How does access to public health insurance affect savings? Evidence from a distributional regression approach

Auteur : Sibille, Paul
Promoteur(s) : Guillot, Malka
Faculté : HEC-Ecole de gestion de l'Université de Liège
Diplôme : Master en sciences économiques, orientation générale, à finalité spécialisée en macroeconomics and finance
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How does access to public health insurance affect savings? Evidence from a distributional regression approach

Jury:

Supervisor:
Prof. Malka Guillot

Readers:
Dr. Maren Ulm
Prof. Jérôme Schoenmaeckers

Master thesis written by
Paul Sibille

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Abstract

This thesis investigates the impact of public health insurance access on savings, using a distributional regression approach. By analyzing Medicaid eligibility and coverage data from the Survey of Income and Program Participation (SIPP) and Current Population Survey (CPS) databases, the study examines how changes in Medicaid coverage influence individual savings across different wealth levels. The research highlights the varying effects of Medicaid coverage on savings, emphasizing significant differences between lower and higher saving groups. The findings suggest that Medicaid coverage positively impacts savings for the poorest individuals while negatively affecting middle-income groups. These results provide insights for policymakers regarding the implications of Medicaid expansion on inequality among the net worth distribution.

Acknowledgments

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"The automatic stabilizer is unemployment insurance, food stamps, additional coverage of medicaid"

Franklin Raines

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List of Abbreviations

ACA	Affordable Care Act
CPS	Current Population Survey
ELIG	Eligibility
FPL	Federal Poverty Level
GED	General Educational Development
GMM	Generalized Method of Moments
IV	Instrumental Variable
IVQR	Instrumental Variable Quantile Regression
MACPAC	Medicaid and CHIP Payment and Access Commission
MCD	Medicaid Coverage Dollar
MED	Medicaid Eligible Dollar
OLS	Ordinary Least Square
QR	Quantile Regression
SIPP	Survey of Income and Program Participation
SIMELIG	Simulated Eligibility
SIMMED	Simulated Medicaid Eligible Dollar
2SLS	Two-Stage Least Squares

1 Introduction

The primary motivation for this research is to investigate the effects of Medicaid eligibility on individual savings behaviors. The 2014 implementation of the Affordable Care Act (ACA), commonly known as Obama Care, mandated that states expand Medicaid eligibility to include non-elderly, non-working individuals without disabilities. This policy change provides a unique opportunity to study the impact of broader Medicaid coverage on personal savings. Understanding these effects is crucial for optimal government policy decisions aimed at improving economic equality.

This paper investigates the effect of Medicaid coverage on individual savings across various quantiles of wealth distribution. Prior to 2014, Maynard and Qiu (2009) analyzed the impact of Medicaid coverage on savings for different income levels from 1984 to 1993. Their findings indicated that Medicaid eligibility had a negative effect on savings for all individuals, with a more pronounced impact at the median of the distribution. More recently, Gallagher et al. (2020) examined the effect of Medicaid eligibility on savings between 2013 and 2017. The study concluded that post-ACA Medicaid eligibility did not significantly impact savings for low-income adults, although it did not explore the program's effect across different levels of net worth.

In this thesis, we first build a pooled cross-section of 78,000 observations with positive net worth and we observe the impact of medicaid coverage on individuals savings using Instrumental Variable Quantile Regression (IVQR). Doing so, we therefore extends the work from Maynard and Qiu (2009) by incorporating the impact of medicaid eligibility expansion on individuals net worth, and the one of Gallagher et al. (2020) by focusing on different quantiles of the net worth distribution and by building a more robust instrument than the one previously used in both research.

This study employs instrumental variable regression as a primary method to address endogeneity issues and account for omitted variable bias. Specifically, Medicaid eligibility is used as an instrument to examine the impact of Medicaid coverage on savings. The instrumental variable approach has been widely used in the literature to address similar research questions. For instance, Chernozhukov and Hansen (2004) analyzed the impact of 401(k) participation on wealth distribution in the U.S. by using eligibility for the 401(k) pension scheme as an instrument. Similarly, Maynard and Qiu (2009) were pioneers in applying instrumental quantile regression to observe the effects of Medicaid coverage. Finally, due to convergence problems when estimating the Instrumental Variable Quantile Regression, we use Simulated Medicaid Eligible Dollar as an instrument, as recommended by Gruber and Yelowitz (1999). This upgraded instrument's main component is the Simulated Medicaid Eligibility, which approximates the likelihood of being eligible for Medicaid based on individuals' characteristics.

Additionally, this study incorporates Quantile Regression (QR) to capture the effects of Medicaid coverage across different levels of net worth. Quantile Regression, as described by Fahrmeir et al. (2013), is a non-linear model that allows for the observation of impacts at various points in the distribution of the dependent variable. Maynard and Qiu (2009) used this method in their analysis, employing the SIPP database to obtain household savings and net worth data, and using Medicaid eligibility criteria as defined by Gruber and Yelowitz (1999) to construct their instrument.

Using this methodology, we primarily conclude that Medicaid coverage has a positive effect on the savings of low-income individuals. Specifically, an additional dollar of Medicaid coverage results in a significant increase of \$0.82 in the savings of the poorest individuals. This finding is particularly important as it diverges from the research of Maynard and Qiu (2009), who found a non-significant negative effect of Medicaid coverage on the savings of the poorest individuals. They attributed this negative effect to increased borrowing, which consequently decreased the net worth of low-income individuals. In contrast, we emphasize the restricted access to credit for this population, which prevents them from borrowing more. Our results also diverge from those of Gallagher et al. (2020), who found no significant effect of increased Medicaid generosity on the wealth of low-income individuals.

Additionally, the pattern of the effect in our study differs from that observed by Maynard and Qiu (2009). They demonstrated a U-shaped effect, indicating that the negative impact of Medicaid generosity on savings was most pronounced at the middle of the distribution. Similarly, we observe a significantly high negative impact of Medicaid coverage on the savings of individuals in the middle of the wealth distribution. However, the magnitude of the effect appears to significantly increase at the top wealth decile, whereas Maynard and Qiu (2009) had shown little impact at this end of the net worth distribution.

To verify the relevance of our findings, we performed two robustness checks. The first extends the sample to include individuals with negative and null net worth, and the second employs individual income as a control variable, which was previously omitted due to orthogonality with the instrument (Maynard and Qiu, 2009). Our analysis confirms the robustness of the positive effect on savings for low-income individuals: increasing Medicaid generosity for those in the lowest decile of the net worth distribution significantly increases their savings. However, the robustness of the observed coefficient pattern across quantiles is not confirmed. This non-robust shape may be the result of limitations within the model.

First, section 2 details the literature and how it links with the motivation and methodology of this research. Second, section 3 provides an overview of Medicaid eligibility and its evolution over the study period. Third, section 4 explains the data used in this research, including the descriptive statistics on the relevant variables discussed in this research. Fourth, section 5 encompasses the two primary methods employed in this analysis: the instrumental variable method combined with quantile regression. Fifth, section 6 discusses statistics on the building of the instrument, and assess its relevance and validity. Sixth, section 7 presents the main findings, first for individuals with positive net worth, and then for the entire sample of individuals (including those with negative, zero, or positive net worth). Seventh, section 8 provides the two robustness checks mentioned above to assess the reliability of our results. Eighth, section 9 summarizes the limitations encountered in this thesis and suggests directions for future research. Ninth, section 10 discusses the new results from this thesis and compares them with existing literature and previous findings.

2 Literature Review

Inequality has been extensively studied over the past centuries. Indeed, Tran, Ong, and Q. D. L. Nguyen (2020) have demonstrated that income inequality also has consequences, such as its impact on savings. Conversely, savings can also be considered a determinant of inequality through mechanisms like capital accumulation (Sabates and Yardeni, 2020). Given the major importance of savings in understanding inequalities, the factors influencing savings are themselves of critical importance. For example, Feldstein (1980) reviewed previous literature on the impact of social security plans on savings, concluding that social security spending negatively affects private savings by approximately 50%. More recently, Maynard and Qiu (2009) analyzed the effect of Medicaid coverage on savings across different income levels from 1984 to 1993. Their findings indicate that the savings of the poorest segments of the population exhibit minimal change, whereas moderately poor households are negatively impacted by Medicaid expansion. This result is significant as it demonstrates that Medicaid coverage can indeed negatively affect savings and has a substantial impact on moderately poor households. Considering the strong positive correlation between savings and inequality among poor individuals, Medicaid can thus have profound implications for inequality.

Since its implementation in 1965 by President Lyndon B. Johnson, Medicaid eligibility has continuously expanded. Sethi and Frist (2014) explain that rising life expectancy and the development of human rights regarding access to healthcare have compelled successive presidents to extend Medicaid eligibility. In 2014, the Affordable Care Act, commonly known as ObamaCare, was introduced, leading to one of the most significant expansions of Medicaid eligibility for states that opted for its implementation. Initially, Medicaid was available only to the elderly, disabled, parents, or pregnant women with low income. Following the extension, non-working and non-elderly individuals without children or disabilities became eligible for Medicaid if their income does not exceed 133% of the Federal Poverty Level. At the time of its implementation in 2014, approximately 50% of the states adopted this expansion, as reported by MACPAC (n.d.). By 2023, 78% of states had implemented the expansion (KFF, 2024). This evolution reflects the dynamic environment surrounding Medicaid eligibility in contemporary literature.

The extension of Medicaid to this new category of individuals raises significant interest in the previously established relationship between Medicaid coverage and savings. Although Maynard and Qiu (2009) conducted their research within a shifting policy environment, the changes they examined differ and pertain to other categories of people. Specifically, in the period analyzed by the authors, Medicaid eligibility was limited to certain women receiving Aid to Families with Dependent Children (AFDC). Throughout the study period, Medicaid eligibility evolved in response to several legislative changes.

More recent research by Gallagher et al. (2020) examines the effect of Medicaid eligibility on savings between 2013 and 2017. The author found that Medicaid eligibility following the extension of the Affordable Care Act (ACA) does not significantly impact savings for low-income adults. However, this research is based on numerous assumptions regarding eligibility. For instance, if state eligibility criteria for non-disabled individuals are set at 100% of the Federal Poverty Level (FPL) and for parents of children under one year at 200%, all households in the state, irrespective of their specific characteristics, are classified as eligible if their income do not exceed 150%, the average of these thresholds. This significant issue underscores the necessity of developing a robust instrument that aggregates eligibility criteria by state and household characteristics. Unlike Gallagher et al. (2020), our study employs quantile regression, thus not limiting the analysis to the central tendency of low-income adults. Additionally, authors study focuses on the relationship between Medicaid eligibility and savings rather than Medicaid coverage and savings, as examined in our research and that of Maynard and Qiu (2009). Consequently, our study would provide substantial contributions to current literature and future research.

Another similar study of Finkelstein et al. (2012) has correlated Medicaid insurance coverage with multiple variables of health utilization, financial strain, and overall health. The main data set used in this study relies on the Oregon Health Plan (OHP) Standard, which is a program that allows signed-up eligible households to randomly get access to Medicaid coverage. Other than this data set, additional information on the signed-up households has been gathered in two other ways: the collection of administrative data and the creation of a survey. The randomization characteristic of the lottery used for the OHP standard is a major point since it allows the authors to observe the net effect of Medicaid coverage by using the instrumental variable approach. Overall, authors have found that Medicaid coverage has increased by 25% the annual spending as compared to the control group. Even though the research does not observe savings but rather other financial variables, a major insight is that the instrumental variable used in their study is not eligibility but rather participation to the lottery. This also shows the major contribution that the creation of a robust instrumental variable for the study of financial variables, namely the eligibility to Medicaid, would have on future research.

As a conclusion, prior literature has emphasized the importance of Medicaid coverage's causal effect on savings and how this effect varies at different quantiles of the income distribution. Since then, Medicaid has extended its eligibility criteria to new categories of people, making old research less relevant. Even though some authors have already contributed to research on Medicaid, none of them are relevant to the present study. Moreover, recent research has shown their dependency on a robust instrumental variable when it comes to observe causal effects on financial variables. Finally, as previous literature has shown, the result of this thesis would be of major insight for policymakers regarding the causal effect of savings on inequalities among people.

3 Institutional Context

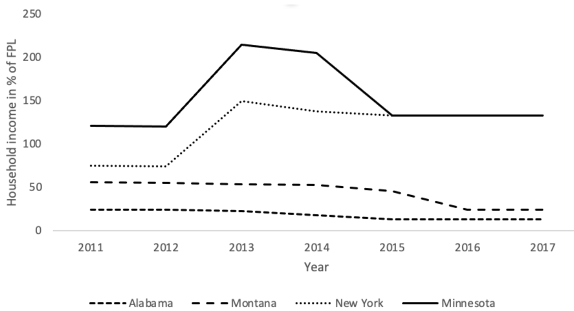
Eligibility for Medicaid is a critical factor in this thesis, as it serves as an instrumental variable, as elaborated in section 5. The criteria for Medicaid eligibility are multiple and vary significantly across states:

- **Employment Status:** Eligibility thresholds differ between employed individuals with dependent children and those who are unemployed without any dependent children.
- **Age:** Individuals aged 65 and older living below a specified threshold may be eligible for Medicaid. Furthermore, households with children and low income may receive Medicaid assistance, with the level of assistance decreasing as the child's age increases (categorized as 0-1 year, 1-6 years, and 6-18 years).
- **Pregnancy:** Pregnant women with low incomes are likely to qualify for Medicaid.
- **Health Status:** low-income disabled individuals and those with significant medical needs are also eligible for Medicaid.

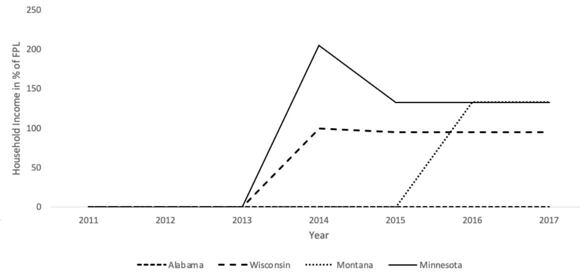
All of the eligibility criteria underwent significant changes between 2011 and 2017, particularly concerning the eligibility of unemployed individuals. Increasingly, states have extended Medicaid access to single, low-income, unemployed individuals without medical problems. Figures 1, 2, 3, 4, and 5 illustrate the evolution of each criterion in four different states. The states are selected to represent both the least and most generous for each eligibility criterion. Additionally, two other states are arbitrarily selected to well-represent the overall trend. Notice that Minnesota has been the most generous state in almost all of the eligibility criteria.

Firstly, Figure 1b represents the core of the Medicaid eligibility extension under the Affordable Care Act (ACA) implemented during the Obama administration. Prior to 2014, some states allowed Medicaid distribution to non-disabled, non-elderly individuals without children, but the criteria were more specific and extended beyond income. Consequently, due to the limited number of households meeting these specific eligibility criteria, this category was considered ineligible prior to 2014. Among the four states represented, only Wisconsin and Minnesota expanded Medicaid eligibility in 2014, while Montana followed in 2016. Initially, the program suggested raising this threshold to 133%, meaning households with incomes at most 1.33 times the Federal Poverty Level (FPL)[1] would be eligible. However, some states decided to set a lower threshold, such as Wisconsin, which set it at 95%. At the time of this research, Alabama has yet to implement the ACA Medicaid expansion. While the majority of states adopted the ACA provisions in 2014, a few outliers still resist adopting such eligibility criteria.

[1] The federal poverty level (FPL) is an economic threshold used to determine if an individual's or family's income qualifies them for specific federal benefits and programs.



(a) Eligibility for dependent children

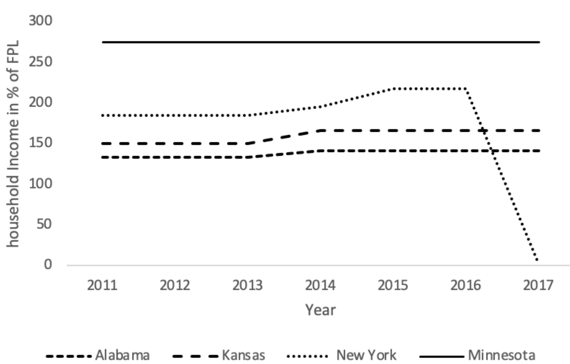


(b) Eligibility for unemployed, healthy, non old people without children

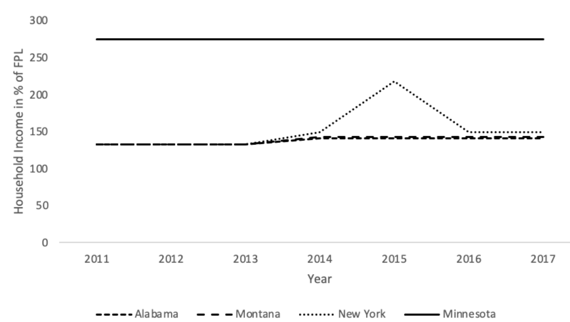
Figure 1: Household Income in % of FPL

Note: The eligibility criteria of the MACPAC archive for the years 2011-2017 has been used for this analysis. MACPAC archives deliver pdf tables regarding the eligibility threshold. We transform the pdf file into an excel file, and then create our time series. In both figures, household income expressed as a percentage of the FPL should be interpreted as a threshold. For example, a graph indicating a threshold of 200% signifies that household income can be no more than twice the FPL for the corresponding year to identify eligible individuals.

Secondly, Figure 2a illustrates a significant change in Medicaid eligibility. Specifically, children under one year of age have experienced a consistent decrease in their eligibility In New York in 2017. Moreover, for Alabama, Kansas and New York, we observe a consistent increase in the eligibility threshold around 2014. Additionally, the eligibility of children under the age of six has remained relatively stable over time.



(a) Eligibility for Children under age 1

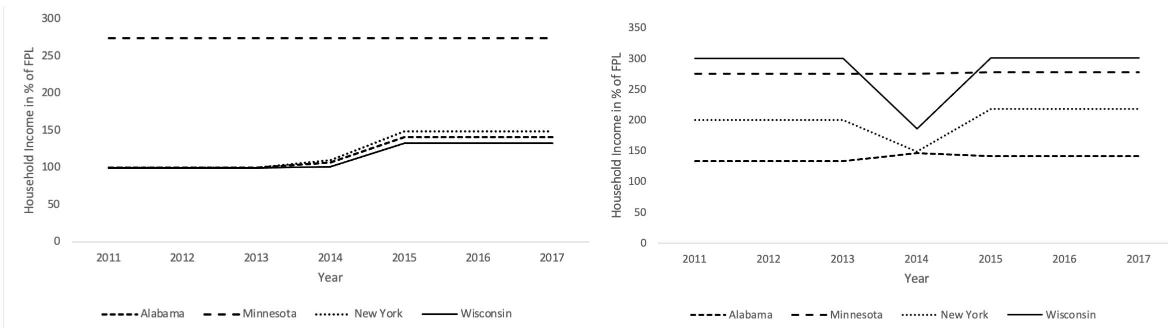


(b) Eligibility for Children under age 6

Figure 2: Household Income in % of FPL

Note: The eligibility criteria of the MACPAC archive for the years 2011-2017 has been used for this analysis. MACPAC archives deliver pdf tables regarding the eligibility threshold. We transform the pdf file into an excel file, and then create our time series. In both figures, household income expressed as a percentage of the FPL should be interpreted as a threshold. For example, a graph indicating a threshold of 200% signifies that household income can be no more than twice the FPL for the corresponding year to identify eligible individuals.

Thirdly, Figure 3a indicates an approximately 50% increase in Medicaid eligibility for older children across Alabama, New York and Wisconsin. Minnesota, which is the most generous state, did not significantly change its threshold. Conversely, Figure 3b illustrates that the eligibility of pregnant women has remained stable, contrary to the findings of Maynard and Qiu (2009), where significant changes were observed in this category.



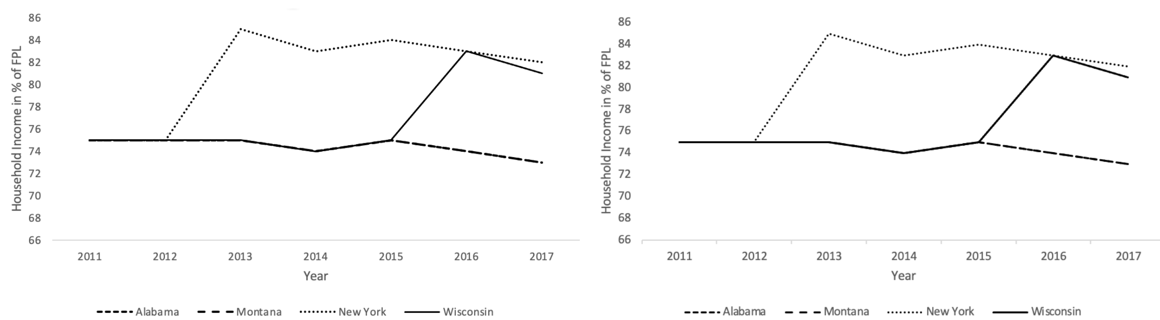
(a) Eligibility for Children under age 12

(b) Eligibility for pregnant women

Figure 3: Household Income in % of FPL

Note: The eligibility criteria of the MACPAC archive for the years 2011-2017 has been used for this analysis. MACPAC archives deliver pdf tables regarding the eligibility threshold. We transform the pdf file into an excel file, and then create our time series. In both figures, household income expressed as a percentage of the FPL should be interpreted as a threshold. For example, a graph indicating a threshold of 200% signifies that household income can be no more than twice the FPL for the corresponding year to identify eligible individuals.

Fourthly, the eligibility criteria for disabled and elderly individuals remain relatively the same across all states, as illustrated in Figure 4. We also observe the divergence of changes among different states and over the years. For instance, New York revised its eligibility criteria annually from 2011 to 2017.



(a) Eligibility for disabled

(b) Eligibility for elderly

Figure 4: Household Income in % of FPL

Note: The eligibility criteria of the MACPAC archive for the years 2011-2017 has been used for this analysis. MACPAC archives deliver pdf tables regarding the eligibility threshold. We transform the pdf file into an excel file, and then create our time series. In both figures, household income expressed as a percentage of the FPL should be interpreted as a threshold. For example, a graph indicating a threshold of 200% signifies that household income can be no more than twice the FPL for the corresponding year to identify eligible individuals.

Finally, Figure 5 illustrates the eligibility of medically needy individuals. However, due to the lack of information in the SIPP and in the CPS database, this eligibility criterion will not be included in the construction of the eligibility variable, as explained in section 5.4.

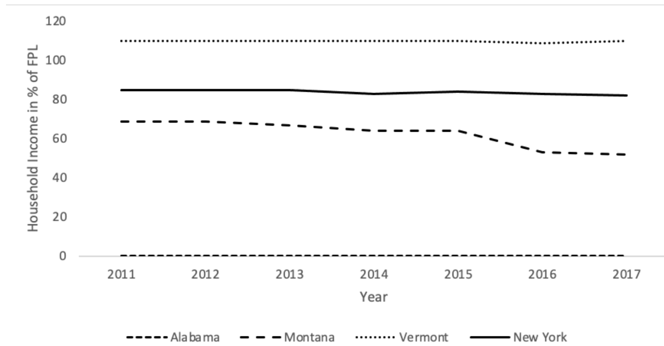


Figure 5: Eligibility for medically needed people

Note: The eligibility criteria of the MACPAC archive for the years 2011-2017 has been used for this analysis. MACPAC archives deliver pdf tables regarding the eligibility threshold. We transform the pdf file into an excel file, and then create our time series. In both figures, household income expressed as a percentage of the FPL should be interpreted as a threshold. For example, a graph indicating a threshold of 200% signifies that household income can be no more than twice the FPL for the corresponding year to identify eligible individuals.

4 Data

4.1 Datasets

The study primarily use three distinct datasets: The SIPP, the CPS and the MACPAC archives.

Firstly, the principal data source for this study is the annual Survey of Income and Program Participation (SIPP) Database. This extensive database comprises observations from approximately 30,000 households, encompassing a wide range of private information, including participation in various programs such as Medicaid. The data is collected through detailed surveys wherein respondents answer over 5,000 questions. Established in 1984, the official SIPP program has undergone numerous modifications over the years. A notable change occurred in 2013 when the survey frequency transitioned from thrice annually to once per year. Despite the shift to an annual collection, respondents continue to report monthly information. Additionally, a significant alteration in 2013 pertained to the nature of responses: prior to 2013, responses were predominantly binary, but post-2013, they have become more quantitative. For example, inquiries regarding the value of financial assets were introduced in 2013, whereas such questions were previously absent.

Additionally, the MACPAC archives document the eligibility criteria for Medicaid across different states on an annual basis. For each state, it specifies the income-to-poverty ratio that a given category of individuals, as detailed in section 3, must not exceed to qualify for Medicaid.

Finally, the Current Population Survey (CPS) database, which is similar to the SIPP database, provides researchers with a sample of observations on specific topics such as demographics and health. In this survey, respondents report their answers on a monthly basis to a variety of questions. CPS is later used as a helper for building the instrument.

For the SIPP and CPS databases, we focus on data from the years 2013-2016, as will be explained in section 4.3 . Additionally, we utilize MACPAC archives from the years 2011-2017 to construct the figures in section 3.

4.2 Variables in used

The SIPP and CPS databases are based on extensive questionnaires administered to each surveyed individual, resulting in a substantial number of variables within these databases. Only a subset of the 5,000 variables from the SIPP and CPS are used in this research. These variables can be categorized into three groups: net worth variables, eligibility variables and control variables.

- **Net Worth Variables:** This group comprises variables used to calculate the dependent variable, namely individual savings, which we approximate by net worth excluding home and vehicle. These include, among others, the total value of financial assets, total value of debt, net equity in the home, and the value of vehicles. This information is exclusively retrieved from the SIPP database.
- **Medicaid Variables:** This group includes all responses utilized to determine Medicaid eligibility, along with variables related to Medicaid coverage. These include, among others, age, household income as a percentage of the FPL, and disability status. Relevant variables from both the CPS and SIPP databases are included here.
- **Control Variables:** This group includes all control variables used in the regression analysis. These variables encompass skin color, education level, marital status, etc. Both databases provide information on this group.

Descriptive statistics on variables in each of the groups, segmented by decile, is given in section 4.2.1, section 4.2.2 and section 4.2.3.

4.2.1 Descriptive statistics for the net worth group

The net worth of individuals excluding home and vehicle assets is employed in this research as the dependent variable of the model, similarly to the approach used by Maynard and Qiu (2009). As elucidated in section 4.2, several components have been utilized to construct this metric. Table 1 presents the mean values of each variable utilized, segmented by each decile of net worth excluding home and vehicle assets. Table 10 shows the same descriptive statistics, segmented across years. It is important to note that we have decided to focus solely on positive net worth values for two reasons. Firstly, to align with the reference study by Maynard and Qiu (2009), which adheres to the methodology established by Gruber and Yelowitz (1999). Secondly, to maintain consistency with the approximation of total net worth excluding home and vehicle assets with savings, as savings cannot be negative in practice.

Table 1: Descriptive statistics for the dependent variable

Quantile of net worth	Income / FPL	Financial asset	Net Debt	% Positive debt	Net equity	equity w/o home	equity w/o home/vehicle
1.0	2.975	775.4	10097.8	0.2	15103.65	4501.95	568.275
2.0	3.6	2346.775	17330.325	0.3	19750.4	6031.225	2211
3.0	4.05	4813.075	25760.85	0.45	26480.125	12833.075	7115.825
4.0	4.475	8327.9	36654.675	0.575	33840.975	25996.175	13946
5.0	5.05	12313.175	45455.5	0.65	45639.8	48192.45	39350.25
6.0	5.8	17950.2	50247.725	0.7	53198.275	76986.875	56891.575
7.0	6.425	30541.225	50075.25	0.65	76678.925	147536.675	138588.375
8.0	7.475	58540.3	33785.3	0.575	92230.225	278198.6	264901.35
9.0	10.725	284845.275	-90534.95	0.425	175692.8	1.725e+06	1.725e+06
Total	5.625	46717.3	19864.8	0.495	59847.2	258364.1	250374.7

Note: The database used in this table is the SIPP. In constructing this table, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009). Net equity, excluding home and vehicle values, is calculated as: net equity - home value - vehicle value. Net debt is derived as: total debt - financial assets.

Several observations can be drawn from this analysis. First, income as a percentage of the federal poverty level appears to increase across quantiles, which is logical: individuals with higher wages tend to have more savings, as their high net worth is likely attributable to higher income. Second, the poorest segment of the population has the least debt (0.2% of the poorest population has positive debt), while the middle segment of the wealth distribution has the most (0.7% of households have positive debt at that time). However, there is a slight decline in the proportion of debt among the wealthiest individuals, which might be due to their reduced need for leverage given their substantial financial assets and high income. This trend mirrors the findings of Maynard and Qiu (2009), who observed that the majority of debtors clustered around the middle quantile of wealth. The small proportion of debt among poorer individuals could be explained by their inability to borrow from banks. Third, net debt appears to peak in the middle of the wealth distribution. Additionally, the wealthiest segment of the population consistently has the lowest net debt, attributable to a high concentration of financial assets and a low proportion of debt.

As a conclusion, the observed statistics indicate the non-validity of Medicaid Eligible Dollar (MED) as an instrument (refer to section 5.4). Specifically, eligibility for Medicaid is inherently linked to an individual's income level relative to the Federal Poverty Level, as emphasized by Maynard and Qiu (2009). As demonstrated in table 1, there is a positive correlation between income and net worth, with higher net worth quantiles corresponding to higher average income. Consequently, the validity condition of the MED as an instrument may not be satisfied, as the MED might influence the outcome variable (net worth) through mechanisms other than the treatment variable (coverage). This limitation is acknowledged in our model, prompting the creation of the Simulated Medicaid Eligible dollars (SIMMED).

4.2.2 Descriptive statistics for the control group

A similar analysis can be performed for control variables included in the quantile regression. Table 2 represents the mean of each variable, which can further be interpreted as the proportion of individuals matching each criteria. Table 12 shows the same descriptive statistics, segmented across years.

Table 2: Descriptive statistics for the control group

Quantile of net worth	white	black	asian	other	high-school diploma	GED or other diploma	no diploma	Receive medicare	Male
	Race				Education				
1	0.9275	0.055	0.01	0.0075	0.66	0.0725	0.2675	1.935	0.5075
2	0.93	0.0625	0.005	0.0025	0.7525	0.0625	0.185	1.955	0.5
3	0.9275	0.06	0.0075	0.005	0.8175	0.0625	0.12	1.9625	0.5025
4	0.94	0.0525	0.005	0.0025	0.8775	0.055	0.0675	1.97	0.495
5	0.95	0.0475	0.0025	0.0	0.895	0.05	0.055	1.9725	0.485
6	0.94	0.0525	0.005	0.0025	0.9175	0.0425	0.04	1.97	0.5125
7	0.945	0.0525	0.0025	0.0	0.94	0.0325	0.0275	1.975	0.515
8	0.9475	0.05	0.0025	0.0	0.95	0.03	0.02	1.9825	0.535
9	0.94	0.0575	0.0025	0.0	0.97	0.02	0.01	1.9875	0.565
Total	0.94	0.05	0.005	0.005	0.86	0.0475	0.088	1.97	0.51

Note: The database used in this table is the SIPP. In constructing this table, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009). The race and education variables each exclude one category to avoid collinearity (see section 5): 'white' for the race variable and 'no diploma' for the education variable. The variable 'Receive Medicare' is coded as 2 for 'yes' and 1 for 'no'. The variable 'Male' is coded as 1 if the individual is male and 0 if the individual is not.

First, table 2 shows a difference between the data of Maynard and Qiu (2009) and the data of this thesis. The previous authors demonstrated that most black individuals were located in the lowest decile of net worth. However, table 2 indicates a less discriminatory society. It is also noteworthy that the database considers a limited number of black individuals, especially in 2013: around 3% of the respondents were black, compared to 12.1% in the total U.S. population according to the Office of

Minority Health. This discrepancy might result from several restrictions imposed on the database, such as the exclusion of individuals with negative net worth. Secondly, a high school diploma is correlated with higher net worth and, consequently, higher income. This observation aligns with the findings of Maynard and Qiu (2009). Thirdly, the higher deciles of wealth comprise more men than women. Fourthly, across all years, there is a clear divergence in the proportion of people covered by Medicare between the lowest and highest deciles. This is logical since low income is the most significant criterion for Medicare eligibility, even though most of the elderly are located in the end of the distribution, as shown by table 3.

4.2.3 Descriptive statistics for the medicaid group

Table 3 delineates the mean values of several pivotal variables, encompassing Medicaid eligibility and coverage, alongside the age distribution across quantiles. Table 11 shows the same descriptive statistics, segmented across years.

Table 3: Descriptive statistics for eligibility group

Quantile of net worth	Age	ELIG	SIMELIG	Beginning month of coverage	Ending month of coverage	Coverage
1	35.825	0.16	0.23	1.6475	12.00	0.21
2	36.6675	0.1175	0.21	1.75	12.00	0.1275
3	39.555	0.095	0.21	1.54	12.00	0.0775
4	42.6025	0.07	0.205	1.94	12.00	0.0525
5	45.23	0.0475	0.2	2.055	12.00	0.0425
6	46.685	0.035	0.2025	1.7975	12.00	0.0275
7	48.6825	0.035	0.195	1.8775	12.00	0.0225
8	50.915	0.0325	0.2	2.08	12.00	0.0225
9	53.065	0.03	0.2	1.8775	12.00	0.01
Total	42.25	0.069	0.205	1.84	12.0	0.065

Note: The table displays statistics for the SIPP database. The SIMELIG instrument is built based on statistics of the CPS database, as explained in section 5.4. In constructing this table, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009). The ELIG and SIMELIG variables correspond to actual eligibility and simulated eligibility, respectively (refer to section 5.4). The variable 'Coverage' is coded as 1 if the individual is covered by Medicaid and 0 if not.

Primarily, the age distribution exhibits a positive correlation with net worth, indicative of the temporal accumulation required for wealth attainment. Remember we arbitrary excluded individuals aged 16 or younger from the dataset, explaining the high mean age in the dataset. Secondly, the average Medicaid coverage starts at the beginning of the year and continues through December, showing full-year coverage. Thirdly, there is a clear declining trend in the ELIG variable across different income levels, meaning wealthier individuals are less likely to be eligible for Medicaid. According to the SIPP database, 16% of the individuals located in the lowest decile are eligible to medicaid. This proportion is high as compared to the one of other decile (there is at least a divergence of 4%). The trend is roughly similar for SIMELIG, which is good since it shows that the procedure of imputation when creating this variable worked correctly. However, the pattern is much smoother than for the ELIG variable, and the eligibility rate remains still higher for the top deciles despite their higher income (see table1). A higher sample from the CPS database might allow the searcher to create a similar pattern to the eligibility computed with the SIPP database. Also, Medicaid coverage is often higher than the eligibility rate of the SIPP database (ELIG), suggesting that more people are covered than just those who meet the eligibility criteria. However, it is important to note that some criteria like the medically needy are not included in the eligibility calculation, which might explain this divergence between eligibility and coverage. Similarly, there is a decreasing trend in Medicaid coverage, likely due to the same factors affecting eligibility. Finally, Medicaid coverage increases after 2013, coinciding with the expansion of the Affordable Care Act.

4.3 Sample definition

Throughout our study, we opted to consider a pooled cross-section spanning December of four different years: 2013, 2014, 2015, and 2016. This decision was made to focus on a single month in order to avoid double-counting information. However, the exclusion of the preceding 11 months might present potential issues regarding data integrity for two reasons. Firstly, individuals might maintain coverage for the first 11 months of the year but lose it in the twelfth month. Secondly, an individual's net worth might fluctuate significantly in the final month of the year, as this period often involves increased investments and dividend distributions. Nevertheless, an analysis of the variation in coverage and eligibility across months revealed that 99% of individuals covered in the last month are covered throughout the entire year, and 98% of those eligible in the last month maintain eligibility for the entire year. Additionally, the net worth variable does not exhibit significant monthly variation, as individuals tend to estimate their net worth at the end of the year. Prior to 2013, it is important to note that the available data did not permit the construction of an efficient variable concerning an individual's net worth.

The objective of this thesis is to examine the impact of changes in Medicaid eligibility and coverage on an individual's net worth. Significant variations in treatment are crucial for obtaining consistent estimates of the effect. Our pooled cross-section exhibits three distinct types of variations:

- **Time Variation:** The implementation of the Affordable Care Act (ACA) was scheduled for January 2014, followed by consistent annual variations, as observed in the preceding figures.
- **State Variation:** Medicaid eligibility and coverage varied significantly across states, particularly in January 2014 when most states implemented the ACA, extending Medicaid eligibility. Subsequent to this date, additional states also adopted the expansion.
- **Variation Across Households:** The sample used in this thesis aggregates monthly observations for 78,000 individuals. Variations across individuals are consistent for all considered variables. For instance, the minimum net worth observed in this sample is $1, while the maximum is $161,000,000.

Extending the dataset to include years beyond 2016 is theoretically feasible. However, the years 2013–2016 form a coherent panel within the SIPP database. Given that the current number of observations is already significantly larger than those used in Maynard and Qiu (2009), we have decided to limit our analysis to data up to 2016 to maintain data integrity and consistent analysis and discussion.

We conclude with information from approximately 10,000 households, resulting in a total of 78,000 observations after excluding individuals who reported a null/negative net worth, who did not report their net worth, their coverage, or for whom eligibility could not be determined. We also exclude individuals under 16 years old, as their net worth is likely influenced by their parents' assets. In contrast to Maynard and Qiu (2009), we decide to include elderly individuals, as they may still qualify for Medicaid, although Medicare is more likely for this demographic. To account for potential interactions between Medicaid and Medicare coverage, we include Medicare coverage as a control variable in our regressions. Medicare is a federal health insurance program in the United States designed primarily for individuals aged 65 and older, but it also covers certain younger individuals with disabilities and those with End-Stage Renal Disease (ESRD) or Amyotrophic Lateral Sclerosis (ALS).

5 Methodology

The statistical approach utilized in this thesis is a combination of two statistical methodologies:

- Instrumental Variable (IV)

- Quantile Regression (QR)

These methods can be combined into an IVQR to obtain accurate results.

5.1 Instrumental Variable

The instrumental variable method allows for the estimation of the causal effect of an independent variable on a dependent variable while controlling for endogeneity. The objective is to identify an instrument (variable Z) that is correlated with the independent variable (variable X) but uncorrelated with the error term in the regression of the dependent variable (variable Y). This instrument, Z, influences Y only through its effect on X.

The instrument should meet the relevance condition and the validity condition. On the one hand, the relevance condition is "*the assumption that the instrumental variable Z and the treatment/endogenous variable X are related to each other*" (Huntington-Klein, 2022). In other words, the instrument should relate to the treatment of the model. On the other hand, the validity condition is defined as "*the assumption that the instrument Z is a variable that has no open back doors of its own*" (Huntington-Klein, 2022). As a result of both properties, the instrument should not be correlated with the outcome variable except through its effect on the treatment.

Once the instrument has been selected, the approach is straightforward and can be decomposed into two stages: the first stage and the second stage. The first stage involves performing a linear regression where the dependent variable is X and the instrument is the independent variable. This results in estimates of variable X (denoted as $\hat{X}$). In the second stage, $\hat{X}$ becomes the independent variable in the model, and we examine its effect on variable Y. This methodology ensures that the resulting coefficient reflects the net causal effect of X on Y. The first stage is summarized by equation 1 while the second stage is then given in equation 2 (Huntington-Klein, 2022):

$$X = \lambda_0 + \lambda_1 Z + \lambda_2 W + v \tag{1}$$

$$Y = \beta_0 + \beta_1 \hat{X} + \beta_2 W + \epsilon \tag{2}$$

where W is the vector of control variables, v and ϵ are both error terms, $\hat{X}$ is the estimated value of X and λ and β are regression coefficients. In contrast to the Ordinary Least Squares (OLS) method, this new regression approach is commonly referred to as Two-Stage Least Squares (2SLS).

In the present study, Medicaid eligibility serves as the instrument, Medicaid coverage is the variable X, and individual savings is the variable Y. Using Medicaid eligibility as an instrument is appropriate if it satisfies both the relevance and validity conditions. To receive Medicaid coverage, an individual must be eligible, indicating a relationship between the instrumental variable and the treatment variable. Furthermore, it is plausible that Medicaid eligibility does not directly impact individual savings except through its effect on Medicaid coverage. This methodology is analogous to the one employed by Finkelstein et al. (2012). In their study, they used an instrumental variable approach to estimate the net causal effect of Medicaid coverage on several outcomes relevant to individuals in the State of Oregon.

Finally, an instrumental variable is a statistical method that allows for reducing the endogeneity of the error term. However, as shown in equations 1 and 2, incorporating additional control variables into the model can further mitigate endogeneity concerns and enhance the robustness of the estimates.

5.2 Quantile Regression

Quantile regression is a form of distributional regression that facilitates the estimation of nonlinear models. This technique examines the distribution of the dependent variable (Y) and applies varying weights based on the desired observation. For example, an analyst interested in understanding the relationship between the tail end of a distribution and endogenous variables might employ quantile regression to emphasize the tail's influence in calculating the regression coefficients. The mathematical formulation, as illustrated by Fahrmeir et al. (2013), is represented in 3.

$$\hat{\beta}_\tau = \arg\min_{\beta} \sum_{i=1}^{n} w_\tau(y_i, \eta_{i\tau})|y_i - \eta_{i\tau}| \tag{3}$$

Where weights are represented by equation 4.

$$w_\tau(y,q) = \begin{cases} 1-\tau & \text{if } y < q \\ 0 & \text{if } y = q \\ \tau & \text{if } y > q \end{cases} \tag{4}$$

In this approach, weights depend on the quantile: a lower quantile beta assigns more weight to the beginning of the distribution (since $1-\tau$ is higher than 0.50). Conversely, a higher quantile beta assigns more weight to the end of the distribution (since τ is higher than 0.50).

In this research, we aim to examine the effect of Medicaid coverage on savings across different levels of the savings distribution. For instance, we analyze how Medicaid exposure influences the savings of individuals who are high savers compared to those who are low savers. This analysis can provide valuable insights for policymakers, enabling them to make informed decisions regarding Medicaid coverage and its potential impact on various segments of the population's savings behavior.

5.3 Instrumental Variable Quantile Regression

Combining both methodologies, we create a model that is nonlinear and provides a better approximation of the net effect of one variable on another. In this case, one can accurately examine the correlation between savings and Medicaid coverage by both accounting for the nonlinear effect (the effect of Medicaid on savings is likely not constant across different levels of the savings distribution) and controlling for the impact of the error term on endogenous variables, thereby statistically controlling for omission bias. The instrumental quantile regression model is developed in line with Maynard and Qiu (2009) and Chernozhukov and Hansen (2004). In practice, the instrumental quantile regression used in this research is developed in stages, as represented by equation 5 and 6

$$\begin{aligned} Q_{MEDICAID}(\tau) = \beta_{1_0}(\tau) + \beta_{1_1}(\tau)ELIGIBILITY + \beta_{1_2}(\tau)BLACK + \beta_{1_3}(\tau)ASIAN + \beta_{1_4}(\tau)OTHER \\ + \beta_{1_5}(\tau)MALE \ + \beta_{1_6}(\tau)HSCHOOL + \beta_{1_7}(\tau)GED + \beta_{1_8}(\tau)STATE\_CAT \\ + \beta_{1_9}(\tau)MEDICARE \ + \sum_{y \neq 2014} \beta_{1_y}(\tau)\mathbb{1}[year = y] + \epsilon(\tau) \end{aligned} \tag{5}$$

$$\begin{aligned} Q_{SAVINGS}(\tau) = \beta_{2_0}(\tau) + \beta_{2_1}(\tau)\widehat{MEDICAID}\tau + \beta 2_2(\tau)BLACK + \beta_{2_3}(\tau)ASIAN + \beta_{2_4}(\tau)OTHER \\ + \beta_{2_5}(\tau)MALE + \beta_{2_6}(\tau)HSCHOOL + \beta_{2_7}(\tau)GED + \beta_{2_8}(\tau)STATE\_CAT \\ + \beta_{2_9}(\tau)MEDICARE \ + \sum_{y \neq 2014} \beta_{2_y}(\tau)\mathbb{1}[year = y] + v(\tau) \end{aligned} \tag{6}$$

Where ELIGIBILITY represents eligibility for Medicaid, BLACK, ASIAN, and OTHER define the skin color of respondents, MALE takes a value of 1 if the respondent is male and 0 otherwise. HSCHOOL and GED define the education level of respondents.. It is important to note that, for each group of control variables, one category is arbitrarily omitted to avoid collinearity: for skin color, the variable white is omitted; for sex, the variable female is omitted; for education, the option "no diploma" is removed. Variable State_cat is a categorical variable representing the state where respondant is living. MEDICARE takes the value of 1 if the individual is covered by Medicare, and 0 if not. Finally, we interpret the coefficients of each year (2013, 2015 and 2016) relative to the year 2014, as most states implemented the Affordable Care Act (ACA) in that year[2].

$\beta_i(\tau)$ are the estimated coefficients for the decile τ. According to the theoretical explanation in the previous subsections, the MEDICAID variable used in the second stage ($\widehat{MEDICAID}$) is the one estimated in the first stage. Furthermore, convergence problems when estimating the model necessitate closely following the methodology used by Maynard and Qiu (2009), where the authors created the Medicaid eligible dollar as an instrument (see section 5.4). Creating such an instrument is challenging for several reasons, including the lack of available data on mean Medicaid spending per enrollee. Indeed, previous research typically considered Medicaid spending per age and sex group for each state, whereas we only have access to mean Medicaid spending for each state for the considered timeframe. Therefore, we regard this lack of data as a limitation, which opens the door for further analysis if new data on Medicaid spending becomes available.

5.4 Building the instrument and the treatment

As explained in the previous subsection, Medicaid eligibility, and more specifically the Medicaid eligible dollar, could constitute the instrument for the model. Initially, we could construct the instrument using the following approach:

$$MED = ELIG \times SPENDINGS \tag{7}$$

where MED represents Medicaid eligible dollars, $ELIG$ is a binary variable that takes a value of 1 if the individual is likely to be eligible for Medicaid, and 0 otherwise, and $SPENDINGS$ are the mean Medicaid spendings in the state.

The SIPP database does not include a pre-constructed variable that aggregates eligibility for the various programs, including Medicaid. Therefore, it is necessary to build the eligibility variable using the available variables in the database:

- *"thcyincpovt2"* which aggregates household income as a percentage of the FPL.
- *"tage"* which represents the current age of each individual at the end of each month.
- *"enj_nowrk5"* which takes the value of one if the respondent did not work for pay due to pregnancy or childbirth. It is important to note that the SIPP database does not provide a more comprehensive variable for pregnancy. Consequently, this is considered a limitation of our model, as this question was not asked to non-working pregnant women.
- *"rpnpar1_ehc"* and *"rpnpar2_ehc"* which record the person number of the household's first and second parents, respectively.
- *"ejb1_scrnr"* which is a flag indicator representing the presence of a job for the reference year.
- *"edepclm"* which is a binary variable indicating if the child is still considered dependent according to the current year's tax record. It is worth noting another limitation of this study: the tax record of the current year is based on the previous year's tax transcript. Therefore, there is a one-year time lag that could impact the final results.

[2]Maynard and Qiu (2009) included an interaction variable between the state categorical variable and each year. However, due to convergence issues encountered when estimating the model in Stata, we were forced to arbitrarily exclude these three interaction covariates to obtain an estimation of the coefficient. This omission is acknowledged as a limitation of our IVQR analysis.

- *"rdis_ alt"* which is a flag variable taking the value of one if the respondent is disabled.

A final limitation regarding these eligibility criteria belongs to the category of "medically needy", which was not accounted for in this study. The reason is twofold: firstly, due to a lack of data on current hospitalization in the SIPP, and secondly, due to the wide variation in the definition of "needy" across different states.

These limitations raise concerns about consistency when discussing "eligibility," as they fail to encompass all individuals who are actually eligible for Medicaid. This creates a disconnect with previous research, which relied on a pre-defined binary variable for eligibility. Such a binary approach lacks the necessary variability to make the instrument relevant and does not accurately reflect the concept of the likelihood of being eligible. Ideally, this likelihood should be represented as a continuous variable ranging from 0 to 1. Furthermore, a second potential source of endogeneity arises because eligibility is influenced by both wealth levels and income levels, which are partially determined by net worth, raising concerns on the validity condition of the instrument.

To address these limitations, we adopt a methodology similar to Gruber and Yelowitz (1999) and define the Simulated Medicaid Eligible Dollar (SIMMED) as follows:

$$SIMMED = SIMELIG \times SPENDINGS \tag{8}$$

Where SIMELIG represents the simulated eligibility. This simulated eligibility differs significantly from the previous method, as it now corresponds to the probability of being eligible based on individual characteristics. To create this variable, we use a random sample from the CPS database and compute the eligibility variable similarly to the one computed in the SIPP database, based on several variables:

- *"ftotval"*, the total value of income for the given month, which we divide by *"offcutoff"*, the poverty threshold, to create the income-to-poverty ratio.
- *"age"*, which summarizes the age of individuals.
- *"whyss1"* and *"whyss2"*, which take the value of 6 if the child of the parent is still dependent.
- *"diffany"*, which amounts to 2 if the individual is suffering from any health problem.

Notice we do not reference the pregnancy as an eligibility factor, as this database has no variable indicating whether a women is pregnant or not. Moreover, for the same reason as for the SIPP database, we do not consider medically needy people in the construction of eligibility.

Once the eligibility variable has been created for the sample, we can now create different groups within the sample based on the following characteristics:

- **State**: The place where the individual is living.
- **Age group**: The first group comprises young individuals (0-18 years), the second group comprises adults (19-65 years), and the third group comprises seniors (65+ years).
- **Education level**: Whether the individual has a high school diploma or not.
- **Race**: Whether the individual is black, white, Asian, or belongs to another racial group.

Finally, we compute the average for each combination of characteristics. This mean corresponds to the probability of being eligible, based on demographic data of a sample of the population. This probability is then merged at the cell level with each individual in the full SIPP database and multiplied by the mean spending of the corresponding state. By assigning each individual a probability of being eligible Medicaid, based solely on exogenous characteristics, we better account for endogeneity between the instrument and the outcome, thus ensuring the validity condition is met.

In their paper, Maynard and Qiu (2009) used the Medicaid eligible dollar (MED) as the treatment variable, thereby approximating coverage, and employed the simulated Medicaid eligible dollar (SIMMED) as the instrument. However, the availability of the coverage binary variable in the SIPP database enables us to enhance the previous treatment approach. Consequently, we use the Medicaid coverage dollar (MCD) as an instrument, as defined in equation 9.

$$MCD = COVERAGE * Spendings \tag{9}$$

This divergence from Maynard and Qiu (2009) enhances the accuracy of the treatment, despite potentially lower variability due to the shift from a continuous variable (likelihood of being covered) to a binary variable (either covered or not covered). Utilizing the Medicaid coverage dollar (MCD) as the treatment provides a more precise measure, improving the robustness of our estimates.

6 The instrument

6.1 Analysis of eligibility per month and year for full sample

Eligibility for Medicaid in the United States has seen a significant increase over the years, especially in 2014, when the Affordable Care Act (ACA), also known as Obamacare, was implemented. At this time, Medicaid was extended to non-disabled, non-elderly individuals with low income. Table 4 illustrates the ELIG variable for each year according to the various eligibility criteria, as well as the SIMELIG variable over the years.

Table 4: Portion of people being eligible in the total population per criteria and per year

Year	Baby	Kid	Teen	Pregn	Dep	Old	Disable	Jobless	**ELIG**	**SIMELIG**
2013	0.000	0.000	0.003	0.003	0.001	0.000	0.027	0.005	**0.037**	**0.078**
2014	0.000	0.000	0.003	0.002	0.001	0.000	0.028	0.107	**0.123**	**0.268**
2015	0.000	0.000	0.004	0.002	0.000	0.000	0.025	0.104	**0.117**	**0.255**
2016	0.000	0.000	0.004	0.002	0.001	0.000	0.028	0.108	**0.119**	**0.252**

Note: The table displays eligibility rates per category for the SIPP database. The SIMELIG instrument is constructed based on statistics from the CPS database, as explained in section 5.4. In constructing this table, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009). The ELIG and SIMELIG variables correspond to eligibility and simulated eligibility, respectively (refer to section 5.4). Note that the sum of each eligibility criteria does not equal the ELIG variable, as individuals can be eligible by satisfying multiple criteria.

Expanding Medicaid to non-elderly and non-disabled individuals increased estimated eligibility from roughly 4% to approximately 12%. Additionally, note that the portion of eligible teenagers did not change despite the evolution of the associated criteria described by Figure 2 and 3a. Lastly, a comparison between eligibility and simulated eligibility shows similar reactions to the expansion of Medicaid eligibility. However, the number of eligible individuals is much higher for SIMELIG than for ELIG. A larger sample from the CPS database might increase the number of consistent criteria for the mean procedure, thereby improving the accuracy of SIMELIG. Finally, the proportion of babies and children eligible equals 0 in table 4, and is the result of the exclusion of individuals aged 16 or lower, as mentioned in section 4.3.

The nature of the SIPP database also allows researchers to perform monthly analyses of the variables. Note that for the remainder of the analysis, we exclude all months except December, as explained in section 4.3. This analysis serves to pave the way for further research on this topic. Figure 6 illustrates the evolution of Medicaid eligibility on a monthly basis.

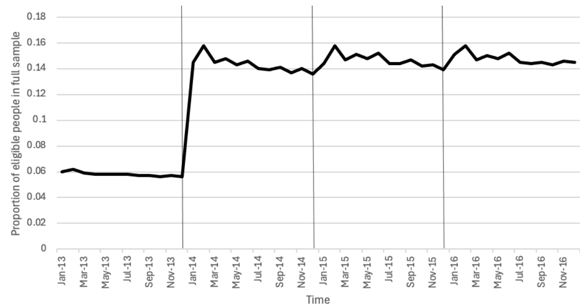


Figure 6: Monthly eligibility for years 2013-2016

Note: The time series displays monthly eligibility rates per category for the SIPP database. In constructing this time series, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009).

The primary conclusion to be drawn is the sharp increase in eligibility in 2014, followed by a more progressive upside. This trend can be attributed to the heterogeneous decisions of states regarding the implementation of the program: some states implemented it in 2014, while others did so later. It is important to note that the implementation of such a program is definitive, meaning a state policy-maker cannot retract the decision to expand Medicaid. Additionally, a monthly seasonality is observed. Specifically, when eligibility for Medicaid increases compared to the previous month, it almost always decreases the following month, and vice versa. This finding is significant and suggests further research into this yearly cyclicity. Although it would be valuable to build a similar figures for the simulated eligibility (SIMELIG), the current dataset restricts this possibility because it only includes data for the month of December. This limitation arises due to CPS constraints that allow for retrieving only a limited number of observations. To maximize the number of observations for December (since our IVQR analysis focuses on December of each year), we prioritized the CPS data for this specific month and therefore exclude all other month. However, we can still compare the SIMELIG with the ELIG of december, on top of the previous comparision we made between the mean with the corresponding SIMELIG of december (see table 4). This analysis displays the result of table 5.

Table 5: Portion of people being eligible in the total population for december of each year

Year	2013	2014	2015	2016
ELIG	0.056	0.136	0.139	0.145
SIMELIG	0.078	0.268	0.255	0.252

Note: The table displays eligibility rates for the SIPP database. The SIMELIG instrument is constructed based on statistics from the CPS database, as explained in section 5.4. In constructing this table, individuals with negative or null net worth, as well as those aged 16 or younger, are excluded, following the methodology of Maynard and Qiu (2009). We also remove all months except December. The ELIG and SIMELIG variables correspond to eligibility and simulated eligibility, respectively (refer to section 5.4).

We observe a similar divergence as the one previously described in Table 4. The same reason as before, namely the small sample extracted from the CPS database, might be the cause of such a divergence. However, we see again that trends are similar, with a considerable increase in SIMELIG and ELIG in 2014, when most states implemented the ACA.

6.2 The relevance and validity of the instrument

As specified in section 5.1, one of the main conditions an instrument must fulfill is the relevance and validity condition.

The relevance condition can be assessed using the method of Staiger and Stock (1997), who found that an instrument is considered relevant if the F-statistic of the first stage is higher than 10. More recently, D. S. Lee et al. (2022) showed that standard errors should be inflated when the first-stage F-statistic is less than approximately 100. This means that if the first-stage F-statistic is below this threshold, the estimates might be less reliable and the standard errors should be adjusted upward to account for potential weak instrument problems. In our case, the F-statistic equals 11, indicating that eligibility is a relevant instrument for Medicaid coverage according to Staiger and Stock (1997), but is weak according to D. S. Lee et al. (2022). Accordingly, standard errors should be inflated when making decisions on the significance of the estimated coefficients. We emphasize this problem and decide to consider it as a limitation, opening the door to further analysis.

The validity condition, in the case of several instruments, can be assessed using over-identification tests such as the Sargan test. However, with a single instrument, these tests are limited (Cameron and Trivedi, 2005). Some studies have developed procedures to assess the validity of a single instrument, such as density comparison and the Kolmogorov-Smirnov test (C. D. Nguyen, Carlin, and K. J. Lee, 2013). Both of these methods rely on strong assumptions, such as the randomization procedure when computing the instrument, which are not met in this research. As a result, we assume the instrument satisfies the validity condition, given that eligibility has been widely used in previous literature as an instrument. Furthermore, the Simulated Eligibility, a major component in the construction of the instrument, is built similarly to the methodology used by Maynard & Qiu (2009).

7 Results

7.1 2SLS regression - Central tendency

The coefficients related to the main variables of the OLS regression are presented in the second column of table 6. Table 14 shows the results of the 2SLS and OLS for all variables used in the regression. Accordingly, an increase of one dollar in medicaid generosity would induce a decrease of \$16.11 in individual savings. This result is statistically significant with a confidence level of 1%. Moreover, all variables related to skin color exhibit a negative effect on individual savings, emphasizing the discrimination that may exist between white and non-white individuals, except for black individuals, as the coefficient shows non-significance. This aligns with the descriptive statistics presented in section 4.2.2. Furthermore, education and Medicare coverage generally appear to have a positive effect on an individual's net worth, in contrast to Medicaid coverage. Finally, it is challenging to draw conclusions about a time trend in the wealth of the sample. The size effect of 2015 is much higher than that of 2016, indicating that individuals included in the 2015 database were, on average, wealthier than those surveyed in 2016. This result is statistically significant at the 5% confidence level. The results of equation 2 representing the 2SLS regression are represented in first column of table 6. The main conclusion drawn from this regression is that, again, there exists a negative relationship between Medicaid coverage and net worth. Specifically, individuals covered by Medicaid tend to have lower savings. According to the analysis, an individual's net worth is likely to decrease by approximately \$17 for each additional dollar of coverage received. However, this conclusion must be tempered by the significance of the treatment, as the p-value is higher than 10%. It is evident that decomposing the effect by quantile to observe the impact of coverage on individual savings is necessary, as wealthier individuals may not experience such a decrease in net worth, and not all net worth deciles are significantly impacted by Medicaid coverage. Indeed, the beta reflects conclusions about the mean of the individual's net worth distribution. This result is likely influenced by extreme values, which can be better controlled through non-linear regression methods such as quantile decomposition.

Table 6: 2SLS vs OLS

	2SLS	OLS
MCD	-17.40	-16.11***
	(54.78)	(0.94)
State Category	4.73	1.09
	(2,596.91)	(2,562.98)
Medicare	99,011.40	101,085.44***
	(88,436.12)	(6,839.61)
2013	10,674.84	11,052.86
	(20,859.57)	(9,743.39)
2015	175,797.70***	175,704.71***
	(29,579.19)	(30,397.11)
2016	19,606.64**	19,487.32**
	(9,602.95)	(9,641.00)
Year FEs	✓	✓
State FEs	✓	✓
Controls	✓	✓
Observations	76,867	76,867
R-squared	0.00	0.00
F-stat	11	

Note: Both regressions were performed with individual net worth as the dependant variable, using the SIPP database, excluding individuals with non-reported net worth, Medicaid coverage, or eligibility. Additionally, individuals aged 16 or younger were removed. The sample in used here focuses on information reported for December. We also exclude individuals with negative/null net worth. Standard errors are in parentheses, and t-tests are two-sided. Significance levels are denoted as follows: p<0.1; p<0.05; p<0.01.

A final observation pertains to the effectiveness of the instrumental variable regression employed in this analysis. Indeed, comparing the OLS to the 2SLS regression shows that the estimated impact of Medicaid coverage is bigger when endogeneity is controlled for using the SIMMED instrument. The p-value associated with the coverage coefficient is smaller in the linear regression model than in the 2SLS regression. To evaluate whether the instrument effectively mitigates endogeneity, the Hausman test can be employed. This test follows a methodology that can be divided into three steps (Wooldridge, 2012):

- Conducting the first stage regression and saving the residuals.
- Performing the main regression, including the residuals from the first stage.
- Testing the significance of the residuals.

A significant coefficient for the residuals would indicate that the instrumental variable regression is advantageous, as the simple linear regression would suffer from greater endogeneity. In our study, the coefficient of the error term is significant at the 1% confidence level, thus justifying the use of instrumental variable regression. A simple linear regression, in the absence of an instrument, would violate the second assumption of the classical regression model, which stipulates that "*The mean of the residuals conditional on x should be zero,* $\mathbb{E}[\varepsilon|x] = 0$*. This also implies that* $Cov(\varepsilon, x) = 0$*, meaning that the errors and our explanatory variable should be uncorrelated. Therefore,* x *must be strictly exogenous to the model.*" (Kenedi et al., 2020).

In terms of policy implications, the results suggest that lower Medicaid coverage positively impacts individuals' net worth. According to our estimates, individuals covered by Medicaid experience an average wealth loss of $17 for each dollar of Medicaid coverage received. This finding is important, as Medicaid spending per enrollee averaged $6,459 according to the Kaiser Family Foundation (KFF). Enhancing coverage thus incurs costs not only at the governmental level but also for individuals. However, it is crucial to interpret these results with caution, as relying solely on a linear regression model for decision-making could lead to unintended consequences and exacerbate disparities between wealthy and poor individuals. A more comprehensive analysis, considering each decile of the net worth distribution, may provide better insights into these externalities.

7.2 Instrumental Quantile regression

7.2.1 Findings for individuals with positive net worth

The results of the quantile regression are presented in table 7. Given the extensive nature of the results matrix, with an estimated coefficient for each variable at each quantile, we have chosen to focus on a subset of variables in the tables. Specifically, the tables display the coefficients and their associated standard deviations for five variables: Medicaid coverage, Medicare coverage, and each year excluding 2014 (due to collinearity). Endogeneity related to medicaid coverage has been controlled using an instrumental variable approach. The coefficient for the whole set of variable is represented in table 13[3] The results obtained diverge significantly from those discussed in section 7.1. Specifically, individuals

Table 7: IVQR - main findings (positive net worth only)

	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.82***	0.39	-0.24*	-1.11**	-2.47***	-6.07***	-4.85	-5.50**	-13.20**
	(0.26)	(0.35)	(0.43)	(0.55)	(0.81)	(1.15)	(3.06)	(2.79)	(5.47)
Medicare	2,617.26***	2,433.15***	3,204.60***	3,560.24***	5,184.28***	9,733.28***	21,985.19***	25,575.67***	43,015.14***
	(620.94)	(689.00)	(748.37)	(796.99)	(1,426.75)	(2,063.35)	(6,802.22)	(4,373.00)	(5,688.68)
2013	426.15*	261.66	47.70	-249.34	-620.08	-2,284.35**	266.01	1,552.02	6,551.15
	(217.84)	(238.42)	(268.08)	(344.34)	(604.70)	(1,048.18)	(2,202.53)	(2,406.83)	(5,030.46)
2015	-409.54**	69.43	478.28**	1,150.11***	2,012.54***	4,883.55***	4,581.90*	6,130.80**	12,903.26***
	(184.65)	(194.32)	(218.13)	(297.40)	(510.77)	(1,027.30)	(2,407.43)	(2,605.92)	(4,786.33)
2016	-506.80**	65.87	587.20**	1,365.57***	2,453.39***	6,016.99***	4,549.08*	8,733.82***	27,799.39***
	(200.69)	(208.88)	(234.11)	(324.03)	(562.88)	(1,098.19)	(2,332.78)	(2,942.75)	(5,475.47)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76,867	76,867	76,867	76,867	76,867	76,867	76,867	76,867	76,867

Note: IVQR is performed with individual net worth as the dependent variable, using the SIPP database, excluding individuals with non-reported net worth, Medicaid coverage, or eligibility. Additionally, individuals aged 16 or younger were removed. The sample in used here focuses on information reported for December. We also exclude individuals with negative/null net worth. Standard errors are in parentheses, and t-tests are two-sided. Significance levels are denoted as follows: p<0.1; p<0.05; p<0.01.

situated in the lowest decile of the wealth distribution benefit the most from Medicaid coverage. At this decile, an increase of one dollar in Medicaid coverage results in a $0.82 increase in individuals' savings, a result that is statistically significant at the 1% confidence level. The second decile also exhibits a positive relationship between Medicaid coverage and savings, though with a smaller effect size: an increase of one dollar in Medicaid coverage is associated, on average, with a $0.39 increase in savings. However, this result is not statistically significant at the 10% level due to its substantial p-value (0.26).

[3]In the IVQR, as well as in the 2SLS regression presented earlier, age is not included as a control variable. Although its relevance would be significant (see table 3), including age in the regression prevents the convergence of the IVQR and thus does not allow the estimation of the coefficient. This omission represents another limitation of our results.

At the third decile, with a mean net worth of approximately \$7,100 (refer to table 1), the findings indicate a negative impact of Medicaid coverage on savings: a one-dollar increase in Medicaid coverage correlates with a \$0.24 decrease in savings. Although this result is not significant at the 5% level, it becomes significant at the 10% level. The negative effect intensifies in the fourth, fifth, and sixth deciles, with respective coefficients of -1.10, -2.47, and -6.07 for Medicaid coverage. These results highlight that the middle of the wealth distribution, on average, is negatively impacted by a one-dollar increase in Medicaid coverage. It is important to note that the results for the fourth decile are only statistically significant at the 5% level, whereas the coefficients for the fifth and sixth deciles are significant at the 1% confidence level. The negative effect persists in the seventh decile, although the magnitude decreases. At this decile, an additional dollar of Medicaid coverage reduces savings by \$4.85. The coefficient begins to increase again in the eighth and ninth deciles, with coefficients of -5.50 and -13.19, respectively. All these effects are statistically significant at the 5% level, except for the seventh decile, which has a p-value of 0.11, indicating non-significance at the 10% confidence level.

The p-values displayed in table 7 indicate that not all quantiles are significantly impacted by a one dollar increase in Medicaid coverage. This may be due to the low proportion of eligible or covered individuals within certain quantiles. As shown in table 4, there is a substantial drop in the proportion of individuals covered by Medicaid after the second quantile. This observation must be considered when concluding the effect of Medicaid coverage on the savings of wealthier individuals, as the low coverage rate may render the treatment less relevant despite the observed low p-values.

The effect of Medicaid coverage on savings from 2013-2016 can be compared to the findings from 1984-1993 presented by Maynard and Qiu (2009), as the methodologies are largely similar. Their results differ slightly from ours, as they examine the logarithm of net worth excluding home and vehicle values, rather than the gross values. We use the gross value for two reasons:

- Stata fails to find convergence when estimating the IVQR, thus preventing the display of coefficients. Specifically, the Generalized Method of Moments (GMM) criterion was not minimized within the given bandwidth parameters, indicating that the algorithm could not stabilize on a set of coefficients due to potential issues like insufficient iterations, inappropriate bandwidth selection, or data irregularities.

- Comparing an additional dollar of Medicaid coverage with a variation in dollar savings makes the results more comprehensible and representative for policy-making decisions.

This divergence in interpretation between our research and that of Maynard and Qiu (2009) may be considered a limitation of our model and opens the door to further research, possibly with a larger dataset. Despite the differences in effect size, the direction and significance of the effects can still be compared. In their study, Maynard and Qiu observe a negative effect of Medicaid coverage on savings across all deciles, a major divergence from our results, which show a positive effect for the first two deciles. They attribute their findings to credit constraints, suggesting that greater Medicaid coverage generosity leads to increased borrowing, thereby reducing savings (as borrowing is considered negative savings). Our findings offer a different interpretation: according to Dokko, Li, and Hayes (2015), credit constraints have become increasingly important, especially for households with low income and wealth. Consequently, individuals in the first and second quantiles may view increased Medicaid coverage generosity as an opportunity to save their remaining funds, as they are unable to borrow more. Furthermore, Maynard and Qiu (2009) observed a U-shaped coefficient across deciles, indicating the highest impact at the middle of the distribution, which diverges from our findings. Their use of a logarithmic transformation, unlike our use of gross values, may account for this difference: while we observe stabilization in the effect size before it increases sharply for the last quantile, translating these effect sizes into comparable metrics across deciles might reveal a similar U-shape given the similar bump in net worth for the last quantile (refer to table 1). Additionally, the high reported SIMELIG in Table 3 which we justified by the restricted sample of the CPS database, and the poor amount of statistics on Medicaid spending per enrollee, might also explain the divergence in shapes and the sharp increase in the coefficient for this ninth quantile.

Finally, Maynard and Qiu (2009) find non-significance for the top and bottom deciles, in addition to the negative impact of Medicaid coverage on savings. The non-significance of the effect for the top deciles was attributed to extended access to other private insurance plans through employers and lower enrollment in Medicaid. The observed U-shape of the coefficients was explained by the reduced reliance on Medicaid among wealthier households. The significance of the top decile in our study must be tempered, as the number of eligible individuals in this decile is limited (refer to table 3). This lack of variability in treatment could bias the significance assessment of the coefficient. Thus, our findings mostly align with theirs, except for the lowest deciles, where the direction of impact differs.

Maynard and Qiu (2009) also discuss the size effect of their results, questioning the relevance of their model, especially at the middle of the distribution. Similar to our findings, they report high coefficient values, suggesting that another relevant variable not included in the model might be inflating the estimated coefficient, despite the use of an instrumental variable.

7.2.2 Findings when expanding to negative/null net worth individuals

Previous findings were based on individuals with positive net worth, in line with Maynard and Qiu (2009) and Gruber and Yelowitz (1999). However, including individuals with null or negative net worth is crucial for robustness checks (see section 8) and for a more comprehensive interpretation of the impact of Medicaid coverage on individuals with very low net worth. Including these additional individuals increases the total number of observations to 108,445, with 15.31% having negative net worth and 12.03% having zero wealth. Due to the increased number of observations, we limited the dataset to a random sample of 50,000 individuals for this part of the analysis.

The methodology applied here is simpler than that of Maynard and Qiu (2009). As a reminder, the authors used a log-linear relationship between net worth and Medicaid coverage. To accommodate negative and null net worth, they employed the inverse hyperbolic sine transformation (Burbidge, Magee, and Robb, 1988; Pence, 2006). In contrast, this thesis does not utilize a log-lin relationship due to convergence issues. Consequently, we apply the same methodology as described in section 5, but with a randomly limited sample of 50,000 observations.

The estimated coefficients and their associated standard deviation are presented in table 8. Descriptive statistics for the random sample are provided in table 15, table 16 and table 17[4]. A complete analysis comprising estimated coefficient for all covariates are represented in table 18. The first three quantiles are of major importance as they encompass individuals who were previously not considered, specifically those with negative or null net worth. The conclusions drawn are unequivocal: for these extremely poor individuals, an increase of one dollar in Medicaid coverage results in higher savings. These findings are statistically significant at the 10% level for the first two quantiles. However, the third quantile does not exhibit statistical significance, likely due to the concentration of individuals with zero net worth within this group. The observed positive effect of Medicaid coverage on net worth among the lowest segments of the distribution can be attributed to similar factors found in individuals with positive net worth. Limited access to credit compels these individuals to save their money instead of borrowing, thereby improving their net worth. The coefficient for the sixth quantile appears excessively large and lacks relevance. Specifically, a one-dollar increase in Medicaid coverage would cause

[4]The third quantile displays missing values due to a high concentration of null net worth in the sample, resulting in the third and part of the fourth quantile being composed entirely of null net worth observations. Consequently, Stata concentrates all these null net worth observations in the fourth quantile, leaving the third quantile with only missing values. We could have displayed statistics for quintiles rather than deciles, but in order to keep consistency with table 8 which displays coefficient across decile, we rather consider deciles in the descriptive statistics.

an average loss of $35.90 for these individuals. Nevertheless, this result is not statistically significant at the 10% confidence level. This overestimation of the coefficient likely stems from the insufficient number of people covered by Medicaid within this quantile.

Table 8: IVQR - all universe

	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.88***	0.41*	0.05	-0.38	-0.92*	-35.90	-5.13***	-2.09	-4.03
	(0.30)	(0.23)	(0.25)	(0.31)	(0.48)	(88.17)	(0.91)	(1.93)	(3.08)
Medicare	-428.81	1,084.00**	1,071.10**	1,223.00**	1,709.64***	33,494.54***	8,749.35***	9,867.75***	22,628.27***
	(595.16)	(513.08)	(462.52)	(497.33)	(596.68)	(4,097.28)	(2,412.49)	(2,166.83)	(2,463.57)
2013	-82.72	-137.77	-108.87	-227.37	-476.13	-27,154.53***	-2,351.33*	689.30	4,180.13*
	(374.68)	(187.21)	(167.27)	(187.18)	(323.57)	(1,854.19)	(1,267.41)	(1,187.46)	(2,466.90)
2015	-502.58	-296.32	70.41	380.28*	1,016.85**	64,473.42**	5,253.20***	3,245.91	9,087.75**
	(421.60)	(205.24)	(173.21)	(198.36)	(455.28)	(32,212.58)	(1,243.03)	(2,075.36)	(4,597.92)
2016	-1,085.31**	-260.34	89.67	438.10**	1,138.09***	54,609.07***	4,904.44***	2,939.81*	9,923.25**
	(480.32)	(200.76)	(171.67)	(195.14)	(438.27)	(15,435.63)	(1,281.46)	(1,743.83)	(4,820.67)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799

Note: IVQR is performed with individual net worth as the dependent variable, using the SIPP database, excluding individuals with non-reported net worth, Medicaid coverage, or eligibility. Additionally, individuals aged 16 or younger were removed. The sample in used here focuses on information reported for December. We do not exclude individuals with negative/null net worth. Standard errors are in parentheses, and t-tests are two-sided. Significance levels are denoted as follows: $p<0.1$; $p<0.05$; $p<0.01$.

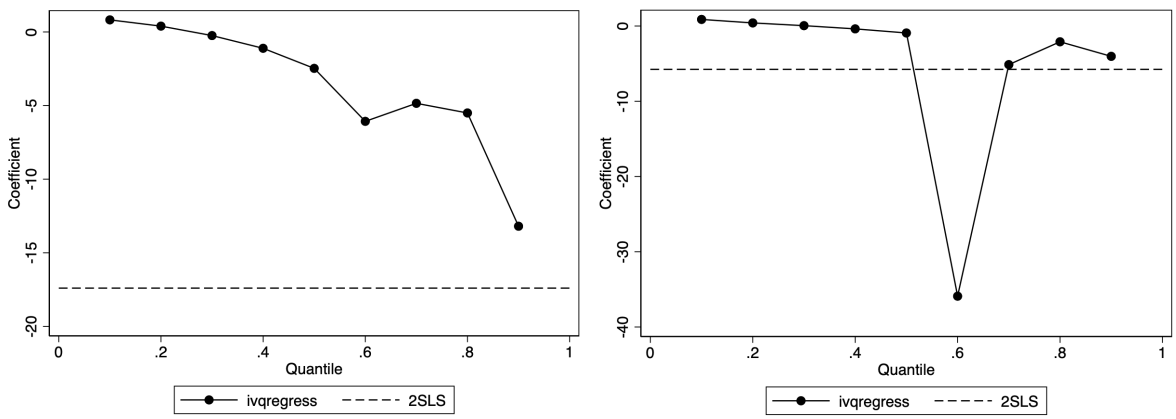
When examining the results presented in the research of Maynard and Qiu (2009), a similar divergence to the one mentioned in section 7.2.1 is observed in terms of the shape and effect direction of the lower quantiles. The log-lin regression shows a negative effect across all quantiles, even for individuals with negative or null net worth. The highest effect size occurs at the middle of the distribution, highlighting the U-shape of the estimated effect. The same reasons as mentioned in section 7.2.1 can explain those divergences in shape and direction.

8 Robustness check

To test the robustness of the findings presented in section 7.2.1, Maynard and Qiu (2009) employed several robustness checks:

- **Extension of the sample:** The sample was extended to include individuals with negative or null net worth, as discussed in section 7.2.2. This extension allows for the observation of the shape and direction of the reported coefficients, and their comparison with the main findings.
- **Inclusion of labor income as an additional control variable:** Initially, income was not included as a covariate due to its assumed orthogonality with the instrument (SIMMED). However, as the authors explain, this assumption of orthogonality can be violated. Income may be correlated with the instrument because it varies with household size, among other factors. Including labor income in the model can therefore provide a more relevant analysis.
- **Labor income as a function of medicaid coverage:** The analysis was further refined by incorporating labor income quintiles. Specifically, the treatment was interacted with dummy variables corresponding to different labor income quintiles. This approach allowed the authors to explore the effects of Medicaid across various income levels, focusing on the savings disincentive effects for households with different labor income levels.

Maynard and Qiu (2009) identified robust results using those three robustness checks. In this thesis, the first robustness check is illustrated in table 8 of section 7.2.2. We can plot the coefficients across different quantiles to observe the underlying curve. Although the effect sizes cannot be directly compared due to the redimensioning of net worth within each decile, the shapes and directions can still be analyzed. A graphical comparison is presented in figure 7. Overall, We observe a similar pattern, with the absolute value of the effect size decreasing in the seventh quantiles before increasing again in the ninth quantile. Again, it is important to note that the deviation from the U-shape observed by Maynard and Qiu (2009) may result from using a lin-lin regression instead of a log-lin regression, due to convergence issues during estimation. Finally, We might argue that the pattern similarity between Figure 7a and Figure 7b is not evident. However, it is important to remember the non-significance associated with the sixth quantile, as well as the redimensioning of net worth across quantiles since the sample has been extended to include negative and null net worth in Figure 7b. The same figure, along with its confidence interval, is represented in 8.



(a) IVQR - positive net worth

(b) IVQR - all universe

Figure 7: Coefficient of MCD across quantiles

Note: IVQR is performed with individual net worth as the dependent variable, using the SIPP database, excluding individuals with non-reported net worth, Medicaid coverage, or eligibility. Additionally, individuals aged 16 or younger were removed. The sample in used here focuses on information reported for December. We do not exclude individuals with negative/null net worth.

Regarding the other two tests, we conduct two IVQR and focus on all deciles. The first IVQR replicates the previous analysis and limits the sample to 50,000 observations of individuals with either positive, negative, or null net worth. We include individual income as an additional control variable while retaining all other covariates. For the second IVQR, we create income deciles and generate interaction terms by multiplying each decile by the Medicaid coverage dollar amount. This process results in interaction terms between the treatment and each income decile. We also apply a similar approach to the instrument, creating an instrument for each interaction dummy. Additionally, we include the gross effects of each income decile as a covariate in the regression. This regression aims to understand the impact of income on savings, considering that an individual with low net worth might experience an increase in savings due to high income. For instance, a young individual recently graduated from university with substantial educational loans may have low net worth due to significant borrowing, despite having a high income. Therefore, their actual savings may be underestimated when considering only net worth. However, due to convergence problems, the second quantile regression cannot be computed. The high number of interaction terms, coupled with their instrument, might create overfitting problems, thereby impacting the relevance condition of the instrument. As a result, only the findings of the first regression are displayed in table 9. Additionally, a complete analysis with estimated coefficients for all covariates is available in table 18.

Table 9: IVQR - robustness check

	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.85**	0.41*	-0.24	-2.72	-1.90	-1.60*	-2.22**	-2.18**	-3.67*
	(0.36)	(0.23)	(0.29)	(12.98)	(1.39)	(0.95)	(0.91)	(1.09)	(2.21)
Income	0.22***	0.25***	0.26***	0.97***	2.03***	4.09***	8.03***	13.99***	27.68***
	(0.05)	(0.04)	(0.04)	(0.22)	(0.14)	(0.17)	(0.19)	(0.41)	(0.85)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799

Note: IVQR is performed with individual net worth as the dependent variable, using the SIPP database, excluding individuals with non-reported net worth, Medicaid coverage, or eligibility. Additionally, individuals aged 16 or younger were removed. The sample in used here focuses on information reported for December. We do not exclude individuals with negative/null net worth. Standard errors are in parentheses, and t-tests are two-sided. Significance levels are denoted as follows: p<0.1; p<0.05; p<0.01.

Income appears to be a statistically significant variable for all coefficients at a 1% confidence level. Additionally, the results display a similarity for poor individuals: the net worth of the highly impoverished individuals (quantiles 1 and 2) is positively impacted by an increase of one dollar in Medicaid received for coverage. The coefficient associated with the third quantile changes direction compared to Table 8, but is also not statistically significant. In terms of shape, the result diverges for the middle of the distribution. Indeed, the negative impact of Medicaid coverage on savings seems to first peak at the fourth quantile, before starting to decrease until the sixth quantile. This shape, however, needs to be rationalized as the statistical significance of the fourth and fifth quantiles is not achieved at a 10% confidence level. Finally, the last quantile is still on a downward trend, but again, this is probably due to the lin-lin nature of the regression, as compared to Maynard and Qiu (2009).

We conclude overall on the robustness of the findings for the lowest quantiles. However, a comparison of the trend of the coefficient across quantiles between the main findings and the robustness check concludes on the non-robustness of such a shape. This non-robustness in the shape of the coefficient might be the result of the limitations mentioned in section 9, and the application of the suggestions mentioned in this subsection could help to provide more robust results.

9 Limitations and Future Research Directions

Along this research, several limitations have been identified. This section aims to summarize these limitations and to suggest directions for future research.

On the one hand, one of the primary issues encountered in this research has been the lack of convergence when estimating the IVQR. This convergence issue prevented the estimation of a log-lin regression and did not allow the estimation of the final robustness check, thereby affecting our ability to compare our findings with those of Maynard and Qiu (2009). There are several approaches to increase the likelihood of convergence:

- Implementing a randomization procedure in the eligibility estimation process could enhance the validity of the instrument, therefore improving convergence. For instance, a lottery system, similar to that used by Finkelstein et al. (2012), where eligible individuals are selected through a draw, could be employed. In this system, individuals in the lottery would represent the treatment group, while those outside the lottery would form the control group. This binary variable could then serve as the instrument for Medicaid coverage. Adopting a similar randomization procedure could significantly enhance the model.

- Increasing the sample size of the CPS database would yield more precise estimates of eligibility likelihood. A larger sample size would provide more data for each age, race, state, and education group, which were the determinants in the eligibility estimation, as explained in section 5.4. Enhanced accuracy would then improve the validity and relevance of the instrument, facilitating better model convergence.

- Providing a more detailed breakdown of spending per enrollee would introduce greater variability in SIMMED. This variability is crucial in the first-stage regression as it may enhance relevance, therefore improving convergence.

- Creating a more detailed database for eligibility estimation is also essential. As discussed in section 5.4, pregnancy and medically needy individuals were not considered in the construction of SIMELIG due to data limitations in the CPS database. Enhancing this database or locating another database that includes these criteria could result in a more accurate SIMELIG and, consequently, a more relevant instrument.

On the other hand, we have demonstrated the importance of access to credit over the past decade, as it may explain the transition from a negative to a positive impact of Medicaid coverage on savings of poor individuals, as discussed in section 7.2.1. To confirm that access to credit is indeed the primary factor behind this shift, future research should develop or identify a database that includes this variable and incorporate it into the regression as a covariate. Additionally, introducing interaction terms between Medicaid coverage and access to credit could facilitate more robust conclusions, similar to the approach taken by Maynard and Qiu (2009) in their final robustness check with income.

10 Discussion and Conclusion

The findings of the present study diverge significantly from those elaborated by Maynard and Qiu (2009). In the 1980s, Medicaid coverage had a negative impact on savings across all quantiles. Specifically, the expansion of Medicaid generosity during that time most significantly impacted individuals in the middle of the net worth quantile, emphasizing a U-shape of the plotted coefficients. The impact was negative for both poor and wealthy individuals, especially when measured in dollar magnitude rather than percentage. Although the negative effect size was notable, the extension of Medicaid generosity showed non-significant changes in the savings of the lowest and top deciles.

This thesis presents quite different changes and policy implications. First, the extension of Medicaid eligibility due to the Affordable Care Act (ACA) might have a positive impact on the lowest quantile, with significant results. In other words, the Medicaid generosity developed by the ACA in 2014 allowed poor individuals to increase their savings, thereby increasing their net worth and contributing to a fairer society. We explain this divergence from Maynard and Qiu (2009) as the result of increased credit constraints on low-income individuals. The effect of Medicaid assistance on bottom decile savers displays statistical significance, which also significantly diverges from what was observed in the 1980s. Previously, the non-statistical significance was attributed to the affiliation of poor households with several other programs more important than Medicaid, making its impact insignificant. Nowadays, Medicaid is one of the main programs dedicated to poor individuals, especially after the ACA extension. Second, for the middle of the distribution, the effect directions of additional Medicaid generosity are comparable to those of the 1980s, even though the effect size diverges. The U-shape emphasized by Maynard and Qiu (2009) showed how increased Medicaid generosity would highly negatively impact middle savers and also showed the statistical significance of those results. Today, the effect direction is still negative, meaning increased Medicaid assistance still negatively impacts savings in the middle of the distribution, but some deciles in this middle segment display non-statistically significant results, specifically the sixth quantile, which tends to show a highly negative effect but non-significance. We explain this non-significance by the poor variability in treatment for individuals in the middle of this distribution, mainly due to lower coverage with increasing income. The negative impact on middle-income groups indicates a potential trade-off for policy-making decisions. Policymakers should consider ways to mitigate this adverse effect, possibly by complementing Medicaid expansion with other financial support measures targeted at middle-income households. Third, the top deciles also display a negative effect of increased Medicaid generosity on savings, and, as divergent from Maynard and Qiu (2009), this result is statistically significant. We also observe that the effect size becomes more negative in the top decile compared to the eighth decile. This effect diverges from the U-shape observed in the 1980s, but these results are questioned by the lin-lin regression of our paper.

The results presented in our study are partly robust. In essence, adding income as a control variable and extending the sample to include individuals with null and negative net worth still shows a positive effect of increased Medicaid generosity on savings. However, the shape of the estimated coefficients across quantiles for main findings diverges from those of the robustness check. Although this divergence might be explained by the non-significance of the sixth quantile, the robustness of our shape seems suspicious, compared to Maynard and Qiu (2009), who showed a similar pattern between their main findings and robustness check using the same robustness test as us. This poor robustness in the shape of the coefficient might result from the limitations mentioned in section 9, and the application of the suggestions for further research mentioned there could help better assess the robustness of the results, as well as the significance of the middle and top of the distribution.

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A Appendix

Table 10: Descriptive statistics for the dependent group - main findings

Year	Quantile	Income / FPL	Financial asset	Net Debt	% Positive debt	Net equity	equity w/o home	equity w/o home/vehicle
2013	1.0	2.8	777.0	9460.9	0.2	13681.3	8368.3	569.0
	2.0	3.5	2416.8	18317.9	0.3	19713.7	6765.1	2328.1
	3.0	3.9	4725.2	28277.7	0.5	25856.7	13835.7	7466.4
	4.0	4.3	7921.0	38412.1	0.6	32203.4	26697.3	1871.3
	5.0	5.0	12443.6	47050.4	0.7	43115.9	49016.1	39881.9
	6.0	5.7	18978.9	47019.2	0.7	48689.4	87278.2	41896.1
	7.0	6.5	33319.2	49483.5	0.6	69513.5	155669.4	143325.8
	8.0	7.3	64465.0	29819.3	0.6	88161.6	283864.3	269745.3
	9.0	10.7	294635.4	-1.1e+05	0.4	151597.0	1.3e+06	1.3e+06
2014	1.0	2.8	685.6	9618.4	0.2	17403.3	3121.0	476.3
	2.0	3.5	1998.2	17504.5	0.3	17211.2	5467.7	1718.6
	3.0	3.8	4198.0	22909.2	0.4	25913.0	11206.8	5820.5
	4.0	4.4	7545.2	35964.7	0.5	31016.0	23243.7	15688.4
	5.0	4.9	12173.4	43003.1	0.6	45959.3	44953.5	35415.3
	6.0	5.9	16984.7	49283.9	0.7	52011.9	79335.9	69233.9
	7.0	6.2	28229.0	51131.2	0.7	87046.7	129174.1	129174.1
	8.0	7.4	51069.9	39359.2	0.6	87046.7	258979.2	245582.3
	9.0	10.7	265170.5	-94332.0	0.4	172905.2	1.1e+06	1.1e+06
2015	1.0	3.1	794.0	10919.6	0.2	15355.8	3368.9	593.5
	2.0	3.7	2405.9	17386.5	0.3	22199.1	6386.1	2350.2
	3.0	4.3	4803.9	24985.1	0.5	26988.7	13108.6	7561.2
	4.0	4.5	8724.1	36775.0	0.6	34984.7	27187.7	19161.2
	5.0	5.3	12335.0	49285.5	0.7	48136.8	49063.1	40010.1
	6.0	5.6	16812.0	49072.0	0.7	53870.5	55089.5	40975.1
	7.0	6.8	28387.4	50189.9	0.6	75773.4	151496.1	139941.9
	8.0	7.3	52639.0	41258.9	0.6	90461.9	277136.6	264130.4
	9.0	10.5	258795.0	-74802.8	0.5	188317.3	3.2e+06	3.2e+06
2016	1.0	3.2	845.0	10392.3	0.2	14374.2	3149.6	634.3
	2.0	3.7	2566.2	16112.4	0.3	19877.6	5506.0	2447.1
	3.0	4.2	5553.2	26871.4	0.4	27162.1	13381.2	7615.2
	4.0	4.7	9121.3	35466.9	0.6	37159.8	26856.0	19263.2
	5.0	5.0	12300.7	42683.0	0.6	45347.2	49737.1	42093.7
	6.0	6.0	19025.2	55615.8	0.7	58241.3	86243.9	75461.2
	7.0	6.2	32229.3	49496.4	0.7	74382.1	153807.1	139911.7
	8.0	7.9	65987.3	24703.8	0.5	102550.7	292814.3	278147.4
	9.0	11.0	318780.2	-1.6e+05	0.4	189951.7	1.3e+06	1.3e+06

Table 11: Descriptive statistics for eligibility and coverage - main findings

Year	Quantile	Age	ELIG	SIMELIG	Beginning month of coverage	Ending month of coverage	Coverage
	1	35.71	0.06	0.09	1.69	12.00	0.14
	2	36.73	0.03	0.09	1.83	12.00	0.08
	3	40.06	0.03	0.08	1.53	12.00	0.04
	4	42.93	0.02	0.07	2.45	12.00	0.03
2013	5	45.35	0.02	0.07	2.06	12.00	0.02
	6	46.54	0.01	0.07	1.21	12.00	0.01
	7	48.68	0.01	0.07	2.00	12.00	0.01
	8	50.72	0.01	0.06	1.35	12.00	0.01
	9	52.63	0.01	0.07	1.00	12.00	0.00
	1	35.64	0.20	0.27	1.70	12.00	0.22
	2	36.46	0.15	0.28	1.66	12.00	0.14
	3	39.41	0.12	0.26	1.69	12.00	0.09
	4	42.12	0.09	0.26	2.13	12.00	0.05
2014	5	45.26	0.07	0.26	2.90	12.00	0.05
	6	46.37	0.05	0.27	1.87	12.00	0.03
	7	48.67	0.05	0.26	2.77	12.00	0.02
	8	50.70	0.03	0.27	2.96	12.00	0.02
	9	53.14	0.03	0.26	2.14	12.00	0.01
	1	36.14	0.19	0.29	1.63	12.00	0.25
	2	37.10	0.15	0.27	1.57	12.00	0.14
	3	39.57	0.11	0.27	1.38	12.00	0.09
	4	43.18	0.08	0.24	1.67	12.00	0.06
2015	5	45.14	0.05	0.25	1.48	12.00	0.05
	6	47.42	0.04	0.24	2.48	12.00	0.03
	7	48.85	0.04	0.23	1.53	12.00	0.03
	8	51.26	0.04	0.23	2.87	12.00	0.02
	9	53.40	0.04	0.25	2.87	12.00	0.01
	1	35.81	0.19	0.29	1.57	12.00	0.23
	2	36.38	0.14	0.27	1.94	12.00	0.15
	3	39.18	0.12	0.28	1.56	12.00	0.09
	4	42.18	0.09	0.25	1.51	12.00	0.07
2016	5	45.17	0.05	0.23	1.78	12.00	0.05
	6	46.41	0.04	0.24	1.63	12.00	0.04
	7	48.53	0.05	0.23	1.21	12.00	0.03
	8	50.98	0.05	0.23	2.40	12.00	0.03
	9	53.09	0.04	0.24	1.50	12.00	0.02

Table 12: Descriptive statistics for the control group - main findings

Year	Quantile	head is black	head is asian	head is other	high-school diploma	GED or other diploma	Receive medicare	Male
	1	0.04	0.01	0.00	0.66	0.08	1.94	0.52
	2	0.03	0.00	0.00	0.76	0.06	1.97	0.53
	3	0.03	0.00	0.00	0.81	0.06	1.97	0.51
	4	0.03	0.00	0.00	0.88	0.05	1.98	0.50
2013	5	0.02	0.00	0.00	0.89	0.06	1.98	0.51
	6	0.03	0.00	0.00	0.92	0.04	1.97	0.51
	7	0.03	0.00	0.00	0.94	0.04	1.98	0.53
	8	0.03	0.00	0.00	0.95	0.03	1.99	0.57
	9	0.03	0.00	0.00	0.97	0.02	1.98	0.59
	1	0.05	0.01	0.01	0.65	0.07	1.94	0.51
	2	0.06	0.01	0.00	0.76	0.05	1.95	0.50
	3	0.07	0.01	0.00	0.82	0.06	1.97	0.50
	4	0.06	0.00	0.00	0.88	0.05	1.97	0.50
2014	5	0.04	0.00	0.00	0.89	0.05	1.98	0.47
	6	0.06	0.00	0.00	0.91	0.05	1.97	0.51
	7	0.06	0.00	0.00	0.94	0.03	1.98	0.53
	8	0.05	0.00	0.00	0.95	0.03	1.98	0.55
	9	0.06	0.00	0.00	0.97	0.02	1.99	0.58
	1	0.05	0.01	0.01	0.66	0.08	1.93	0.50
	2	0.09	0.00	0.00	0.75	0.07	1.94	0.47
	3	0.06	0.00	0.00	0.81	0.06	1.96	0.49
	4	0.05	0.00	0.00	0.88	0.05	1.96	0.46
2015	5	0.06	0.00	0.00	0.91	0.05	1.97	0.50
	6	0.06	0.00	0.00	0.92	0.04	1.97	0.51
	7	0.06	0.00	0.00	0.94	0.03	1.98	0.50
	8	0.06	0.00	0.00	0.95	0.03	1.98	0.55
	9	0.06	0.00	0.00	0.97	0.02	1.99	0.58
	1	0.08	0.01	0.01	0.67	0.06	1.93	0.50
	2	0.07	0.01	0.00	0.74	0.07	1.96	0.50
	3	0.08	0.02	0.00	0.83	0.07	1.95	0.51
	4	0.07	0.02	0.00	0.87	0.06	1.97	0.52
2016	5	0.07	0.01	0.00	0.91	0.04	1.96	0.48
	6	0.06	0.02	0.00	0.92	0.04	1.97	0.52
	7	0.06	0.01	0.00	0.94	0.03	1.98	0.50
	8	0.08	0.01	0.00	0.95	0.03	1.98	0.52
	9	0.08	0.01	0.00	0.97	0.01	1.99	0.59

Table 13: IVQR - main findings

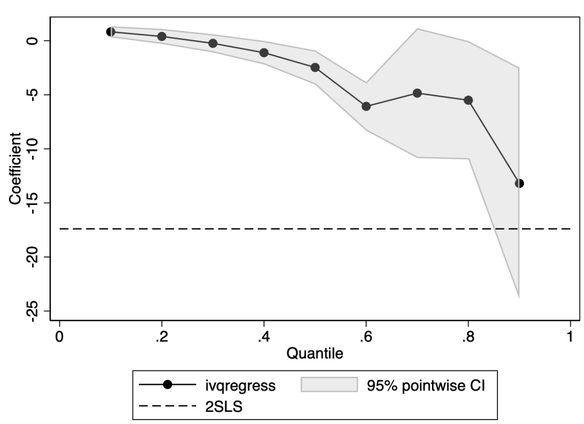
	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.82***	0.40	-0.24	-1.11**	-2.47***	-6.07***	-4.85	-5.50**	-13.20**
	(0.26)	(0.35)	(0.43)	(0.55)	(0.81)	(1.15)	(3.06)	(2.79)	(5.47)
Black	672.30**	626.46*	1,048.38***	1,626.34***	2,645.09**	7,543.50***	8,260.69**	15,689.45***	22,942.25**
	(341.26)	(366.09)	(403.21)	(544.83)	(1,060.61)	(2,153.60)	(4,050.03)	(5,009.72)	(9,497.86)
Asian	550.99	-25.34	-286.03	-496.79	-785.34	-1,507.09	-11,693.39	-10,094.68**	-23,401.68**
	(579.50)	(630.97)	(718.32)	(840.54)	(1,295.84)	(2,586.38)	(8,073.92)	(5,090.91)	(9,941.25)
Other	1,646.78**	368.49	448.08	-35.96	-870.10	-3,630.80*	-10,505.87	-16,284.13*	-31,987.56**
	(761.32)	(838.86)	(918.29)	(995.16)	(1,262.73)	(2,195.13)	(9,846.26)	(8,426.90)	(13,686.91)
Male	1,118.99***	905.20***	887.94***	1,045.11***	2,064.30***	7,304.19***	11,853.79***	21,010.81***	49,588.71***
	(205.69)	(217.05)	(238.01)	(277.56)	(400.84)	(833.11)	(2,431.14)	(2,296.14)	(5,191.50)
High School	1,402.51***	1,706.69***	4,629.81***	6,624.99***	17,320.86***	38,767.27***	60,744.79***	125,902.50***	231,829.08***
	(382.11)	(413.35)	(428.28)	(280.64)	(1,752.52)	(3,430.28)	(12,207.99)	(16,826.52)	(36,826.82)
GED	-721.56***	-336.10	599.66**	1,165.25***	3,165.24***	15,033.97***	10,825.29***	14,762.57***	32,820.04***
	(223.94)	(237.54)	(261.50)	(272.05)	(529.38)	(2,645.99)	(1,934.87)	(2,135.29)	(10,178.54)
State Category	-37.48*	-6.05	16.64	56.65*	104.28*	370.17***	453.63*	361.20	919.56
	(20.14)	(21.48)	(23.94)	(29.69)	(53.82)	(111.71)	(256.11)	(292.75)	(642.89)
Medicare	2,617.26***	2,433.15***	3,204.60***	3,560.24***	5,184.28***	9,733.28***	21,985.19***	25,575.67***	43,015.14***
	(620.94)	(689.00)	(748.37)	(796.99)	(1,426.75)	(2,063.35)	(6,802.22)	(4,373.00)	(5,688.68)
2013	426.15*	261.66	47.70	-249.34	-620.08	-2,284.35**	266.01	1,552.02	6,551.15
	(217.84)	(238.42)	(268.08)	(344.34)	(604.70)	(1,048.18)	(2,202.53)	(2,406.83)	(5,030.46)
2015	-409.54**	69.43	478.28**	1,150.11***	2,012.54***	4,883.55***	4,581.90*	6,130.80**	12,903.26***
	(184.65)	(194.32)	(218.13)	(297.40)	(510.77)	(1,027.30)	(2,407.43)	(2,605.92)	(4,786.33)
2016	-506.80**	65.87	587.20**	1,365.57***	2,453.39***	6,016.99***	4,549.08*	8,733.82***	27,799.39***
	(200.69)	(208.88)	(234.11)	(324.03)	(562.88)	(1,098.19)	(2,332.78)	(2,942.75)	(5,475.47)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	76,867	76,867	76,867	76,867	76,867	76,867	76,867	76,867	76,867
R-squared									

Table 14: 2SLS vs OLS

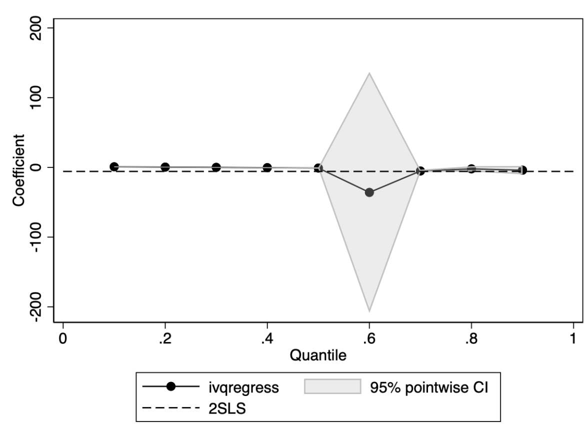
	2SLS	OLS
MCD	-17.40	-16.11***
	(54.78)	(0.94)
Black	-17,244.07	-15,963.74
	(41,409.22)	(34,747.55)
Asian	-68,248.00***	-66,486.51***
	(24,349.08)	(11,734.76)
Other	-37,264.29**	-36,182.66**
	(18,982.94)	(15,699.78)
Male	90,631.30***	91,107.62***
	(26,525.53)	(13,417.81)
High School	134,204.37	141,013.47***
	(99,903.99)	(15,048.60)
GED	18,901.18	21,750.71
	(37,825.25)	(16,175.35)
State Category	4.73	1.09
	(2,596.91)	(2,562.98)
Medicare	99,011.40	101,085.44***
	(88,436.12)	(6,839.61)
2013	10,674.84	11,052.86
	(20,859.57)	(9,743.39)
2015	175,797.70***	175,704.71***
	(29,579.19)	(30,397.11)
2016	19,606.64**	19,487.32**
	(9,602.95)	(9,641.00)
Year FEs	✓	✓
State FEs	✓	✓
Controls	30 ✓	✓
Observations	76,867	76,867
R-squared	0.00	0.00
F-stat	11	

Table 15: Descriptive statistics for the dependent group - all universe

Year	Quantile	Income / FPL	Financial asset	Net Debt	% Positive debt	Net equity	equity w/o home	equity w/o home/vehicle
	1.0	3.1	1374.2	36184.3	1.0	13980.4	-936.1	-8482.1
	2.0	2.3	273.9	9073.3	0.3	8137.1	1684.1	-421.5
	3.0	2.3	.	.	.	.	.	.
	4.0	2.3	182.1	8051.2	0.1	9187.7	2133.1	115.7
2013	5.0	3.2	1642.7	15606.1	0.3	15755.9	5104.8	1445.7
	6.0	4.0	5530.0	32670.7	0.5	26826.7	10424.1	467.3
	7.0	5.0	12961.9	47389.1	0.7	40349.9	51629.5	42173.6
	8.0	6.2	30427.4	48140.1	0.6	69183.2	167043.8	114150.7
	9.3	7.3	195756.6	-52085.8	0.5	124875.4	878983.3	862300.1
	1.0	3.2	1390.8	32998.3	1.0	17160.1	-670.5	-7745.1
	2.0	2.4	255.2	8174.8	0.3	9969.8	1670.4	-307.5
	3.0	.	.	.	.	.	.	.
	4.0	2.3	161.5	7836.1	0.1	11367.8	2159.4	111.9
2014	5.0	3.3	1541.7	15974.2	0.3	18500.1	4652.2	1272.9
	6.0	4.0	5427.5	30575.3	0.5	26354.0	15505.7	9383.4
	7.0	5.0	12501.1	45386.1	0.7	43124.5	49120.8	39931.9
	8.0	6.3	26709.4	50845.0	0.6	72873.4	134853.2	123349.7
	9.0	9.3	175095.9	-36818.1	0.5	136050.5	766586.4	751050.6
	1.0	3.3	1638.6	35890.4	1.0	16701.6	-584.9	-7986.9
	2.0	2.4	326.9	8285.7	0.3	9916.9	1579.3	-325.7
	3.0	.	.	.	.	.	.	.
	4.0	2.6	306.9	8194.9	0.1	11627.1	2442.6	192.5
2015	5.0	3.6	2054.7	18539.6	0.3	18873.5	5822.2	2020.1
	6.0	4.4	6623.2	32076.0	0.5	32757.3	19241.6	12489.8
	7.0	5.3	12886.4	48319.9	0.7	47856.9	55432.9	46130.0
	8.0	6.5	26902.6	50926.9	0.7	70669.2	147467.3	135704.7
	9.0	9.3	174593.0	-27465.6	0.5	149285.7	2.0e+06	2.0e+06
	1.0	3.2	845.0	10392.3	0.2	14374.2	3149.6	634.3
	2.0	2.4	416.0	9886.0	0.4	9667.4	1633.9	-464.3
	3.0	.	.	.	.	.	.	.
	4.0	2.7	315.1	7188.9	0.1	8397.1	2189.5	212.8
2016	5.0	3.7	2395.3	15965.5	0.3	19612.0	5892.9	2384.2
	6.0	4.5	7610.1	33689.0	0.5	32645.5	20557.5	1384.4
	7.0	5.7	14128.6	48140.9	0.7	51764.0	58875.9	49195.7
	8.0	6.3	32483.0	46889.6	0.5	119630.3	153767.5	141941.3
	9.9	9.9	218465.5	-82305.0	0.4	189951.7	845410.4	867853.9



(a) IVQR - positive net worth



(b) IVQR - all universe

Figure 8: Coefficient of MCD across quantiles

Table 16: Descriptive statistics for the control group - all universe

Year	Quantile	head is black	head is asian	head is other	high-school diploma	GED or other diploma	Receive medicare	Male
	1	0.02	0.00	0.00	0.80	0.10	1.94	0.45
	2	0.02	0.03	0.01	0.50	0.09	1.94	0.49
	3	.	.	.	.	.	.	.
	4	0.02	0.01	0.01	0.60	0.10	1.90	0.46
2013	5	0.04	0.00	0.00	0.72	0.07	1.96	0.53
	6	0.03	0.00	0.00	0.84	0.06	1.97	0.51
	7	0.03	0.00	0.00	0.90	0.05	1.98	0.50
	8	0.03	0.00	0.00	0.93	0.04	1.98	0.54
	9	0.03	0.00	0.00	0.96	0.02	1.99	0.58
	1	0.03	0.00	0.00	0.81	0.09	1.93	0.46
	2	0.04	0.03	0.01	0.49	0.09	1.93	0.49
	3	.	.	.	.	.	.	.
	4	0.04	0.01	0.00	0.60	0.11	1.90	0.47
2014	5	0.05	0.01	0.00	0.72	0.06	1.95	0.51
	6	0.06	0.00	0.00	0.84	0.06	1.97	0.50
	7	0.05	0.00	0.00	0.89	0.05	1.97	0.49
	8	0.05	0.00	0.00	0.93	0.04	1.98	0.52
	9	0.06	0.00	0.00	0.96	0.02	1.99	0.57
	1	0.03	0.00	0.00	0.80	0.09	1.93	0.45
	2	0.04	0.04	0.01	0.49	0.09	1.92	0.48
	3	.	.	.	.	.	.	.
	4	0.04	0.01	0.01	0.60	0.09	1.89	0.51
2015	5	0.08	0.00	0.00	0.74	0.07	1.94	0.48
	6	0.06	0.00	0.00	0.84	0.06	1.96	0.48
	7	0.05	0.00	0.00	0.91	0.04	1.97	0.50
	8	0.05	0.00	0.00	0.94	0.04	1.98	0.50
	9	0.07	0.00	0.00	0.96	0.03	1.98	0.57
	1	0.04	0.02	0.00	0.82	0.09	1.92	0.44
	2	0.04	0.05	0.01	0.51	0.09	1.91	0.48
	3	.	.	.	.	.	.	.
	4	0.06	0.02	0.01	0.61	0.10	1.90	0.50
2016	5	0.07	0.01	0.00	0.73	0.07	1.95	0.50
	6	0.07	0.02	0.00	0.85	0.07	1.96	0.51
	7	0.07	0.02	0.00	0.91	0.04	1.97	0.50
	8	0.06	0.01	0.00	0.94	0.03	1.98	0.50
	9	0.07	0.01	0.00	0.97	0.02	1.98	0.57

Table 17: Descriptive statistics for eligibility and coverage - all universe

Year	Quantile	Age	ELIG	SIMELIG	Beginning month of coverage	Ending month of coverage	Coverage
	1	38.71	0.05	0.08	1.97	12.00	0.11
	2	33.71	0.13	0.12	1.56	12.00	0.25
	3	.	.	.	.	.	.
	4	36.79	0.09	0.10	1.34	12.00	0.23
2013	5	36.05	0.04	0.09	1.82	12.00	0.10
	6	40.98	0.03	0.08	1.75	12.00	0.04
	7	45.02	0.01	0.07	2.12	12.00	0.02
	8	48.44	0.01	0.07	1.64	12.00	0.01
	9	51.89	0.01	0.07	1.32	12.00	0.01
	1	39.60	0.16	0.27	2.09	12.00	0.15
	2	34.17	0.30	0.28	1.68	12.00	0.32
	3	.	.	.	.	.	.
	4	37.45	0.27	0.28	1.62	12.00	0.32
2014	5	36.13	0.17	0.28	1.72	12.00	0.16
	6	40.45	0.11	0.26	1.93	12.00	0.08
	7	45.04	0.06	0.26	2.46	12.00	0.04
	8	48.38	0.05	0.26	2.40	12.00	0.02
	9	52.26	0.03	0.27	2.73	12.00	0.01
	1	39.78	0.16	0.26	1.62	12.00	0.18
	2	34.33	0.31	0.28	1.36	12.00	0.38
	3	.	.	.	.	.	.
	4	37.35	0.25	0.28	1.41	12.00	0.32
2015	5	37.14	0.16	0.28	1.54	12.00	0.16
	6	41.17	0.10	0.26	1.57	12.00	0.08
	7	45.49	0.05	0.25	1.79	12.00	0.04
	8	49.16	0.04	0.24	1.61	12.00	0.03
	9	52.53	0.04	0.24	2.45	12.00	0.01
	1	40.21	0.15	0.25	1.82	12.00	0.17
	2	35.41	0.31	0.28	1.40	12.00	0.38
	3	.	.	.	.	.	.
	4	36.62	0.25	0.30	1.46	12.00	0.34
2016	5	36.90	0.15	0.27	1.78	12.00	0.16
	6	41.15	0.10	0.27	1.51	12.00	0.07
	7	45.21	0.04	0.23	1.70	12.00	0.04
	8	48.39	0.05	0.23	1.73	12.00	0.03
	9	52.47	0.04	0.24	1.81	12.00	0.02

Table 18: IVQR - all universe

	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.88***	0.41*	0.05	-0.38	-0.92*	-35.90	-5.13***	-2.09	-4.03
	(0.30)	(0.23)	(0.25)	(0.31)	(0.48)	(88.17)	(0.91)	(1.93)	(3.08)
Black	1,809.15***	1,433.43***	1,243.29***	1,534.75***	2,839.49***	100,375.06	10,534.90***	12,892.49**	30,614.90**
	(699.48)	(320.22)	(300.31)	(352.11)	(877.25)	(123,019.52)	(2,459.45)	(5,303.92)	(12,563.73)
Asian	514.80	-35.89	110.45	432.18	1,022.61	79,803.29	5,187.26***	-792.85	-2,930.17
	(517.31)	(391.33)	(394.83)	(467.31)	(834.65)	(425,053.85)	(1,646.37)	(1,810.53)	(2,983.81)
Other	1,294.85**	474.21	314.27	404.86	619.88	46,149.87	2,451.13	-1,126.46	-5,226.06
	(516.91)	(407.64)	(415.98)	(460.17)	(663.12)	(440,785.69)	(2,545.60)	(1,458.01)	(3,195.33)
Male	1,579.27***	1,487.72***	746.96***	647.20***	728.74***	27,536.00***	6,957.93***	7,554.80***	26,618.46***
	(494.91)	(259.97)	(193.78)	(202.07)	(246.72)	(3,748.10)	(1,221.34)	(2,722.48)	(3,109.66)
High School	-9,611.42***	-1,826.82***	296.41	1,431.63***	3,585.37***	-21,667.23	22,955.07***	96,135.80***	225,227.72***
	(1,330.99)	(273.33)	(315.43)	(301.52)	(179.46)	(13,201.42)	(2,455.27)	(9,738.12)	(18,075.34)
GED	-11,977.72***	-3,847.08***	-1,212.31***	-804.16***	-227.29	35,059.64	3,483.11**	5,412.04***	26,502.66***
	(1,367.74)	(311.46)	(198.40)	(219.67)	(242.16)	(57,294.81)	(1,397.77)	(1,530.02)	(3,637.99)
State Category	-3.42	-12.89	1.18	12.79	38.42	1,958.85***	359.92**	155.26	402.82
	(48.38)	(20.23)	(17.25)	(18.35)	(27.08)	(282.35)	(154.03)	(162.28)	(391.72)
Medicare	-428.81	1,084.00**	1,071.10**	1,223.00**	1,709.64***	33,494.54***	8,749.35***	9,867.75***	22,628.27***
	(595.16)	(513.08)	(462.52)	(497.33)	(596.68)	(4,097.28)	(2,412.49)	(2,166.83)	(2,463.57)
2013	-82.72	-137.77	-108.87	-227.37	-476.13	-27,154.53***	-2,351.33*	689.30	4,180.13*
	(374.68)	(187.21)	(167.27)	(187.18)	(323.57)	(1,854.19)	(1,267.41)	(1,187.46)	(2,466.90)
2015	-502.58	-296.32	70.41	380.28*	1,016.85**	64,473.42**	5,253.20***	3,245.91	9,087.75**
	(421.60)	(205.24)	(173.21)	(198.36)	(455.28)	(32,212.58)	(1,243.03)	(2,075.36)	(4,597.92)
2016	-1,085.31**	-260.34	89.67	438.10**	1,138.09***	54,609.07***	4,904.44***	2,939.81*	9,923.25**
	(480.32)	(200.76)	(171.67)	(195.14)	(438.27)	(15,435.63)	(1,281.46)	(1,743.83)	(4,820.67)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799
R-squared									

Table 19: IVQR - robustness check

	q1	q2	q3	q4	q5	q6	q7	q8	q9
main									
MCD	0.85**	0.41*	-0.24	-2.72	-1.90	-1.60*	-2.22**	-2.18**	-3.67*
	(0.36)	(0.23)	(0.29)	(12.98)	(1.39)	(0.95)	(0.91)	(1.09)	(2.21)
Income	0.22***	0.25***	0.26***	0.97***	2.03***	4.09***	8.03***	13.99***	27.68***
	(0.05)	(0.04)	(0.04)	(0.22)	(0.14)	(0.17)	(0.19)	(0.41)	(0.85)
Black	1,939.47***	1,344.17***	1,178.54***	2,830.68	2,481.69*	775.87	-1,680.84	-2,644.51	-11,487.32**
	(662.55)	(337.00)	(337.12)	(2,430.72)	(1,453.67)	(1,067.66)	(1,674.22)	(2,901.61)	(5,802.31)
Asian	731.61	124.63	628.59	3,446.50	3,463.45	2,879.61	3,481.29	599.13	-2,172.76
	(488.76)	(376.17)	(447.87)	(3,637.03)	(3,261.36)	(2,717.42)	(2,803.63)	(3,035.80)	(4,625.05)
Other	1,329.26***	340.00	327.15	1,141.19	238.19	-1,204.21	-1,928.42	-5,073.53	-12,437.69**
	(470.20)	(408.18)	(461.04)	(1,292.83)	(2,022.69)	(2,416.67)	(2,913.87)	(3,683.43)	(5,830.57)
Male	1,615.60***	1,315.05***	522.82***	600.62	722.69*	1,553.99***	3,058.74***	6,816.12***	13,487.29***
	(506.95)	(235.45)	(179.51)	(1,133.86)	(428.23)	(529.12)	(654.42)	(1,046.88)	(2,680.91)
High School	-10,102.90***	-2,217.30***	-170.26	1,930.18	3,548.42***	6,680.32***	11,060.29***	18,421.49***	38,056.90***
	(1,367.94)	(227.17)	(303.82)	(1,549.78)	(310.06)	(349.72)	(597.33)	(1,150.37)	(4,248.84)
GED	-12,086.77***	-4,018.11***	-1,288.60***	-476.59	115.28	1,045.73	2,761.90***	5,574.09***	9,904.32***
	(1,397.13)	(325.00)	(245.03)	(1,659.88)	(378.90)	(642.36)	(861.57)	(1,188.03)	(2,118.67)
State Category	-3.05	-4.81	7.60	57.94*	61.77	109.31*	116.18	107.88	339.72
	(46.94)	(20.99)	(17.66)	(34.64)	(41.29)	(58.19)	(99.61)	(156.21)	(347.59)
Medicare	-831.87	479.58	123.76	-2,443.41	-1,502.25	-383.15	41.75	5,255.72**	13,523.19***
	(606.91)	(425.83)	(430.29)	(6,080.19)	(2,155.28)	(1,890.34)	(2,196.91)	(2,255.65)	(3,883.24)
2013	21.77	-78.16	-167.74	-704.49	-545.44	-250.93	-485.49	1,556.77	2,751.95
	(369.47)	(194.97)	(179.97)	(811.08)	(554.59)	(681.57)	(918.67)	(1,233.46)	(2,688.90)
2015	-549.67	-266.54	114.58	1,081.30	1,585.74**	2,204.65**	2,655.53**	4,248.77***	6,988.48**
	(428.40)	(209.36)	(187.95)	(1,076.32)	(752.77)	(952.76)	(1,085.72)	(1,518.10)	(2,923.78)
2016	-1,133.94**	-423.53**	-28.77	735.42	1,080.70	1,474.51	1,512.77	2,648.00*	5,524.24*
	(477.64)	(215.98)	(191.68)	(1,576.64)	(902.09)	(899.50)	(1,131.35)	(1,424.71)	(3,162.09)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799	48,799
R-squared									

B Declaration of Authenticity

I, Paul Sibille, affirm that I have independently written this work and that no sources other than those explicitly mentioned in this research have been used. All quotes and references from other works are properly cited and clearly marked. This thesis has not been submitted in the past in the same or similar form to any examination board. Finally, I confirm that I am aware my thesis will be subjected to electronic plagiarism checks. For this purpose, I consent to the anonymous distribution of my thesis to servers located outside the University of Liège.

Liège, 06$^{\text{nd}}$ August 2024

C Executive summary

Public health insurance, particularly Medicaid, plays a crucial role in the economic behaviors of individuals, including their savings. This study gather data from the Survey of Income and Program Participation (SIPP) and the Current Population Survey (CPS) to analyze how variations in Medicaid coverage influence savings across different wealth levels, especially in the context of the Affordable Care Act (ACA) implemented in 2014.

The methodology employed in this research combines 2-Stages Least Squares (2SLS) regression with Quantile Regression (QR) to address endogeneity issues and capture the differential impacts across the different deciles wealth distribution. A recent instrument, the Simulated Medicaid Eligible Dollar (SIMMED), was developed and used as an instrument in the Instrumental Variable Quantile Regression (IVQR).

The key findings of this study indicate that Medicaid coverage significantly increases savings for the poorest individuals, with an additional dollar of coverage resulting in an increase of $0.82 in savings. Conversely, for middle-saver groups, Medicaid coverage is associated with a reduction in savings. These results highlight the complexity of Medicaid's impact on economic inequality and show the importance of considering both the benefits and drawbacks of Medicaid expansions.

We assess the robustness of our findings by extending the sample to include individuals with negative or zero net worth and incorporating income as a control variable. Our analysis concludes with partial robustness of the results: while the positive effect of Medicaid coverage on savings remains significant for the lower deciles, the coefficient's pattern across all quantiles deviates from that observed in the main regression analysis.

Overall, this thesis provides valuable insights into the relationship between Medicaid coverage and individual savings, offering important implications for policymakers. By using IVQR and robust data analysis, the study contributes to the existing literature on public health insurance and economic inequality.

Keywords: Medicaid, savings, economic inequality, Affordable Care Act, 2-Stage Least Square (2SLS), Quantile Regression (QR) Instrumental Variable Quantile Regression (IVQR). [5]

[5] Word Count: 12455