ABSTRACT

BREAK A LEG- JUST NOT IN ALABAMA: ANALYZING THE TIMING OF MEDICAID'S ADOPTION AND STATE VARIATION IN MEDICAID ELIGIBILITY

by Haley Grace Liqing Mull

Medicaid is a joint federal-state health insurance program targeting the low-income population. The program covers nearly 20% of all Americans and accounted for $592 billion in 2017. Medicaid was originally introduced in 1965 as an optional program without mandatory financial eligibility minimums. By 1982, all 50 states had established a program but at vastly different levels of eligibility. In this paper, I analyze the factors that impacted a state's adoption of Medicaid and the factors affecting eligibility generosity for pregnant women, infants, children, and other adults. I find that politics and health environment factors were insignificant in explaining the adoption of Medicaid. However, with respect to eligibility, these same health environment and political factors become significant in explaining differential levels of eligibility generosity. Moreover, higher income states had an increased probability of having a Medicaid program in the following year and are more generous in their eligibility limits. In both models, demographic factors provide conflicting evidence to support the basic ideas of the Median Voter Theorem. Regression findings for adoption and eligibility generosity are generally robust across models. Finally, future work might examine eligibility generosity for other populations benefiting from Medicaid or apply the models to a variety of optional benefits.

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Haley Grace Liqing Mull

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Adviser: Dr. Melissa Thomasson

Reader: Dr. Austin Smith

Reader: Dr. Gregory Niemesh

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by

Haley Grace Liqing Mull

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Farmer School of Business

and

Department of Economics

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Dr. Melissa Thomasson

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Dr. Austin Smith

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Dr. Gregory Niemesh

# Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction

Reflecting on the passage of Medicare and Medicaid in the Social Security Amendments of 1965, Wilbur Cohen, former Secretary of the Department of Health, Education, and Welfare wrote, "For 9 years (1957-65), Medicare and Medicaid were highly controversial issues" (Cohen 1985). However, with 2020 Democratic candidates spending 12% of airtime debating health care over the course of three primaries, it appears the contention Cohen noted did not simply vanish when the programs were enacted (Brown and Scott 2019). Questions the architects of Medicare and Medicaid asked in the early 1960s still exist today. Should we have government sponsored health insurance? If so, who is eligible, what benefits should be offered, and how do we go about financing such an ambitious program?

Medicaid, specifically, was not originally thought of as anything more than a collection of legalese overshadowed by the novelty of Medicare Part B (Cohen 1985). Neither the program's drafters nor health policy experts estimated the impact Medicaid would eventually come to have on the American people or on government budgets. For example, costs for the program were originally estimated to increase federal health care spending by $250 million, but within its first year, Medicaid expenditures for both the federal and state governments totaled $1.5 billion (Oberg and Polich 1988). More recently, during the 2017 fiscal year, the government spent $592 billion and provided approximately 74 million Americans with health insurance coverage- including 38% of all children- through Medicaid alone (Medicaid and CHIP Payment and Access Commission

2019b; "Health Insurance Coverage of Children 0-18" 2020).

Unsurprisingly, the sheer enormity of federally funded health insurance has inspired countless researchers to examine the effects of these programs on a variety of health and economic outcomes. Medicaid is a particular program of interest due to wide cross-state variation in Medicaid programs. Unlike Medicare, Medicaid was established as a joint program between the federal and state governments and remains as such today (Skowronski 2018). This means that while the federal government sets mandatory minimums for benefits and eligibility[1], states have wide latitude to expand their Medicaid program.

Diversity amongst state Medicaid programs has existed since the program's beginning (Cohen 1985). Moreover, this variation occurs on both interstate and intertemporal dimensions. For example, Oklahoma was one of the first states to establish a Medicaid program in January of 1966, before the legislation even took effect. In contrast, Arizona did not adopt a Medicaid program until 1982 (Kaiser Commission on Medicaid and the Uninsured 2012). Today, however, non-disabled, non-elderly, non-pregnant, childless adults are ineligible for Medicaid in Oklahoma, but are covered up to 138% of the federal poverty level (FPL) in Arizona. While many empirical researchers have exploited the broad variation in Medicaid programs to infer causality, few have studied the factors that first led and that continue to impact the intertemporal and interstate variation in the program. I aim to synthesize the qualitative knowledge of Medicaid's evolution with empirical data. Specifically, I seek to identify the variables that impacted a state's decision to first adopt Medicaid, as well as identify the factors that have contributed to the differential levels of generosity in financial eligibility.

In sections 2 and 3, I lay out the historical context for Medicaid, trace the evolution of eligibility expansions, and summarize the most important aspects of the current Medicaid program. Section 4 expands on the existing literature referenced above. In Section 5, I examine the data, empirical strategies employed, and hypothesized signs for coefficients. My analysis begins in section 6, where I explore states' decisions to adopt Medicaid. In Section 7, I then turn to analyzing cross-state variation in financial eligibility. Due to a change in how eligibility for Medicaid was calculated, I divide Section 7 into two subsections. The first subsection examines eligibility generosity using the

[1]Federal minimums have evolved over time. See section 3 for a list of Medicaid eligibility expansions.

Aid to Families with Dependent Children "payment" and "need" standards[2]. The second subsection measures eligibility generosity by comparing a state's eligibility to any existing federally mandated minimum levels of eligibility. Finally, I conclude in Section 8.

[2]See Section 3 for a detailed description of Medicaid eligibility.

# Chapter 2

# Fundamentals of Medicaid

## 2.1 Program background

The underpinnings of Medicaid can be traced back to the Progressive Era, when labor reformers began campaigning for mandatory sickness insurance at the state level. Inspired by existing European programs, proponents called for compensation to workers who had to forego wages due to illness. It is important to note that the focus of sickness insurance was on providing cash benefits to the ill rather than paying for treatment, as the costs associated with foregone wages and funerals far outweighed the costs of medical care (Berkowitz 2005). During this time, sickness insurance was provided by a combination of "fraternal societies, mutual benefit organizations ... trade unions... employers... [and] commercial casualty firms" (State of Illinois 1919).

Reformers with the American Association for Labor Legislation (AALL) first proposed a plan where employers, employees, and the state would contribute to a fund and, in turn, workers would receive both cash benefits to cover disability induced foregone wages and funerals as well as medical care and medicine. However, the demand for true health insurance had not yet been established and the demand for sickness insurance was already met. In addition to a lack of demand, key stakeholders were opposed to the AALL's plan. Existing commercial insurance companies were excluded and did not have a systematic calculate to measure the risks associated with the subjective idea of "health." After initial interest, physicians and the American Medical Association (AMA) officially rejected any mandatory government-sponsored health or medical insurance program in 1920, primarily citing potential reductions in income and negative experiences with prior labor reform legislation (Thomasson 2020).

During the New Deal Era, the cost of medical care overtook the cost of foregone wages, and the focus shifted to what we now consider health insurance. Founded in the twenties, the Committee on the Costs of Medical Care, a privately funded organization consisting of economists and health specialists, officially recognized the need for medical insurance but suggested a private system could provide it. However, this did not stop lobbyists from trying to persuade the government to enact national health insurance. Proponents attempted to embed a national health insurance program in the original Social Security Act of 1935. Unfortunately for advocates, unemployment insurance and old age benefits took precedence. Fearing AMA opposition could kill the entire Social Security Act, legislators opted to exclude government sponsored health insurance. Four years later, the Roosevelt administration once again tried to establish a national health program with the introduction of the Wagner Bill, or National Health Care Act of 1939. The Wagner Bill was intended to allot federal grants to state and local governments in order to administer a general national health program. This time, an increase in conservative power in Congress and the start of WWII prevented the bill from becoming law (Palmer 1999).

Following World War II was a concentration of power at the national level and a boost in confidence of the federal government's capabilities. Having witnessed the government guide the U.S. to victory, Americans believed the federal government could further extend its abilities to improve the economic and social environments (Higgs 1999). It is unsurprising that the health insurance debate reappeared during this time. Due to the trust in and power of the federal government, policy makers specifically focused on the establishment of a national health insurance program. Unfortunately, bills did not pass due to a variety of reasons such as not targeting the majority population and opposition from interest groups. Moreover, private plans like Blue Cross had been established and enjoyed a first mover advantage by crowding out the need for a federally sponsored program. The federal government did, however, succeed in rebranding the idea of health insurance as a program for the elderly rather than the unemployed. Additionally, they learned states were too ingrained in existing welfare systems to simply be tossed aside (Berkowitz 2005).

The first idea of a program resembling the original Medicaid legislation came in 1942 when Rhode Island requested to use public assistance funds to pay providers for some citizens' medical care. While the Social Security Board ultimately refused to authorize Rhode Island's request, members began to draft amendments to the original Social Security Act of 1935 that would allow states to use federal funds to pay medical vendors directly. After years of debate, these so called vendor payments were approved and included in the 1950 Social Security Amendments (Cohen 1985). According to Moore and Smith (2005), "this law provided Federal matching funds for a limited program of State medical payments to vendors... for people who were receiving cash welfare payments" ("Evolution of Public Welfare Programs" 1970).

The medical vendor payment program was further extended with the passing of the Kerr-Mills bill in 1960. Kerr-Mills introduced the Medical Assistance for the Aged (MAA) program which allowed for medical vendor payments to be made on behalf of "medically indigent" elderly Americans not currently receiving Old Age Assistance (OAA) ("Evolution of Public Welfare Programs" 1970). To track the success of the MAA program, Congress created the following four objectives:

> (1) all States establish MAA programs, (2) the programs include a comprehensive range of medical services consistent with the needs created by the poorer health generally suffered by the aged, (3) the eligibility requirements be realistic in terms of the health expense and financial resources of the aged, and (4) the assistance be made available without humiliating or degrading our older people (Subcommittee on Health of the Elderly 1963)

However, the Subcommittee on Health of the Elderly and Special Committee on Aging determined MAA to be inefficient and riddled with issues. By 1963, only 28 states had programs established and less than 1% of the nation's elderly received the minimal benefits offered. Moreover, financing was concentrated in a few states despite the fact that these states had small populations of the elderly (Subcommittee on Health of the Elderly 1963). Figure 2.1 indicates which states had an MAA program by 1965 when legislation for Medicaid was first introduced.

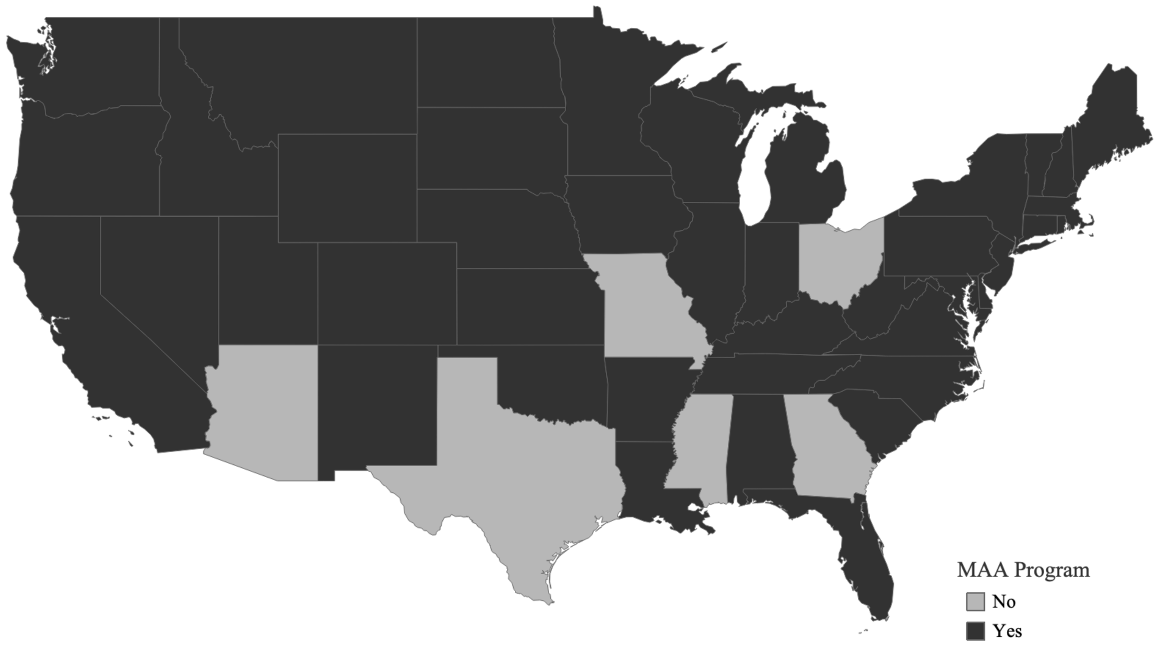



Figure 2.1: States with a Medical Assistance for the Aged Program in 1965

With the Special Committee on Aging concluding “that the congressional intent has not and will not be realized,” it is no surprise Congress decided to discontinue the program by 1970 (Subcommittee on Health of the Elderly 1963). However, rather than completely abandoning Kerr-Mills, Congress decided to keep the goal of assisting the needy with medical costs and transform it into what we know today as Medicaid. In the midst of the War on Poverty, the Johnson administration signed Medicaid into law under Title XIX of the Social Security Amendments of 1965. Though states were not required to adopt the program, the federal government threatened to cease reimbursing states for existing Kerr-Mills vendor payments after December 31, 1969 (Moore Smith, 2005). Despite this threat, Alaska and Arizona did not adopt Medicaid until July 1972 and October 1982, respectively (Kaiser Commission on Medicaid and the Uninsured 2012).

| 1966 | 1967 | 1968 | 1969 | 1970 | 1982 |
|---|---|---|---|---|---|
| CA ME PA | GA TX | SC | CO | AL | AZ |
| CT MI RI | IA WY | | TN | AR | |
| DE MN UT | KS | | VA | FL | |
| ID ND VT | MO | | | IN | |
| IL NE WA | MT | | | MS | |
| KY NM WI | NH | | | NC | |
| LA NY WV | NV | | | NJ | |
| MA OH | OR | | | | |
| MD OK | SD | | | | |

Figure 2.2: Year of Initial Medicaid Adoption

As seen in Figure 2.2, most states had adopted Medicaid by 1968, and those that had not adopted were primarily located in the South. This is not too shocking, especially after noting that all Democratic party defectors in the Senate and 95% of the party's defectors in the House came from Southern states during the vote for the Social Security Amendments of 1965[1] ("Senate Vote 151 in 1965 (89th Congress)" 1965; "House Vote 35 in 1965 (89th Congress)" 1965). Furthermore, during the 1960s, the political ideologies of office holding Southern Democrats aligned more closely with the Dixiecrats- a conservative sect of the evolving national Democratic party who supported segregation and limiting Black Americans' voting rights (History.com Editors 2019). As Medicaid would disproportionately benefit the Black American population, it is unsurprising that the Southern Democrats in power would prevent Medicaid's adoption for as long as possible.

Originally, Medicaid was limited to only those receiving benefits from Aid to Families with Dependent Children, AFDC (Medicaid and CHIP Payment and Access Commission 2018; Grogan 1994). AFDC, formerly known as Aid to Dependent Children, has its origins in the Social Security Act of 1935. Under AFDC, states were provided funding to help "needy children who had been deprived of parental support or care because their father or mother was absent from the home, incapacitated, deceased, or unemployed." By the time Medicaid was being drafted, all 50 states plus the District of Columbia, Guam, Puerto Rico, and the Virgin Islands had established an AFDC program. Each state was allowed to define its own "need standard," "payment standard," income

[1]Note, because legislation for Medicare and Medicaid were both contained in the 1965 amendments, we cannot attribute defection entirely to Medicaid's existence.

and resource limit, and benefit level subject to a federal minimum (Hansan n.d.). As stated in Grogan's paper, Political-Economic Factors Influencing State Medicaid Policy, "the need standard is supposed to be an objective measure reflecting the state's true determination of need and the payment level is that which the state can realistically afford to offer" (Grogan 1994).

As previously mentioned, Medicaid coverage was initially only available to those receiving AFDC benefits. In other words, the "payment standard" dictated Medicaid financial eligibility (Grogan 1994). Prior to 1981, most states had a "needy standard" equivalent to their "payment standard." Over time though, "need standards" began to increase while "payment standards" stagnated ("A Brief History of the AFDC Program" 1998). This further generated variation in state generosity as measured by the ratio of "need" to "payment." It is also important to note that AFDC "payment" standards were often far below the official federal poverty level.

Medicaid financial eligibility no longer depends on receipt of AFDC. In fact, AFDC was abolished in 1996 and replaced with Temporary Assistance to Needy Families (TANF)[2](Medicaid and CHIP Payment and Access Commission 2018). While AFDC has been dissolved, Medicaid's two dimensions of eligibility remain: categorical eligibility and financial eligibility. Categorical eligibility essentially segments recipients into groups who generally have similar health needs and treatments. These include dependents, pregnant women, the disabled, the aged, parents/caretakers, and more recently, non-disabled, non-elderly childless adults. It is important to note that states are required to extend eligibility to all of the listed groups except the non-disabled, non-elderly, non-pregnant, childless adults. Meanwhile, financial eligibility is based on the federal poverty level (FPL). States must cover all federally mandated categories at their 1996 AFDC "payment" standards. Subject to federal minimums, each state can choose a cutoff percentage of the FPL for each categorical group eligible to receive Medicaid (Medicaid and CHIP Payment and Access Commission 2020c).

In general, persons who are blind or disabled, and persons over age 65 who also receive Supplementary Security Income (SSI) benefits also qualify for Medicaid. The latter group, known as dually eligible, are enrolled in both Medicaid and Medicare and, in 2013 made up 15% of Medicaid enrollees and accounted for 32% of Medicaid expenditures (Medicaid and CHIP Payment

[2]A detailed discussion of major eligibility expansions can be found in Section 3.

and Access Commission 2020b). While all states with a Medicaid program are required to cover SSI beneficiaries, some states have elected to enact stricter Medicaid financial eligibility standards for SSI recipients. States that choose this option are known as 209(b) states. While financial eligibility is stricter, 209(b) states are required to grant a spend down allotment, which allows individuals to deduct certain medical expenses in order to meet the stricter financial standard (Office of the Assistant Secretary for Planning and Evaluation 2010). In 2019, eight states including Hawaii utilized the 209(b) option (Medicaid and CHIP Payment and Access Commission 2019c, 37).

There is one more avenue through which an individual may qualify for Medicaid: Medically Needy programs. Similar to 209(b) states, Medically Needy programs allow individuals to deduct medical expenses from countable income in order to meet the state's financial eligibility level. It is important to note that individuals must still meet the state's categorical eligibility (Medicaid and CHIP Payment and Access Commission 2020c). Medically Needy programs are optional, and in 2018, 34 states including Hawaii ran a Medically Needy program (Kaiser Family Foundation 2018b).

## 2.2 A glance at the program today

In addition to eligibility, there are other aspects of Medicaid that are important to understand. These include the difference between Medicaid and Medicare, Medicaid financing, provider reimbursement systems, benefits offered, and waivers, which are used to make states' programs more flexible.

There are several important distinctions to be made between Medicaid and Medicare. First, Medicaid is a program meant to serve low income persons. This may include, but is not limited to, citizens over 65 years. Second, Medicaid is a joint program run by both the states and the federal government. As a result, there is wide variation in Medicaid policies between states. In contrast, Medicare is a federalized program and fairly uniform across the country. Third, most recipients of Medicaid receive services for free or at minimal cost, while Medicare beneficiaries pay typical insurance costs like deductibles, premiums, and co-pays (Skowronski 2018).

Medicaid expenses are shared between the states and federal government. In order to receive federal funding, states must meet the minimum federal requirements for the program. Each fiscal year, the federal government calculates a federal medical assistance percentage (FMAP) to determine what percentage of state contributions it will match. The FMAP is inversely related with a state's average per capita income, so that states with the lowest per capita income receive the highest matching rates. Additionally, there is a minimum FMAP of 50% and maximum FMAP of 83%; though both boundaries have been adjusted for certain exceptions like the Great Recession and Hurricane Katrina (Mitchell 2018).

When Medicaid was first established in 1965, only five services were mandatory: inpatient hospital care, outpatient hospital care, laboratory and x-ray services, skilled nursing home services for those over 21, and physicians' services (Moore and Smith 2005). Over the course of fifty-five years, Congress expanded mandatory benefits to include home health services, federally qualified health center services, family planning services, nurse midwife services, certified pediatric and family nurse practitioner services, licensed freestanding birth center services, transportation to medical care, and tobacco cessation counseling services for pregnant women (Centers for Medicare and Medicaid Services n.d.). All other benefits are optional, further contributing to overall variation in state Medicaid policies. For example, only 43 states cover optometry services, while all 50 offer outpatient prescription drugs to the categorically eligible (Centers for Medicare and Medicaid Services n.d.; Kaiser Family Foundation 2018a).

One of the most common ways for states to modify their Medicaid policies is through the use of Medicaid waivers. The three main types of waivers are Section 1915(b) waivers, Section 1915(c) waivers, and Section 1115 waivers. Section 1915(b) waivers promote the use of managed care plans by requiring Medicaid beneficiaries enroll in a managed care plan. Section 1915(c) waivers give certain enrollees the option of choosing home- and community- based services rather than being institutionalized (National Association of Community Health Centers n.d.). Finally, Section 1115 waivers grant states the ability to experiment with and innovate their Medicaid programs to further promote the goals of Medicaid (Centers for Medicare and Medicaid Services n.d.).

One way in which Section 1115 waivers had been used was to develop supplementary health insurance programs for groups not specifically meeting the criteria for categorical eligibility. As early as 1989, states used Section 1115 waivers to obtain federal matching funds to begin extending benefits to non-elderly, non-disabled, non-pregnant, childless adults. Rather than using a Section 1115 waiver, a few other states created a fully funded program for this category. Programs for this group were often limited in benefits, subject to enrollment caps, and included sliding scale fees or higher cost sharing. Finally, some states opted to subsidize private insurance rather than offering these limited Medicaid plans to non-elderly, non-disabled, non-pregnant, childless adults (Rudowitz, Artiga, and Arguello 2013).

# Chapter 3

# Evolution of Medicaid Eligibility

Since its implementation, Medicaid has been amended to better accommodate the ever-changing American landscape. For example, only two years after Medicaid's adoption, Congress established the Early and Periodic Screening, Diagnosis, and Treatment Service as a required benefit for Medicaid beneficiaries under the age of twenty-one (Provost and Hughes 2000). In 1972, the government federalized state-run assistance programs for the aged and combined them with the Aid to the Blind and Aid to the Permanently and Totally Disabled programs to create Supplementary Security Income, or SSI ("Overview and Background" 2006). States that adopted Medicaid were required to extend coverage to nearly all SSI recipients or those meeting 1972 state criteria (Schneider et al. 2003). This 1972 legislation also created the 209(b) state option discussed in the prior section (Office of the Assistant Secretary for Planning and Evaluation 2010).

During the 1980s, Congress began to incrementally decouple Medicaid from AFDC using a series of expansions to increase income eligibility beyond AFDC standards for pregnant women and children. The Deficit Reduction Act of 1984 (DEFRA) required that states cover all children under the age of 6 who met the state's AFDC standard, a state designated level of income qualifying a person as "needy," regardless of family composition. Additionally, states had to extend coverage to "first-time pregnant women, and pregnant women in 2-parent unemployed families meeting state AFDC income and resource standards" (Schneider et al. 2003). A year later, the Consolidated Omnibus Budget Reconciliation Act (COBRA) of 1985 annulled the unemployment requirement for pregnant women in 2-parent families. OBRA-86 gave states the option to cover pregnant women and children under age 6 at or below 100% of the federal poverty level (FPL). Meanwhile, OBRA-87 expanded the 100% FPL cutoff to 185% for pregnant women and infants and extended optional coverage to children under the age of 9 at 100% FPL. In 1988, the Medicare Catastrophic Coverage Act and Family Support Act (MCCA) mandated that states begin to phase-in coverage for pregnant women and infants with incomes below 100% FPL and cover 2-parent unemployed families meeting AFDC standards. OBRA-89 required states to cover pregnant women and children 5-years and younger at 133% FPL (Schneider et al. 2003).

While fewer amendments were made, the 1990s continued the trend of expanding coverage to pregnant women and children. OBRA-90 created a requisite phase-in of children ages 6 through 18 in families with income at or below 100% FPL (Schneider et al. 2003). Congress anticipated that by September 30, 2002 all dependents less than 19 and meeting the income cutoff and AFDC resource standards would be eligible for Medicaid. The passing of the Personal Responsibility and Work Opportunity Act of 1996 (PRWOA) signified the complete separation between AFDC and Medicaid. AFDC was formally abolished and replaced with Temporary Aid to Needy Families, TANF. Families that received TANF benefits were no longer automatically eligible for Medicaid. However, at a minimum, states were required to cover all families meeting July 16, 1996 AFDC eligibility standards. The Ticket to Work and Work Incentives Improvement Act of 1999 allowed states to cover the working disabled with income above 250% FPL but required income-related premiums (Medicaid and CHIP Payment and Access Commission 2018).

In perhaps the biggest expansion for children since Medicaid's establishment, Congress passed the Balanced Budget Act of 1997, which created the State Children's Health Insurance Program, commonly known as SCHIP or CHIP. This program provided states with the ability to cover uninsured children living in families too rich for Medicaid but too poor to afford private insurance, and supplemented state funding with an enhanced FMAP for CHIP (Schneider et al. 2003; Medicaid and CHIP Payment and Access Commission 2018). Some states have elected to use CHIP funds to also cover pregnant women and/or unborn children (Medicaid and CHIP Payment and Access Commission 2020a). States implement CHIP with either a separate program, Medicaid expansion, or a combination of the two (Hearne and Neisner 1998). Separate programs and Medicaid expansions generally follow different federal guidelines. Separate programs tend to be more flexible by "allow[ing] states to design benefit packages that look more like commercial insurance than Medicaid... charge premiums,... create waiting periods,... and brand and market their CHIP programs separate from Medicaid" (Medicaid and CHIP Payment and Access Commission 2020d). In 2019, an overwhelming majority of states used a combination approach in implementing CHIP (Medicaid and CHIP Payment and Access Commission 2019a). Various pieces of legislation have made CHIP even more robust by increasing the enhanced FMAPs, linking a child's Medicaid eligibility to participation in other programs such as HeadStart and the Supplemental Nutritional Assistance Program (SNAP), and extending CHIP through 2027 (Medicaid and CHIP Payment and Access Commission 2018).

After the major expansions of the late 1980s and 1990s, Congress hesitated to extend eligibility further and even called for a phasing out of coverage for parents in the Children's Health Insurance Program Reauthorization Act (CHIPRA) of 2009. However, only a year later, the Patient Protection and Affordable Care Act, or ACA, made it through the gauntlet of bureaucracy. The ACA originally called for mandatory Medicaid expansions to nearly all individuals under the age of 65 with income less than 133% of the federal poverty level and proposed a tax on all citizens who did not comply with the requirement to have health insurance coverage (Medicaid and CHIP Payment and Access Commission 2018; National Federation of Independent Business v. Sebelius 2012). Furthermore, states who refused to enforce the mandate were threatened with the loss of their Medicaid funding. However, 26 state Attorneys General, the National Federation of Independent Businesses, and two private citizens challenged the constitutionality of the ACA. The case eventually made its way to the Supreme Court, where the Justices decided that with the removal of the threat to withhold Medicaid funding, the ACA was constitutional. This essentially made expansion voluntary (National Federation of Independent Business v. Sebelius 2012). Since the Court's decision was passed down, 36 states and Washington DC have expanded Medicaid (Kaiser Family Foundation 2020).

# Chapter 4

# Previous Empirical Research

Since Medicaid's adoption in 1965, most empirical literature about the program and its expansions focuses on the policy's effects on a wide variety of topics, such as health outcomes, utilization and take up, and costs. Currie and Gruber (1996; 1994; 2001), Bronchetti (2014), and Goodman-Bacon (2018) each study the effects of Medicaid on health outcomes, specifically for pregnant women, children, or infants. Between 1994 and 2001, Currie and Gruber published three papers investigating the effects of eligibility expansions in the late 1980s and early 1990s on birth outcomes, child mortality, and treatment intensity for pregnant women. In their 1994 and 1996 papers, Currie and Gruber use a simulated measurement for infant and child eligibility to combat omitted variable bias. Cross-state variation in simulated eligibility is exploited to identify the causal effect of Medicaid eligibility for children on their utilization of care and health outcomes (Currie and Gruber 1996) and eligibility for pregnant women and birth outcomes (Currie and Gruber 1994). Currie and Gruber (1996) find that while take up rates while low, insured children increased their utilization of medical care and child mortality decreased. Meanwhile, policies that expanded eligibility to previously ineligible groups of pregnant women were associated with large and significant decreases in infant mortality but insignificant changes in low birthweight incidences (Currie and Gruber 1994). Finally, Currie and Gruber (2001) utilize CPS data to simulate eligibility and match it to Vital Statistics data in order to study the effect of expansions on treatment intensity for pregnant women. They conclude that expansions to pregnant women led to crowd out effects. Moreover, expansions increased treatment intensity for the newly eligible but decreased treatment intensity for the population that was crowded out.

Similarly, Bronchetti (2014) uses a simulated instrumental variable method to study the effect of changes in eligibility for legal immigrant children on health utilization and outcomes. Bronchetti's paper reveals higher take up and lower crowd out, increased usage of ambulatory care and preventative services, and decreased usage of emergency care for legal immigrant children compared to US-born children. Bronchetti's findings thus indicate Medicaid's value may be underestimated. Meanwhile, Goodman-Bacon (2018) contributes to research by looking at the effects of the initial adoption of Medicaid on infant mortality. Using a regression discontinuity approach, Goodman-Bacon finds significant decreases in infant mortality in states with higher eligibility levels and amongst non-white infants.

Cutler and Gruber (1996) also employ a simulated eligibility measurement but focus on the cost of expanding public insurance eligibility on private insurance coverage. They propose a crowd out effect of nearly 50% from eligibility expansions in 1987 and 1992. In other words, they find that on net about half of the expansions were associated with reductions to private insurance coverage. However, a more recent paper from Card and Shore-Sheppard (2004) suggests Cutler and Gruber's restrictive empirical specifications overestimate crowd out effects and take up rates. Instead, Card and Shore-Sheppard examine expansions in 1989 and 1990 using regression discontinuity and differences in differences. They propose low take up rates as an alternative driver for the modest coverage increases.

With wide cross-state variation in Medicaid programs, it is logical to assume there also exists extensive variation in states' Medicaid expenditures. Buchanan, Cappelleri, and Oshfeldt (1991) and Wade and Berg (1995) employ a variety of health, economic, and political indicators to estimate causes of variation in state-level Medicaid and enrollment group spending. Contrary to conventional wisdom, Buchanan et al. (1991) finds the political factors of state liberalism and interparty competition are insignificant in explaining differences between state Medicaid spending. However, personal income per capita, past year's expenditures, patient care physicians per 1000 population, number of Medicaid recipients, and level at which Medicaid was administered in the state (ie: local v. state) are substantial drivers of expenditure variation. As a result, Buchanan et al. recommend states reclaim autonomy over Medicaid's administration in order to restrain the rampant growth in expenditures.

Meanwhile, Wade and Berg's (1995) paper examines state-level expenditures by enrollment groups and services. Because of reverse causality between enrollment and expenditures, Wade and Berg rely on a two stage least squares model where the instrument is predicted enrollment. Additionally, they include state fixed effects to control for potential unobserved state characteristics that affect expenditures. However, a drawback of the state fixed effects is that it obscures a large amount of expenditure variation and thus makes results weaker. As theory suggests, Wade and Berg find strong relationships between expenditures and federal Medicaid policy, predicted enrollment, and state Medicaid policy determinants. The magnitude of these relationships varies by enrollment group and service, suggesting "one-size fits all" policies will not be effective in reducing expenditure growth.

Many of the papers described above take advantage of state Medicaid policy variation to identify or motivate their research. However, few have breached the causes of cross-state variation. A 1994 paper by Grogan presents a theoretical model to determine if the Medicaid policy dimensions of financial eligibility, categorical eligibility, and benefit coverage require different political processes. In each process, politicians must simultaneously minimize political disutility, which arises from actions such as increasing taxes, and maximize political utility. To maximize political utility, politicians are subjected to voter preferences, interest group power, and personal ideology. Between policy dimensions, Grogan assumes each constraint will take on a different value. Using a cross-sectionally heteroskedastic timewise autoregressive random effects model, Grogan finds evidence to support her theoretical models and hypothesis that Medicaid policy dimensions depend on different political processes. Specifically, traditional welfare politics are the greatest influence on eligibility dimensions while interest groups drive benefit policies (Grogan 1994).

Additionally, a recent paper by Jacobs and Callaghan (2013) seeks to identify factors that motivated Republican-dominated states to accept the ACA. Expanding on the Kaiser Family Foundation's trichotomous groups of "have expanded," "have not expanded," and "considering expansion," Jacobs and Callaghan measure two other components to capture a more holistic picture of state responses to the ACA. First, they count the number of level-one and level-two grants a state had received to fund planning and implementation of the ACA. Second, they quantify changes in Medicaid policy taken in 2013; these included actions such as expanding or reducing benefit coverage, simplifying the application and renewal process, decreasing or implementing co-payments, and reducing eligibility. In addition to generating additive measures, Jacobs and Callaghan allot scores of -3, 0, and 3 to states that have not expanded, are undecided, or have expanded, respectively. Finally, they assign each state an expansion score ranging from a low of -4 to a high of 7 where the higher number represents movements toward expansion. Next, they examine correlations of state expansion scores to partisanship, per capita personal income, past policy, and state administrative power. Jacobs and Callaghan find political party cannot alone account for state decisions on expansion. Additionally, state income is actually positively correlated, meaning states who made a stronger effort to adopt expansion also had higher incomes. This is in contrast to the belief that the ACA's generous financial incentives should motivate poorer states to adopt the expansion. Finally, past policy decisions appear to influence current decisions and reinforce the status quo while state administrative capacity also contributes to a state's ability to expand.

Currie and Gruber, Bronchetti, Goodman-Bacon, Cutler and Gruber, and Card and Shore-Sheppard all take advantage of cross-state policy variation to study the effects of the Medicaid program on a variety of topics. Buchanan et al. and Wade and Berg investigate drivers of variation in state Medicaid expenditures but not the policy itself. Finally, Grogan and Jacobs and Callaghan begin to explore the factors that impact state Medicaid policy. However, Grogan takes a theoretical approach and only utilizes a sample of 5-years of data to support her hypothesis. Additionally, Jacobs and Callaghan focus solely on the ACA expansion.

It is clear that cross state, intertemporal variation has been used to identify causal links between health insurance on health and economic outcomes. However, studies neglect to explain why the variation exists. Moreover, no paper has sought to address the timing of a state's decision to initially adopt a Medicaid program. My paper seeks to fill both gaps by identifying the variables that impacted a state's decision to adopt Medicaid. Additionally, I will identify factors that have contributed to and still affect the differential levels of generosity in eligibility. Section 5 reviews the data. In sections 6 and 7, I explore the timing aspect of Medicaid's original adoption and cross-state variation in financial eligibility. I conclude in Section 8.

# Chapter 5

# Data and Hypothesized Effects of Key Parameters

## 5.1 Data

To estimate the impact of various factors on a state's adoption of Medicaid and on the generosity of a state's eligibility criteria, I compile a panel of data on the 48 contiguous states over the period of 1965 through 2018 for a total of 2592 observations. I exclude Washington D.C., Hawaii, Alaska, and U.S. territories due to their lack of consistent data. Since policy tends to be drafted a year prior to its effective date, I create one-year lags for my political, economic, demographic, and health environment variables. As a result, the effective number of observations I have is 2545. Additionally, I freeze state expenditures for MAA programs, percentage of population receiving AFDC, and years of existence of an MAA program at their 1965 level. This is to avoid any endogeneity issues that may arise from the enactment of Medicare and Medicaid in 1965.

Regressor variable data comes from the Statistical Abstracts of the United States 1960-2012, U.S. Census tables, U.S. Bureau of Economic Analysis, the Federal Reserve Economic Data in St. Louis, National Governors' Association, Ballotopedia, and Michael Dubin's book Party Affiliations in the State Legislatures: A Year by Year Summary 1796-2006. Due to limitations, the following variables were linearly interpolated: percentage of citizens living in urban areas, percentage of

Black Americans, percentage of citizens under 65, percentage of foreign-born citizens, percentage of female citizens, percentage of citizens living in poverty, active physicians per 1000 population, and hospital beds per 1000 population.

Medicaid data are compiled from the Kaiser Family Foundation, National Governors' Association, Office of the Assistant Secretary for Planning and Evaluation, and various historical federal publications. In calculating state generosity, I use two measures. The first is a ratio of a state's "payment standard" to its "need standard." As mentioned previously, Medicaid financial eligibility was tied directly to the recipients of AFDC from 1966 through 1996. In order to receive AFDC payments, an individual had to meet the state's payment standard, which was often below the state's need standard ("A Brief History of the AFDC Program" 1998). Table 5.1 provides a count of states' "payment" to "need" standard ratios starting in the first year for which I have data. A higher "payment" to "need" ratio indicates more generosity in financial eligibility.

Table 5.1: Frequency of "Payment" v. "Need" Standards Over Time

| Year | 20-29% | 30-39% | 40-49% | 50-59% | 60-69% | 70-79% | 80-89% | 90-99% | 100% | No Program | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1968 | | | 1 | 5 | 3 | 3 | 1 | 4 | 21 | 10 | 48 |
| 1969 | | | 3 | 5 | 4 | 1 | 7 | 5 | 15 | 8 | 48 |
| 1970 | | 1 | | 2 | 1 | 3 | 9 | 6 | 25 | 1 | 48 |
| 1971 | | 1 | | 3 | 2 | 3 | 3 | 6 | 29 | 1 | 48 |
| 1972 | | | 1 | 2 | 1 | 3 | 4 | 7 | 28 | 1 | 47* |
| 1973 | | | 1 | 1 | 2 | 4 | 1 | 6 | 31 | 1 | 47* |
| 1974 | | | | 2 | 2 | 3 | 3 | 4 | 33 | 1 | 48 |
| 1975 | | | | 1 | 2 | 6 | 7 | 2 | 29 | 1 | 48 |
| 1976 | 1 | | | 1 | 2 | 9 | 6 | 4 | 24 | 1 | 48 |
| 1977 | | | 1 | | 6 | 5 | 5 | 4 | 26 | 1 | 48 |
| 1978 | | | 2 | 1 | 6 | 6 | 5 | 4 | 23 | 1 | 48 |
| 1979 | | | 2 | | 4 | 8 | 4 | 4 | 25 | 1 | 48 |
| 1980 | | 1 | 1 | | 5 | 7 | 3 | 3 | 27 | 1 | 48 |
| 1981 | | 1 | 2 | 4 | 5 | 6 | 1 | 3 | 25 | 1 | 48 |
| 1982 | | 2 | 1 | 5 | 6 | 5 | 7 | 3 | 19 | | 48 |
| 1983 | | 4 | | 6 | 4 | 7 | 6 | 2 | 19 | | 48 |
| 1984 | | 4 | 1 | 8 | 3 | 4 | 8 | 2 | 18 | | 48 |
| 1985 | | 3 | 4 | 6 | 5 | 3 | 7 | 2 | 18 | | 48 |
| 1986 | | 4 | 3 | 6 | 6 | 3 | 8 | | 18 | | 48 |
| 1987 | 1 | 5 | 4 | 6 | 4 | 5 | 5 | 1 | 17 | | 48 |
| 1988 | 2 | 4 | 4 | 4 | 5 | 6 | 5 | 1 | 17 | | 48 |
| 1989 | 3 | 3 | 6 | 4 | 5 | 4 | 6 | 1 | 16 | | 48 |
| 1990 | 3 | 3 | 6 | 5 | 6 | 3 | 6 | 1 | 15 | | 48 |
| 1991 | 3 | 4 | 5 | 6 | 5 | 3 | 6 | 1 | 15 | | 48 |
| 1992 | 3 | 4 | 5 | 7 | 4 | 3 | 6 | 2 | 14 | | 48 |
| 1993 | 4 | 7 | 6 | 6 | 2 | 4 | 8 | | 11 | | 48 |
| 1994 | 5 | 6 | 7 | 6 | 2 | 5 | 7 | | 10 | | 48 |
| 1995 | 7 | 4 | 6 | 3 | 3 | 6 | 6 | 3 | 10 | | 48 |
| 1996 | 7 | 5 | 5 | 3 | 2 | 4 | 3 | 5 | 14 | | 48 |

Note, WV did not respond in 1972 and 1973

Starting in the late 1980s, states were allowed to increase the financial eligibility level to a percentage of the federal poverty level (FPL) for pregnant women and children under a specific age. Once PRWOA[1] was enacted in 1996, the FPL became the standard measure used to determine

[1]See Section 3 for a description of the Personal Responsibilities and Work Opportunities Act.

financial eligibility. To measure generosity starting in the late 1980s, I create a dummy variable for infants and pregnant women, children ages 1-5, children ages 6-18, and other adults to indicate whether the financial eligibility level was above the mandated amount for each respective group. Due to conflicting data from multiple sources, parents/caretakers were omitted from my analysis.

Table 5.2 shows what percentage of states covered a specific group above the mandatory financial eligibility minimum. As discussed in Section 3, OBRA-89 established the mandatory minimum for infants and pregnant women and children ages 1-5 at 133% FPL. This mandate has not changed since OBRA-89. In contrast, between 1986 and 1989, there was no mandatory minimum for children ages 6-18. Thus, I omit 1986-1989 when analyzing generosity for children ages 6-18. OBRA-90 set a mandated minimum for children ages 6-18 at a maximum of 100% FPL (Schneider et al. 2003). In 2014, the ACA increased the mandatory minimum for children ages 6-18 to 138% FPL, the same mandatory minimum for infants and pregnant women and children ages 1-5 (Rudowitz, Artiga, and Arguello 2014). The ACA was also intended to mandate coverage for non-elderly, non-disabled, non-pregnant, childless adults- the other adult category- but the Supreme Court nullified this component of the ACA. Thus, other adults still have no mandated financial eligibility minimum. As a result, the Other Adults column indicates what percent of states extended Medicaid or any Medicaid-like assistance to other adults.

Table 5.2: Percent of States Covering Group Above Mandatory Minimum

| Year | Infants/Pregnant Women | Children Ages 1-5 | Children Ages 6-18 | Other Adults |
|---|---|---|---|---|
| 1987 | 31.25 | 54.17 | - | - |
| 1988 | 72.92 | 68.75 | - | - |
| 1989 | 50.00 | 6.25 | - | 4.17 |
| 1990 | 43.75 | 8.33 | 25.00 | 6.25 |
| 1991 | 56.25 | 10.42 | 8.33 | 6.25 |
| 1992 | 58.33 | 20.83 | 12.50 | 8.33 |
| 1993 | 62.50 | 29.17 | 25.00 | 8.33 |
| 1994 | 66.67 | 18.75 | 33.33 | 12.5 |
| 1995 | 68.75 | 20.83 | 47.92 | 14.58 |
| 1996 | 68.75 | 27.08 | 50.00 | 16.67 |
| 1997 | 70.83 | 45.83 | 56.25 | 17.78 |
| 1998 | 77.08 | 52.08 | 75.00 | 20.00 |
| 1999 | 79.17 | 52.08 | 79.17 | 23.26 |
| 2000 | 81.25 | 52.08 | 77.08 | 36.04 |
| 2001 | 81.25 | 52.08 | 56.25 | 33.33 |
| 2002 | 81.25 | 47.92 | 58.33 | 25.00 |
| 2003 | 81.25 | 47.92 | 58.33 | 29.17 |
| 2004 | 81.25 | 50.00 | 56.25 | 39.17 |
| 2005 | 81.25 | 47.92 | 56.25 | 33.33 |
| 2006 | 79.17 | 47.92 | 54.17 | 33.33 |
| 2007 | 79.17 | 47.92 | 54.17 | 41.67 |
| 2008 | 79.17 | 47.92 | 56.25 | 50.00 |
| 2009 | 79.17 | 47.92 | 56.25 | 43.75 |
| 2010 | 79.17 | 47.92 | 58.33 | 43.75 |
| 2011 | 79.17 | 47.92 | 58.33 | 43.75 |
| 2012 | 79.17 | 47.92 | 60.42 | 45.83 |
| 2013 | 79.17 | 47.92 | 62.50 | 54.17 |
| 2014 | 100 | 97.92 | 64.58 | 79.92 |
| 2015 | - | - | - | 75.00 |
| 2016 | - | - | - | 77.08 |
| 2017 | - | - | - | 77.08 |
| 2018 | - | - | - | 75.00 |

## 5.2 Introduction to the models

Using the data described above, I analyze the effects of a variety of factors on both the decision for a state to adopt Medicaid and Medicaid eligibility generosity. Equation 5.1 specifies a linear probability model for analyzing state Medicaid adoption. Equations 5.2 and 5.3 explore eligibility generosity. As discussed above, generosity between 1968 and 1996 is measured as a ratio of the "payment" to "need" standard. As a continuous dependent variable, I rely on the ordinary least squares method in Equation 5.2. Finally, I return to a linear probability model for estimating generosity starting in the late 1980s when a period of eligibility expansions began.

(5.1)

$$\begin{aligned} Pr(MedicaidProgram_{sy} = 1|x) = \beta_0 + \boldsymbol{\beta_1} * Political_{sy} + \boldsymbol{\beta_2} * Economic_{sy} \\ + \boldsymbol{\beta_3} * Demographic_{sy} + \boldsymbol{\beta_4} * Health\ Environment_{sy} \\ + \alpha_y + u_{sy} \end{aligned}$$

(5.2)

$$\begin{aligned} Payment\ to\ Need\ Standard\ Ratio_{sy} = \beta_0 + \boldsymbol{\beta_1} * Political_{sy} + \boldsymbol{\beta_2} * Economic_{sy} + \\ \boldsymbol{\beta_3} * Demographic_{sy} + \boldsymbol{\beta_4} * Health\ Environment_{sy} \\ + \alpha_y + u_{sy} \end{aligned}$$

(5.3)

$$\begin{aligned} Pr(Category\ X\ Elig.\ Above\ Mandatory\ Min_{sy} = 1|x) = \beta_0 + \boldsymbol{\beta_1} * Political_{sy} \\ + \boldsymbol{\beta_2} * Economic_{sy} \\ + \boldsymbol{\beta_3} * Demographic_{sy} \\ + \boldsymbol{\beta_4} * Health\ Environment_{sy} \\ + \alpha_y + u_{sy} \end{aligned}$$

In the above equations, each $\boldsymbol{\beta}$ represents a vector of the coefficient estimates for the corresponding group of factors, $\alpha_y$ represents year fixed effects, and $u_{sy}$ is an idiosyncratic error term. Model specific details can be found in Sections 6 (Medicaid Adoption) and 7 (Eligibility Generosity).

## 5.3 Hypothesized coefficient signs of key parameters

The key parameters in Equations 5.1-5.3 can be grouped into four broad categories: political factors, economic factors, demographics, and health environment factors. Political factors include lagged dummies for the governor's political party, state legislature majority party, split party state legislature, and split party government.

Starting in the 20th century, the Democratic party has been associated with supporting issues such as the rights of minorities and social welfare (History.com Editors 2019). In 1965 when Medicare and Medicaid were enacted, Democrats enjoyed a unified government. The Democratic party held a supermajority in both the House and Senate, while President Johnson was just beginning his plans for a Great Society following a landslide victory in 1964 ("89th Congress (1965-1967)" n.d.). With Democrats' clear relationship to Medicare and Medicaid and support of social welfare programs, it is logical to hypothesize a governor's political party had a positive effect on both the probability of Medicaid adoption and the level of generosity in eligibility. Contrasting, a split party state government, which is a situation where the governor and state legislature majority are of different political parties, may be associated with a negative effect on the probability of Medicaid adoption and eligibility generosity. Having a split party state government may introduce bureaucratic friction and thus make it harder to pass one party (Democratic v. Republican) or branch's (Legislature v. Governor) agenda.

The effects of having a Democratic majority in the state legislature or a split party state legislature on the probability of adoption and eligibility generosity are ambiguous. For example, depending on the state's demographic composition and political climate, an election year may sway members of one party to defect and vote against party lines in hopes of retaining a seat in the state legislature. Thus, while Democrats may hold a majority in the state legislature, given an election year and a potentially weak majority- such as 51% Democrats in the House and Senate- the effect of having a Democratic or split party state legislature may go either way.

Economic factors include lagged real state GDP per capita and state expenditures for MAA programs in 1965. Medicaid's legislation introduced a new matching rate for medical vendor payments known as the federal medical assistance percentage (FMAP). The FMAP is inversely related to state income, meaning a higher income state receives a lower matching rate. Faced with a lower matching rate, these higher income states, as measured by real state GDP per capita, may have been less inclined to adopt a Medicaid program. I expect a negative coefficient on the lagged value of real state GDP per capita in the adoption regression. After adoption however, higher income states may be more likely to have eligibility levels above the federally mandated minimum. Thus, in regressions of eligibility generosity, I hypothesize a positive effect of lagged real state GDP per capita. Meanwhile, state expenditures for MAA programs in 1965 is solely used in Equation 5.1. I estimate a state with higher expenditures for its MAA program in 1965 may be more likely to adopt Medicaid at the risk of losing federally matched funds in 1970.

Equations 5.1-5.3 utilize the following demographic factors: U.S. region indicators, percentage of individuals living in poverty, percentage of Black Americans, percentage of females, percentage of individuals under 65, percentage of foreign-born, and percentage of citizens living in urban areas. Note, the percentage of citizens living in poverty is used only in Equations 5.2 and 5.3, as it led to a high variance inflation factor (VIF) in Equation 5.1. Also, the percentage of citizens living in urban areas is primarily used as a control and is not a key parameter of interest.

As previously discussed, Arizona was the only state not to enact Medicaid by the time the federal government ceased Kerr-Mill medical vendor payments in 1970. Figure 5.1 presents a visual depiction of the geographical variation of states' timing decisions to adopt Medicaid. Excluding Indiana and New Jersey, states that adopted Medicaid at the last moment were concentrated in the South. Considering this detail, I use the South as my base group in the adoption regression and thus estimate positive coefficients on indicators for the Northeast, West, and Midwest.

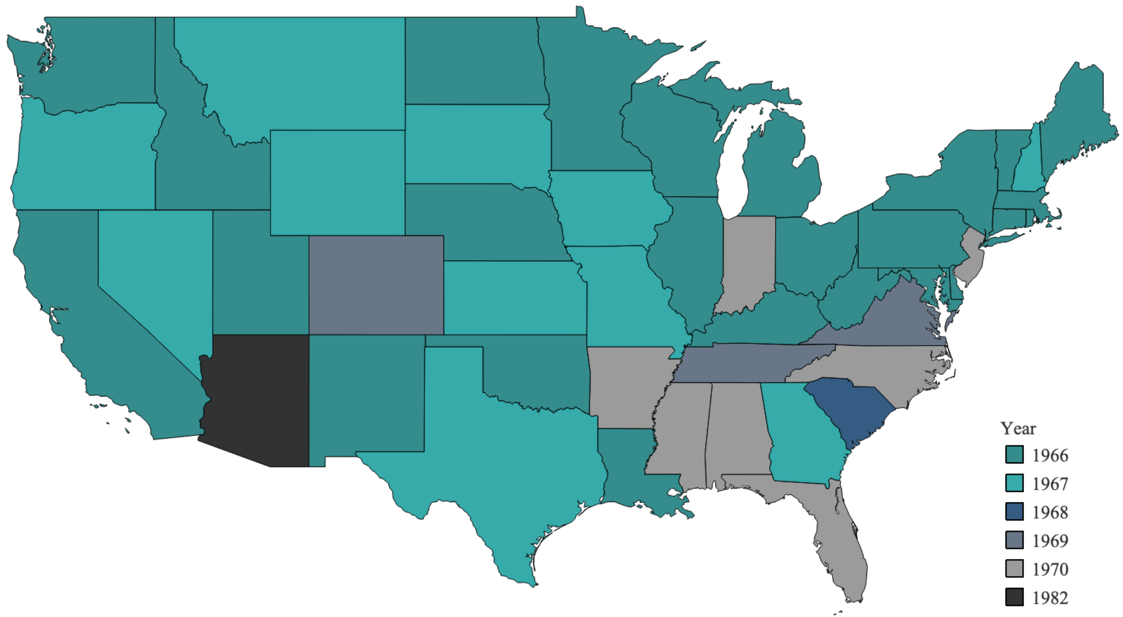



Figure 5.1: Geographical Variation in the Year of Initial Medicaid Adoption

Under the basic idea of the Median Voter Theorem, politicians in a simple majority rules setting seek to maximize votes to stay in power. The optimal method to maximize votes is for politicians to align themselves with the median voter. In the two-party system dominating U.S. politics, targeting the median voter hypothetically allows politicians to appeal to at least 50% of the electorate and thus maintain power.

Applying the Median Voter Theorem to my models, I hypothesize the percentage of Black Americans, females, individuals living in poverty, and individuals under-65 years will be associated with positive effects on the probability of a state having a Medicaid program in a given year and on eligibility generosity. These populations have benefited disproportionately from Medicaid itself or AFDC and therefore have an incentive to maintain a generous Medicaid program. On the other hand, racism and sexism may drive the percentage of Black Americans and females to have a negative impact on the probability of a state having a Medicaid program and on eligibility generosity. For example, hospitals were still segregated in the early 1960s. The framers of Medicare and Medicaid were avid civil rights activists and used Title VI of the Civil Rights Act of 1964 to prohibit segregated hospitals from participating in Medicare and Medicaid (Andrews 2016). This meant hospitals would need to desegregate in order to receive federal funding for Medicare and Medicaid. In 1965, states with the highest percentage of Black Americans were located in the South, which was known to resist segregation. Finally, younger voters (ie: voters under 65-years) have historically been the least likely to turn out and vote. Knowing this fact, politicians may elect to ignore the non-voting population, so the percentage of individuals under 65-years could have no effect on the likelihood of a state having a Medicaid program or in eligibility generosity. In sum, the effect of increases in the percentage of Black Americans, females, and individuals under 65-years is ambiguous.

The remaining regressors I utilize are health environment factors including hospital beds per 1000 population, active physicians per 1000 population, AFDC recipients in 1965, and an indicator for the existence of an MAA program in 1965. Hospital beds per 1000 population and active physicians per 1000 population represent supply constraints and may proxy for American Hospital Association (AHA) and American Medical Association (AMA) presence. I hypothesize hospital beds per 1000 population will have a positive effect and active physicians per 1000 population an ambiguous effect on the probability of a state having a Medicaid program and eligibility generosity. As supply constraints, higher hospital beds per 1000 population and active physicians per 1000 population may indicate a stronger ability for a state's health care infrastructure to accommodate newly eligible Medicaid beneficiaries. Additionally, both hospitals and physicians may have an incentive to adopt Medicaid to increase revenues. Prior to 1965, care of uninsured patients, especially those not covered by MAA, often went uncompensated. By adopting Medicaid, hospitals and physicians would be able to recoup at least some of the costs of care. As proxies for AHA and AMA presence, hospital beds per 1000 population is estimated to have a positive effect and active physicians per 1000 population to have a negative effect. The AHA openly supported Medicare and Medicaid (American Hospital Association 2020). Meanwhile, the AMA neither supported nor opposed the 1965 legislation but had historically opposed early versions of Medicare and Medicaid (Cohen 1985).

Finally, the percentage of AFDC recipients in each state in 1965 is only used in the adoption regression. Noting that Medicaid and AFDC were initially directly linked and applying the Median Voter Theorem, it is plausible that the percentage of AFDC recipients in a state in 1965 will have a positive effect on the probability a state has a Medicaid program in a given year. However, as previously mentioned, the recipients of AFDC disproportionally belong to groups such as Black Americans that have historically low voter turnout rates. Moreover, AFDC recipients do not have the funds required to influence politicians. Low voter turnout and an inability to pressure politicians could result in the percentage of AFDC recipients in a state in 1965 having no effect on the probability a state has a Medicaid program in a given year. Thus, the hypothesized effect of the percentage of AFDC recipients in each state in 1965 is ambiguous.

# Chapter 6

# Factors Driving The Timing of States' Medicaid Adoption

## 6.1 Empirical model

In order to estimate the factors impacting the timing of a state's decision to adopt Medicaid, I employ a Linear Probability Model (LPM) with year fixed effects. This model is robust and produces similar results to Probit and Logit models or an LPM with a trend[1]. The major benefit of the LPM is its intuitive interpretation. Coefficients may be interpreted as percentage-point changes in the likelihood state S has a Medicaid program in year Y after netting out the effects of all other variables. It is important to note, however, that the LPM suffers from heteroskedasticity. Thus, robust standard errors are used in all regressions. While both a trend and year fixed effects capture shocks that affect all states equally, year fixed effects allow for greater flexibility than a trend, which assumes a constant change over time. The full model is written below where each $\boldsymbol{\beta}$ represents a vector of the coefficient estimates for the corresponding group of factors, $\alpha_y$ represents the year fixed effects, and $u_{sy}$ is idiosyncratic error.

$$Pr(MedicaidProgram_{sy} = 1|x) = \beta_0 + \boldsymbol{\beta_1} * Political_{sy}$$
$$+\boldsymbol{\beta_2} * Economic_{sy} + \boldsymbol{\beta_3} * Demographic_{sy} + \boldsymbol{\beta_4} * Health\ Environment_{sy} + \alpha_y + u_{sy}$$

[1]See Appendix Table 9.5 for robustness checks

I limit my sample from 1966 to 1970 when the federal government's threat to cease MAA vendor payments took effect. I also remove Arizona, an outlier that did not adopt Medicaid until 1982.

## 6.2 Analysis of key parameters

Table 6.1 presents the results from the LPM estimating the probability state S had a Medicaid program in year Y.

Table 6.1: Factors Impacting States' Adoption of Medicaid

| | Indicator if State had Medicaid Program in Year Y |
|---|---|
| | (1) |
| | LPM |
| Lag Democratic Governor Dummy | 0.0350 |
| | (0.0438) |
| Lag Majority Democratic Legislature Dummy | -0.0326 |
| | (0.0709) |
| Lag Split Party Legislature Dummy | -0.0488 |
| | (0.0719) |
| Lag Split Party State Dummy | 0.0577 |
| | (0.0536) |
| State Expenditures for MAA in 1965 | 0.0000 |
| | (0.0000) |
| Log of Lagged Real State GDP per Capita (2018$) | 0.5837** |
| | (0.2379) |
| West | -0.1453 |
| | (0.1080) |
| Midwest | -0.0428 |
| | (0.0905) |
| Northeast | -0.0672 |
| | (0.1262) |
| Lag of % Black | -0.0166*** |
| | (0.0041) |
| Lag of % Under 65 | 0.0017 |
| | (0.0023) |
| Lag of % Female | 0.0584** |
| | (0.0277) |
| Lag of % Urban | -0.0011 |
| | (0.0027) |
| Lag of % Foreign Born | -0.0185 |
| | (0.0192) |
| Lag of Hospital Beds per 1000 Pop. | 0.0188 |
| | (0.0191) |
| Lag of Active Physicians per 1000 Pop. | 0.0918 |
| | (0.1392) |
| % of Pop. Receiving AFDC in 1965 | 0.0109*** |
| | (0.0033) |
| Year Fixed Effects | Yes |
| Arizona Included | No |
| Observations | 135 |
| R-squared | 0.382 |
| Robust Standard Errors | *p<0.1; **p<0.05; ***p<0.01 |

Despite the common notion that politics dictate public programs, I find no evidence that political factors significantly affected a state's decision to adopt Medicaid. While seemingly counterintuitive, this finding does relate to Buchanan et al. who found that political factors did not significantly influence state expenditures on Medicaid (Buchanan, Cappelleri, and Oshfeldt 1991). Perhaps political party plays a less important role at the state-level compared to the federal-level. For example, at the state-level, politicians are one degree closer to constituents. This may grant them a better ability to tailor policy to the specific needs of voters. Compared to lawmakers at the national level, these politicians need only unite a state under a common goal. In turning to the data, nearly 50% (23 of 47) of states had split party governments and 43% (20 of 47) of states had a Republican governor in the year prior to adopting a Medicaid program.

Besides politics, state expenditures for MAA in 1965, U.S. region indicators, percent of individuals under 65-years, and the lags for hospital beds per 1000 population and active physicians per 1000 population also did not have statistically significant impacts on the probability of a state having a Medicaid program in a given year. The fact that regions compared to the South did not significantly impact the timing of adoption is especially surprising. As previously discussed, southern states were slower to adopt Medicaid and historically more likely to maintain segregated hospitals. It is possible that region indicators were insignificant because the control variables effectively capture all of the regional variation, especially when noting this model spans only 5 years.

A 10-percent increase in the prior year's real state GDP per capita is associated with a 5.84 percentage-point increase in the probability that a state had a Medicaid program in a given year. The direction of the effect is opposite of what was hypothesized. However, it matches a finding of Jacobs and Callaghan that higher income states were more likely to adopt the ACA expansion. Here, higher income states were more likely to adopt the original Medicaid program.

The effects of the percentage of Black Americans and percentage of females on the probability of adoption provide conflicting evidence for the arguments of the Median Voter Theorem. A one percentage-point increase in the percent of Black Americans in the prior year is associated with a 1.66 percentage-point decrease in the probability a state had a Medicaid program in a given year.

In contrast, a one percentage-point increase in the percent of females in the prior year is associated with a 5.84 percentage-point increase in the probability a state adopted a Medicaid program in following year. This discrepancy may be attributable to the difference in each demographic's voting participation rate. In the 1964 and 1968 presidential elections, fewer than 60% of eligible Black Americans voted (Michael Dimock, Kiley, and Suls 2013; U.S. Department of Commerce 1968). On the other hand, 67% of eligible females voted in the 1964 national elections (U.S. Department of Commerce 1968). If they were aware of the relatively low voter turnout for Black Americans in the 1960s, politicians may have been driven more by racism than the Median Voter Theorem.

While hospital beds per 1000 population and active physicians per 100 were not statistically significant, the percentage of AFDC beneficiaries in 1965 did statistically significantly impact when a state adopted Medicaid. A 1 percentage-point increase the percentage of the population receiving AFDC benefits in 1965 is associated with a 1.09 percentage-point increase in the probability a state had a Medicaid program in the given year. This effect might also be evidence to support the Median Voter Theorem. As AFDC and Medicaid were directly linked, citizens receiving AFDC would have an incentive to push their state to adopt Medicaid.

# Chapter 7

# Factors Influencing Cross-State Variation in Medicaid Financial Eligibility

## 7.1 Modelling generosity as a ratio of the AFDC "payment" to "need" standard

### 7.1.1 Empirical model

To measure generosity prior to AFDC's abolishment in 1996, I compare a state's "payment" and "need" standard. Recall that, "the need standard is supposed to be an objective measure reflecting the state's true determination of need and the payment level is that which the state can realistically afford to offer" (Grogan 1994). "Payment" and "need" standards are measured as a continuous value dollars per month. Thus, to calculate generosity, I divide the "payment" standard by the "need" standard to generate the "payment" to "need" standard ratio. I then multiple this ratio by 100% to simply interpretations of marginal effects. Because this measurement is continuous, my model for generosity pre-1996 relies on OLS with year fixed effects. Including a trend produces similar results[1]. The full model is written below where each $\boldsymbol{\beta}$ represents a vector of the coefficient estimates for the corresponding group of factors, $\alpha_y$ represents the year fixed effects, and $u_{ys}$ is

[1]See Appendix Table 9.6-9.10 for robustness checks

idiosyncratic error. Additionally, the model is estimated using robust standard errors. I use data from 1968, the first year I observe "payment" and "need" standards, through 1996 and exclude Alaska and Hawaii. Additionally, West Virginia is missing observations in 1972 and 1973, because it did not report "payment" and "need" standards.

$$Payment\ to\ Need\ Standard\ Ratio_{sy}) = \beta_0 + \boldsymbol{\beta_1} * Political_{sy}$$
$$+\boldsymbol{\beta_2} * Economic_{sy} + \boldsymbol{\beta_3} * Demographic_{sy} + \boldsymbol{\beta_4} * Health\ Environment_{sy} + \alpha_y + u_{sy}$$

### 7.1.2 Analysis of key parameters

Table 5.1 presents the OLS estimates for the continuous measurement of eligibility generosity.

Table 7.1: Factors Impacting State 'Payment' to 'Need' Standard Ratios

| | Payment to Need Standard Ratio |
|---|---|
| | (1) OLS |
| Lag Democratic Governor Dummy | -0.7754 |
| | (1.0870) |
| Lag Independent Governor Dummy | 0.8705 |
| | (3.9631) |
| Lag Majority Democratic Legislature Dummy | 1.9751 |
| | (1.4661) |
| Lag Split Party Legislature Dummy | 2.5045 |
| | (1.6145) |
| Lag Split Party State Dummy | -0.7418 |
| | (1.1886) |
| Log of Lagged Real State GDP per Capita (2018$) | 22.1500*** |
| | (4.8919) |
| West | 3.5106 |
| | (2.7203) |
| Midwest | 9.5037*** |
| | (2.2393) |
| Northeast | 7.8024*** |
| | (2.5160) |
| Lag of % Poverty | -0.1450 |
| | (0.2069) |
| Lag of % Black | -0.5811*** |
| | (0.1024) |
| Lag of % Under 65 | 0.0173 |
| | (0.1066) |
| Lag of % Female | -1.6493* |
| | (0.9390) |
| Lag of % Urban | -0.1045* |
| | (0.0576) |
| Lag of % Foreign Born | 0.2327 |
| | (0.2332) |
| Lag of Hospital Beds per 1000 Pop. | 0.8600* |
| | (0.4874) |
| Lag of Active Physicians per 1000 Pop. | 6.3871*** |
| | (1.8753) |
| Year Fixed Effects | Yes |
| Arizona Included | Yes |
| Observations | 1360 |
| R-squared | 0.397 |
| Robust Standard Errors | *p<0.1; **p<0.05; ***p<0.01 |

Like in the regression for Medicaid adoption, political factors do not significantly impact states' financial eligibility generosity. This finding may further validate the conclusion of Buchanan et al. that politics were insignificant in explaining variation in state Medicaid expenditures from 1977-1987 (Buchanan, Cappelleri, and Oshfeldt 1991).

State income in the prior year, as measured by the lag of real state GDP per capita, positively affects the payment to need standard ratio. A 10% increase in real state GDP per capita in the prior year is associated with an increase in the "payment" to "need" standard ratio of 2.22 percentage-points. This coefficient is unsurprising. Theoretically, states with relatively more income should have a wider latitude to extend financial eligibility.

Compared to states in the South, states in the Midwest and Northeast have higher "payment" to "need" standard ratios. In contrast, there is not a statistically significant difference in the "payment" to "need" standard ratio between states in the South and states in the West. One potential explanation for this insignificant difference is that Arizona is now included, and as previously stated, Arizona did not adopt a Medicaid program until 1982. However, in the first four years of Medicaid's existence in Arizona, 100% of the "need" standard was met. In other words, despite the late adoption, Arizona was one of the most generous states at the beginning of its program.

Turning to demographics, an increased percentage of Black Americans in a state's population in the prior year is associated with a decrease in eligibility generosity. This finding is inconsistent with the Median Voter Theorem. However, despite legislature like the Civil Rights Act in 1964 and desegregation of hospitals participating in Medicaid, racism still existed in America, perhaps explaining the negative coefficient. The prior year's percentage of females in a state is associated with a 1.649 percentage-point decrease in the "payment" to "need" standard ratio but is only significant at the 10% level.

The number of both hospital beds and active physicians in a state positively affected eligibility generosity. An additional hospital bed per 1000 population and an additional active physician per 1000 population are associated with increases to the "payment" to "need" standard ratio of 0.860 percentage-points and 6.387 percentage-points, respectively. Note, the coefficient for hospital beds per 1000 population is small compared to active physicians per 1000 population and only significant at the 10% level. Previously, I hypothesized an ambiguous effect of active physicians per 1000 population on eligibility generosity. Active physicians per 1000 population serve as both a medical supply capacity constraint and a proxy for AMA presence in a state. As the coefficient is positive, it appears the potential negative effect of AMA presence may be smaller in absolute than the potential positive effect of a relaxed capacity constraint. Moreover, once Medicare and Medicaid were signed into law at the start of a "blue wave," in 1965, the AMA might have realized the programs would not be dissolved anytime soon and softened its views against federalized medical care.

## 7.2 Alternative model of generosity: Examining the probability a category is above the mandatory minimum

### 7.2.1 Empirical model

Having looked at generosity in eligibility as a fraction of the "payment" to "need" standard, I now turn to measuring generosity as the probability a state covers a specific category above the federal minimum. As a reminder, AFDC was formally abolished in 1996 and states relied primarily on the federal poverty level to establish Medicaid eligibility. To examine the probability a category is covered above the mandatory minimum, I return to an LPM with year fixed effects when estimating the impact of various factors on a state's eligibility generosity for four broad groups: infants and pregnant women, children ages 1-5, children ages 6-18, and other adults. The dependent variable is an indicator equal to 1 if a state had an eligibility level for the group above the mandatory minimum. No mandatory minimum exists for other adults, so the indicator instead equals 1 if the state covered other adults under Medicaid or any Medicaid-like program. This includes state-funded programs and subsidies. The full model is written below where each $\boldsymbol{\beta}$ represents a vector of the coefficient estimates for the corresponding group of factors, $\alpha_y$ represents the year fixed effects, and $u_{ys}$ is idiosyncratic error.

$$Pr(Category\ X\ Elig.\ Above\ Mandatory\ Min_{sy} = 1|x) = \beta_0 + \boldsymbol{\beta_1} * Political_{sy}$$
$$+ \boldsymbol{\beta_2} * Economic_{sy} + \boldsymbol{\beta_3} * Demographic_{sy} + \boldsymbol{\beta_4} * Health\ Environment_{sy} + \alpha_y + u_{sy}$$

For regressions of infants and pregnant women and children ages 1-5, analysis is limited to the period 1987 – 2013 since states were first allowed to expand eligibility above AFDC limits for these groups in 1987 when OBRA-86 became effective. Variation in eligibility generosity as measured by an indicator variable essentially disappears by 2014. While optional expansions had been extended to children ages 6-8 prior to 1990, no state had adopted these expansions. Thus, I limit the regression for children ages 6-18 to the years 1990, when OBRA-90 mandated phase-in at 100% FPL, through 2014, when the mandated minimum increased to 138% FPL. Finally, for other adults, I run the model on the years 1989 through 2018. Similarly, 1989 was the first year a state extended assistance to other adults.

### 7.2.2 Analysis of key parameters

Table 7.2 provides coefficient estimates for the three categorically mandated groups of interest: infants and pregnant women, children ages 1-5, and children ages 6-18.

Table 7.2: Factors Impacting State Financial Eligibility Generosity

| | Indicator Above Mandatory Minimum | | |
|---|---|---|---|
| | (1) | (2 | (3) |
| | Infants/Pregnant Women | Children 1-5 | Children 6-18 |
| Lag Democratic Governor Dummy | 0.0313 | -0.0589** | 0.0162 |
| | (0.0218) | (0.0245) | (0.0263) |
| Lag Independent Governor Dummy | 0.0549 | 0.0348 | 0.0242 |
| | (0.0350) | (0.0852) | (0.0620) |
| Lag Majority Democratic | 0.0707** | 0.1837*** | 0.1203*** |
| Legislature Dummy | (0.0291) | (0.0335) | (0.0341) |
| Lag Split Party Legislature Dummy | 0.0226 | 0.0847** | 0.0430 |
| | (0.0335) | (0.0364) | (0.0388) |
| Lag Split Party State Dummy | -0.0307 | 0.0552** | 0.0642** |
| | (0.0244) | (0.0274) | (0.0298) |
| Log of Lagged Real State | 0.0492 | -0.1973* | -0.0664 |
| GDP per Capita (2018$) | (0.0831) | (0.1065) | (0.1175) |
| West | -0.4925*** | -0.1998*** | -0.2081*** |
| | (0.0437) | (0.0506) | (0.0580) |
| Midwest | 0.1531*** | 0.2159*** | 0.2973*** |
| | (0.0342) | (0.0435) | (0.0428) |
| Northeast | 0.0093 | 0.1006* | 0.0308 |
| | (0.0448) | (0.0561) | (0.0562) |
| Lag of % Poverty | 0.0268*** | 0.0163*** | 0.0006 |
| | (0.0047) | (0.0047) | (0.0050) |
| Lag of % Black | -0.0079*** | -0.0082*** | -0.0062*** |
| | (0.0017) | (0.0020) | (0.0023) |
| Lag of % Under 65 | -0.0065 | 0.0016 | 0.0236** |
| | (0.0046) | (0.0019) | (0.0105) |
| Lag of % Female | 0.0749*** | -0.0296 | -0.0013 |
| | (0.0268) | (0.0287) | (0.0314) |
| Lag of % Urban | -0.0048*** | -0.0020 | -0.0062*** |
| | (0.0013) | (0.0015) | (0.0016) |
| Lag of % Foreign Born | 0.0202*** | -0.0286*** | -0.0107** |
| | (0.0030) | (0.0036) | (0.0044) |
| Lag of Hospital Beds per 1000 Pop. | -0.1627*** | -0.1813*** | -0.1681*** |
| | (0.0141) | (0.0158) | (0.0191) |
| Lag of Active Physicians per 1000 Pop. | 0.0360* | 0.2138*** | 0.1829*** |
| | (0.0200) | (0.0555) | (0.0332) |
| Years of Interest | 1987-2013 | 1987-2013 | 1990-2014 |
| Observations | 1296 | 1296 | 1152 |
| R-squared | 0.401 | 0.366 | 0.353 |

Robust Standard Errors $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Across all three categories, a majority Democratic legislature, West, Midwest, percentage Black Americans, hospital beds per 1000 population, active physicians per 1000 population, and percentage foreign-born are all statistically significant. Compared to state legislatures with Republicans as the majority party, majority Democratic state legislatures are between 7 percentage-points and 18 percentage-points more likely to extend eligibility for infants and pregnant women and children ages 1-18 above the federal minimum. Looking at children ages 1-5, nearly all political factors significantly impact generosity. Having a Democratic governor compared to a Republican governor is actually associated with a 5.89 percentage-point decrease in the likelihood children ages 1-5 are covered above the mandatory minimum. At first glance, this may seem counterintuitive to the idea that Democrats are generally associated with supporting social welfare and the rights of minorities and women. However, it was under Republican presidents that states were required to expand eligibility for pregnant women and infants and children ages 1-18. Thus, Republican governors may be voting to support past Republican presidents' legislation[2].

Compared to the South, states in the West are less likely to extend Medicaid to the three groups above the mandatory minimum. In contrast, states in the Midwest are more likely to extend eligibility beyond the federally mandated levels for the three categories. A one percentage point increase in the prior year's percentage of Black Americans is associated with between a 0.64 percentage-point and 0.82 percentage-point decrease in the likelihood a category is more generous in its eligibility. Like the previous measure of generosity, this finding aligns less with the Median Voter Theorem and more with the idea of racial prejudice. Another interesting demographic trend is the effect of the prior year's percentage of foreign-born citizens in a state's population. For infants and pregnant women, a one percentage-point increase in the percentage of foreign-born citizens in the year before is associated with a 2.02 percentage-point increase in the probability a state covers infants and pregnant women above the mandated minimum. When looking at children ages 1-18, however, a one percentage-point increase in the percentage of foreign-born citizens in the prior year is associated with between a 2.86 percentage-point and 1.07 percentage-point decrease in the probability of a state being more generous to children ages 1-5 and children ages 6-18, respectively. Since PRWOA was enacted in 1996, foreign-born individuals have encountered different Medicaid

[2]See Appendix Figure 2 for a breakdown of States covering children ages 1-5 above the mandated minimum.

eligibility requirements than US-born citizens. For example, immigrants often face a five-year waiting period before they can be considered eligible for public assistance programs like Medicaid. Second, prior to CHIPRA in 2009, states were limited in receiving federal matching funds to cover immigrants during the five-year waiting period (Kaiser Commission on Medicaid and the Uninsured 2009). In 2004, 23 states, including D.C. and Hawaii, used their own funds to cover immigrants during the five-year waiting interval (Fremstad and Cox 2004). As a result, foreign-born individuals represent a constraint on generosity for US-born individuals and the negative coefficients for children ages 1-18 seem logical. The positive effect of the percentage of foreign-born individuals in the prior year's population might arise because we tend to consider infants and pregnant women of any nativity some of the most vulnerable in society.

Looking at health environment factors, hospital beds per 1000 population is now associated with a decrease in the likelihood a state covered infants and pregnant women and children ages 1-18 above the mandated minimum. An additional hospital bed per 1000 population is associated with a maximum decrease of 18.1 percentage-points in the probability of a state being relatively generous. In contrast, an additional active physician per 1000 population is associated with a maximum increase of 21.4 percentage-points in the probability of a state covering the three groups of interest above the mandatory federal minimum. The maximum effects of both hospital beds per 1000 population and active physicians per 1000 population are concentrated in the generosity of children ages 1-5. Both hospitals and physicians have a financial incentive to increase maximum eligibility in order to receive guaranteed compensation through the government. However, hospitals may be more constrained than physicians. For example, a physician does not necessarily need to admit a patient and use a hospital bed in order to receive compensation for treatment. Moreover, hospitals have faced continuous financial issues with Medicaid. In 2002, the American Hospital Association (AHA) released a white paper that found "from 1997 to 2000, Medicaid margins dropped from -4.2 percent to -5.1 percent. . . [and that] hospitals cannot break even on patient care services" ("AHA: U.S. Hospitals Still Suffering Financially" 2002). A more recent article from 2009 noted that "one-third of the nation's 5,000 hospitals [were] losing money, while another third [were] just breaking even" (M2 Presswire 2009).

Turning to Table 7.3, I now focus on factors impacting state generosity for other adults. As a reminder, other adults are not required to be covered. Thus, a state is considered generous if it extends any assistance to other adults through either Medicaid or a Medicaid-like program.

Table 7.3: Factors Impacting State Eligibility Generosity for Other Adults

| | Indicator Any Assistance |
|---|---|
| | (1) |
| | LPM |
| Lag Democratic Governor Dummy | 0.0446* |
| | (0.0229) |
| Lag Independent Governor Dummy | -0.0596 |
| | (0.1116) |
| Lag Majority Democratic Legislature Dummy | 0.0823*** |
| | (0.0308) |
| Lag Split Party Legislature Dummy | 0.1169*** |
| | (0.0352) |
| Lag Split Party State Dummy | -0.0351 |
| | (0.0266) |
| Log of Lagged Real State GDP per Capita (2018$) | 0.2693** |
| | (0.1141) |
| West | 0.2245*** |
| | (0.0499) |
| Midwest | 0.1359*** |
| | (0.0397) |
| Northeast | 0.1050** |
| | (0.0505) |
| Lag of % Poverty | 0.0164*** |
| | (0.0043) |
| Lag of % Black | -0.0050*** |
| | (0.0019) |
| Lag of % Under 65 | -0.0144 |
| | (0.0092) |
| Lag of % Female | 0.0636*** |
| | (0.0243) |
| Lag of % Urban | -0.0011 |
| | (0.0015) |
| Lag of % Foreign Born | -0.0020 |
| | (0.0038) |
| Lag of Hospital Beds per 1000 Pop. | -0.0826*** |
| | (0.0149) |
| Lag of Active Physicians per 1000 Pop. | 0.1253*** |
| | (0.0298) |
| Years of Interest | 1989-2018 |
| Observations | 1428 |
| R-squared | 0.353 |
| Robust Standard Errors | *p<0.1; **p<0.05; ***p<0.01 |

Compared to majority Republican legislatures, states with majority Democratic legislatures and split party legislatures are more likely to cover other adults. Additionally, having a Democratic governor is associated with a 4.46 percentage-point increase in the likelihood other adults are covered though only at the 10% significance level.

A 10 percent increase in the prior year's real state GDP per capita is associated with a 2.69 percentage point increase in the probability a state provides assistance to other adults. Similar to the prior measure of generosity, the "payment" to "need" standard, the positive impact of state income seems reasonable. Higher income states may have more capacity to extend aid to other adults. One interesting finding is the positive impact of the percentage of individuals living in poverty on probability of a state extending assistance to other adults. The positive impact seems counterintuitive to the link established between state income and other adults' eligibility generosity.

Compared to the South, all other regions are associated with increases in the probability a state provided medical assistance to other adults. A one percentage-point increase in the percentage of Black Americans in the population in the prior year is associated with a 0.498 percentage-point decrease in the likelihood a state extended assistance to other adults. Combined with statistically significant differences between other regions and the South, the negative impact of the percentage of Black Americans provides the strongest evidence that racial prejudices affect the eligibility generosity of Medicaid. Meanwhile, a larger population of females in the prior year is associated with a higher probability of extending eligibility to other adults.

Similar to the eligibility generosity for infants and pregnant women and children 1-18, hospital beds per 1000 population and active physicians per 1000 population have the same directional effect on the probability of a state covering other adults. An additional hospital bed per 1000 population is associated with an 8.62 percentage-point decrease while an additional active physician per 1000 population is associated with a 12.5 percentage-point increase in the probability a state extends assistance to other adults. The prior arguments of differing capacity constraints and financial troubles with Medicaid leading to opposite signs for the two measures of the health environment may apply to other adults.

# Chapter 8

# Conclusion

While we consider Medicaid to be a staple social welfare program today, Medicaid was nothing but an afterthought in the 1965 legislation. Even William Cohen, a major architect of the Medicare and Medicaid programs, admits he did not predict the impact Medicaid would have on the American people and on government budgets (Cohen 1985). In 2019, 20% of Americans were covered under Medicaid (Rudowitz, Hinton, and Garfield 2019). Naturally, the sheer scope and impact of Medicaid has generated numerous empirical studies. Research on the impact of Medicaid on a variety of health outcomes generally exploits the cross-state variation in state Medicaid eligibility to identify causal effects. However, few have yet to analyze why this variation in eligibility exists. In this paper, I pose the following questions about Medicaid's adoption and eligibility generosity. First, what factors impacted a state's decision to adopt Medicaid? Second, what factors impact state generosity in Medicaid eligibility as measured by a ratio of the "payment" to "need" standard and probability of a state covering a category above the mandatory minimum?

Overall, I find that political factors were insignificant in explaining both the probability of a state having a Medicaid program in the following year and on the "payment" to "need" standard ratio. This contrasts with the common idea that politics dictates policy on public programs. However, when measuring generosity as a bivariate variable equal to 1 if a state covered a particular category above the federal minimum, I find state legislature composition positively impacts eligibility generosity while governor political party has conflicting effects. Interestingly, higher income states were more likely to have a Medicaid program in year Y. Additionally higher income states are more generous in their eligibility limits.

Looking at demographic factors, there is inconsistent evidence to support the ideas of the Median Voter Theorem. States with higher female populations in the prior year were associated with a higher likelihood of a having a Medicaid program in year Y while states with lower Black American populations were associated with lower probabilities of states having a Medicaid program in year Y. As for eligibility, increases in these same populations were generally associated with less generous eligibility levels.

Similar to the demographic factors, the past year's hospital beds per 1000 population had opposing effects on eligibility measurements. When looking at the "payment" to "need" standard ratio, an increase in hospital beds per 1000 population was associated with an increase in generosity. However, increase in hospital beds per 1000 population are associated with decreases in the dichotomous measure of generosity. Contrasting, additional active physicians per 1000 population were associated with increases in both measurements of generosity. Perhaps the reason hospital beds per 1000 population has opposing signs in the eligibility models is driven by a stricter capacity constraint relative to physicians and hospitals' negative financial experiences with Medicaid. Considering the adoption of Medicaid, hospital beds per 1000 population and active physicians per 1000 population were insignificant factors. However, an additional 1 percentage-point increase in the AFDC recipients in 1965 is associated with a 1.09 percentage-point increase in the probability a state had a Medicaid program in the given year.

Due to issues such as simultaneity and omitted variable bias, I cannot claim causality, but I do find strong associations between a variety of factors and the timing of Medicaid and Medicaid eligibility generosity. Additionally, I am unable to capture all aspects that may affect eligibility generosity. For example, the existence of asset tests and interviews may reduce the true generosity of a state. A state with a low asset maximum or strict interview requirements may counter the benefits of higher financial eligibility levels.

Future extensions of this paper might study the effects of the various factors on a variety of optional benefits. For example, do the same variables that impact a state's Medicaid financial eligibility also impact benefits? Moreover, is there a tradeoff between benefits and higher eligibility? Are states with higher eligibility levels less likely to offer optional benefits or do they offer fewer? Finally, we can apply the models to other populations benefiting from Medicaid such as parents and caretakers, immigrant children, and foster kids.

# Chapter 9

# Appendix

Table 9.1: Percentage of States At or Above Mandatory Financial Minimum for Infants and Pregnant Women

| Year | At Mandatory Financial Minimum | Above Mandatory Financial Minimum |
|---|---|---|
| 1987 | 68.75 | 31.25 |
| 1988 | 27.08 | 72.92 |
| 1989 | 50.00 | 50.00 |
| 1990 | 56.25 | 43.75 |
| 1991 | 43.75 | 56.25 |
| 1992 | 41.67 | 58.33 |
| 1993 | 37.50 | 62.50 |
| 1994 | 33.33 | 66.67 |
| 1995 | 31.25 | 68.75 |
| 1996 | 31.25 | 68.75 |
| 1997 | 29.17 | 70.83 |
| 1998 | 22.92 | 77.08 |
| 1999 | 20.83 | 79.17 |
| 2000 | 18.75 | 81.25 |
| 2001 | 18.75 | 81.25 |
| 2002 | 18.75 | 81.25 |
| 2003 | 18.75 | 81.25 |
| 2004 | 18.75 | 81.25 |
| 2005 | 18.75 | 81.25 |
| 2006 | 20.83 | 79.17 |
| 2007 | 20.83 | 79.17 |
| 2008 | 20.83 | 79.17 |
| 2009 | 20.83 | 79.17 |
| 2010 | 20.83 | 79.17 |
| 2011 | 20.83 | 79.17 |
| 2012 | 20.83 | 79.17 |
| 2013 | 20.83 | 79.17 |
| 2014 | 0 | 100 |

Table 9.2: Percentage of States At or Above Mandatory Financial Minimum for Children Ages 1-5

| Year | At Mandatory Financial Minimum | Above Mandatory Financial Minimum |
|---|---|---|
| 1987 | 72.92 | 27.08 |
| 1988 | 45.83 | 54.17 |
| 1989 | 31.25 | 68.75 |
| 1990 | 93.75 | 6.25 |
| 1991 | 91.67 | 8.33 |
| 1992 | 89.58 | 10.42 |
| 1993 | 79.17 | 20.83 |
| 1994 | 70.83 | 29.17 |
| 1995 | 81.25 | 18.75 |
| 1996 | 79.17 | 20.83 |
| 1997 | 72.98 | 27.08 |
| 1998 | 54.17 | 45.83 |
| 1999 | 47.92 | 52.08 |
| 2000 | 47.92 | 52.08 |
| 2001 | 47.92 | 52.08 |
| 2002 | 47.92 | 52.08 |
| 2003 | 52.08 | 47.92 |
| 2004 | 52.08 | 47.92 |
| 2005 | 50.00 | 50.00 |
| 2006 | 52.08 | 47.92 |
| 2007 | 52.08 | 47.92 |
| 2008 | 52.08 | 47.92 |
| 2009 | 52.08 | 47.92 |
| 2010 | 52.08 | 47.92 |
| 2011 | 52.08 | 47.92 |
| 2012 | 52.08 | 47.92 |
| 2013 | 52.08 | 47.92 |
| 2014 | 2.08 | 97.92 |

Table 9.3: Percentage of States At or Above Mandatory Financial Minimum for Children Ages 6-18

| Year | At Mandatory Financial Minimum | Above Mandatory Financial Minimum |
|---|---|---|
| 1987 | 100 | 0 |
| 1988 | 100 | 0 |
| 1989 | 100 | 0 |
| 1990 | 75.00 | 25.00 |
| 1991 | 91.67 | 8.33 |
| 1992 | 87.50 | 12.50 |
| 1993 | 75.00 | 25.00 |
| 1994 | 66.67 | 33.33 |
| 1995 | 52.08 | 47.92 |
| 1996 | 50.00 | 50.00 |
| 1997 | 43.75 | 56.25 |
| 1998 | 25.00 | 75.00 |
| 1999 | 20.83 | 79.17 |
| 2000 | 22.92 | 77.08 |
| 2001 | 43.75 | 56.25 |
| 2002 | 41.67 | 58.33 |
| 2003 | 41.67 | 58.33 |
| 2004 | 43.75 | 56.25 |
| 2005 | 43.75 | 56.25 |
| 2006 | 45.83 | 54.17 |
| 2007 | 45.83 | 54.17 |
| 2008 | 43.75 | 56.25 |
| 2009 | 43.75 | 56.25 |
| 2010 | 41.67 | 58.33 |
| 2011 | 41.67 | 58.33 |
| 2012 | 39.58 | 60.42 |
| 2013 | 37.50 | 62.50 |
| 2014 | 35.42 | 64.58 |

Table 9.4: Percentage of States Offering Any Medical Assistance to Other Adults

| Year | At Mandatory Financial Minimum | Above Mandatory Financial Minimum |
|---|---|---|
| 1989 | 95.83 | 4.17 |
| 1990 | 93.75 | 6.25 |
| 1991 | 93.75 | 6.25 |
| 1992 | 91.67 | 8.33 |
| 1993 | 91.67 | 8.33 |
| 1994 | 87.50 | 12.50 |
| 1995 | 85.42 | 14.58 |
| 1996 | 83.33 | 16.67 |
| 1997 | 82.22 | 17.78 |
| 1998 | 80.00 | 20.00 |
| 1999 | 76.74 | 23.26 |
| 2000 | 65.96 | 34.04 |
| 2001 | 66.67 | 33.33 |
| 2002 | 75.00 | 25.00 |
| 2003 | 70.83 | 29.17 |
| 2004 | 70.83 | 29.17 |
| 2005 | 66.67 | 33.33 |
| 2006 | 66.67 | 33.33 |
| 2007 | 58.33 | 41.67 |
| 2008 | 50.00 | 50.00 |
| 2009 | 56.25 | 43.75 |
| 2010 | 56.25 | 43.75 |
| 2011 | 56.25 | 43.75 |
| 2012 | 54.17 | 45.83 |
| 2013 | 45.83 | 54.17 |
| 2014 | 27.08 | 72.92 |
| 2015 | 25.00 | 75.00 |
| 2016 | 22.92 | 77.08 |
| 2017 | 22.92 | 77.08 |
| 2018 | 25.00 | 75.00 |

Table 9.5: Medicaid Timing Model Robustness

| | Indicator if State had Medicaid Program in Year Y | | | | |
|---|---|---|---|---|---|
| | LPM | LPM | LPM | Probit | Logit |
| | (1) | (2) | (3) | (4) | (5) |
| Lag Democratic | 0.0350 | 0.0397 | 0.0369 | 0.0257 | 0.0267 |
| Governor Dummy | (0.0438) | (0.0449) | (0.0460) | (0.0373) | (0.0408) |
| Lag Majority Democratic | -0.0326 | -0.0219 | 0.0027 | -0.0589 | -0.0704 |
| Legislature Dummy | (0.0709) | (0.0720) | (0.0733) | (0.0615) | (0.0643) |
| Lag Split Party | -0.0488 | -0.0362 | -0.0471 | -0.0537 | -0.0512 |
| Legislature Dummy | (0.0719) | (0.0717) | (0.0729) | (0.0596) | (0.0622) |
| Lag Split Party State Dummy | 0.0577 | 0.0511 | 0.1095$^{**}$ | 0.0384 | 0.0378 |
| | (0.0536) | (0.0536) | (0.0553) | (0.0460) | (0.0487) |
| State Expenditures | 0.0000 | 0.0000 | 0.0000$^{*}$ | 0.0000$^{*}$ | 0.0000$^{*}$ |
| for MAA in 1965 | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Log of Lagged Real State | 0.5837$^{**}$ | 0.5953$^{**}$ | 0.7859$^{***}$ | 0.4665$^{**}$ | 0.4680$^{*}$ |
| GDP per Capita (2018$) | (0.2379) | (0.2362) | (0.2337) | (0.1942) | (0.2417) |
| West | -0.1453 | -0.1443 | -0.2084$^{*}$ | -0.2344$^{**}$ | -0.2526$^{**}$ |
| | (0.1080) | (0.1081) | (0.1072) | (0.1152) | (0.1197) |
| Midwest | -0.0428 | -0.0394 | -0.0455 | -0.1245 | -0.1482$^{*}$ |
| | (0.0905) | (0.0916) | (0.0912) | (0.0853) | (0.0888) |
| Northeast | -0.0672 | -0.0631 | -0.0258 | -0.1623 | -0.1833$^{*}$ |
| | (0.1262) | (0.1258) | (0.1221) | (0.1047) | (0.1071) |
| Lag of % Black | -0.0166$^{***}$ | -0.0169$^{***}$ | -0.0167$^{***}$ | -0.0152$^{***}$ | -0.0160$^{**}$ |
| | (0.0041) | (0.0041) | (0.0040) | (0.0043) | (0.0067) |
| Lag of % Under 65 | 0.0017 | 0.0016 | 0.0010 | 0.0019 | 0.0020 |
| | (0.0023) | (0.0022) | (0.0021) | (0.0020) | (0.0022) |
| Lag of % Female | 0.0584$^{**}$ | 0.0595$^{**}$ | 0.0559$^{**}$ | 0.0638$^{***}$ | 0.0661$^{**}$ |
| | (0.0277) | (0.0269) | (0.0282) | (0.0194) | (0.0273) |
| Lag of % Urban | -0.0011 | -0.0013 | -0.0025 | -0.0019 | -0.0014 |
| | (0.0027) | (0.0027) | (0.0028) | (0.0027) | (0.0027) |
| Lag of % Foreign Born | -0.0185 | -0.0184 | -0.0304 | -0.0070 | -0.0078 |
| | (0.0192) | (0.0191) | (0.0186) | (0.0131) | (0.0140) |
| Lag of Hospital Beds | 0.0188 | 0.0185 | 0.0196 | 0.0168 | 0.0179 |
| per 1000 Pop. | (0.0191) | (0.0198) | (0.0197) | (0.0202) | (0.0223) |
| Lag of Active Physicians | 0.0918 | 0.0943 | 0.0347 | 0.0008 | -0.0090 |
| per 1000 Pop. | (0.1392) | (0.1400) | (0.1335) | (0.1225) | (0.1284) |
| % of Population Receiving | 0.0109$^{***}$ | 0.0110$^{***}$ | 0.0096$^{***}$ | 0.0125$^{***}$ | 0.0130$^{***}$ |
| AFDC in 1965 | (0.0033) | (0.0033) | (0.0033) | (0.0031) | (0.0049) |
| Year | | 0.0865$^{***}$ | | | |
| | | (0.0187) | | | |
| Year Fixed Effects | Yes | No | Yes | Yes | Yes |
| Arizona Included | No | Yes | No | No | No |
| Observations | 235 | 235 | 240 | 188 | 188 |
| R-squared | 0.382 | 0.370 | 0.371 | | |

Robust Standard Errors $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9.6: Medicaid Eligibility Generosity

| | Payment to Need Standard Ratio | | |
|---|---|---|---|
| | OLS | OLS | OLS |
| | (1) | (2) | (3) |
| Lag Democratic Governor Dummy | -0.7754 | -1.2337 | -0.0164 |
| | (1.0870) | (1.0706) | (1.0631) |
| Lag Independent Governor Dummy | 0.8705 | 0.8088 | 1.2183 |
| | (3.9631) | (3.9938) | (3.6767) |
| Lag Majority Democratic Legislature Dummy | 1.9751 | 1.1202 | 2.6195* |
| | (1.4661) | (1.4528) | (1.4133) |
| Lag Split Party Legislature Dummy | 2.5045 | 2.2198 | 2.3654 |
| | (1.6145) | (1.5975) | (1.6050) |
| Lag Split Party State Dummy | -0.7418 | -1.1216 | -1.0104 |
| | (1.1886) | (1.1770) | (1.1829) |
| Log of Lagged Real State | 22.1500*** | 20.0590*** | 25.4650*** |
| GDP per Capita (2018$) | (4.8919) | (4.8496) | (4.6103) |
| West | 3.5106 | 3.6992 | 3.8404 |
| | (2.7203) | (2.7359) | (2.7565) |
| Midwest | 9.5037*** | 9.1940*** | 9.5525*** |
| | (2.2393) | (2.2482) | (2.2820) |
| Northeast | 7.8024*** | 7.5752*** | 7.5999*** |
| | (2.5160) | (2.5302) | (2.5582) |
| Lag of % Poverty | -0.1450 | -0.0971 | -0.2942 |
| | (0.2069) | (0.2055) | (0.2019) |
| Lag of % Black | -0.5811*** | -0.5932*** | -0.5728*** |
| | (0.1024) | (0.1029) | (0.1060) |
| Lag of % Under 65 | 0.0173 | 0.0082 | 0.0583 |
| | (0.1066) | (0.1064) | (0.1453) |
| Lag of % Female | -1.6493* | -1.7258* | -0.1395 |
| | (0.9390) | (0.9385) | (0.8095) |
| Lag of % Urban | -0.1045* | -0.0703 | -0.13104** |
| | (0.0576) | (0.0565) | (0.0572) |
| Lag of % Foreign Born | 0.2327 | 0.2596 | 0.3036 |
| | (0.2332) | (0.2310) | (0.2335) |
| Lag of Hospital Beds per 1000 Pop. | 0.8600* | 0.8402* | 0.6450 |
| | (0.4874) | (0.4856) | (0.5097) |
| Lag of Active Physicians per 1000 Pop. | 6.3871*** | 6.2538*** | 4.6540*** |
| | (1.8753) | (1.8621) | (1.6925) |
| Year | | | -1.3928*** |
| | | | (0.1419) |
| Year Fixed Effects | Yes | Yes | No |
| Arizona Included | Yes | No | Yes |
| Observations | 1360 | 1345 | 1360 |
| R-squared | 0.397 | 0.397 | 0.371 |
| Robust Standard Errors | | *p<0.1; **p<0.05; ***p<0.01 | |

Table 9.7: Medicaid Eligibility Generosity- Infants and Pregnant Women

| | Indicator Above Mandatory Minimum | | | |
|---|---|---|---|---|
| | LPM | LPM | Probit | Logit |
| | (1) | (2) | (3) | (4) |
| Lag Democratic Governor Dummy | 0.0313 | 0.0129 | 0.0146 | 0.0114 |
| | (0.0218) | (0.0212) | (0.0209) | (0.0214) |
| Lag Independent Governor Dummy | 0.0549 | 0.0621* | 0.2772*** | 0.2867*** |
| | (0.0350) | (0.0330) | (0.0095) | (0.0095) |
| Lag Majority Democratic Legislature Dummy | 0.0707** | 0.0669** | 0.0921*** | 0.0860*** |
| | (0.0291) | (0.0287) | (0.0302) | (0.0312) |
| Lag Split Party Legislature Dummy | 0.0226 | 0.0172 | 0.0450 | 0.0455 |
| | (0.0335) | (0.0339) | (0.0305) | (0.0312) |
| Lag Split Party State Dummy | -0.0307 | -0.0252 | -0.0338 | -0.0354 |
| | (0.0244) | (0.0249) | (0.0228) | (0.0235) |
| Log of Lagged Real State | 0.0492 | 0.0640 | -0.0939 | -0.0929 |
| GDP per Capita (2018$) | (0.0831) | (0.0828) | (0.0963) | (0.0921) |
| West | -0.4925*** | -0.4968*** | -0.4807*** | -0.4706*** |
| | (0.0437) | (0.0446) | (0.0453) | (0.0480) |
| Midwest | 0.1531*** | 0.1361*** | 0.1493*** | 0.1502*** |
| | (0.0342) | (0.0360) | (0.0303) | (0.0324) |
| Northeast | 0.0093 | -0.0152 | 0.1258*** | 0.1211*** |
| | (0.0448) | (0.0442) | (0.0397) | (0.0426) |
| Lag of % Poverty | 0.0268*** | 0.0215*** | 0.0256*** | 0.0248*** |
| | (0.0047) | (0.0046) | (0.0043) | (0.0047) |
| Lag of % Black | -0.0079*** | -0.0074*** | -0.0066*** | -0.0063*** |
| | (0.0017) | (0.0018) | (0.0014) | (0.0015) |
| Lag of % Under 65 | -0.0065 | -0.0046 | -0.0057** | -0.0056** |
| | (0.0046) | (0.0049) | (0.0026) | (0.0024) |
| Lag of % Female | 0.0749*** | 0.0709** | 0.0102 | 0.0184 |
| | (0.0268) | (0.0276) | (0.0234) | (0.0240) |
| Lag of % Urban | -0.0048*** | -0.0055*** | -0.0046*** | -0.0051*** |
| | (0.0013) | (0.0012) | (0.0016) | (0.0017) |
| Lag of % Foreign Born | 0.0202*** | 0.0211*** | 0.0167*** | 0.0181*** |
| | (0.0030) | (0.0030) | (0.0032) | (0.0041) |
| Lag of Hospital Beds per 1000 Pop. | -0.1627*** | -0.1597*** | -0.1468*** | -0.1448*** |
| | (0.0141) | (0.0130) | (0.0138) | (0.0182) |
| Lag of Active Physicians per 1000 Pop. | 0.0360* | 0.0406** | 0.1056*** | 0.1047*** |
| | (0.0200) | (0.0190) | (0.0242) | (0.0265) |
| Year | | -0.0076*** | | |
| | | (0.0024) | | |
| Year Fixed Effects | Yes | No | Yes | Yes |
| Observations | 1296 | 1296 | 1296 | 1296 |
| R-squared | 0.401 | 0.369 | | |
| Robust Standard Errors | | | *p<0.1; **p<0.05; ***p<0.01 | |

Table 9.8: Medicaid Eligibility Generosity- Children Ages 1-5

| | Indicator Above Mandatory Minimum | | | |
|---|---|---|---|---|
| | LPM | LPM | Probit | Logit |
| | (1) | (2) | (3) | (4) |
| Lag Democratic Governor Dummy | -0.0589** | -0.0680*** | -0.0679*** | -0.0826*** |
| | (0.0245) | (0.0256) | (0.0250) | (0.0231) |
| Lag Independent Governor Dummy | 0.0348 | 0.0066 | 0.0071 | -0.0085 |
| | (0.0852) | (0.0947) | (0.0966) | (0.0984) |
| Lag Majority Democratic Legislature Dummy | 0.1837*** | 0.1807*** | 0.1788*** | 0.1716*** |
| | (0.0335) | (0.0333) | (0.0344) | (0.0319) |
| Lag Split Party Legislature Dummy | 0.0847** | 0.0579 | 0.0907** | 0.0879*** |
| | (0.0364) | (0.0379) | (0.0358) | (0.0336) |
| Lag Split Party State Dummy | 0.0552** | 0.0646** | 0.0418 | 0.0378 |
| | (0.0274) | (0.0290) | (0.0274) | (0.0259) |
| Log of Lagged Real State | -0.1973* | -0.1195 | -0.1732 | -0.2154* |
| GDP per Capita (2018$) | (0.1065) | (0.1104) | (0.1254) | (0.1141) |
| West | -0.1998*** | -0.1600*** | -0.1698*** | -0.1722*** |
| | (0.0506) | (0.0567) | (0.0453) | (0.0475) |
| Midwest | 0.2159*** | 0.1723*** | 0.2267*** | 0.2164*** |
| | (0.0435) | (0.0477) | (0.0390) | (0.0395) |
| Northeast | 0.1006* | 0.0682 | 0.1269** | 0.0878 |
| | (0.0561) | (0.0617) | (0.0630) | (0.0599) |
| Lag of % Poverty | 0.0163*** | 0.0072 | 0.0146*** | 0.0150*** |
| | (0.0047) | (0.0052) | (0.0046) | (0.0046) |
| Lag of % Black | -0.0082*** | -0.0082*** | -0.0075*** | -0.0076*** |
| | (0.0020) | (0.0022) | (0.0018) | (0.0020) |
| Lag of % Under 65 | 0.0016 | 0.0048 | 0.0047 | 0.0042 |
| | (0.0019) | (0.0038) | (0.0077) | (0.0077) |
| Lag of % Female | -0.0296 | 0.0007 | -0.0071 | -0.0208 |
| | (0.0287) | (0.0304) | (0.0374) | (0.0320) |
| Lag of % Urban | -0.0020 | -0.0024 | -0.0036* | -0.0043** |
| | (0.0015) | (0.0016) | (0.0020) | (0.0018) |
| Lag of % Foreign Born | -0.0286*** | -0.0251*** | -0.0238*** | -0.0262*** |
| | (0.0036) | (0.0036) | (0.0045) | (0.0055) |
| Lag of Hospital Beds per 1000 Pop. | -0.1813*** | -0.1336*** | -0.1850*** | -0.1914*** |
| | (0.0158) | (0.0162) | (0.0182) | (0.0271) |
| Lag of Active Physicians per 1000 Pop. | 0.2138*** | 0.1944*** | 0.1806** | 0.2350*** |
| | (0.0555) | (0.0584) | (0.0899) | (0.0681) |
| Year | | -0.0006 | | |
| | | (0.0030) | | |
| Year Fixed Effects | Yes | No | Yes | Yes |
| Observations | 1296 | 1296 | 1296 | 1296 |
| R-squared | 0.366 | 0.257 | | |
| Robust Standard Errors | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 9.9: Medicaid Eligibility Generosity- Children Ages 6-18

| | Indicator Above Mandatory Minimum | | | |
|---|---|---|---|---|
| | LPM | LPM | Probit | Logit |
| | (1) | (2) | (3) | (4) |
| Lag Democratic Governor Dummy | 0.0162 | -0.0227 | -0.0072 | -0.0072 |
| | (0.0263) | (0.0260) | (0.0249) | (0.0249) |
| Lag Independent Governor Dummy | 0.0242 | 0.0359 | 0.0305 | 0.0305 |
| | (0.0620) | (0.0689) | (0.0754) | (0.0754) |
| Lag Majority Democratic Legislature Dummy | 0.1203*** | 0.0950*** | 0.1045*** | 0.1045*** |
| | (0.0341) | (0.0336) | (0.0289) | (0.0289) |
| Lag Split Party Legislature Dummy | 0.0430 | 0.0295 | 0.0471 | 0.0471 |
| | (0.0388) | (0.0392) | (0.0334) | (0.0334) |
| Lag Split Party State Dummy | 0.0642** | 0.0515* | 0.0418 | 0.0418 |
| | (0.0298) | (0.0299) | (0.0256) | (0.0256) |
| Log of Lagged Real State | -0.0664 | 0.0460 | -0.0875 | -0.0875 |
| GDP per Capita (2018$) | (0.1175) | (0.1224) | (0.0975) | (0.0975) |
| West | -0.2081*** | -0.2147*** | -0.1841*** | -0.1841*** |
| | (0.0580) | (0.0599) | (0.0456) | (0.0456) |
| Midwest | 0.2973*** | 0.2957*** | 0.2588*** | 0.2588*** |
| | (0.0428) | (0.0449) | (0.0317) | (0.0317) |
| Northeast | 0.0308 | 0.0134 | 0.0688 | 0.0688 |
| | (0.0562) | (0.0566) | (0.0546) | (0.0546) |
| Lag of % Poverty | 0.0006 | 0.00001 | 0.0004 | 0.0004 |
| | (0.0050) | (0.0051) | (0.0045) | (0.0045) |
| Lag of % Black | -0.0062*** | -0.0045* | -0.0046*** | -0.0046*** |
| | (0.0023) | (0.0023) | (0.0017) | (0.0017) |
| Lag of % Under 65 | 0.0236** | 0.0107 | 0.0172 | 0.0172 |
| | (0.0105) | (0.0102) | (0.0108) | (0.0108) |
| Lag of % Female | -0.0013 | -0.0240 | -0.0322 | -0.0322 |
| | (0.0314) | (0.0321) | (0.0291) | (0.0291) |
| Lag of % Urban | -0.0062*** | -0.0078*** | -0.0083*** | -0.0083*** |
| | (0.0016) | (0.0016) | (0.0017) | (0.0017) |
| Lag of % Foreign Born | -0.0107** | -0.0106** | -0.0070* | -0.0070* |
| | (0.0044) | (0.0043) | (0.0038) | (0.0038) |
| Lag of Hospital Beds per 1000 Pop. | -0.1681*** | -0.1960*** | -0.1715*** | -0.1715*** |
| | (0.0191) | (0.0170) | (0.0189) | (0.0189) |
| Lag of Active Physicians per 1000 Pop. | 0.1829*** | 0.1843*** | 0.1836*** | 0.1836*** |
| | (0.0332) | (0.0374) | (0.0437) | (0.0437) |
| Year | | -0.0016 | | |
| | | (0.0031) | | |
| Year Fixed Effects | Yes | No | Yes | Yes |
| Observations | 1200 | 1200 | 1200 | 1200 |
| R-squared | 0.351 | 0.302 | | |
| Robust Standard Errors | | | *p<0.1; **p<0.05; ***p<0.01 | |

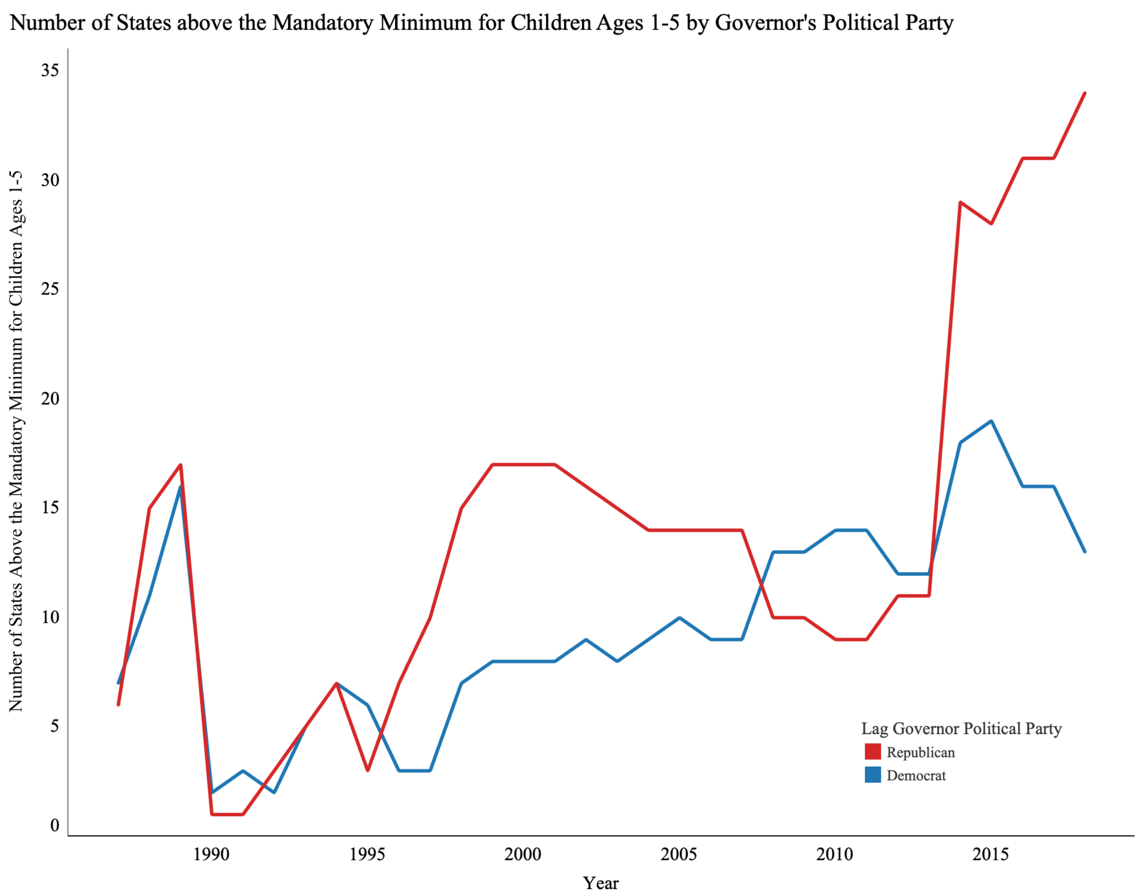
Table 9.10: Medicaid Eligibility Generosity- Other Adults

| | Indicator Any Assistance | | | |
|---|---|---|---|---|
| | LPM | LPM | Probit | Logit |
| | (1) | (2) | (3) | (4) |
| Lag Democratic Governor Dummy | 0.0446* | 0.0349 | 0.0497** | 0.0547** |
| | (0.0229) | (0.0232) | (0.0226) | (0.0231) |
| Lag Independent Governor Dummy | -0.0596 | -0.0619 | -0.0185 | -0.0074 |
| | (0.1116) | (0.1138) | (0.0838) | (0.0843) |
| Lag Majority Democratic Legislature Dummy | 0.0823*** | 0.0873*** | 0.0601* | 0.0440 |
| | (0.0308) | (0.0307) | (0.0317) | (0.0326) |
| Lag Split Party Legislature Dummy | 0.1169*** | 0.1197*** | 0.1132*** | 0.1164*** |
| | (0.0352) | (0.0358) | (0.0316) | (0.0319) |
| Lag Split Party State Dummy | -0.0351 | -0.0428 | -0.0398 | -0.0498* |
| | (0.0266) | (0.0267) | (0.0267) | (0.0274) |
| Log of Lagged Real State | 0.2693** | 0.2526** | 0.2504*** | 0.2380** |
| GDP per Capita (2018$) | (0.1141) | (0.1155) | (0.0968) | (0.0971) |
| West | 0.2245*** | 0.2511*** | 0.1776*** | 0.1715*** |
| | (0.0499) | (0.0503) | (0.0546) | (0.0558) |
| Midwest | 0.1359*** | 0.1122*** | 0.1047*** | 0.1039*** |
| | (0.0397) | (0.0399) | (0.0368) | (0.0370) |
| Northeast | 0.1050** | 0.1103** | 0.0741 | 0.0714 |
| | (0.0505) | (0.0505) | (0.0506) | (0.0507) |
| Lag of % Poverty | 0.0164*** | 0.0121*** | 0.0158*** | 0.0156*** |
| | (0.0043) | (0.0041) | (0.0041) | (0.0044) |
| Lag of % Black | -0.0050*** | -0.0040** | -0.0059*** | -0.0060*** |
| | (0.0019) | (0.0019) | (0.0022) | (0.0023) |
| Lag of % Under 65 | -0.0144 | -0.0226** | -0.0135 | -0.0154* |
| | (0.0092) | (0.0089) | (0.0086) | (0.0089) |
| Lag of % Female | 0.0636*** | 0.0613*** | 0.0584** | 0.0530** |
| | (0.0243) | (0.0235) | (0.0229) | (0.0239) |
| Lag of % Urban | -0.0011 | -0.0004 | -0.0003 | -0.0003 |
| | (0.0015) | (0.0015) | (0.0014) | (0.0014) |
| Lag of % Foreign Born | -0.0020 | -0.0020 | -0.0028 | -0.0027 |
| | (0.0038) | (0.0038) | (0.0033) | (0.0033) |
| Lag of Hospital Beds per 1000 Pop. | -0.0826*** | -0.0548*** | -0.0882*** | -0.0928*** |
| | (0.0149) | (0.0134) | (0.0165) | (0.0193) |
| Lag of Active Physicians per 1000 Pop. | 0.1253*** | 0.1161*** | 0.1205*** | 0.1244*** |
| | (0.0298) | (0.0295) | (0.0273) | (0.0294) |
| Year | | 0.0144*** | | |
| | | (0.0027) | | |
| Year Fixed Effects | Yes | No | Yes | Yes |
| Observations | 1428 | 1428 | 1428 | 1428 |
| R-squared | 0.353 | 0.326 | | |
| Robust Standard Errors | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 9.11: Timeline of Medicaid Eligibility Expansions

| Year | |
|---|---|
| 1965 | Medicaid is passed under Title XIX of the Social Security Amendments of 1965 |
| 1972 | Mandated eligibility for SSI recipients (formerly Aid to the Blind and Aid to the Permnanently and Totally Disabled) |
| 1984 | Required states to cover all children under the age of 6 that met state AFDC standards regardless of family composition |
| | Extended coverage to first time pregnant women and pregnant women in 2-parent unemployed families meeting state AFDC income/resources standards |
| 1985 | Annulled unemployment requirement for pregnant women in 2-parent families |
| 1986 | Optional eligibility expansion up to 100% FPL for pregnant women and infants |
| | Optional phase-in of coverage for children up to age 5 at 100% FPL |
| 1987 | Optional eligibility expansions up to 185% FPL for pregnant women and infants |
| | Optional phase-in up to 100% FPL for children up to age 8 |
| 1988 | Mandated eligibility expansion for pregnant women and infants at 100% FPL with 2-year phase-in period |
| 1989 | Mandated eligibility expansion for children up to age 6 at 133% FPL |
| 1990 | Mandates phase-in* of children through age 18 at 100% FPL |
| | *Upper age limit to be reached by Oct. 2002 |
| 1996 | AFDC and Medicaid formally decoupled |
| 1997 | State Children's Health Insurance Program implemented |
| 2010 | ACA mandates eligibility expansion to nonelderly, nondisabled, nonpregnant, childless adults at 138% FPL |
| 2012 | *NFIB v. Sebelius* makes ACA expansion optional |

Figure 9.1: Number of States above the Mandatory Minimum for Children Ages 1-5 by Governor's Political Party



# Chapter 10

# R Codes

Note, the coefficient estimates for all probit and logit models will not match the estimates from Stata (and my Honor's Thesis) unless you use the option "asis" in Stata when running the regressions. Stata drops any observations that perfectly predict success/failure in order to increase stability for optimization. For more information on the "asis" option see https://www.stata.com/manuals/rprobit.pdf.

Information on Packages Used

AER: https://cran.r-project.org/web/packages/AER/AER.pdf

margins: https://cran.r-project.org/web/packages/margins/vignettes/Introduction.html

mfx: https://cran.r-project.org/web/packages/mfx/mfx.pdf

stargazer: https://cran.r-project.org/web/packages/stargazer/vignettes/stargazer.pdf

stargazer: http://online.sfsu.edu/mbar/ECON312_files/LabProbit_stargazer.R

readstata13: https://cran.r-project.org/web/packages/readstata13/readme/README.html

```r
#Thesis Regressions Using R
#Import Packages

library(readstata13)
library(foreign)
library(writexl)
library(AER)

library(lmtest)
library(sandwich)
library(stargazer)

library(margins)
library(mfx)

library(sampleSelection)

library(tinytex)

options(scipen = 100)
options(digits = 5)
options(width = 100)

#Import data
data = read.dta13("thesis_r_data.dta")


# Cleaning Data -----------------------------------------------------------
names(data)[names(data) == "T"] <- "Trend"

# Medicaid Adoption -------------------------------------------------------

ma_data <- data[which(data$ABB!= "AZ" & data$YEAR > 1965 & data$YEAR <= 1970), ]
ma_data_az <- data[which(data$YEAR > 1965 & data$YEAR <= 1970), ]

#Year FE
m1 = lm(MED_PRG~ LAG_D_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
        MAA_EXP_65+log_lrgdp_pc+
        WEST+MIDWEST+NORTHEAST+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+PERC_AFDCP65+year_fe3+year_fe4+year_fe5+year_fe6,
        data = ma_data)
summary(m1)

het_corr_m1 = vcovHC(m1, type = "HC1" )
m1r = coeftest(m1, vcov = het_corr_m1)
m1r

#Trend
m2 = lm(MED_PRG~ LAG_D_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
        MAA_EXP_65+log_lrgdp_pc+
        WEST+MIDWEST+NORTHEAST+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+PERC_AFDCP65+Trend,
        data = ma_data)
summary(m2)

het_corr_m2= vcovHC(m2, type = "HC1" )
m2r = coeftest(m2, vcov = het_corr_m2)
m2r

#Include AZ
m3 = lm(MED_PRG~ LAG_D_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
         MAA_EXP_65+log_lrgdp_pc+
        WEST+MIDWEST+NORTHEAST+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+PERC_AFDCP65+year_fe3+year_fe4+year_fe5+year_fe6,
        data = ma_data_az)
summary(m3)

het_corr_m3= vcovHC(m3, type = "HC1" )
m3r = coeftest(m3, vcov = het_corr_m3)
m3r

#Probit
probit_m4 <- glm(MED_PRG ~ LAG_D_GOV + LAG_D_LEG + LAG_SPLIT_LEG + LAG_SPLIT_STATE +
                         MAA_EXP_65 + log_lrgdp_pc +
                         WEST + MIDWEST + NORTHEAST + LAG_PERC_BLACK + LAG_PERC_UNDER_65 + LAG_PERC_FEMALE +
```

```r
                         LAG_PERC_URBAN + LAG_PERC_FOREIGN_BORN +
                         LAG_HBEDS_PER_1000 + LAG_AP_PER_1000 + PERC_AFDCP65 +
                         year_fe3 + year_fe4 + year_fe5 + year_fe6 ,
                 data = ma_data,
                 family = binomial(link = "logit"))

m4 = probitmfx(MED_PRG ~ LAG_D_GOV + LAG_D_LEG + LAG_SPLIT_LEG + LAG_SPLIT_STATE +
                  MAA_EXP_65 + log_lrgdp_pc +
                  WEST + MIDWEST + NORTHEAST + LAG_PERC_BLACK + LAG_PERC_UNDER_65 + LAG_PERC_FEMALE +
                  LAG_PERC_URBAN + LAG_PERC_FOREIGN_BORN +
                  LAG_HBEDS_PER_1000 + LAG_AP_PER_1000 + PERC_AFDCP65 +
                  year_fe3 + year_fe4 + year_fe5 + year_fe6 , data = ma_data, atmean = F, robust = T)

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

m4

#Extract estimated marginal effects and standard errors
probit_mfx_coef <- m4$mfxest[,1]
probit_mfx_se <- m4$mfxest[,2]

#Logit
logit_m5 <- glm(MED_PRG ~ LAG_D_GOV + LAG_D_LEG + LAG_SPLIT_LEG + LAG_SPLIT_STATE +
                        MAA_EXP_65 + log_lrgdp_pc +
                        WEST + MIDWEST + NORTHEAST + LAG_PERC_BLACK + LAG_PERC_UNDER_65 + LAG_PERC_FEMALE +
                        LAG_PERC_URBAN + LAG_PERC_FOREIGN_BORN +
                        LAG_HBEDS_PER_1000 + LAG_AP_PER_1000 + PERC_AFDCP65 +
                        year_fe3 + year_fe4 + year_fe5 + year_fe6 ,
                data = ma_data,
                family = binomial(link = "probit"))

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

m5 = logitmfx(MED_PRG ~ LAG_D_GOV + LAG_D_LEG + LAG_SPLIT_LEG + LAG_SPLIT_STATE +
                      MAA_EXP_65 + log_lrgdp_pc +
                      WEST + MIDWEST + NORTHEAST + LAG_PERC_BLACK + LAG_PERC_UNDER_65 + LAG_PERC_FEMALE +
                      LAG_PERC_URBAN + LAG_PERC_FOREIGN_BORN +
                      LAG_HBEDS_PER_1000 + LAG_AP_PER_1000 + PERC_AFDCP65 +
                      year_fe3 + year_fe4 + year_fe5 + year_fe6, data = ma_data, atmean = F, robust = T)
m5

#Extract estimated marginal effects and standard errors
logit_mfx_coef <- m5$mfxest[,1]
logit_mfx_se <- m5$mfxest[,2]


# Eligibility: Payment to Need Standard Ratio -----------------------------

#AZ, YEAR FE
m6 = lm(PMT_V_NEED~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe5+year_fe6+year_fe7+year_fe8+year_fe9+year_fe10+

year_fe11+year_fe12+year_fe13+year_fe14+year_fe15+year_fe16+year_fe17+year_fe18+year_fe19+year_fe20+year_fe21

+year_fe22+year_fe23+year_fe24+year_fe25+year_fe26+year_fe27+year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32,
        data = data[which(data$YEAR>=1968 & data$YEAR<=1996), ])
summary(m6)

het_corr_m6 = vcovHC(m6, type = "HC1" )
m6r = coeftest(m6, vcov = het_corr_m6)
m6r

#NO AZ, YEAR FE
m7 = lm(PMT_V_NEED~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe5+year_fe6+year_fe7+year_fe8+year_fe9+year_fe10+

year_fe11+year_fe12+year_fe13+year_fe14+year_fe15+year_fe16+year_fe17+year_fe18+year_fe19+year_fe20+year_fe21

+year_fe22+year_fe23+year_fe24+year_fe25+year_fe26+year_fe27+year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32,
        data = data[which(data$YEAR>=1968 & data$YEAR<=1996 & data$ABB != "AZ"), ])
summary(m7)
```

```
het_corr_m7 = vcovHC(m7, type = "HC1" )
m7r = coeftest(m7, vcov = het_corr_m7)
m7r

#AZ, TREND
m8 = lm(PMT_V_NEED~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+Trend,
        data = data[which(data$YEAR>=1968 & data$YEAR<=1996), ])
summary(m8)

het_corr_m8 = vcovHC(m8, type = "HC1" )
m8r = coeftest(m8, vcov = het_corr_m8)
m8r

# Eligibility: Above Mandatory Minimum -----------------------------------
{##Infants/Pregnant Women ====
        #LPM with Year FE (preferred model)
        m9 = lm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ])
        summary(m9)
        het_corr_m9 = vcovHC(m9, type = "HC1" )
        m9r = coeftest(m9, vcov = het_corr_m9)
        m9r

        #LPM with Trend
        m10 = lm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+Trend,
        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ])
        summary(m10)
        het_corr_m10 = vcovHC(m10, type = "HC1" )
        m10r = coeftest(m10, vcov = het_corr_m10)
        m10r

        #Probit with year FE
        m11_pr = glm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                         log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                         year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                 data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("probit"))

         m11 = probitmfx(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                                year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
      m11
        probit_mfx_coef_0pw <- m11$mfxest[,1]
        probit_mfx_se_0pw <- m11$mfxest[,2]

        #Logit with year FE
        m12_lg = lm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                         log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+
```

```
year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                         year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                 data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("logit"))

        m12 = logitmfx(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                                year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
        m12
        logit_mfx_coef_0pw <- m12$mfxest[,1]
        logit_mfx_se_0pw <- m12$mfxest[,2]
}

## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
##  extra argument 'family' will be disregarded

{##Children 1-5 ====
        #LPM with Year fE
        m13 = lm(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ])
        summary(m13)
        het_corr_m13 = vcovHC(m13, type = "HC1" )
        m13r = coeftest(m13, vcov = het_corr_m13)
        m13r

        #LPM with Trend
        m14 = lm(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+Trend,
                data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ])
        summary(m14)
        het_corr_m14 = vcovHC(m14, type = "HC1" )
        m14r = coeftest(m14, vcov = het_corr_m14)
        m14r

        #Probit with Year FE
        m15_pr = glm(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                        year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("probit"))

        m15 = probitmfx(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                          year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
        m15
        probit_mfx_coef_15 <- m15$mfxest[,1]
        probit_mfx_se_15 <- m15$mfxest[,2]
```

```
        #Logit with Year FE
        m16_lg = glm(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                        year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("logit"))

        m16 = logitmfx(ABOVE_MANDATE_1_5~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                          year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
        m16
        logit_mfx_coef_15 <- m16$mfxest[,1]
        logit_mfx_se_15 <- m16$mfxest[,2]

}
{##Children 6-18 ====
        #LPM with Year FE
        m17 = lm(ABOVE_MANDATE_6_18~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50,
        data = data[which(data$YEAR>=1990 & data$YEAR<=2014), ])
        summary(m17)
        het_corr_m17 = vcovHC(m17, type = "HC1" )
        m17r = coeftest(m17, vcov = het_corr_m17)
        m17r

        #LPM with Trend
        m18 = lm(ABOVE_MANDATE_6_18~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+Trend,
                data = data[which(data$YEAR>= 1990 & data$YEAR<=2014), ])
        summary(m18)
        het_corr_m18 = vcovHC(m18, type = "HC1" )
        m18r = coeftest(m18, vcov = het_corr_m18)
        m18r

        #Probit with Year FE
        m19_pr = glm(ABOVE_MANDATE_6_18~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                        year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("probit"))

        m19 = probitmfx(ABOVE_MANDATE_6_18~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                          year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
```

```
        m19
        probit_mfx_coef_618 <- m19$mfxest[,1]
        probit_mfx_se_618 <- m19$mfxest[,2]

        #Logit with Year FE
        m20_lg = lm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                        year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], family = binomial("logit"))

        m20 = probitmfx(ABOVE_MANDATE_6_18~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe24+year_fe25+year_fe26+year_fe27+year_fe28+year_fe29+year_fe30+

year_fe31+year_fe32+year_fe33+year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+
                          year_fe42+year_fe43+year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49,
                        data = data[which(data$YEAR>=1987 & data$YEAR<=2013), ], atmean = F, robust = T)
        m20
        logit_mfx_coef_618 <- m20$mfxest[,1]
        logit_mfx_se_618 <- m20$mfxest[,2]
}

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
##  extra argument 'family' will be disregarded

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

{##Other Adults ====
       #LPM with Year FE
        m21 = lm(ANY_OA~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe26+
year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32+year_fe33+
                year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+year_fe42+year_fe43+

year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50+year_fe51+year_fe52+year_fe53+year_fe54,
        data = data[which(data$YEAR>=1989), ])
      summary(m21)
      het_corr_m21 = vcovHC(m21, type = "HC1" )
      m21r = coeftest(m21, vcov = het_corr_m21)
      m21r


        #LPM with Trend
        m22 = lm(ANY_OA~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                        LAG_HBEDS_PER_1000+LAG_AP_PER_1000+Trend,
                data = data[which(data$YEAR>=1989), ])
        summary(m22)
        het_corr_m22 = vcovHC(m22, type = "HC1" )
        m22r = coeftest(m22, vcov = het_corr_m22)
        m22r
                #Probit with Year FE
        m23_pr = glm(ANY_OA~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                   log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+
                   LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                   LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe26+
year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32+year_fe33+
                   year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+year_fe42+year_fe43+
```

```
year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50+year_fe51+year_fe52+year_fe53+year_fe54,
                 data = data[which(data$YEAR>=1989), ], family = binomial("probit"))

        m23 = probitmfx(ANY_OA~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                          LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe26+
year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32+year_fe33+

year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+year_fe42+year_fe43+

year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50+year_fe51+year_fe52+year_fe53+year_fe54,
                        data = data[which(data$YEAR>=1989), ], atmean = F, robust = T)
        m23
        probit_mfx_coef_oa <- m23$mfxest[,1]
        probit_mfx_se_oa <- m23$mfxest[,2]

        #Logit with Year FE
        m24_lg = lm(ABOVE_MANDATE_0_PW~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                        log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+

LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32+year_fe33+

year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+year_fe42+year_fe43+

year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50+year_fe51+year_fe51+year_fe53+year_fe54,
                data = data[which(data$YEAR>=1989), ], family = binomial("logit"))

        m24 =logitmfx(ANY_OA~LAG_D_GOV+LAG_I_GOV+LAG_D_LEG+LAG_SPLIT_LEG+LAG_SPLIT_STATE+
                          log_lrgdp_pc+WEST+MIDWEST+NORTHEAST+

LAG_PERC_POVERTY+LAG_PERC_BLACK+LAG_PERC_UNDER_65+LAG_PERC_FEMALE+LAG_PERC_URBAN+LAG_PERC_FOREIGN_BORN+
                          LAG_HBEDS_PER_1000+LAG_AP_PER_1000+year_fe26+
year_fe27+year_fe28+year_fe29+year_fe30+year_fe31+year_fe32+year_fe33+

year_fe34+year_fe35+year_fe36+year_fe37+year_fe38+year_fe39+year_fe40+year_fe41+year_fe42+year_fe43+

year_fe44+year_fe45+year_fe46+year_fe47+year_fe48+year_fe49+year_fe50+year_fe51+year_fe52+year_fe53+year_fe54,
                        data = data[which(data$YEAR>=1989), ], atmean = F, robust = T)
        m24
        logit_mfx_coef_oa <- m24$mfxest[,1]
        logit_mfx_se_oa <- m24$mfxest[,2]
}

## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
##  extra argument 'family' will be disregarded

# Exports to Stargazer -----------------------------------------------------
#Medicaid Adoption
stargazer(m1r, m2r, m3r, probit_m4, logit_m5, title = "Medicaid Timing Model Robustness I",
          dep.var.caption = "Indicator if State had Medicaid Program in Year Y",
          align = T, no.space = T, digits = 4,
          column.labels= c("LPM", "LPM", "LPM"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "State Expenditures for MAA in 1965", "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "% of Population Receiving AFDC in 1965", "Year"),
          coef = list(NULL, NULL, NULL, c(NA,probit_mfx_coef), c(NA,logit_mfx_coef)),
          se = list(NULL, NULL, NULL, c(NA, probit_mfx_se), c(NA, logit_mfx_se)),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "No", "Yes", "Yes", "Yes"), c("Arizona Included", "No", "Yes",
"No", "No", "No"))
        )

#Medicaid PMT to ND
stargazer(m6r, m7r, m8r, title = "Medicaid Eligibility Generosity",
          dep.var.caption = "Payment to Need Standard Ratio",
          align = T, no.space = T, digits = 4,
```

```r
          column.labels = c("OLS", "OLS", "OLS"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Governor Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = "year_fe",
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "Yes", "No"), c("Arizona Included", "No", "Yes", "No"))
          )

#Medicaid Infants/PW
stargazer(m9r, m10r, m11_pr, m12_lg, title = "Medicaid Eligibility Generosity- Infants and Pregnant Women",
          dep.var.caption = "Indicator Above Mandatory Minimum",
          coef = list(NULL, NULL, c(NA, probit_mfx_coef_0pw), c(NA, logit_mfx_coef_0pw)),
          se = list(NULL, NULL, c(NA, probit_mfx_se_0pw), c(NA, logit_mfx_se_0pw)),
          align = T, no.space = T, digits = 4,
          column.labels = c("LPM", "LPM", "Probit", "Logit"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Govenror Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "No", "Yes", "Yes"),c("Observations", 1296, 1296, 1296, 1296),
c("R-squared", 0.401, 0.369)))

#Medicaid Children 1-5
stargazer(m13r, m14r, m15_pr, m16_lg, title = "Medicaid Eligibility Generosity- Children Ages 1-5",
          dep.var.caption = "Indicator Above Mandatory Minimum",
          coef = list(NULL, NULL, c(NA, probit_mfx_coef_15), c(NA, logit_mfx_coef_15)),
          se = list(NULL, NULL, c(NA, probit_mfx_se_15), c(NA, logit_mfx_se_15)),
          align = T, no.space = T, digits = 4,
          column.labels = c("LPM", "LPM", "Probit", "Logit"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Govenror Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "No", "Yes", "Yes"),c("Observations", 1296, 1296, 1296, 1296),
c("R-squared", 0.366, 0.257)))

#Medicaid Children 6-18
stargazer(m17r, m18r, m19_pr, m20_lg, title = "Medicaid Eligibility Generosity- Children Ages 6-18",
          dep.var.caption = "Indicator Above Mandatory Minimum",
          coef = list(NULL, NULL, c(NA, probit_mfx_coef_618), c(NA, logit_mfx_coef_618)),
          se = list(NULL, NULL, c(NA, probit_mfx_se_618), c(NA, logit_mfx_se_618)),
          align = T, no.space = T, digits = 4,
          column.labels = c("LPM", "LPM", "Probit", "Logit"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Govenror Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "No", "Yes", "Yes"),c("Observations", 1200, 1200, 1200, 1200),
c("R-squared", 0.351, 0.302)))

#Medicaid Other Adults
stargazer(m21r, m22r, m23_pr, m24_lg, title = "Medicaid Eligibility Generosity- Other Adults",
```

```r
          dep.var.caption = "Indicator Any Assistance",
          coef = list(NULL, NULL, c(NA, probit_mfx_coef_oa), c(NA, logit_mfx_coef_oa)),
          se = list(NULL, NULL, c(NA, probit_mfx_se_oa), c(NA, logit_mfx_se_oa)),
          align = T, no.space = T, digits = 4,
          column.labels = c("LPM", "LPM", "Probit", "Logit"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Govenror Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes", "No", "Yes", "Yes"),c("Observations", 1428, 1428, 1428, 1428),
c("R-squared", 0.353, 0.326)))

#Paper Tables
stargazer(m1r, title = "Factors Impacting States' Adoption of Medicaid",
          dep.var.caption = "Indicator if State had Medicaid Program in Year Y",
          align = T, no.space = T, digits = 4,
          column.labels= c("LPM"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "State Expenditures for MAA in 1965", "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "% of Population Receiving AFDC in 1965", "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes"), c("Arizona Included", "No"))
)

stargazer(m6r, title = "Factors Impacting State 'Payment' to 'Need' Standard Ratios",
          dep.var.caption = "Payment to Need Standard Ratio",
          align = T, no.space = T, digits = 4,
          column.labels = c("OLS"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Governor Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = "year_fe",
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Year Fixed Effects", "Yes"), c("Arizona Included", "Yes"), c("Observations", 1360), c("R-
squared",0.397))
)

stargazer(m9r, m13r, m17r, title = "Factors Impacting State Financial Eligibility Generosity",
          dep.var.caption = "Indicator Above Mandatory Minimum",
          align = T, no.space = T, digits = 4,
          column.labels = c("Infants/Pregnant Women", "Children 1-5", "Children 6-18"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Governor Dummy",
                               "Lag Majority Democratic Legislature Dummy",
                               "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                               "Log of Lagged Real State GDP per Capita (2018$)",
                               "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                               "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                               "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                               "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Years of Interest", "1987-2013", "1987-2013", "1990-2014"),c("Observations", 1296, 1296,
1152), c("R-squared", 0.401, 0.366, 0.353)))

stargazer(m21r, title = "Factors Impacting State Eligibility Generosity for Other Adults",
          dep.var.caption = "Indicator Any Assistance",
          align = T, no.space = T, digits = 4,
          column.labels = c("LPM"),
          covariate.labels = c("Lag Democratic Governor Dummy", "Lag Independent Governor Dummy",
                               "Lag Majority Democratic Legislature Dummy",
```

```
                                "Lag Split Party Legislature Dummy", "Lag Split Party State Dummy",
                                "Log of Lagged Real State GDP per Capita (2018$)",
                                "West", "Midwest", "Northeast", "Lag of % Poverty", "Lag of % Black", "Lag of % Under 65",
                                "Lag of % Female", "Lag of % Urban", "Lag of % Foreign Born",
                                "Lag of Hospital Beds per 1000 Population", "Lag of Active Physicians per 1000 Population",
                                "Year"),
          omit = c("year_fe"),
          notes.label = "Robust Standard Errors",
          add.lines = list(c("Years of Interest", "1989-2018"),c("Observations", 1428), c("R-squared", 0.353)))
```

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