

The Medicaid Expansion: Modeling of Important Factors in State Decision Making

Senior Thesis

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Abstract

Expansion of the Medicaid program was a crucial component of the 2010 Affordable Care Act (ACA). This expansion was intended to allow individuals with incomes up to 138% of the federal poverty level to be eligible for their state's Medicaid program, with most of the requisite funding coming from the federal government. While the program was originally designed to apply to all states, in 2012 the Supreme Court allowed states to decide whether and when they wished to participate in the expansion, resulting in a natural experiment of state based health policy making. To date, 19 states have yet to adopt the ACA's Medicaid expansion. Cross-sectional studies have previously been used to examine the determinants of expansion decisions. Many of these studies have concluded that *political* factors are the key drivers of expansion decisions (Barilleaux and Rainey, 2014). More recent studies, however, contend that factors related to *state-need* are of greater importance (Henley, 2016). Using a discrete-time-logit model of state conditions and decisions from 2012 to 2016, this study addresses the disagreement found in the literature and permits the introduction of time varying covariates into the study of expansion decisions. Results of this work indicate that when expansion decisions are examined over time, the odds of expanding Medicaid with a Republican governor are found to be roughly a tenth of what they are with a Democratic governor. Further, factors related to *state-need* fail to achieve statistical significance. Evidence of a "regional diffusion" effect for Medicaid expansions is also uncovered, with the odds of a state expanding in a given time-step being doubled for each standard deviation increase in the percentage of states within its census region having previously expanded. These findings improve our understanding of what factors may prompt future adoptions of the Medicaid expansion and highlight the tensions that often exist between federal and state actors.

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Introduction

Since the turn of the 20th century, attempts at fundamentally altering the system of healthcare delivery and finance in the United States have been routinely met with insurmountable opposition (Starr, 1982). There have been some rare instances of success, however, of significant policy change. The establishment of Medicaid in 1965 serves as one such example.

Medicaid is an important public health program dedicated to improving access to healthcare among low-income and medically needy individuals (Engel, 2006). Over the last 50 years, the program has transformed how the poor and disabled access the US health system. Due to Medicaid's unique administrative structure, however, this transformation has not been consistent across the country (ibid). Although the federal government provides critical oversight and funding, states have a high degree of policy autonomy in determining benefit and eligibility rules. This administrative structure has created a policy-making environment that has contributed to wide variations in the Medicaid programs offered by each of the states (Artiga, 2017).

The challenge presented by this federal-state partnership was highlighted by the implementation of the 2010 Patient Protection and Affordable Care Act's (ACA) Medicaid expansion. Among its many reforms to the health system, the ACA proposed replacing all state-based Medicaid eligibility criteria with a simple income-based criterion. Under the ACA's proposal, all individuals making below 138% of the federal poverty line (approximately \$16,600) would be eligible for Medicaid through their state's program. This would be the single largest expansion of coverage in the history of the Medicaid program and was a key component of the ACA's larger aim of reducing the overall uninsured rate (Garfield, 2016).

In order to compel state governments to agree to the expansion, the federal government attempted to condition the entirety of a state's federal Medicaid funding upon their acceptance of the expansion. A US Supreme Court (SCOTUS) decision in 2012, however, gave each state the option to decide whether to participate in the expansion, without fear of losing their existing Medicaid funding (*NFIB v. Sebelius*, 2012). In response, the federal government announced that they would fully cover the expenses associated with a state expanding for 4 years (through 2016), at which point the federal contribution would begin scaling down to a permanent rate of 90% by the year 2020. This promise of financial support has not been enough to entice many of the states to participate in the Medicaid expansion. At the time of this writing (April 2018), only 31 states have agreed to the expansion.

The policy decisions made by each state on the Medicaid expansion have had a large impact the healthcare choices of millions of low-income Americans. Estimates published by the Kaiser Family Foundation indicate that 15 million Americans have enrolled in their state Medicaid program thanks to the expansion ("Medicaid Expansion Enrollment," 2017). This represents almost 20% of the total national enrollment for Medicaid (*ibid*). In the non-expansion states, however, an estimated three million individuals fall within the "Coverage Gap" – those individuals who make too much money to qualify for Medicaid, but not enough to qualify for subsidies to purchase private market insurance (*ibid*).

This research will answer the following questions: What factors operating within a state were influential in its decision-making on the Medicaid expansion? What lessons might this experience provide for future federal-state health policy initiatives? This work will build on current scholarship regarding Medicaid expansion decisions by detailing their history and

context, investigating conflicting findings within the literature on the topic, and furthering the existing body of work through the introduction of longitudinal methods of analysis.

Using a discrete-time-logit-model for event history analysis, this work shows that when expansion decisions are analyzed over time, *political* factors — namely the political party of the governor — are the single most significant predictors of expansion decisions. In contrast, factors related to *state-need*, which previous research described as being important drivers of expansion decisions, lack statistical significance when considered in this longitudinal analysis (Henley, 2016). Additionally, this study uncovers evidence that a *regional policy diffusion*¹ effect may be influencing expansion decisions. These findings improve knowledge of which factors may prompt future adoptions of the Medicaid expansion and highlight the importance of state-level politics in the adoption of federal health policy initiative.

¹ This effect is evidenced by increases in the percentage of states having previously expanded within a particular census region, consequently increasing the likelihood that other states in that same region will expand in future time-steps.

Policy History and Background

What is Medicaid?

Established in 1965 as part of President Lyndon Johnson's "Great Society" initiative, Medicaid is a public health insurance program dedicated to supporting low-income and medically needy individuals in covering their healthcare related costs. Initially overshadowed by the contentious debate surrounding the establishment of Medicare, Medicaid has since grown into one of the single largest payers in the American healthcare system. In 2016 alone, Medicaid expenses surpassed \$550 billion dollars, nationally ("Federal and State Share of Medicaid," 2016).

Medicaid was limited in scope at its inception, intended only to be a supplemental welfare program. However, over the last 50 years, various expansions to the program have pushed Medicaid into covering more people in need of medical services (Berkowitz, 2005). Groups such as pregnant women, nursing home patients, children, among others, are now routinely covered under the program. As a result, in 2017 Medicaid insured roughly 74 million Americans, or 18% of the country's population ("September 2017 Medicaid Eligibility," 2017). Additionally, state Medicaid programs are now required to help certain hospitals offset the costs incurred from providing care to disproportionately high numbers of Medicaid and uninsured patients ("DSH Payments," 2018). All this to say, Medicaid is a diverse and multi-functional program that serves as the safety-net for the healthcare coverage of many people and institutions.

Medicaid's State-Based Administrative Structure

Medicaid features a state-based administrative structure to carry out its mission, rooted to some extent in initial skepticism regarding the long-term prospects of the program (Engel, 2006). State-level policymakers and program directors are primarily responsible for defining eligibility

criteria and benefit packages for enrollees. In contrast, the federal government's role is to provide oversight, set minimum standards for eligibility and benefits, and to offer financial support to the state programs ("Medicaid - An Overview," 2017). Despite initial trepidation on the part of some states (most notably, Arizona took 17 years to establish a Medicaid program), all 50 states now offer a Medicaid program to their residents.

This administrative structure has created a unique and challenging policy making environment. Prior to the enactment of the ACA, eligibility criteria between state programs often varied widely. This meant that an individual's access to healthcare coverage through Medicaid could be simply the result of living on the "wrong" side of a state border. Furthermore, in many states, conditions other than income were used to disqualify individuals from enrolling in Medicaid — for instance, if you were a "childless adult" ("Medicaid - An Overview," 2017). Addressing the inconsistency and limitations that pervaded the Medicaid system was a major target of the ACA (Obama, 2016).

The Affordable Care Act (ACA) and the Medicaid Expansion

Pursuant to its goals of increasing coverage and access to care while reducing healthcare related costs for patients, the ACA laid out a "paired approach" to achieving *near* universal coverage. As initially conceived in the ACA, Medicaid eligibility was to be expanded across the country for all citizens with incomes less than 138% of FPL (\$16,643) ("US Federal Poverty Guidelines," 2018)². Furthermore, individuals making between 138-400% of the FPL were to receive government subsidies to purchase insurance on the private market (Obama, 2016). Most important, this proposed income cutoff was intended to be the sole criteria for determining

² The Federal Poverty Level (FPL) is an economic measure that is used to decide whether the income level of an individual qualifies them for certain federal benefits and programs and is set by the Department of Health and Human Services (HHS). In 2018, the FPL for individuals has been set to \$12,140 ("US Federal Poverty Guidelines," 2018).

Medicaid eligibility (“Medicaid Expansion & What It Means,” 2018). This expansion, if implemented by all states, would have meant that an estimated 20 million Americans would become newly eligible for the Medicaid program (Garfield and Damico, 2017). The full effect of the expansion on reducing the uninsured rate has not been felt, however, because of difficulties that have arisen during the implementation phase of the policy making process.

National Federation of Independent Businesses v. Sebelius (2012)

The ACA has been a contentious piece of legislation and the subject of a great deal of litigation. One particularly noteworthy case was *National Federation of Independent Businesses (NFIB) v. Sebelius (2012)*. In this Supreme Court case, the NFIB (joined by 25 states’ Attorneys General) sued Health and Human Services (HHS) Secretary Kathleen Sebelius over the implementation of the ACA. Specifically, the case hinged on the constitutionality of Congress’s ability to enforce the individual mandate (requiring the purchase of insurance for all individuals) and the proposed Medicaid expansion. The plaintiffs challenged that because Medicaid is a state-administered program, Congress and the administration had overstepped their constitutional authority by conditioning the receipt of future federal Medicaid dollars on states expanding their Medicaid programs.

The Court, in a 5-4 decision, generally agreed with the arguments of the plaintiffs and cited the restrictions placed on Congress as enumerated in the “Spending Clause”³ of the Constitution. The Court reasoned that since a state Medicaid program could not continue to

³ Article 1, Section 8, Clause 1 of the United States Constitution reads, “The Congress shall have the Power To lay and collect Taxes, Duties, Imposts and Excises, to pay the Debts and provide for the common Defense and general Welfare of the United States....” This clause and powers enumerated therein are collectively referred to as the Constitution “Spending Clause.” For more information, readers are encouraged to consult the following resource from the Wex Legal Dictionary operated by Cornell University: https://www.law.cornell.edu/wex/spending_power

function if all its federal funding was lost⁴, the proposed expansion was “unconstitutionally coercive to the states” (*NFIB v. Sebelius*, 2012)⁵. The Court went on to uphold the constitutionality of much of the ACA, but the legal challenges did significantly hamper the implementation of the law’s Medicaid Expansion.

The Medicaid Expansion Post-NFIB

Because of the Court’s decision in *NFIB v. Sebelius* (2012), each state been able to decide whether it would participate in the Medicaid expansion program offered by the federal government, without fear of losing its existing federal funding. Understandably, this decision removed much of the administration’s leverage in compelling state governments to participate in the expansion. Difficulties in persuading conservative leaning states to expand were further exacerbated by the highly politicized nature of the ACA itself (Hall, 2014). To attempt to overcome resistance to expansion, the federal government offered significant financial subsidies for the program, allowed states to modify eligibility requirements under a waiver system, and reduced the income cut-off for the purchase of insurance on the exchange market.

If a state elected to expand their Medicaid program, the federal government agreed to cover 100% of the costs for new enrollees until December 31, 2016, at which point the federal contribution would begin scaling back to 90% by 2020 (“Affordable Care Act,” 2016). The federal government pledged to sustain this level of funding in perpetuity. After some initial uncertainty, the Centers for Medicare and Medicaid Services (CMS) also announced that it

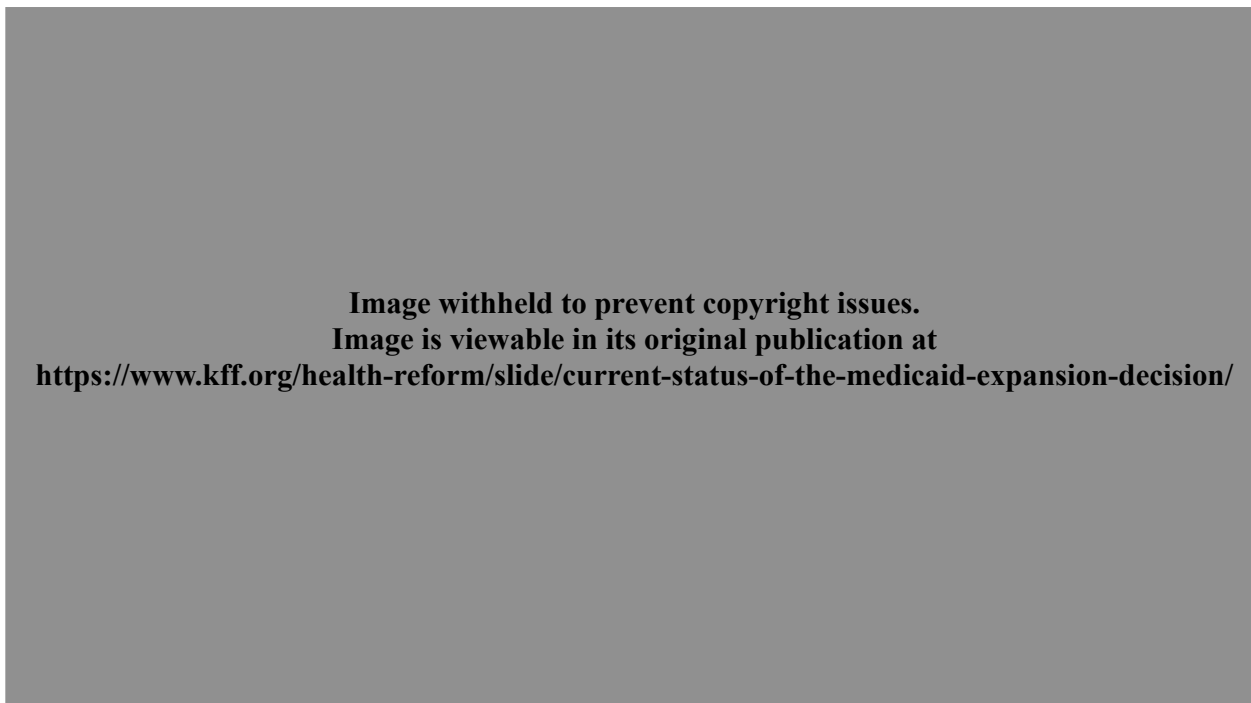
⁴ While exact financial support levels vary between states, the federal government often funds between 50% and 70% of each state’s Medicaid program. The exact share of Medicaid spending that comes from the federal government is reported in a state’s Federal Medical Assistance Percentage (FMAP)—calculated by comparing the average per-capita income within a state to the average per-capita income nationally, with “poorer” states receiving more federal support. More information on FMAPs can be found at: <https://aspe.hhs.gov/federal-medical-assistance-percentages-or-federal-financial-participation-state-assistance-expenditures>

⁵ For readers interested in the legal arguments used in this case, the following resource developed by Oyez is recommended: <https://www.oyez.org/cases/2011/11-393>

would accept Section 1115 waiver expansion proposals. Section 1115 waivers were established by CMS to encourage and support state innovation in Medicaid and allowed states to participate in the expansion, but with their own state-specific modifications (such as a work requirement or imposition of “co-pays” for higher income enrollees). Seven states⁶ have successfully utilized the waiver process to expand their Medicaid program. Finally, the federal government reduced the income cutoff for receiving subsidies to purchase insurance on the private market to 100% of the federal poverty level in non-expansion states (“Affordable Care Act,” 2016).

Figure (1) below shows the state-by-state decisions that have been made on the Medicaid expansion. As can be seen below, 24 states have fully adopted the expansion, 7 states have expanded through a CMS approved waiver, and the 19 remaining states have yet to agree to the expansion in any form (“Current Status of State Action,” 2017).

Figure 1. Status of State Decisions on the Medicaid Expansion

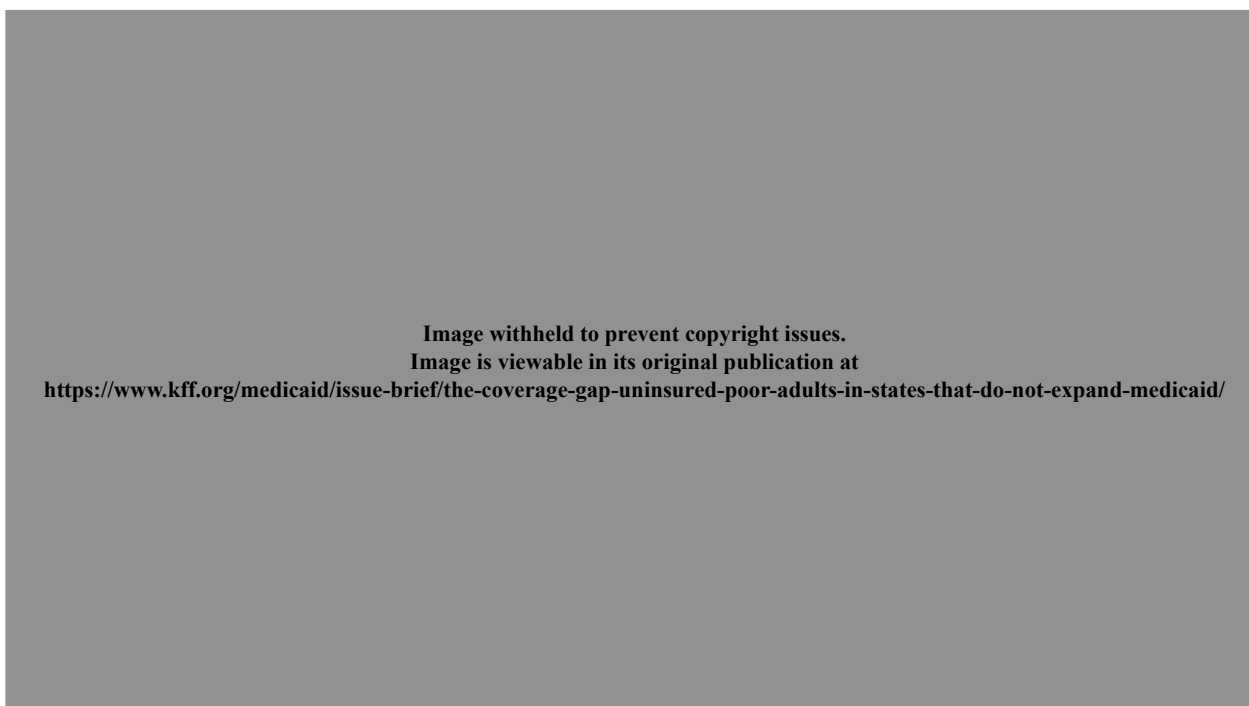


Note: This map shows the state-by-state decisions on the Medicaid Expansion. (“*Current Status of State Action*,” 2017).

⁶ The seven waiver expansion states are: New Hampshire, Indiana, Michigan, Arkansas, Iowa, Montana, and Arizona.

Electing to not participate in the expansion has meant that individuals making between a state's existing income eligibility cut off (a median value of 44% of FPL, among non-expansion states) and 100% of the FPL would not be eligible for Medicaid. These individuals would also not be eligible to receive federal subsidies to purchase insurance on the private health insurance exchange markets ("Federal Poverty Level," 2017). Additionally, failing to expand would allow provisions within a state that further restricted Medicaid eligibility, generally based on whether you were a "childless adult" to persist, even if one would otherwise qualify for coverage. The key point is that a decision to not expand severely restricted the access of low-income individuals to health coverage and consequently, health care. This phenomenon has been termed the "Coverage Gap" and affects approximately 3 million people nationally (Garfield, 2016). Figure (2) below summarizes (for a hypothetical non-expansion state) the different categories in which an individual could fall (Garfield and Damico, 2017).

Figure 2. Categories of coverage for an average non-expansion state.



Note: This figure summarizes the different coverage levels an individual living in a theoretical non-expansion state could fall within. (Garfield and Damico, 2017).

How Does a State Expand Medicaid

Before endeavoring to explain *why* states expand Medicaid, it is important to first establish *how* states could expand their Medicaid programs through the ACA. This is a difficult question to answer because each state considered the expansion through its own, unique set of procedures. Most of the 31 expansions have been the result of “normal legislative processes” whereby the legislature passed a bill⁷ which the governor then signed (“An Overview of Actions Taken by State Lawmakers,” 2015). In at least two states (Kentucky and West Virginia), however, executive action was the mechanism by which the expansion decision was made. Perhaps out of fear that this type of unilateral action might occur, at least four state legislatures⁸ have passed bills requiring that the governor or any other state official receive explicit consent from the legislature before attempting to expand their state’s Medicaid program (ibid). While the exact mechanisms for expanding Medicaid are by no means uniform, for the purposes of this analysis, a state is said to have “expanded” once they have internally resolved to expand their Medicaid program⁹. Furthermore, while there are no explicit regulations preventing a state from “unexpanding” Medicaid¹⁰, no state has thus far made a true attempt at doing so. Given the number of individual and institutions that have benefited from and rely on the Medicaid expansion, this researcher contends that it is extremely unlikely that we will observe true “unexpansion” events in the future.

⁷ These bills were either stand-alone expansion bills or the language authorizing expansion of Medicaid was included as part of broader budget legislation.

⁸ These states include: Tennessee, Georgia, Virginia, and North Carolina.

⁹ This is often evidenced by the date a bill was signed, and executive order issued, or a state supreme court case decided.

¹⁰ While this researcher could find no laws that explicitly guard against *unexpansion*, any change in eligibility criteria would need to be approved by CMS. Furthermore, there has been some debate in Kentucky about “scaling back” its expansion, however, all that has been done thus far is adding a work requirement for expansion enrollees (Yetter, 2018).

Arguments For and Against the Medicaid Expansion

Expansion of Medicaid was and remains an important topic for state policymakers to consider because it has implications on many aspects of society — from healthcare quality and access, to workforce productivity, to a state’s budget and relationship with the federal government. As one might expect, both proponents and opponents of accepting the Medicaid expansion routinely touch on these topics to justify their positions — often offering conflicting analyses of the effects expansion would have.

Henninger (2016) provides numerous quotes and excerpts from those arguing for and against adoption of the expansion. This work reports that arguments offered in opposition to the Medicaid expansion relied heavily upon the idea that it would “bust state and federal budgets” and relatedly, that the federal government would not be able to meet its pledged level of financial support (ibid). In contrast, those supporting the expansion emphasized the potential improvements to state economies, health outcomes, healthcare expenses, and solvency of rural hospitals as justification for their position (ibid).

This basic framing of positions can be useful in the initial construction of empirical models. It is important to note, however, that these are merely the *stated reasons* used to support or oppose the expansion. It is plausible that policymakers may be hiding their true motivations behind what they find to be more politically convenient arguments and talking points. Indeed, this is exactly what a public choice framework would predict. While proving that disconnect is likely an impossible task, it is important to be mindful that the *stated* and *revealed* (revealed through empirical modeling and analysis, as this paper will explore) may be divergent.

Literature Review

Several national studies have been conducted analyzing the consequences of Medicaid expansion decisions. Most have found that states that have implemented the Medicaid expansion are observing a reduction in their uninsured population and in the economic burden on families related to health care costs (Antonisse, Garfield, & Rudowitz, 2017; Kaester, Garrett, & Chen, 2017; Wherry & Miller, 2016). For expansion states, these effects have also been paired with increases in the utilization of care, healthcare related jobs, and profit revenues for hospitals (ibid). Consequently, many researchers have argued that expansion has led to an overall net savings for adopting states (ibid). Despite these reported benefits, however, many states are still struggling with the decision to expand. Opponents of the expansion routinely cite objections related to state Medicaid budgets being stretched thin, as well as concerns regarding growing governmental involvement in healthcare, as justification for their apprehension. Using these basic arguments as a starting point, several researchers have attempted to understand the decisions made by state governments on the Medicaid expansion.

Politics as the Main Driver of Medicaid Expansion Decisions

Much of this work has placed an emphasis on the political aspects of the Medicaid expansion, specifically in regards to electoral ramifications and partisanship. In an article written for the *North Carolina Law Review*, Hall (2014) goes so far as to suggest that the true motivation for rejecting the expansion among non-expanders is “crass partisanship” and political allegiances to oppose President Obama and Congressional Democrats. In contrast, Barrilleaux and Rainey (2014) hypothesized that both political and factors related to health deficits and needs (such as the uninsured rate, poverty rate, etc.) would prove influential in state decision-making. What they found, however, was that the political party composition of the state legislature held the

most explanatory power in predicting gubernatorial support for the Medicaid expansion (ibid). Furthermore, they concluded that need-based metrics had only minimal effects on expansion decisions (ibid).

Other research, focusing on electoral posturing, has echoed the conclusion that politics is the main predictor of expansion decisions. Using a mixed-method approach, one paper found that governors opted for Medicaid expansion decisions in instances that positively affected their prospects at re-election (Flagg, 2014). This is further supported by the work of Henninger (2016) — who conducted a case study of five southern Republican governors who stood for re-election following the *NFIB v. Sebelius* (2012) decision. Henninger (2016) argued that the Republican governors he studied were reluctant to support the Medicaid expansion because they faced tougher challenges from conservative opponents in their primaries than from Democrats in the general elections. Thus, to avoid encouraging a challenge from within their own party, the governors shied away from expansion (ibid).

Finally, Hall (2018) examined the oft-used claim that Medicaid expansion has “busted state budgets.” Citing reports published by the National Council of State Budget Officers, Hall finds this argument deficient, as the Medicaid expansion has not resulted in significant spending increases among states that expanded (ibid). This work suggests, at least in Hall’s view, that states that have not expanded have failed to expand more out of ideological objections than for evidence-based reasons (ibid).

Other Factors as Drivers of Medicaid Expansion Decisions

In contrast, Jacobs and Callaghan (2014) approached the analysis of expansion decisions in a novel manner. Instead of treating the expansion decision as a simple binary choice (e.g. expansion vs. no expansion), they conceptualized state decisions as simply being on “differing

degrees of implementation.” Their argument for using this “process approach” was that by forcing states into limited and rigid categories, important information about the relative progress on *implementation* that states have made with the expansion is lost (ibid). The authors posit that just because two states are both classified as “non-expanders,” that does not mean they have handled the Medicaid expansion in the same way. Furthermore, such states should not be analyzed as though all non-expansion decisions were monolithically motivated and static. Using this framework, they concluded that although political variables did appear to hold the most explanatory power, the possibility remained that partisanship is “an obstacle, rather than a death sentence” and need-based factors may later emerge as equally important in motivating expansions of Medicaid (Jacobs and Callaghan, 2013). Taking this argument as a starting point, recent research has found that examining explanatory models (political, economic, etc.) in isolation suggests that the political model does have the most predictive power. When explanatory models are integrated into a single, unified model with variables competing against and controlling for each other, however, factors related to state-need¹¹ and health status emerge as the strongest drivers of expansion decisions (Henley, 2016).

In addition to its conceptual contributions to the study of the Medicaid expansion, these findings indicate that previous research may have omitted variable bias. When the incorporation of new variables markedly changes the results of a regression, that is evidence that the initial regression was incorrectly specified (Lee, 1982). If present, this type of bias is particularly troublesome as it affects the estimates of variable coefficients (ibid). Although removing all of the omitted variable bias from a model is often more of an aspiration than a practical reality, the divergent findings in the literature provide evidence that such an issue needs to be addressed.

¹¹ This is measured by the uninsured rate, the poverty rate, and the portion of a state’s population over the age of 65.

Understanding the Divergence in the Literature

Recent work suggests that the cause of expansions may not be limited to simple political maneuvering and instead involves more complex and dynamic decision-making. This complexity needs to be modeled to better understand state decisions on the Medicaid expansion that have already been made, and more importantly to more clearly define the environments that are conducive to future expansions. That is the objective of this research.

The majority of previous work in this space is cross-sectional and attempts to explain Medicaid expansion decisions based on a single year of observation, usually 2012. These types of studies are often ill-suited to modeling dynamic and complex environments, such as the ones observed with the Medicaid expansion. In addition, these type of models fail to account for expansions that have occurred in recent years, do not take into account the influence that the passage of time may be exerting on the policymaking environment, and neglect trends in identified factors that might help explain expansion decisions. Finally, cross-sectional studies run the risk of misattributing the effects that “system shocks”¹² have on the dependent variable to the explanatory variables.

For these reasons, previous research may suffer from methodological issues that adversely affect the accuracy and robustness of findings. The divergent findings in the literature could also be explained by these modeling choices. Improved methods of modeling Medicaid expansion decisions should be explored. That is what current research endeavors to accomplish.

¹² The idea behind a “system shock” is that some unexpected or unpredictable event affects the system being studied, either in a positive or negative way. If unaccounted for or unmitigated, their effect on the outcome of interest can be caught in the explanatory variables specified -- leading to potentially misleading conclusions about the effect of the independent variables to be drawn.

Contributions to the Existing Literature of this Study

Much of the previous literature has highlighted the need for time-varying analyses to be conducted (Henley, 2016; Jacobs and Callaghan, 2013). Until this point, such studies have not been possible because enough time had not passed since expansion decisions were able to be made. Five full years have now elapsed since the *NFIB* decision. Consequently, there is now sufficient data to make a longitudinal study possible. Conducting such a study mitigates many of the modeling problems previously described in the existing literature, as will be explained in subsequent section of this paper. Thus, this work fills a void in the literature and offers a new method for analyzing state Medicaid expansion decisions. By accomplishing this aim, this research contributes to the larger debate on the Medicaid expansion and provides clarity to the existing literature regarding what factors are motivating expansion decisions.

Data and Methods

Numerous explanations for Medicaid expansion decisions have been scrutinized by previous researchers. The methods used, however, have not been able to account for more recent expansions and such analyses do not consider the influence of time. Time is an important factor to incorporate in my study as its progression can allow for the policy-making process to more fully play out, as well as for changes to occur within a state which may affect its propensity to expand. Thus, I conclude that it is appropriate for me to feature a time-variant approach to studying Medicaid expansion decisions, in lieu of an OLS¹³ or other cross-sectional method, as a unique and important contribution to the literature.

Description of Data

As mentioned previously, past researchers have published their work on Medicaid expansion decisions and routinely feature the same basic set of variables and factors. These generally include data on gubernatorial party affiliation, the uninsured rate, federal aid for state Medicaid programs, etc. (Henley, 2016; Jacobs and Callaghan, 2013; Barilleaux and Rainey, 2014). For this reason, it seems appropriate that I adopt many of those same measures for my own analysis. This will create consistency between my paper and previous scholarship.

I will use the variables identified by Henley's research as my starting point. Henley's (2016) research begins with a replication analysis¹⁴ of previous papers and offers a representative set of variables for what has been used by other researchers. The data points featured in my analysis are drawn primarily from resources published by: The Department of Health and Human

¹³ OLS stands for Ordinary Least Squares (OLS) regression and is a commonly used method for analyzing the marginal effect that a covariate has on a dependent variable. This models are powerful in certain contexts, but ill-suited to deal with time-series and panel data (Cox, 1972).

¹⁴ This is a type of analysis whereby the research attempts to replicate the work of past researchers in order to confirm findings and prove competency at performing different data manipulations.

Services, the Centers for Medicare and Medicaid Services, National Council of State Legislatures, and the Center for Disease Control. I also intend to introduce several new variables to the model, namely: President Obama's approval rating within the state and the state's Medicaid spending growth rate, among others¹⁵.

There is one other critical distinction in the data I intend to use, as opposed to the data used in most of the literature, that should be disclosed. I have collected values for the variables listed in Appendix A for each year in the 2012 to 2016 timeframe, in annual intervals beginning on June 28, 2012 (the day *NFIB v. Sebelius* was decided). This will generate *panel data*¹⁶, which is associated with greater statistical power and will allow for the incorporation of time-varying covariates in the model, satisfying the stated aims of this research.

Finally, for reasons that will be explained in the subsequent section, the data must be restructured into a state-period (also known as a "person-period")¹⁷ data file. This involves expanding the times and censor indicators (y_i , s_i) to a sequence of binary responses, y_{ti} . The y_{ti} term will indicate whether the state expanded Medicaid during a particular time interval. By doing this, the 50 observation data set (50 states) is expanded into a 250 line data set (50 states over 5 years), with the associated covariates for each entry. Next, all the observations for states in the time-steps *after* they had expanded must be removed (Steele, 2005). This is done because expansion of Medicaid through the ACA, for the purposes of this analysis, is treated as a non-

¹⁵ In total, 35 variables have been collected across five broad categories of expansion decision motivators: Political, economic and budgeting, state-need and health status, regional diffusion, and past history with Medicaid innovation. A full variable codebook can be found in Appendix A.

¹⁶ Panel data is defined as a "longitudinal data set that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample" (Hurlin, 2010). Whenever research subjects are observed at more than one point in time, the data can be described as panel data.

¹⁷ This type of data file is arranged by giving every observation (state) a separate entry for each time-interval (year) it is under study (has not expanded Medicaid). For example, the state of Tennessee would have separate entries for 2012, 2013, 2014, 2015, and 2016 instead of simply one entry, containing the data for each year.

repeatable event. Observations were then right-censored if they failed to expand by the end of the study time (June 28, 2012 to June 27, 2017). Adopting these approaches guards against biasing the “expanding” or “non-expanding” outcomes with misleading or endogenous observations. This reduces the final data set to 151 state-period observations containing 31 positive event indicators (y_{ti}) — one for each state that expanded, in the time period that it expanded.

Model Specification

The specific type of investigative model that most appropriately satisfies the constraints of my data is an *Event History Analysis (EHA)*. EHA is a term commonly used to describe “a variety of statistical methods that are designed to describe, explain or predict the occurrence of events” (Allison, 2004). Within EHA, however, there are two distinct modes of analysis: Continuous-Time-Models (CTM) and Discrete-Time-Models (DTM). Each of these flavors of EHA comes with its own set of basic assumptions regarding the data and underlying relationships that may be present. Thus, it is worthwhile to consider the merits of both, before committing to one method.

Continuous-Time-Models (CTM)

Continuous Time Models are used to characterize events, where those in the risk pool are vulnerable to experience the event at any time from the start of their observation until either the study ends or they exit the study population. An important feature of CTM’s is that the timing of the event for each subject is recorded precisely when it occurs, on a continuous time scale (Steele, 2005). Most commonly, CTMs are executed using a Cox-Proportional-Hazards-Model (ibid).

In this model, a set of covariates are analyzed to determine how they impact the ‘survival’ of an observation. Essentially, the Cox model analyzes how the identified

factors impact how long it takes for the event of interest to occur. It accomplishes this objective by generating what are known as *hazard ratios*. Hazard ratios can be understood as the ‘hazard’ (or risk) of experiencing an event for a given observation in the treatment group, at the next time step of the analysis, compared to the control group (ibid).

These models, as the name implies, also rely on the assumption of proportionality to function optimally. Put simply, this model assumes that over the course of time, the relative effect of each covariate on the dependent variable is unchanging. If, however, it is found that a variable (for example, party of the governor) is more influential at the occurrence of an event (expanding Medicaid) than at early time intervals, then the proportionality assumption is said to be violated. Finally, because time is measured *continuously*, these models function best when there are no tied failures¹⁸ in the data (Borucka, 2014).

I have concerns regarding the appropriateness of this type of model for my analysis. This apprehension is based in the fact that my data are collected in annual intervals rather than continuously¹⁹, there are multiple ‘tied failures’ in the dataset, and I am skeptical that the proportionality assumption will hold true²⁰. Thus, while CTMs

¹⁸ In survival analysis, a ‘failure’ is not inherently bad and instead indicates that the event of interest has occurred. For example, when a state expands Medicaid it is said to have “failed.” Thus, “tied failures” is a phrase used to describe the instance where multiple observations (states) in the data set experience failures/events (expanding Medicaid) at the same moment in (study) time.

¹⁹ A state that expands on August 1, 2013 is not treated differently than a state that expands on August 2, 2013 or even January 1, 2014. ‘Years’ are indexed to begin and end on the anniversary of the decision being issued in *NFIB v. Sebelius* – June 28, 2012. The study time extends over 5 time intervals, concluding on June 27, 2017 (the 2016 time step).

²⁰ The Jacobs and Callaghan (2014) paper argues that while politically based factors are important early on, that state-need factors may emerge as being drivers of later expansions. If this is true, it would be a blatant violation of the proportionality assumption and as such, I think skepticism regarding the proportional effect of the covariates over time is well-founded.

generally accomplish what this research aims to do, the assumptions and mathematics associated with such an approach may not be well tailored to addressing the identified research question, given the collected data. Consequently, other models should be explored.

Discrete-Time-Model (DTM)

In contrast to Continuous-Time-Models, Discrete-Time-Models (DTMs) utilize data that is retrospectively collected in regular intervals. Whereas CTMs can distinguish between events based on the precise time in which they occur, discrete time models group all the events that happen within a given interval of time together (interval-censored). This is precisely how the data for this analysis has been collected (annual intervals).

Considering the underlying assumptions inherent to DTMs is the next critical step to evaluating the appropriateness of this model. The DTM has no requirements in terms of proportionality, unlike the Cox model (Steele, 2005). In addition, the semi-parametric nature of the DTM indicates that it makes no assumptions regarding the baseline hazard function²¹, allowing the analyst to specify the baseline hazard (Turner, Batchelor, & Firth, 2010). Further, the model easily incorporates time-varying covariates and right-hand censoring²² of data (Steele, 2005).

A key distinction to make between DTMs and CTMs is that while CTMs generate hazard ratios, DTMs generate *odds ratios* using a logistic regression (logit) estimators (Steele, 2005). An odds ratio represents the odds that an event will occur given a

²¹ The baseline hazard function is the hazard function when all covariates have values of “0” or the ‘base value’

²² Observations are said to be ‘right censored’ if they do experience the event of interest by the conclusion of the analysis, or they drop out of the study population prior to both the conclusion of the study and experiencing the event.

particular status, compared to the odds of that same event occurring in the absence of that status (Szumilas, 2010). This allows the analyst to generate results and interpretations like: “The odds of an event occurring are X times greater for observations with Y as opposed to those in the ‘reference group’²³.” In other words, I will be able to say, “For a state picked at random, the odds of expanding Medicaid are X times what they are if a state has Y compared to if that same state were in the ‘reference group’.”

Thus, I conclude that the discrete-time-logit-model is the appropriate method for this analysis to adopt. I have arrived at this conclusion because the data for this analysis has been collected in discrete time intervals (annual), I have reservations as to whether the proportionality assumption would hold true based on suggestions from previous literature, and the interpretation of results are more easily applied to my research question. The precise method by which a discrete-time-logit-model should be executed will be the focus of the remainder of this section.

Exploration of Hazard and Survival Functions

The first step in completing an event history analysis is to construct a life-table (Steele, 2015). Life-tables are a succinct and clear way to summarize how many events occur at a given time interval and calculate the hazard and survivor rates. The life-table for Medicaid expansion decisions is provided below in table (1). The event is said to have occurred (or “failed”) when a state internally resolves to expand its Medicaid program.

²³ For instance, if “Democratic governor” is specified as the reference group, the odds ratio allows you to compare the odds of expanding Medicaid with a Republican or Independent governor *relative to* the odds of expanding with a Democratic governor.

Table 1. Medicaid Expansion Life-Table

t (time-step)	r_t (# at risk)	d_t (# of events)	w_t (# censored)	h_t (hazard rate)	s_t (survivor rate)
1 (2012-2013)	50	13	0	0.26	1
2 (2013-2014)	37	13	0	0.351	0.74
3 (2014-2015)	24	3	0	0.125	0.48
4 (2015-2016)	21	2	0	0.095	0.42
5 (2016-2017)	19	0	19 ²⁴	0	0.38

t = time interval (annual interval, beginning on June 28 of each year - the anniversary of the NFIB v. Sebelius decision);
 r_t = Number of states remaining at risk at the start of the interval;
 d_t = Number of events occurring during that time-step;
 w_t = Number of censored individuals;
 h_t = Hazard function for time step (ratio of the number of events to the number of individuals at risk in that time interval, adjusted for censoring);
 s_t = Survivor function for time step (the probability that an observation 'survives' to that time-step)

Inspection of the hazard (h_t) and survivor (s_t) functions yield insightful information. It appears that after time-period two, there is a marked decrease in the hazard rate — indicating that most states that opted to expand Medicaid did so quickly. The rate of failures then decreases dramatically, with no failures observed in the final time-step among the 19 remaining states. The survivor function decreases exactly as we would expect.

Methodology

Fitting a binary response model (discrete-time-logit model) using the Stata program is now possible. A population averaged estimator²⁵ will be used to calculate coefficients and standard errors for each variable, as the small number of observations and variability in the dataset precludes the usage of fixed or random effects. Before any of this occurs, however, the

²⁴ This represents that 19 states that did not expand Medicaid. They are “right-censored” at this time step because the study time has elapsed and they have not yet expanded Medicaid (they have yet to experience a “failure”).

²⁵ The population averaged estimator is a way in which the odds ratios can be computed across all observations in the data set, with the average result reported. This is in contrast to a clustered approach (which when modeled, would not converge), where the odds ratios reported would be unique to each individual state. Population averaged odds ratios can also be understood as the odds ratios for a state “picked at random” (Sribney, 2018).

dataset must first be declared as a panel dataset with *state ID* declared as the panel variable and *year* declared as the time variable.

The final regression equation specified by Henley (2016) will serve as the starting point for this analysis. Doing so will allow for a clear distinction to be drawn between the results of this longitudinal analysis and the results of previously published cross-sectional methodologies²⁶. A series of refinements to the model will then be explored — attempting to most correctly model Medicaid expansion decisions. Both the original and refined models will be evaluated for validity and goodness of fit by generating predicted outcomes (e.g. whether a state expanded) for each observation and then comparing those results to the actual outcomes. The two models will be compared directly using a proportional-reduction-in-error methodology²⁷.

Upon completing the numerical analysis component of the project, interpretations of the regression outputs will then be generated that read in the general form: For a state picked at random, the odds of expanding Medicaid with [X] are $[\exp(\beta)]$ times the odds of expanding with [reference group]. This will allow for the creation of an “expansion profile” that will more clearly identify the factors conducive to adopting the Medicaid expansion.

²⁶ Due to page and time restrictions (and after consultation with research advisors), I will not carry out an exact replication of Henley’s (2016) cross-sectional work. Instead, I will immediately begin with the longitudinal analysis, but use the final set of explanatory variables Henley (2016) specified as the initial model.

²⁷ The proportional reduction in error is a method for quantifying the increased precision associated with predicting a dependent variable when a set of independent variables are specified.

Data Analysis

The data set was converted into a state-period file and specified as a panel data set, with *state ID* designated as the panel variable and *year* set as the time variable. The outcome of interest is whether a state opts to expand Medicaid during a given time-step. If a state expands, its *event* variable is given a value of 1 for that interval and subsequent observations of that state during future time periods are dropped. If a state does not expand during a given time step, *event* is given a value of 0. As these possible outcomes are discrete and binary in nature, logistic regression is employed. For a particular variable to be considered statistically significant, it must achieve significance at the 95% confidence level (p-value < .05).

Output from the Initial Model

To begin the analysis, the final equation specified by Henley (2016) is taken as a starting point. As a reminder, a full variable codebook can be found in Appendix A. The initial regression equation is reported below (see equation 1):

Equation 1. Initial Logit Regression

$$\begin{aligned}
 \text{logit}(\text{ExpandedMedicaid}) &= \alpha + \beta_1 \text{GovernorParty} + \beta_2 \text{FMAP} + \beta_3 \text{PovertyRate} \\
 &+ \beta_4 \text{ElderlyRate} + \beta_5 \text{UninsuredRate} + \beta_6 \text{HealthStatus} \\
 &+ \beta_6 \text{PercentOfRegionExpanded} + \beta_7 \text{AverageLegisSessionLength}
 \end{aligned}$$

A logit model was fitted to the state-period data file, using covariates found in equation (1) and a population-averaged estimator. Odds ratios were generated for each covariate from this regression and the results can be seen in table (2) below.

Table 2. Regression Output from Model 1

Variables	Model 1			
	OR	Robust SE	Z	95% C.I.
Governor Party				
<i>Independent</i>	.554	.72	-0.45	.043-7.07
<i>Republican</i>	.102	.063	-3.69***	.031-.344
FMAP Ratio	.944	0.39	-1.39	.871-1.02
Poverty Rate	1.12	.138	0.93	.880-1.43
Elderly Rate	.887	.116	-0.91	.687-1.15
Uninsured Rate	1.05	.082	0.58	.898-1.22
Health Status	1.11	.139	0.81	.865-1.42
% of Region Expanded	1.04	.017	2.57**	1.01-1.08
Average Legis. Session	1.01	.006	1.17	.996-1.02
(Constant)	.267	.952	-0.37	.000-289
Model χ^2			30.65**	

Note: *p < .05, **p<.01, ***p<.001

Using the odds-ratio precludes a direct comparison to previous research (which analyzed marginal effects), however, these results are intriguing in the context of previous research. The party affiliation of the governor retains its significance. The odds for a state picked at random of expanding Medicaid with a Republican governor are 1/10 of what they are if that state had a Democratic governor (p-value of 0.000), holding the other included variables constant. Thus, we would expect to see states that are “on the fence” on the question of the expansion most likely opt to expand if a Democratic governor were to replace a Republican. Indeed, this is precisely what happened with Louisiana in 2016. In fact, the state decided to expand Medicaid less than a week after Governor Bel Edwards (Democrat) replaced Governor Jindal (Republican) (O’Donoghue, 2017).

More interestingly, the factors related to state-need (poverty rate, size of elderly population, uninsured rate) that Henley (2016) reported as being significant, no longer appear to

be so when expansion decisions are considered with this time-variant methodology. The only other variable reporting statistical significance is the regional diffusion variable, measured by the percentage of a state's Census region (South, West, Northeast, Midwest) that had expanded Medicaid at the start of a particular time-step. Based on these results, the odds of expanding for a state picked at random are 1.8 times higher for each one standard deviation increase in the percentage of "peer region states" having previously expanded (p-value of 0.01), holding all else constant. Previous cross-sectional research had reported that the geography of a state and policy diffusion had no statistically significant effect on expansion decisions (Henley, 2016).

Initial Model Diagnostics

Predicted outcomes were generated for each observation in the state-period data set, using a linear prediction of the logit index. The initial model correctly predicts the outcome, for a given state in a given period, 84% of the time (127 of 151 total observations). This corresponds to a proportional reduction in error (PRE) of 22.58%.

It is worth noting that when the scope of analysis is limited to the "censoring time interval" — the time-step in which a state either opts to expand or the study time elapses (representing the state's ultimate decision) — the model is correct in only 66% of cases (33 of 50 cases). Specifically, 15 of the 31 (48%) expansions were correctly predicted as well as 18 of the 19 (95%) of the non-expansion events. This demonstrates that the initial model does a good job at predicting non-expansion, but performs only moderately well in terms of predicting expansions. Consequently, model refinement should focus on better predicting the occurrence of expansions.

Output of the Refined Model

Because the initial regression equation is the product of previous research and does accurately predict a fair number of cases in the 151 observation data set, those covariates will be retained in the refined model. Based on statements made by lawmakers about the size and importance of Medicaid budgets, however, I posit that including information about Medicaid spending trends will improve the model's accuracy. Pursuant to such, the refined model will include data about the spending growth rate between years for each state, as well as the proportion of a state's budget that is consumed by its Medicaid program.

Additionally, I contend that President Obama's popularity in a state may be a strong predictor of expansion decisions. The ACA was very closely attached to the President himself, so much so that the legislation is often referred to simply as "Obamacare." In fact, polling of the ACA's popularity has reported marked differences²⁸ in the popularity of the law based on whether it was referred to as "the Affordable Care Act" or "Obamacare." (Bryan, 2017). Lastly, a variable that reports the party controlling the state legislature will be introduced. This is done to create a more representative picture of the political dynamics within a given state — particularly in light of the importance that state legislatures had in the decision making process on the Medicaid expansion, as previously described.

Given these amendments to the original model, the refined model (seen below in equation 2) now takes the form of:

²⁸ One study found that 46% of respondents disagreed with "Obamacare" but that number dropped to 40% when respondents were asked if they approved or disapproved of the Affordable Care Act (Bryan, 2017).

Equation 2. Refined Logit Model

$$\begin{aligned}
\text{logit(ExpandedMedicaid)} &= \alpha + \beta_1 \text{GovernorParty} + \beta_2 \text{FMAP} + \beta_3 \text{PovertyRate} \\
&+ \beta_4 \text{ElderlyRate} + \beta_5 \text{UninsuredRate} + \beta_6 \text{HealthStatus} \\
&+ \beta_7 \text{PercentOfRegionExpanded} + \beta_8 \text{AverageLegisSessionLength} \\
&+ \beta_9 \text{MedicaidSpendGrwthRate} + \beta_{10} \text{PortionOfBudgOnMedicaid} \\
&+ \beta_{11} \text{ObamaApprovalRate} + \beta_{12} \text{LegislativePartyComposition}
\end{aligned}$$

An identical method of analysis is used for this model as was done previously. The odds ratios for the covariates in this model are reported below in table (3).

Table 3. Odds Ratios of Refined Regression

Variables	Model 2			
	OR	Robust SE	Z	95% C.I.
Governor Party				
<i>Independent</i>	.704	.855	-0.29	.065-7.60
<i>Republican</i>	.137	.087	-3.13**	.039-.477
FMAP Ratio	.978	.043	-0.49	.897-1.07
Poverty Rate	1.10	.149	0.73	.846-1.43
Elderly Rate	.807	.124	-1.39	.597-1.09
Uninsured Rate	1.04	.097	0.39	.863-1.25
Health Status	1.18	.153	1.27	.914-1.52
% of Region Expanded	1.06	.023	2.69**	1.02-1.10
Average Legis. Session	1.00	.006	0.88	.993-1.02
Medicaid Spending Growth	1.04	.026	1.55	.989-1.09
Medicaid budget %	.966	.050	-0.67	.873-1.07
Obama Approval Rating	1.06	0.57	1.06	.952-1.18
Legislative Party				
<i>Split</i>	1.02	.944	0.981	.167-6.25
<i>Republican</i>	.297	.254	-1.42	.055-1.59
(Constant)	.007	.041	-0.84	.000-742
Model χ^2			44.41***	

Note: *p < .05, **p<.01, ***p<.001

As before, the party of the governor has a strong and statistically significant effect on the outcome of interest. The odds of a state picked at random deciding to expand Medicaid are 0.13

times what they are with Republican governor as compared to a Democratic governor (p-value 0.002), holding all other included variables constant. Also as before, the “state-need” variables identified by Henley (2016) are not statistically significant. The percentage of states within a census region that had previously expanded remains a statistically significant predictor of expansion decisions for states in that region. In this iteration of the model, however, the odds of a state picked at random expanding Medicaid are 2.1 (compared to 1.8) times higher for each standard deviation increase in the percentage of peer-region states expanding, holding all else constant.

Additionally, the variables that were added in this refined model were found to not be statistically significant predictors of expansion decisions. This included the Medicaid spending growth rate, the percentage of a state’s budget dedicated to Medicaid spending, the political party composition of the state’s legislature, and President Obama’s approval rating within the state. These results are surprising, however, it is important to investigate whether the inclusion of these variables improves the overall performance of the model.

Refined Model Diagnostics

As was done previously, predicted outcomes are generated for each observation in the state-period data set. The refined model correctly predicts the outcome, for a given state in a given period, 89% of the time. This is an improvement upon the 84% accuracy rate of the initial model. Further, the proportional reduction in error is 45.16% for the refined model — a marked improvement upon the initial model’s value of 22.58%. These findings support the conclusion that the refined model is an improvement upon the initial model, at least in terms of its predictive power.

Additionally, when restricting the scope of the analysis to the censoring time interval as was done with the initial model, the number of correctly predicted states increases from 33 to 36²⁹. The model accurately predicts 17 total expansion events, compared to the actual value of 31. This is an improvement upon the initial model which accurately predicted only 15 expansion events. Additionally, the refined model accurately predicts all 19 non-expansions — compared to the 18 so predicted by the initial model. Consequently, there are 14 remaining cases³⁰ in which the refined model made an inaccurate prediction of non-expansion when an expansion did in-fact occur. A full listing of the states and their predicted outcomes from each model is provided below in Table (4).

²⁹ The refined model correctly predicts the outcome for Missouri, New Jersey, Nevada, and West Virginia whereas the initial model did not. The refined model does, however, incorrectly predict the outcome for Montana, which the initial model correctly predicted as an expansion.

³⁰ Those states are: Arizona, Connecticut, Delaware, Iowa, Indiana, Louisiana, Maryland, Michigan, Minnesota, Montana, North Dakota, New Mexico, Ohio, and Pennsylvania. Most of these states are either “waiver expansion” states or expanded Medicaid during the first time-step (June 28, 2012 to June 27, 2013).

Table (4). State by State Predicted Outcomes for Each Model

State	Actual Outcome	Model 1 Prediction	Model 2 Prediction	State	Actual Outcome	Model 1 Prediction	Model 2 Prediction
<i>Alaska</i>	Expand	Expand	Expand	<i>Montana</i>	Expand	Expand	No expansion
<i>Alabama</i>	No Expansion	No Expansion	No Expansion	<i>North Carolina</i>	No Expansion	No Expansion	No Expansion
<i>Arkansas</i>	Expand	Expand	Expand	<i>North Dakota</i>	Expand	No Expansion	No Expansion
<i>Arizona</i>	Expand	No expansion	No expansion	<i>Nebraska</i>	No Expansion	No Expansion	No Expansion
<i>California</i>	Expand	Expand	Expand	<i>New Hampshire</i>	Expand	Expand	Expand
<i>Colorado</i>	Expand	Expand	Expand	<i>New Jersey</i>	Expand	No expansion	Expand
<i>Connecticut</i>	Expand	No expansion	No expansion	<i>New Mexico</i>	Expand	No expansion	No expansion
<i>Delaware</i>	Expand	No expansion	No expansion	<i>Nevada</i>	Expand	No expansion	Expand
<i>Florida</i>	No expansion	No expansion	No expansion	<i>New York</i>	Expand	Expand	Expand
<i>Georgia</i>	No expansion	No expansion	No expansion	<i>Ohio</i>	Expand	No expansion	No expansion
<i>Hawaii</i>	Expand	Expand	Expand	<i>Oklahoma</i>	No Expansion	No Expansion	No Expansion
<i>Iowa</i>	Expand	No expansion	No expansion	<i>Oregon</i>	Expand	Expand	Expand
<i>Idaho</i>	No expansion	No expansion	No expansion	<i>Pennsylvania</i>	Expand	No expansion	No expansion
<i>Illinois</i>	Expand	Expand	Expand	<i>Rhode Island</i>	Expand	Expand	Expand
<i>Indiana</i>	Expand	No expansion	No expansion	<i>South Carolina</i>	No Expansion	No Expansion	No Expansion
<i>Kansas</i>	No expansion	No expansion	No expansion	<i>South Dakota</i>	No Expansion	No Expansion	No Expansion
<i>Kentucky</i>	Expand	Expand	Expand	<i>Tennessee</i>	No Expansion	No Expansion	No Expansion
<i>Louisiana</i>	Expand	No expansion	No expansion	<i>Texas</i>	No Expansion	No Expansion	No Expansion
<i>Massachusetts</i>	Expand	Expand	Expand	<i>Utah</i>	No Expansion	No Expansion	No Expansion
<i>Maryland</i>	Expand	No expansion	No expansion	<i>Virginia</i>	No Expansion	No Expansion	No Expansion
<i>Maine</i>	No expansion	No expansion	No expansion	<i>Vermont</i>	Expand	Expand	Expand
<i>Michigan</i>	Expand	No expansion	No expansion	<i>Washington</i>	Expand	Expand	Expand
<i>Minnesota</i>	Expand	No expansion	No expansion	<i>Wisconsin</i>	No Expansion	No Expansion	No Expansion
<i>Missouri</i>	No expansion	Expand	No expansion	<i>West Virginia</i>	Expand	No expansion	Expand
<i>Mississippi</i>	No expansion	No expansion	No expansion	<i>Wyoming</i>	No Expansion	No Expansion	No Expansion

The newly added variables were investigated to determine the robustness of their effects. Individually removing each of the four newly added variables prompts a dip in accuracy of more than 3%, except for the variable which reports the percentage of a state's budget consumed by Medicaid spending. The effect of excluding that variable from the regression was to decrease the model's accuracy by just 1%.

One interaction effect was investigated. It was thought that interacting the variables reporting the political party of the governor and state legislature could produce a more accurate view of the political environment within a state. However, including this interaction reduces the accuracy of the model by 2%. Consequently, it is determined that this interaction term does not improve the performance of this particular model and should not be included.

Finally, it should be noted that the refined model contains a number of "precise zeros." These are variables that have odds ratios and associated confidence intervals that are tightly centered around 1 — indicating they have little to no effect on the odds of a state expanding Medicaid. These include the Medicaid spending growth rate in a state from one year to the next, as well as the average length (days per year) of the state's legislative session.

Conclusion

Summary of Results and Findings

This analysis introduced a new method for studying Medicaid expansion decisions, through use of a discrete-time-logit model. This research has built upon previous cross-sectional work by allowing for the incorporation of time-varying covariates and panel data into the empirical analysis of Medicaid expansion decisions. Results from the regressions run are largely supportive of the hypothesis that the political party affiliation of the governor is a strong determinant of expansion decisions — in some instances, reducing the odds of expansion to as little as a tenth of what they would be otherwise. While stating the magnitude of this effect in this manner is novel, conceptually it fits well within the existing framework of what state-level factors were conducive to expanding Medicaid. Additionally, when moving from a cross-sectional to longitudinal study, the factors related to “state-need” that were previously reported as being statistically significant drivers of expansion decisions lose that quality (Henley, 2016).

As a further contribution to the literature, for the first time, there is evidence that a “regional diffusion” effect for Medicaid expansion decisions might be present. A standard deviation increase in the percentage of states within a census region having previously expanded doubled the odds that another (randomly picked) state in that same region would then expand. Additionally, including information related to President Obama’s approval rating, the political composition of the state legislature, and the Medicaid budget significantly improved the predictive performance of models previously specified in the literature – despite the fact that these variables lacked statistical significance on their own.

In sum, the results of this analysis mostly support the conclusions reached by past researchers (Barilleux and Rainey, 2014; Hall, 2014; Jacobs and Callaghan, 2013). The findings

of this work are that while Medicaid expansion is certainly an issue that touches on many aspects of society, from an empirical standpoint, politics appears to be the main motivator of expansion decisions — at least at this stage of the policy making process. With that said, states may also be susceptible to “peer pressure” to expand and while factors related to state-need and health status may lack individual significance, they are important control variables and should not be wholly dismissed.

Limitations of Study

There are several important limitations to this study that should be noted. The choice of a given model and set of covariates is an important decision each researcher must make, but one must also entertain the possibility that alternative pathways might exist. While I advocate strongly for the further inclusion of longitudinal methods of analysis in this space, I offer very little in the way of nuanced variable manipulation in this paper. The results of this study should serve merely as a starting point for future researchers to consider other variables and methods that could explain expansion decisions.

Additionally, there is a strong argument to be made for the notion that expanding Medicaid through a CMS approved section 1115 waiver (as 7 states did) is a fundamentally different choice than expanding through the conventional pathway. Waiver expansion may present as a compelling path by which future expansions may occur, particularly to states with more conservative tendencies. This analysis makes no distinction between waiver and conventional expansions.

One other limitations to this study has to do with “common shocks.” If for instance, all “early expanders” opted to expand for the same reason at the same time, the model would not be able to pick up on these non-independent changes. Indeed, the model poorly identifies early

expanders of Medicaid. This could be the result of a “common shock” and/or the fact that no data was incorporated into the model before the first time-interval. Perhaps including a “0 time step”, measuring variable values in the year before expansion decisions could first be made, might improve the predictive power of the model in terms of correctly identifying early expanders.

Furthermore, this analysis should not be interpreted as giving guidance on how expansion has or may occur in any *particular* state. Rather, this reported results of this work merely constructed a generalized profile of what conditions in a *state picked at random* would be most conducive to expansion of Medicaid. This is a subtle but important difference, as every state has its own unique history and goals and must decide how Medicaid expansion fits within its particular priorities. I will discuss in the *Future Research* section though, one way in which specific state-level conclusions could be drawn from this work.

There is also an important issue to be considered with any state level analysis in regards to sample size. With only 50 states and 31 expansion events, even when the data is expanded into a state-period file over 5 years, there is only a small amount of variability in the data. This condition can make it difficult for models to report statistical significance or feature clustered analysis techniques. As such, the findings from this work should not be taken as *causes* of Medicaid expansion, rather as a set of conditions that are well *correlated* with expansion.

This is particularly true of the effect observed with the *PercentRegionExpanded* variable. No causal mechanism is evaluated to explain why the actions of other states within a census region should impact the decision-making of a state still evaluating the expansion. In truth, there are likely omitted variables whose effects are being “caught up” in this measure and contributing to its size and impact. Nevertheless, it is plausible that a regional diffusion effect may be working via non-expansion states having to reconcile their decisions against the improved

outcomes observed in “peer-states” that did opt to expand Medicaid. However, this idea is merely a hypothesis and was not evaluated in this analysis.

Furthermore, the usage of census region boundaries is admittedly, a bit of an arbitrary choice for classifying states. Under this framework, states that border each other may not be allowed to “interact” with one another – even though a state could “interact” with some other state that is several hundred miles away. For example, Tennessee (South) and Missouri (Midwest) share a border but are in different census regions. Meanwhile, Tennessee and Florida are separated by the entirety of the state of Georgia, but only Florida’s expansion decision – not Missouri’s – could influence Tennessee’s expansion decision, based on how this variable was created. This is preferable still to constructing the variable to be based on the percentage of bordering states that had previously expanded – because some states have 0 (Alaska and Hawaii) bordering states while others have up to 8 (Tennessee and Missouri). The point being, there is a great degree of difficulty in identifying a regional variable that creates an accurate picture of policy diffusion and it is certainly a limitation of this study.

Policy Implications

The results of this study have several important implications for the future of the Medicaid expansion and public health policy. Namely, any attempt at the crafting of federal health policy must be mindful of state level politics. As the saying goes, “all politics are local.” Thus, proponents of the Medicaid expansion in current non-expansion states may benefit from changing their strategy from advocating for expansion to instead creating political environments that are conducive to expansion. This approach, coupled with the regional diffusion effect observed, could push some of the 19 states that have not yet expanded towards doing so. Additionally, it appears that emphasizing factors related to state-need as justification for

expansion may not be as compelling as one might think. Perhaps, pro and anti-Medicaid expansion groups should devote more money towards gubernatorial races than to issue advocacy, to more effectively achieve their aims.

In that spirit, in November of 2018, 36 gubernatorial seats will be up for election. This includes governorships in 14 of the 19 non-expansion states (all of which are currently held by Republicans)³¹. Of these, according to Real Clear Politics, 12 of these states are likely to stay in Republican control, while Florida is classified as a toss-up and Maine³² as a likely win for Democrats (“Latest Election Polls,” 2018). If the Democratic candidate were to win these races, particularly in Maine, we would likely see a few more expansions occur. Furthermore, as of April 2018, the state of Virginia appears to be closing in on a deal to expand Medicaid. If Virginia (who flipped from a Republican to a Democratic governor in November of 2017) were to expand and Florida elected a Democratic governor that expanded Medicaid, we may expect that other southern states (most of the current non-expansions states) – through the regional diffusion effect detailed previously – may soon follow suit.

Finally, this work further underscore the point that making profound changes to the Medicaid program and the US health system in general, is an extremely challenging prospect. This is based in no small part to the diverse set of stakeholders and policymakers that often have divergent interests, but each leverage considerable influence in state decision making. Nevertheless, continued interest in the Medicaid expansion among proponents in non-expansion states will likely keep the debate on this issue running for the foreseeable future.

³¹ These states include: Alabama, Florida, Georgia, Idaho, Kansas, Maine, Nebraska, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Wisconsin, and Wyoming.

³² Maine approved a public referendum by 58.9% to 41.1% margin in December of 2017. However, despite this vote, Republican Governor Paul LePage has stated he does not intend to expand Medicaid and has taken no action in the direction of expansion.

Recommendations for Future Research

Future research should continue using longitudinal methods of analysis in studying the Medicaid expansion. As time goes on, more data will become available and more observations generated - hopefully serving to clear up what types of factors are driving Medicaid expansion decisions. This is important work because it is entirely possible that as time goes on, the Medicaid expansion might become less politically charged and the reasons for future expansions may differ markedly from those we have seen thus far.

Looking at the 14 expansion events that the model incorrectly predicted suggests that there may still be omitted variables that if included, would be able to capture these expansions. Among the incorrectly predicted states, many are waiver expansion states and/or early expanders. Better characterizing these expansions should certainly be a next-step for subsequent research. It would be also prudent for future research to distinguish between waiver and conventional expansions by implementing *relative-risk* models and to investigate how the method of expansion (legislation, executive action, public referendum, etc.) changes the odds ratios of the explanatory variables. This type of information would be extremely helpful to political strategists who aspire to see more states expand Medicaid.

One other future research direction would be to use qualitative analysis of state lawmaker statements/speeches/bills to compare stated rationales for expansion with these quantitative results. It would also be intriguing to see whether the state policymakers leading this debate (in either direction) eventually left their positions for careers in national politics or the health insurance industry. Any of these areas of research would be worthwhile to pursue and I intend to support those efforts by making my dataset publicly available via TRACE.

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Appendix A – Variable Code Book

id_c

Unique state ID code

type: numeric (long)

label: id_c

range: [1,50]

units: 1

unique values: 50

missing .: 0/151

examples: 12 IA

22 MI

32 NM

42 TN

expansionstatus_c

Whether the state expanded by end of study

type: numeric (long)

label: expansionstatus_c

range: [1,3]

units: 1

unique values: 3

missing .: 0/151

tabulation: Freq. Numeric Label

95 1 No

42 2 Yes

14 3 Yes (waiver)

year

Year (time-period) under consideration. Indexed to June 28.

type: numeric (int)

range: [2012,2016]

units: 1

unique values: 5

missing .: 0/151

tabulation: Freq. Value

50 2012

37 2013

24 2014

21 2015

19 2016

eventBinary value indicating whether a state expanded in that year

type: numeric (byte)

range: [0,1]	units: 1
unique values: 2	missing .: 0/151

tabulation: Freq. Value	
120	0
31	1

region_cWhat census region the state is categorized in.

type: numeric (long)
label: region_c

range: [1,4]	units: 1
unique values: 4	missing .: 0/151

tabulation: Freq. Numeric Label		
38	1	Midwest
20	2	Northeast
60	3	South
33	4	West

sesslengthAverage length of regular state legislative session, 2011-2014.

type: numeric (float)

range: [45.5,516.88]	units: .00001
unique values: 47	missing .: 0/151

mean: 126.54
std. dev: 53.593

percentiles:	10%	25%	50%	75%	90%
	75.26	89.5	127.8	148.5	185.245

perbudgmedicaidPercent of state budget spent on Medicaid

type: numeric (float)

range: [7,37.2] units: .1
unique values: 107 missing .: 0/151

mean: 23.2391
std. dev: 6.6374

percentiles: 10% 25% 50% 75% 90%
 15.9 18.5 23.4 27.8 32

medicaidspendgrwthrate

Percent change in total medicaid spending from previous year

type: numeric (float)

range: [-46.6,24.1] units: .1
unique values: 108 missing .: 0/151

mean: 3.69934
std. dev: 7.94481

percentiles: 10% 25% 50% 75% 90%
 -3.3 .5 4.1 7.5 11.2

fmap

Federal Medical Assistance Percentage (FMAP) for that year

type: numeric (float)

range: [50,74.199997] units: 1.000e-06
unique values: 92 missing .: 0/151

mean: 60.3682
std. dev: 7.57515

percentiles: 10% 25% 50% 75% 90%
 50 53.3 61 66.3 70.6

poverty

State poverty rate for that year

type: numeric (float)

range: [8.7,24.2] units: .1
unique values: 81 missing .: 0/151

mean: 14.8768
std. dev: 3.11336

percentiles:	10%	25%	50%	75%	90%
	11.1	12.4	14.6	17	19

unemp

State unemployment rate for that year

type: numeric (float)

range: [2.8,10.4]	units: .1
unique values: 60	missing .: 1/151

mean: 6.14467
std. dev: 1.71157

percentiles:	10%	25%	50%	75%	90%
	4	4.8	6.05	7.4	8.5

uninsured

State's uninsured rate for that year

type: numeric (float)

range: [3.6,28.1]	units: .1
unique values: 96	missing .: 0/151

mean: 12.2828
std. dev: 3.88573

percentiles:	10%	25%	50%	75%	90%
	8.5	9.6	11.8	14.4	16.9

disabilityprev

State's prevalence of disabilities for that year

type: numeric (float)

range: [9.3,18.6]	units: .1
unique values: 65	missing .: 0/151

mean: 13.1331
std. dev: 1.97267

percentiles:	10%	25%	50%	75%	90%
	10.7	11.7	12.9	14.5	16.1

perelderly

Percent of the state's population classified as elderly.

type: numeric (float)

range: [8,21] units: 1.000e-06
unique values: 12 missing .: 0/151

mean: 14.2384
std. dev: 1.9586

percentiles: 10% 25% 50% 75% 90%
 12 13 14 15 16

budgpercap

Size of state's budgetary expenditures, per capita

type: numeric (float)

range: [760,18644] units: .0001
unique values: 150 missing .: 0/151

mean: 5987.89
std. dev: 2731.5

percentiles: 10% 25% 50% 75% 90%
 3965 4492 5296.6 6320.97 8252.61

healthstatus

Percent of population rating themselves as 'poor or fair' health

type: numeric (float)

range: [11.7,25.200001] units: 1.000e-06
unique values: 85 missing .: 0/151

mean: 17.3
std. dev: 3.23617

percentiles: 10% 25% 50% 75% 90%
 13.4 14.8 16.9 19.3 22.2

percentregionexpanded

Percent of peer states expanding at that time within census region

type: numeric (float)

range: [16.666668,88.888893] units: 1.000e-06
unique values: 13 missing .: 0/151

mean: 43.611
std. dev: 19.5459

percentiles:	10%	25%	50%	75%	90%
	22.2222	31.25	37.5	58.3333	76.9231

obamaapp

Pres. Obama's approval percentage for that year

type: numeric (byte)

range: [19,64] units: 1
unique values: 38 missing .: 0/151

mean: 41.9536
std. dev: 8.50281

percentiles:	10%	25%	50%	75%	90%
	32	36	42	47	54

govparty_c

Party controlling the governor's position

type: numeric (long)
label: govparty_c

range: [1,3] units: 1
unique values: 3 missing .: 0/151

tabulation:	Freq.	Numeric	Label
	38	1	Democrat
	2	2	Independent
	111	3	Republican

legisparty_c

Party controlling state legislature

type: numeric (long)
label: legisparty_c

range: [1,3] units: 1
unique values: 3 missing .: 0/151

tabulation:	Freq.	Numeric	Label
	57	1	Democrat
	83	2	Republican
	11	3	Split