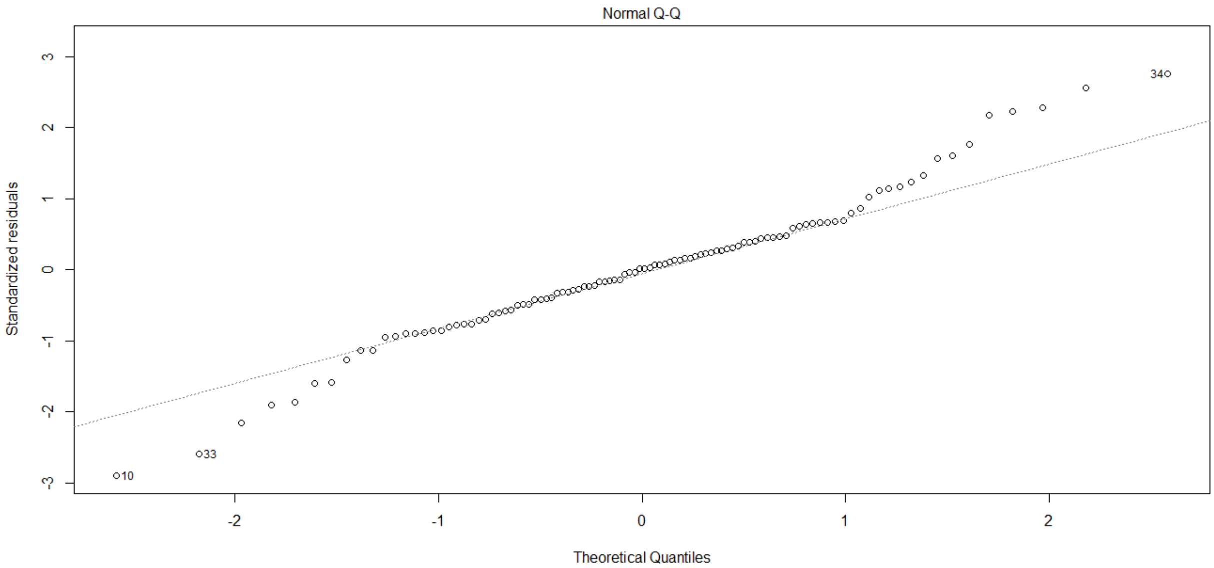
APPENDIX: ADDITIONAL FIGURES



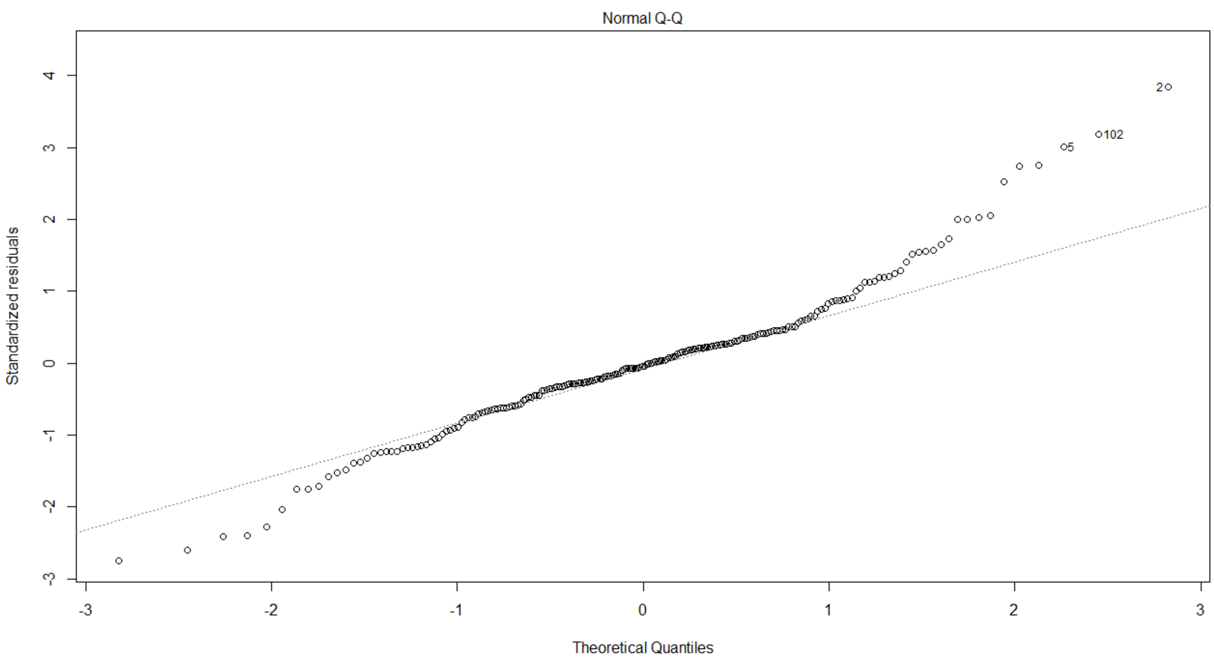
Equation 1 Standardized Residuals vs. Theoretical Quartiles



Equation 2 Standardized Residuals vs. Theoretical Quartiles



Equation 3 Standardized Residuals vs. Theoretical Quartiles



Equation 4 Standardized Residuals vs. Theoretical Quartiles