Unraveling the Diverse State Policy Directives Amidst the COVID-19 Pandemic: Their Impact on Infections and Fatalities, and Key Insights

by

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Abstract

The COVID-19 pandemic has been one of the most significant global health crises in modern history, putting public health systems, economies, and political institutions around the world to the test. In the United States, states implemented a variety of non-pharmaceutical interventions (NPIs), such as mask mandates, stay-at-home orders, travel restrictions, school closures, and limits on gatherings. However, the timing, scope, and enforcement of public health interventions varied significantly between states. This study examines how states responded to the pandemic from March 2020 to October 2021, covering both major waves of COVID-19 and extending beyond the periods analyzed in most existing studies. Drawing on the dataset compiled by Mayer et al. (2022), which tracks weekly state-level policy actions alongside infection and death counts, this research addresses three main questions: (1) Which states were early adopters, late adopters, or non-adopters of NPIs, and what political, economic, and demographic factors explain these differences? (2) How effective were these policies in slowing infections and reducing deaths? (3) How did state politics shape enforcement and influence health outcomes? Using the Policy Innovation and Diffusion framework to guide the policy adoption analysis and an epidemiological approach to evaluate policy effectiveness, this study offers a comprehensive view of how states navigated an evolving crisis. The findings reveal the complex interplay between political context, demographic characteristics, and public health decision-making, and provide lessons for crafting effective, context-specific responses to future public health emergencies.

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This dissertation may have my name on it, but it belongs just as much to all of you who have walked this road with me. I am forever grateful.

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Chapter 1: Introduction

The COVID-19 pandemic, which began in late 2019, quickly evolved into one of the most significant global health crises in contemporary history. The virus, caused by the novel coronavirus SARS-CoV-2, spread swiftly across borders, impacting nearly every country worldwide. Seemingly overnight, a localized outbreak escalated into a global pandemic, prompting rapid government action to safeguard public health. Countries were unable to quarantine the virus, so there was widespread illness and death in addition to unprecedented strain on healthcare systems. Beyond its immediate health impacts, COVID-19 triggered extensive political, economic, and social repercussions, fundamentally transforming the structures and functions of societies worldwide.

The United States has historically shown both vulnerabilities and strengths in the face of pandemics. History demonstrates that crises put the resilience and effectiveness of any governance model to the test, and COVID-19 served as a critical examination of public health infrastructure, political leadership, and social unity. The virus outbreak highlighted the challenges confronting the healthcare sector, showing that neither national health systems nor public health officials were fully prepared for the magnitude and rapid spread of the pandemic. The human toll of COVID-19 has been devastating, with millions of infections and hundreds of thousands of deaths globally. In the United States alone, as of December 2024, over 111 million cases and 1,219,487 deaths have been reported (CDC). Especially at the start of the pandemic, healthcare facilities around the world struggled with a lack of ventilators, hospital beds, and essential medical equipment. Many people, including healthcare workers, died as a result. Survivors often face ongoing health problems, with some women and men developing heart and lung issues that can last a lifetime. Several countries adopted measures such as stay-at-home orders and business restrictions at both local and regional levels designed to increase social distancing to slow the spread of the epidemic. As a result, these actions caused a loss of essential economic activities in various areas and significantly altered people's daily lives and overall well-being.

The economic costs have been massive as countries implemented lockdowns to combat the spread of this highly communicable disease, leaving many businesses shuttered for good. As the number of infection and death rates of COVID-19 surged across the United States, corresponding policies were rolled out from the federal, state, and local levels of government. To control the transmission of COVID-19, states adopted a range of executive policies, including mask mandates, quarantine orders, restrictions on interstate and international travel, closures of schools and businesses, limits on gatherings, stay-at-home orders, state of emergency declarations, and increased funding to expand testing capacity. Many state governments felt compelled to act fast, rolling out policies recommended often by the Center for Disease Control to deal with the pandemic's impact, while other state government chose to do almost nothing.

In this research, I study state policy responses in the face of the pandemic. Each state in the United States has unique socio-economic, cultural, and demographic characteristics that influence both policy adoption and policy effectiveness in slowing infections and deaths. Analyzing state-level initiatives provides insights into tailored solutions, local accountability structures, and the dynamic interplay between policymakers and constituents. This way, we can see how policies impact specific regions and understand why some strategies work better in certain areas. Focusing on states also helps us notice important differences that might be missed if we only look at national policies. Each state adapts its strategies based on its unique challenges, and understanding these differences can show us what works best in specific situations. For instance, a policy that works in a densely populated state might not work as effectively in a rural state. Therefore, studying states offers insights into effective governance models and policy responses tailored to unique characteristics, providing a nuanced perspective on policy adoption and policy outcomes. Moreover, studying states aligns with the constitutional principles of federalism, which recognize the importance of preserving state autonomy and promoting efficient, responsive governance, especially during times of crisis. This approach shows how federalism allows for innovative solutions that fit the needs of divergent states.

The goal of this study is to provide a political analysis of how states responded to this novel policy environment created by the COVID-19 pandemic. Much of the existing research on state policy choices has focused whether states took any action to mitigate the spread of the virus. The evidence suggests that states have substantial variation in the policies adopted during the COVID-19 pandemic (Hallas et al., 2021), and policy choices such as state-level shutdown orders and mask mandates were significant factors driving interstate differences on COVID-19 infection growth rates (Zhang & Warner, 2020). It is essential to acknowledge that the diverse responses of states to the pandemic were influenced not only by immediate public health concerns but also by a complex mix of political, cultural, and economic factors unique to each state. By examining these underlying factors, this research aims to uncover how states navigated their distinct challenges, offering a more nuanced understanding of what guided their policy choices during the pandemic.

Additionally, this study seeks to analyze the relationship between multiple state-level COVID-19 policies and their impact on infections and deaths during the pandemic. This analysis is crucial because, unfortunately, similar crises are inevitable. By conducting a comprehensive examination of the effectiveness of state-level non-pharmaceutical interventions in curbing the spread of COVID-19, this research offers valuable insights to aid policymakers in assessing and minimizing disruptions to daily life and livelihoods.

Gap Definition and Research Questions

Previous research during the COVID-19 pandemic primarily focused on assessing the impact of state policy decisions related to Non-Pharmaceutical Interventions (NPIs) on weekly infection cases and fatalities within a limited timeframe starting in January 2020 and generally ending before January 2021, prior to the wide-spread introduction of the COVID-19 vaccines in April of 2021. In COVID-19 research, NPIs are public health measures such as social distancing, mask-wearing, and other prevention techniques designed to control virus spread without relying on pharmaceutical solutions such as vaccines or antiviral drugs by increasing social distancing. Wibbens et al. (2020) and Pozo-Martin et al. (2021) investigated the effects of NPIs on COVID-19 case growth rates up to November and December 2020, respectively, while Zhang et al. (2020) analyzed NPI impacts on case growth rates up to August 2020. However, as of now, no studies have delved into how NPIs affect death counts over time at the state/week level of analysis, spanning from the onset of the pandemic in the first quarter of 2020 to the conclusion of major state policymaking on the pandemic in October 2021.

Before COVID-19 vaccines become widely available, numerous states implemented measures to curb the virus's spread. As vaccine development progressed, some states began easing these restrictions. By October 2021, most states had largely reopened and relaxed the majority of pandemic-related restrictions (POLITICO, 2021). Consequently, while there has been some research on the impact of state policy decisions during the initial wave of the COVID-19 pandemic in the 2020 calendar year, there is a notable scarcity of studies addressing both waves of the pandemic in 2020 and 2021.

This study standouts for its comprehensive analysis of a longer timeframe than other studies and the use of more detailed variables associated with COVID-19 restrictions. This enables me to offer valuable insights into the considerable disparities in infections and deaths across states during the pandemic. Existing studies often focus on whether states implemented policies, but fewer examine why states choose specific policies or what factors drove their adoption and relaxation of COVID-19 measures. For instance, research questions from other studies include: What causes a government to adopt a new program or policy (Adolph et al., 2021)? How do internal determinants (such as political, economic, and social factors) and diffusion models explain variations in state policy adoption (Gollwitzer et al., 2020; Weible et al., 2020; Bump et al., 2021)? Additionally, there is an interest in understanding the impact of state executive directives on infection counts and fatalities (Chernozhukov et al., 2021; Ruhm, 2024), and why some states choose to adopt more restrictive policies than others (Kavanagh & Singh, 2020; Gollwitzer et al., 2020). These questions also consider how sociodemographic factors like unemployment rates, population density, political ideology, and race contribute to differences in infection and death counts among states (Hsiang et al., 2020; Jay et al., 2020; Clouston et al., 2020). This study expands by analyzing three fundamental research questions:

1. Policy Adoption:

   Which states were the leaders in the adoption of non-pharmaceutical COVID-19 interventions (NPI) and which states were the laggards? Alternatively, which states were the first to relax these interventions? What factors predict which states are the leaders, laggards, or never adopted COVID-19 NPIs? This includes investigating what factors predict whether states are leaders, laggards, or non-adopters of COVID-19 NPIs. This analysis incorporates internal determinants such as political ideology, economic conditions, and demographic characteristics to understand how they influence policy adoption decisions.

2. Policy Effectiveness:

   How effective were the COVID-19 NPIs implemented by states in mitigating the virus's spread and decreasing fatalities? This question focuses on the effectiveness of different state-level policies, assessing whether measures like stay-at-home orders, mask mandates, travel restrictions, school closures, and gathering restrictions successfully mitigated the spread of the virus. It also examines the impact of state executive directives on infection counts and fatalities, uncovering how sociodemographic factors—like unemployment claims, population density, governor ideology, and race—influence policy outcomes.

3. Policy Enforcement:

   How did state politics influence the enforcement of COVID-19 policies and impact COVID-19 infections and deaths? This research question explores how the politics of each state shaped adoption and enforcement decisions and whether differences in enforcement contributed to variations in infections and deaths.

This study utilizes quantitative methodologies to explore the research questions outlined. To help answer these questions, I use data from Mayer et al. (2022) that monitors weekly COVID-19 policy developments within in each state combined with weekly infection and death counts. This study uses this dataset to evaluate first the differences in state adoption of COVID-19 policies (questions 1 and 3), and second, the effectiveness of these policies on infections and deaths (questions 2 and 3). The policy adoption model that I am using in this study is grounded in the policy innovation and diffusion framework that was initially developed in a public policy setting by Jack Walker (1969) and updated by Berry & Berry (1990) and DellaVigna and Kim (2022). This model helps explain not just the timing and diffusion of policy adoption across states but also the underlying factors driving those decisions. The policy effectiveness model is grounded in an epidemiological framework that assesses the impact of NPIs based on the weeks that each state has them in effect controlling for underlying state political inclinations and economic capacity.

This study combines a comprehensive dataset with a policy innovation framework to uncover new insights into the factors influencing state policy decisions during the COVID-19 pandemic. By exploring these factors, it addresses key gaps in the current research and offers practical lessons for policymakers looking to navigate similar challenges in the future.

Overview of Chapters

This study is organized as follows. Chapter 2 reviews the current literature on COVID-19 policies and their impact on infections and fatalities across different states. It focuses on the role of NPIs and examines how these policies are implemented and enforced at the state level. The chapter also investigates how the political affiliations of governors, along with demographic factors such as race, ethnicity, income, and age, influence the effectiveness of state responses. The hypotheses explore the timing of NPI adoption, the enforcement of these measures, and the political influences at play, while also considering factors like vaccine availability. This chapter also places the study within the broader context of pandemic response strategies, providing the necessary theoretical background to comprehend differences in policy effectiveness at the state level.

Chapter 3 provides the research design for studying the relationship between state COVID-19 policies and infections and fatalities. This includes the data sources, operationalization of variables, and analytical strategies. The dataset includes 49 states from March 2020 to October 2021, with key variables such as NPIs, political affiliations, demographic data, and regional classifications. Because of missing data, Wyoming is not included in this analysis. This chapter also explains the PID framework to highlight its role in understanding policy adoption and diffusion.

Chapter 4 provides an analysis of policy adoption and enforcement mechanisms. This chapter examines how states adopt COVID-19 policies, incorporating two models: the Policy Innovation and Diffusion Model and the COVID-19 Policy Adoption Model. The first model focuses on state adoption of NPIs, while the second retains states in the analysis after adoption to assess diffusion effects and policy duration. The chapter accounts for various factors influencing policy adoption and longevity, including geographic proximity, political dynamics, demographic characteristics, economic conditions, and public health indicators. A diffusion variable measuring the proportion of neighboring states adopting the same policy is included to assess regional influence. By retaining states in the analysis post-adoption, this model also provides insights into the duration of COVID-19 policies, examining factors that contribute to their continuation or relaxation. The chapter concludes by evaluating how these interconnected factors shape the spread and persistence of COVID-19 measures, comparing differences across regions to understand variations in policy responses.

Chapter 5 provides the empirical analysis of the impact of COVID-19 policies on health outcomes. This chapter evaluates the effectiveness of NPIs in reducing COVID-19-related infections and deaths, with a focus on the timing, enforcement, and political context of these policies. It examines how variations in policy adoption and enforcement shaped health outcomes, considering the role of state politics in influencing these decisions. This chapter employs a random-effects negative binomial regression model to analyze the impact of five NPIs—mask mandates, travel restrictions, stay-at-home orders, gathering restrictions, and school closures—on health outcomes. In addition to assessing the effectiveness of these policies, the analysis explores how state-level political dynamics influenced enforcement decisions. Specifically, it examines whether conservative GOP-controlled states, which generally adopted more lax enforcement measures (Adolph et al., 2021; Rosenfeld 2020), experienced higher infections and fatalities than liberal Democratic states that implemented stricter policies. This chapter also compares the effectiveness of these policies across different regions to explore whether political and regional factors influence policy outcomes. This analysis highlights which policies are most effective in mitigating the spread of COVID-19 and reducing deaths, concluding with a summary of the key findings and their implications for public health strategies.

Chapter 6 summarizes and compares the findings from the analyses on policy adoption, policy effectiveness, and policy enforcement. This chapter reviews the overall effectiveness of NPIs in reducing infections and fatalities, along with the challenges states faced in implementing these policies. It also discusses the broader contributions of the research to public administration, political science, and public health, emphasizing the need for adaptable, context-specific policy responses in future crises. The study concludes by addressing the innovations and limitations of the research and offers suggestions for future research, identifying areas where further investigation is needed to build on this study's findings.

Chapter 2: Literatures, Hypotheses, and Theoretical Basis

Introduction

Prior to the administration of the COVID-19 vaccine, social distancing was the primary means to retard the growth of COVID-19 infections and deaths. The primary means that states used to increase social distancing were through shelter-in-place (or stay-at-home) orders, mask mandates, travel restrictions, school closures, and limits on restaurants and bans on large gatherings, most prominently sporting events and churches. Most empirical research in this area has focused on the question of what other most common social-distancing directives in the United States reduced mobility during the early stages of the pandemic (Abouk & Heydari, 2021). While stay-at-home orders increased the time people spent at home by 15.2% (Abouk & Heydari, 2021, p. 248), limits on restaurants and bars ranked second, increasing the time people spent at home by 8.5% when compared to the day before the implementation of the statewide stay-at-home policy (pp. 248-249). Below I review the epidemiological research on the major NPIs that were commonly adopted by states, often at the behest of the CDC during the pandemic. In the Chapter 4, I will analyze the patterns of state adoption for each of these NPIs and in Chapter 5, I will study how effective each of these NPIs were in lowering the number of infections and deaths.

Shelter-in-place/Stay-at-home orders

During the COVID-19 pandemic, 43 states issued shelter-in-place orders (SIPOs) that prescribed residents to remain inside their dwellings for all but essential activities (such as buying food or medicine, caring for others, exercising, and traveling for employment deemed essential). Worldwide, over 90 countries, representing over half of the world's population, also issued SIPOs (Sanford, 2020). The common wisdom was that SIPOs fostered significant benefits relative to other NPIs, largely from generating social distancing behavior, which would then slow the spread of the novel coronavirus (Cronin & Evans, 2020; Courtemanche et al. 2020a, 2020b; Friedson et al., 2020; Dave et al., 2020b; Sears et al., 2020). SIPOs were the most common comprehensive social distancing policy adopted across states in the United States.

California was the first state to implement comprehensive SIPOs to prevent a statewide COVID-19 outbreak on March 19, 2020. In California, violations of the SIPOs were subject to a $1,000 fine and up to six months of imprisonment (Allday, 2020). California SIPOs increased social distancing (Abouk & Heydari, 2020; Fry, 2020) and reduced non-essential travel by 40 to 60 percent (COVID-19 Community Mobility Report), which in turn reduced COVID-19 cases from 345.2 to 219.7 per 100,000 population and reduced related deaths by 1.661 per 100,000 (Friedson et al., 2020). After California's adoption of SIPOs, 41 additional states, as well as the District of Columbia, enacted similar SIPOs between March 20, 2020, and April 20, 2020.

The impact of SIPOs and the spread of COVID-19 in the U.S. varied depending on the timing of a state's order, with early adopting states clearly benefitting the most (Friedson et al., 2020; Dave et al., 2020b; Sears et al., 2020). Dave et al. (2020) found that SIPOs were most effective in early adopting states and those with high population densities. Siedner et al. (2020) found that early social distancing restrictions of any type, but not later SIPOs, decreased states' COVID-19 growth rates. Courtemanche et al. (2020) evaluated an event-study model with all U.S. counties showing that SIPOs strongly scaled down COVID-19 cases while closing entertainment-related businesses had a moderate effect. In another study, Courtemanche et al. (2020) found that Kentucky would have gained 44,482 confirmed COVID-19 cases without the enactment of social distancing policies, i.e., shelter-in-place orders (SIPOs), closing public schools and restaurants, as opposed to 3,857 that were actually observed. Most vividly, Texas counties showed that early adoption of SIPOs mattered. Eighty-five of Texas' 254 counties enacted their own county-level SIPOs prior to the statewide order enacted on April 2 (National Association of Counties 2020). Scholars found that COVID-19 case growth fell by 21 to 26 percentage points two-and-a-half weeks following the statewide SIPO adoption. However, 90% of the curbed growth in COVID-19 cases in Texas came from the early adoption counties, most of which were urbanized Texas counties (Dave et al., 2020). All totaled, SIPOs in Texas led to a 9%-10% increase in the rate at which residents remained in their homes full-time. The resulted in a reduction of COVID-19 cases by 53.5%, or 3,073 fewer cumulative cases almost three weeks following the adoption of a SIPO (Dave et al., 2021).

Public health researchers calculate that statewide shelter-in-place orders issued by forty-two states plus Washington, D.C. reduced the daily mortality growth rate of COVID-19 deaths by up to 6.1 percentage points nearly forty-two days from enactment and also reduced the daily hospitalization growth rate by up to 8.4 percentage points in nineteen states with SIPOs and hospitalization data (Lyu & Wehby, 2020). Fowler et al. (2020) found that SIPOs led to a reduction in confirmed cases by 390,000 and fatalities by 41,000 after three weeks of when orders were enacted in the United States. These SIPOs played a significant role in flattening the curves, reducing peak incidence not just only for COVID-19 cases but also for hospitalizations and overall deaths.

School closures

The COVID-19 pandemic significantly impacted education systems worldwide, with school closures being a common public health intervention to curb the spread of the virus. Several studies have examined the impact of these closures on COVID-19 infections and deaths in the United States. Research consistently shows that school closures in the U.S. during the pandemic were associated with reduced virus transmission and mortality. For instance, Auger et al. (2020) found that earlier school closures, particularly in states with low initial incidence rates, were associated with greater reductions in COVID-19 cases and deaths. Rauscher (2020) supported these findings, demonstrating that earlier closures were correlated with fewer deaths and slower case growth. Furthermore, the authors discuss the implementation of early school closures to reduce disease prevalence during the COVID-19 pandemic as part of a broader strategy to slow virus transmission. Their analysis suggests that early closures were a proactive measure to mitigate the spread of the virus (Zviedrite et al., 2024).

Moreover, Rauscher and Burns (2021) indicated that delayed school closures had a more severe impact on counties with higher concentrations of Black or economically disadvantaged residents, suggesting that schools play an unequal role in transmission. However, Donohue and Miller (2020) highlighted the complexities in decision-making, noting substantial uncertainty regarding children's role in virus transmission and the need to balance potential benefits against the significant academic, health, and economic consequences of school closures. These studies emphasize the complex trade-offs involved in school closure policies during pandemics.

Despite the tradeoffs, studies found that school closures were an effective NPI. Head et al. (2020) reported that school closures during the spring 2020 semester in the San Francisco Bay Area prevented 13,842 confirmed COVID-19 cases and 663 deaths, with high schools and middle schools having the most significant impact.

Gathering Restrictions (restaurants/churches/sporting events and the like)

Nearly all fifty states issued orders restricting the number of people who were allowed to gather together for sporting events or to attend in-door church services. Ahammer et al. (2020)

found that each time there was an indoor mass gathering, such as NBA or NHL games, there was a 10.3% increase in cumulative COVID-19 deaths in adjacent counties. Conversely, limiting gatherings to 10 people or fewer was shown to lower the growth rate of COVID-19 cases (Ahlers et al., 2021). In essence, stricter gathering limits are more effective in mitigating transmission dynamics.

Indoor dining bans and other similar restrictions on gathering indoor were also associated with reduced COVID-19 case and death rates (Ahlers et al., 2021). These measures were particularly beneficial in highly vulnerable communities such as minority and low socioeconomic status communities, helping to mitigate the impact of COVID-19 despite inconsistencies in federal policy guidance (Page-Tan & Corbin, 2021). In stark contrast, the partial and full reopening of public businesses in 83 U.S. counties significantly increased COVID-19 infection rates (Bruckhaus et al., 2021).

Mask Mandates

To mitigate COVID-19 contagion, the Centers for Disease Control and Prevention recommended that individuals wear face masks in public (April 3, 2020). A total of thirty-nine states adopted mask mandates at some point during the pandemic. Public health authorities emphasized that masks would be one of the most effective ways to help fight the pandemic, and many U.S. states early in the pandemic introduced mask requirements. However, well-documented inconsistencies among various state mandates for mask-wearing led to much confusion among the public. In addition, because of the actions of politicians, particularly then-President Donald Trump, who refused to wear a mask, the mask mandate became one of the most controversial recommendations made by the CDC in response to the COVID-19 pandemic.

Studies show that states that enforced mask mandates had a more significant decline in COVID-19 infection rates than states lacking a mask mandate. Huang et al. (2020) found that the mask mandates conferred benefits in reducing community case incidence during an early period of the COVID-19 pandemic. Lyu and Wehby (2020) provide evidence that face mask use in public decreased the average daily county-level growth rate by 0.9, 1.1, 1.4, 1.7, and 2.0 % in 1–5, 6–10, 11–15, 16–20, and 21 or more days after implementation (pp. 1421-1423). These findings highlight the role of mask mandates in slowing the spread of COVID-19.

Travel restrictions

Many countries implemented travel restrictions early in the pandemic to reduce the number of infectious individuals that travel into the country from the outside (Chinazzi et al., 2020). Those international travel bans were one of the fastest and most viable responses to limit the spread of the COVID-19 variants. For instance, a travel ban in Australia delayed the widespread transmission of COVID-19 by 79% within one month, and it reduced cases by about 86%, showing how effective this measure was in containing the epidemic (Adekunle et al., 2020; Costantino et al., 2020). While travel bans are a controversial topic, they were nonetheless were deemed to be a highly effective measure to manage the outbreak dynamics in the pandemic (Zlojutro et al., 2019).

In the United States, however, travel restrictions were delayed. The CDC confirmed the first travel-related case in Washington on January 21, 2020. Still, Washington waited to enact a travel restriction order until June 27, 2020. As a result, by the time Washington issued an executive order to mitigate the virus, they already had 33,031 COVID-19 cases and 1311

COVID-19-related deaths in the city (Johns Hopkins University, 2020). This delay in implementation highlights how late action may have contributed to the spread of the virus.

Travel restrictions were implemented in other states besides Washington. Travel restrictions took several forms and were enforced with varying levels of strictness. One approach involved border closures, where states restricted non-essential travel across their borders but allowed exceptions for essential workers and critical supply chains. Some states issued mandatory quarantine orders, requiring travelers from high-risk areas or states with high COVID-19 case rates to self-isolate for 14 days. Travel advisories were another standard measure, recommending that travelers voluntarily quarantine upon entering the state, although these were not mandatory. Additionally, some states set up checkpoints or border screenings, where law enforcement or public health officials stopped vehicles to check the purpose of travel and give guidance about quarantine rules. These measures were intended to limit the movement of potentially infected individuals and reduce the spread of COVID-19. Research on these travel restrictions suggest that states that restricted travel into borders from other states and countries tended to experience fewer COVID-19 cases compared to states with quarantine requirements (Linka et al., 2020). But, many states in the US (Alabama, Colorado, Georgia, Illinois, Indiana, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Carolina, South Dakota, and Tennessee) did not issued any travel restrictions at all during the pandemic; only a few states issued a travel advisory requesting their constituents to self-quarantine for 14 days upon arrival, and several states actually enacted an order for their residents to self-quarantine for any out of state travel.

State Policy Adoption Model

One component of this study is to understand the effects of NPI adoption patterns, assessing how implementation of NPIs across states influenced infection cases and the number of deaths, another component is to explain the patterns of NPI policy adoption. To accomplish this goal, I use policy innovation and diffusion (PID) framework. In the PID literature, a state government innovation is defined as a "program or policy that is new to the state adopting it" (Walker, 1969), and the central research question about state innovation is what causes a government to adopt a new program or policy. The existing literature has identified two primary explanations for state government policy adoption: internal determinants and diffusion models (Berry & Berry, 1990; Shipan & Volden, 2008). Internal determinants are the factors that lead state governments to innovate, and these are political, economic, and social characteristics internal to the state (Berry, 1987). Political factors such as party influence and political alignment play a vital role in driving policy innovation within states. Berry and Berry (1990) suggest that when a single political party holds both the governorship and both houses of the legislature, it is more likely to implement a lottery system than in situations where the government is under the control of different parties. This is because a unified government can avoid obstacles that arise due to the need for compromise between two parties. As a result, the government becomes more capable of obtaining the necessary agreement to shape state-level policies.

Various economic factors, such as a state's economic capacity and resources, can stimulate innovative policymaking by state governments. States may be driven to innovate in policy-making due to economic competition, as larger and richer states tend to have greater resources and capacity, leading to the development of new policies that promote economic growth and competitiveness (DellaVigna & Kim, 2022, 8). Additionally, states with more resources and capacity may be more likely to innovate in policymaking (Walker, 1969; Besley & Persson, 2009). This could include factors such as larger state budgets, stronger administrative capacity, and higher Gross State Product (GSP), which provide the necessary financial and institutional resources to support policy innovation. Moreover, the fiscal health of a state's government is also a crucial factor that can lead to policy innovation. A poor fiscal health, especially during an election year, may be a necessary condition for the adoption of certain policies, such as lotteries (Berry & Berry, 1990).

Several social factors can lead state governments to innovate in policymaking. One of these is demographic similarity. States with similar demographics are more likely to adopt comparable policies, indicating that demographic similarity can significantly affect policy innovation (DellaVigna & Kim, 2022, 3). Additionally, the type of policy area can also play a role in the likelihood of innovation. Social issues, often more divisive, tend to prompt more policy innovation than economic policies (DellaVigna & Kim, 2022, 16). This suggests that social issues prevalent in a given state, such as healthcare, education, and social welfare, can stimulate policy innovation (DellaVigna & Kim, 2022, 16). Finally, personal income levels can also be a factor. Lower income levels in a state can make it more difficult to successfully adopt a lottery, as lottery participation rates are typically highest among middle- to upper-income levels (Berry & Berry, 1990).

The diffusion of innovations theory, a key component of policy innovation and diffusion theory, provides a framework for understanding how new ideas and practices are communicated and adopted within a social system over time (Berry & Berry, 1990). Early diffusion of innovations theory focused on geographic proximity, demographic similarity, and political party alignment as essential predictors of policy diffusion across states. The advantage of using this framework for understanding the spread of COVID-19 NPIs is that it recognizes that innovations are not always universally accepted or adopted but rather are initially embraced by a few states and gradually spread to others over time (Berry & Berry, 1990). Boehmke et al. (2025) found that the adoption of COVID-19 policies followed an S-curve pattern. Early adopters implemented measures quickly, but the rate of adoption slowed as additional states enacted similar policies. Furthermore, while historically innovative states showed a moderate inclination to adopt new policies, the correlation between policy innovativeness and policy stringency remained weak (Boehmke et al., 2025). These findings indicate that adopting new policies did not necessarily result in more restrictive measures. In addition, there are complexities inherent in policy diffusion because there were diverse factors influencing state-level decision-making during the pandemic.

A study by DellaVigna and Kim (2022) successfully utilized the policy innovation and diffusion framework (PID) in their research. Using the State Policy Innovation and Diffusion (SPID) Database that includes data on over 700 state law policies adopted in the last century, the authors effectively demonstrate that the policy innovation and diffusion framework is a robust theoretical choice for understanding the spread of state policies. The authors argue that states are "laboratories of democracy" with comparable political institutions, which makes the PID model appropriate for any analysis of the innovation and adoption of policies among states (DellaVigna & Kim, 2022, 1). The authors found three distinctive eras of PID policy adoption, demonstrating the evolving nature of policy diffusion dynamics. These eras provide valuable insights into changing factors influencing policy adoption over time. The first era of policy adoption, from the 1950s to the 1990s, was mainly influenced by geographic proximity and demographic similarity

(DellaVigna & Kim, 2022, 3). In addition, states with similar demographics, including income and urban population, were also inclined to adopt similar policies during this period. This era reflects a time when policy adoption was primarily driven by physical proximity and shared demographic features among states.

In the second era, from the 2000s to the 2010s, politically aligned states emerged as the primary drivers of policy adoption (DellaVigna & Kim, 2022, 3). Specifically, the Republican presidential vote share in recent elections was the most influential factor in predicting policy adoption during this time. This shift indicates a departure from the previous era, where geographic proximity and demographic similarity significantly influenced policy adoption.

Lastly, the most recent era, known as the third era, highlights a significant impact of political similarity on policy adoption (DellaVigna & Kim, 2022, 3). This recent period has seen a significant increase in the importance of political similarity, particularly regarding state party control (Republican versus Democrat PID model). The result of this study indicates a shift towards a party-driven model for policy adoption, with state-level party discipline playing a pivotal role in shaping policy diffusion in today's landscape (DellaVigna & Kim, 2022, 19-20).

Building on the principles of the diffusion of innovations theory, this research explores how geographic proximity, political alignment, and state resources influence the adoption of various NPIs during the COVID-19 pandemic. Geographic proximity has long been a critical factor in policy diffusion, as states often look to their neighbors when adopting new policies. Given the contagious nature of COVID-19, one would naturally expect that neighboring states' NPI policies would have an effect on any given state's NPI policy adoption. Political alignment, including shared ideological perspectives, further shapes the likelihood of policy adoption, as ideologically similar states often emulate one another. Additionally, state resources and capacity are vital in determining whether a state can effectively adopt and implement these policies.

This study adapts the PID model to analyze the political climate characterized by distinct Republican and Democratic PID models that may have shaped the adoption of COVID-19-related policies. Therefore, I plan to adopt a similar theoretical framework to comprehensively understand policy innovation and diffusion and its interaction with political polarization in my research.

Significantly, like DellaVigna & Kim (2022), most diffusion of innovation models in the literature use the state/year as the unit of analysis and cover several years of policy adoption by state. The COVID-19 policy diffusion model as applied in this study is much more compressed over a shorter timeframe. This policy environment is the product of a public health emergency that required immediate actions by states. For this reason, the unit of analysis is state/week.

In addition, while most the PID literature focuses on legislation passed and signed into law by state governments, a slow and deliberative process with the chance for national policy networks to play a large role in encouraging the spread of a policy; adopted NPIs in each state were the result of actions taken by the governor of each state using their police powers to safeguard the general health and welfare of citizens. As such, the adoption of NPIs by states is a unique policy adoption environment, where internal factors within each state were largely unmitigated in their possible influence on each governor's policy choices, policy recommendations mostly emanating from public health officials from the CDC, or recommendations from social media sources, replete with much disinformation, or national cable news networks that added yet another layer to the noise. No matter the external source, this national policy environment was a constant affecting all states equally, leaving each state's executive to their own devices to choose whether to adopt or not to adopt NPIs.

Even with the more compressed timeframe and the focus on executive decision-making, the PID model is appropriate theoretical framework for understanding how COVID-19 policies were developed, propagated, and accepted across different states. First, PID theory may explain governmental and health organizations' initial acceptance and implementation of COVID-19 policies. As the pandemic unwrapped, these entities swiftly presented innovative policy proposals like lockdowns, social distancing rules, or mask mandates. This illustrates PID's "innovation" part, where a novel issue (i.e., a global pandemic) encourages rapid policy intervention.

Second, the "diffusion" part of PID theory may be used to explain how these policies spread across states. Some states quickly embraced and implemented these policies, serving as 'early adopters.' Then, after witnessing their effectiveness, other 'late adopter' states gradually adopted these measures.

Third, PID theory can be used to also provide insights into the variance in adoption rates of COVID-19 policies. This is explicable through a social system's political, cultural, or socio-economic contexts, which can influence how readily a policy is adopted. One such complexity involves how states with older populations responded to the crisis. While it may seem intuitive that states with older populations would adopt stronger public health interventions, the opposite may occur in certain contexts. For example, states like Florida and Arizona, which have a significant number of retirees, often have strong political leanings that prioritize limited government intervention and individual freedoms. These values can lead to resistance against implementing NPIs. Moreover, economic factors, such as heavy reliance on tourism and retirement communities, can force state leaders to avoid strict measures such as lockdowns or travel bans. In these situations, political beliefs and economic interests often take precedence over the safety of vulnerable older individuals. Consequently, public health policies may be implemented more slowly or less effectively, even when health risks are higher (Lee, 2021).

Similarly, states with higher proportions of non-white individuals have often faced structural disadvantages such as limited political representation and unequal access to healthcare services (Mamelund et al., 2021). These inequities can contribute to policy delays or reduce the willingness to implement aggressive public health measures. Moreover, minorities and low-income populations are disproportionately employed in essential sectors that remained operational during nonessential business closures, heightening their risk of exposure to COVID-19 and complicating the feasibility of strict interventions (Raifman & Raifman, 2020). Collectively, these factors underscore the economic vulnerability of these communities and help explain why state leaders may hesitate to impose early and stringent NPIs that could further burden already disadvantaged populations.

Structural and economic vulnerabilities may have delayed policy adoption in states with larger non-white populations. Moreover, these factors combined with the greater health burdens in these communities likely required longer enforcement of NPIs once implemented. States with higher proportions of non-white residents may have faced increased public health pressures to sustain restrictions for extended periods. Racial and ethnic minority populations significantly experienced higher rates of COVID-19 infection, hospitalization, and mortality, underscoring the disproportionate burden faced by these groups (Upshaw et al., 2021). These elevated risks made it challenging to lift restrictions quickly. Additionally, structural inequalities such as limited healthcare infrastructure and fewer economic resources may have further delayed reopening efforts. Therefore, in many instances, keeping NPIs in place for longer was not merely a policy decision, but a necessity driven by deeper inequalities and a need to protect vulnerable populations.

Using the PID theory, one can gain a nuanced understanding of the formulation, circulation, and assimilation of COVID-19 policies in different state policy environments.

In this research, I use the Policy Innovation and Diffusion model to analyze the state policy responses implemented in response to the COVID-19 pandemic in the United States. I did consider other established policy development models like the Advocacy Coalition Framework (Sabatier, 1987, 1988), which underscores the influence of interest groups, Multiple Streams Framework (Kingdon, 1984), and Kingdon’s Multiple Streams Theory (Kingdon, 2010), which both accentuate the convergence of problem, policy, and political streams. However, none of these models are well suited to capture the swift and dynamic nature of policy diffusion inherent in urgent crises like COVID-19. Moreover, the PID model has been successfully used for analyzing policy diffusion in public health and crisis management contexts (Green et al., 2009; Nykiforuk et al., 2007).

Analytic Approach

The research model, depicted in Figure 1, highlights distinguishable patterns in the factors contributing to COVID-19 policy adoption, emphasizing the interplay between social, economic, and political considerations in shaping state-level responses during the pandemic. Unlike generic policy innovation models, this framework is tailored to the unique context of COVID-19, where urgency, public health pressures, and partisan influences played pivotal roles in driving policy decisions. Innovations in GOP-led states may be influenced by factors such as partisan influence, policy objectives, state capacity and resources, and political similarity. GOP-led states tend to prioritize policies that align with conservative ideologies, such as limited government intervention, fiscal conservatism, and deregulation, which may lead to different policy objectives than those of Democratic-led states. For instance, GOP-led states were slower to adopt restrictive measures such as mask mandates and gathering limits, often citing economic considerations and individual freedoms. States with larger budgets, stronger administrative capacity, and an experienced legislative body may also be more likely to innovate in policymaking. Furthermore, GOP-led states may adopt innovative policies from other politically aligned states through policy diffusion. These differences reflect broader ideological divides, with partisan alignment playing a significant role in the diffusion of COVID-19 policies across states.

Geographic proximity and ideological similarities, as illustrated in Figure 1, are also expected to play critical roles in shaping policy adoption during the pandemic. States often modeled their COVID-19 responses on neighboring states, with policies diffusing more rapidly among geographically proximate states. For example, the timing and implementation of measures such as mask mandates and travel restrictions were influenced by neighboring states' decisions, creating clusters of similar policy adoption. Similarly, ideological alignment between states facilitated the spread of policies that aligned with shared political and cultural values. Republican-led states, emphasizing individual freedoms and economic priorities, tended to adopt less restrictive policies, while Democratic-led states pursued more stringent measures focused on public health. These dynamic underscores the role of both proximity and shared political identity in driving policy diffusion during the pandemic.

In general, Democratic-led states have proven to be more innovative when it comes to policymaking (DellaVigna and Kim 2022). This can be attributed to factors such as partisan influence, policy objectives, state capacity, and political similarity. Due to their liberal ideologies, Democratic-led states are more likely to introduce innovative policies that align with social welfare programs, environmental protection, and progressive taxation. Furthermore, Democratic-led states prioritize different policy objectives than GOP-led states, resulting in innovative policies that reflect their specific goals and values. States with higher levels of resources, capacity, or legislative professionalism are more likely to innovate in policymaking, as they have access to larger budgets, stronger administrative capacity, and a more experienced legislative body. Additionally, Democratic-led states are influenced by the policy innovations of other politically aligned states, leading to the adoption of similar policies through policy diffusion.

During the policy diffusion stage, several factors affect the spread of policies across different states. Recent research has shown there may be differences in the likelihood of policy diffusion among states led by Republicans versus states led by Democrats. This research suggests that political alignment has become a stronger predictor of policy adoption since the 2000s (DellaVigna & Kim, 2022, 3). In GOP-led states, political similarity plays a more significant role in policy diffusion, indicating that these states are more likely to follow policies that align with conservative ideologies and priorities. Conversely, Democratic diffusion may be more influenced by policies that align with liberal ideologies and priorities, with political similarity also playing an essential role in Democrat-led states. The impact of political similarity on policy adoption has grown significantly in recent years, highlighting the growing influence of partisan forces in shaping state-level policies. Moreover, the diffusion of COVID-19 policies also follows similar patterns of political polarization, further emphasizing the role of political alignment in policy adoption (Cui et al., 2021; DellaVigna & Kim, 2022).

Policy Adoption and Diffusion Hypotheses

Based on Figure 1 and the previous discussion I expect the following regarding the adoption of each NPI.

- **Neighboring States:** States that share borders will be more likely to adopt the same NPIs (Walker 1969; Berry and Berry 1999; DellaVigna and Kim 2022).
- **Governor's Political Affiliation:** Democratic governors will be more likely to enact NPIs than states with Republican governors (Shvetsova et al., 2022; Baccini and Brodeur, 2020; Adolph et al., 2021).
- **Support for President Trump:** States that more strongly supported Trump will be less likely to adopt NPIs than those that did not (Adolph et al., 2021; Hill et al., 2021).
- **State Ideology:** Conservative states will be less likely to adopt NPIs than more liberal states (Hsiehchen at al., 2020; Cevasco et al., 2021).
- **Race and Ethnicity:** States with higher the percentages of Black, Latino, and indigenous individuals will be less likely to adopt NPIs than those will lower percentages.
- **Retired Population:** States with older populations (greater than 65 years old) and higher comorbidities will be less likely to adopt NPIs (Lee 2021).
- **Vaccine Availability:** The NPIs will be negatively related to the availability of the COVID-19 vaccines (Kraay et al., 2021; Ge et al., 2021).
- **Population Density:** States with higher population densities will be more likely to adopt NPIs than those with lower densities (Gozzi et al., 2023; Choi et al., 2022).

- **State Capacity:** States with higher levels of per-capita gross domestic product will be more likely to adopt NPIs than those with lower levels (Banholzer et al., 2022; Summan and Nandi 2020).

Mayer et al. (2022) found that the severity of the COVID-19 pandemic, as measured by deaths per capita, initially influenced the implementation of public health measures in many states. Adolph et al. (2020) also found that controlling for political factors, states with fewer COVID-19 cases were slightly less likely to implement social distancing measures than states with more cases. The number of COVID-19 cases avoided by lockdowns at the start of a pandemic was the most important factor for reducing the ultimate disease spread (Saletta et al., 2020). In other words, early lockdowns are most closely associated with reduced death rates. Thus, in addition to above hypotheses, I also include the levels of COVID-19 infections and deaths as independent variables. This is a recognition that all governors in all states may have simply been forced to give into the realities of the pandemic (Mayer et al, 2022). That because their citizens were getting infected and dying, that they were forced to act to address this reality. I expect that the higher the number of infections and deaths in states will have a positive effect on the adoption of NPIs.

Policy Longevity Hypotheses

- **Neighboring States:** States that share borders will be more likely to maintain similar timelines in adopting NPIs, reflecting policy diffusion.
- **Governor's Political Affiliation:** Republican governors will be more likely to de-adopt NPIs earlier than states with Democratic governors.

- **Support for President Trump:** States that more strongly supported Trump will be more likely to end NPIs sooner than states with lower levels of Trump support.
- **State Ideology:** Conservative states will be more likely to shorten the duration of NPIs compared to more liberal states.
- **Race and Ethnicity:** States with higher the percentages of Black, Latino, and indigenous individuals may keep NPIs for longer periods due to higher vulnerability to COVID-19.
- **Retired Population:** States with older populations (greater than 65 years old) and higher comorbidities will be more likely to lift NPIs sooner than other states.
- **Vaccine Availability:** The NPIs will be negatively related to the availability of the COVID-19 vaccines.
- **Population Density:** States with higher population densities will be more likely to maintain NPIs for extended periods than those with lower densities.
- **State Capacity:** States with higher levels of per-capita gross domestic product will be more likely to sustain NPIs for longer duration than those with lower levels.

COVID-19 Policy Effectiveness

How effective were the adoption of these NPIs on lowering the number of infections and deaths? Earlier in this chapter, I reviewed the epidemiological literature regarding each of the major NPIs. These studies, mostly conducted in the early stages of the pandemic, found that states that adopted SIPOs earlier saw significant reductions in infections and deaths (Friedson et al., 2020; Dave et al., 2020b). States that closed their schools had lower transmission rates and deaths (Auger et al., 2020; Rauscher, 2020). States that limiting large gatherings reduces COVID-19 case growth (Ahammer et al., 2020; Ahlers et al., 2021). States that adopted mask mandates had lower infection rates (Huang et al., 2020; Lyu & Wehby, 2020). And states enforcing travel limits saw fewer imported cases (Linka et al., 2020).

Based on this literature, I expect that all of these NPIs will have a negative effect on the number of COVID-19 infections and deaths. However, the literature on COVID-19 politics suggests that states differed systematically in their willingness to adopt and enforce COVID-19 policies. Some states acted swiftly with strong enforcement measures to prevent the spread, while others enacted NPIs only after the spread had started and did not strictly enforce their NPIs. While still others, never adopted any of the NPIs but only made recommendations regarding best practices to avoid infection. This means that the implementation of NPIs varied greatly by state.

For example, California was not only an early adopter of SIPOs, it also strictly enforced its SIPOs. But not all's states enforced its SIPO as strictly as California did (Friedson et al., 2020). There were significant variations in the enforcement methods, penalties, and lists of "essential workers" associated with these orders, which did impact the overall outcomes. States that had more strict enforcement of SIPOs issued monetary fines, warnings, citations, and in extreme circumstances, even business license revocation. Friedson et al. (2020) conducted a study highlighting the role of early adopters of comprehensive SIPOs, similar to California's approach of imposing fines of up to $1,000 for violations. Their findings showed significant reductions in non-essential travel and decreased COVID-19 cases. Similarly, Lyu and Wehby (2020) found in the 19 states with SIPOs that included fines or penalties for non-compliance the daily mortality growth rate of COVID-19 deaths declined by up to 6.1 percentage points and the daily hospitalization growth rate declined by up to 8.4 percentage points. Nonetheless, issuing a SIPO, whether enforced with fines or not, contributed to reducing confirmed cases and fatalities

(Fowler et al., 2020). These research findings underscore the discernible impact of fines and penalties in SIPOs on outcomes related to COVID-19 cases, hospitalizations, and fatalities. Therefore, the presence or absence of enforcement mechanisms played a significant role in shaping the overall success of SIPOs in mitigating the spread of the virus.

Among those states that did not adopt SIPOs, few adopted some limited shutdown directives that fell short of full SIPOs, including mandates to close non-essential businesses (Kentucky, Massachusetts) and more narrowly targeted SIPOs, which applied only to elderly individuals and those with pre-existing health conditions (Georgia and Oklahoma). Only Arkansas, Iowa, Nebraska, North Dakota, and South Dakota did not adopt a SIPO, a limited shutdown, or a targeted SIPO. Consequently, if we compare the number of new COVID-19 cases between Kentucky and Arkansas, we find a considerable difference between these two states. As per Johns Hopkins University (2020), on June 30, 2020, Kentucky reported a total of 15,916 COVID-19 infection cases (353 new cases per 100,000 population), while Arkansas reported a total of 20,777 COVID-19 infection cases (688 new cases per 100,000 population) at the same time of the month. These figures highlight the differences in COVID-19 case counts at the state level, which may result from variations in policy adoption, enforcement, and compliance.

The effectiveness of SIPOs in reducing COVID-19 infections and deaths relied not only on their adoption but also on how long they were enforced and the level of public compliance. Research indicates that SIPOs implemented earlier and maintained for a longer duration were more effective in slowing the transmission of the virus and decreasing mortality rates.

The implementation of school closure policies also varied significantly across states. In particular, political ideology influenced these decisions, as Democratic-led states typically enacted school closures more swiftly and maintained them for longer periods than Republican-led states. Furthermore, states with greater economic and administrative resources were better equipped to handle remote learning and sustain extended closures. The implementation of travel restrictions also varied significantly among states. Democratic-led states tended to be more inclined to enforce travel restrictions, while Republican-led states often avoided them due to economic concerns and political opposition. Similar to school closures, states with more financial and administrative resources were better positioned to enforce and maintain travel restrictions over the long term.

And then there is the adoption of mask mandates, which was in no way uniform across the country. Similar to the other NPIs, partisan and ideological proclivities played a significant role in these decisions. Democratic-led states tended to be more supportive of enforcing mask mandates, while Republican-led states often resisted or lifted such mandates earlier due to political and economic factors.

For each NPI, I expect that infections and deaths will decline during the weeks that these policies are enacted in each state. But, in order to properly specify the effects, I need to control for a list of political conditions, state's economic capacity, and state comorbidities, which as noted above, may have negatively or positively impact the implementation of each NPI within a state. I introduce each of these control variables below.

State's governor political affiliation

Most countries followed a central policy scheme during the COVID-19 pandemic; however, in the United States, the authority to place a state under any directive is left to its governor, which created a natural experiment resulting from a high level of variation in type, location, and timing of enacted COVID-19 policies (Adolph et al., 2020; Painter et al., 2020; Allcott et al., 2020). Of course, agencies of the federal government, i.e., the executive branch or

Centers for Disease Control and Prevention (CDC), can make recommendations on any policies to state and local officials. But it's up to the governor of each respective state to implement these recommendations. I include a measure of the political party of the governor because the governors that enacted the most restrictive policies more quickly tended to be Democrats, while Republican governors tended to be slower and enact the least restrictive policies (Adolph et al., 2021; Fowler et al., 2021; Gusmano et al., 2020). In addition, GOP governors were less likely to include enforcement language in their COVID-19 directives (Curley et al., 2021) and were inclined to wait to declare states of emergency until President Trump announced a national emergency. Whereas Democratic governors gravitated to act on their own timelines to fight President Trump's messaging (Fowler et al., 2021). Similarly, Gadarian et al. (2020) found that Republicans were less likely to take personal precautions against COVID-19 and mostly believed the COVID-19 death toll to be smaller than Democrats believed it to be. Although this study primarily analyzes state-level responses to COVID-19, it is essential to acknowledge the insights from existing literature on county-level dynamics. This literature reinforces the observation that partisanship was a hindrance to public health measures against COVID-19, which made the adoption of NPIs less effective in Republican counties (Amuedo-Dorantes et al., 2021). Consequently, I expect that states with Republican governors were less likely to adopt and enforce NPIs, leading to higher COVID-19 infections and deaths compared to states with Democratic governors.

Support for President Trump

Research shows a clear connection between support for Donald Trump and COVID-19 outcomes in the United States. Initially, counties that supported Trump had fewer cases and deaths (Morris, 2021). However, as the pandemic continued, these areas saw higher infection and mortality rates (Morris, 2021; Liebl & Schüwer, 2021; Albrecht, 2022). This pattern is linked to lower compliance with public health measures in pro-Trump areas, such as reduced mask-wearing and social distancing (Chopra & Wydick, 2021). Similarly, Gadarian et al. (2020) found that Republicans were less likely to take personal precautions against COVID-19 and mostly believed the COVID-19 death toll to be smaller than Democrats. Other researchers conclude that partisanship was a hindrance to public health measures against COVID-19, which made the adoption of NPIs less effective in Republican counties (Amuedo-Dorantes et al., 2021). Finally, the impact of political affiliation on COVID-19 spread became more apparent after vaccines became available (Albrecht, 2022). Building on this, I expect states with higher levels of support for Trump in the 2020 election were less likely to adopt and enforce NPIs, leading to higher COVID-19 infections and death counts.

State Ideology

Research indicates that political ideology significantly influenced COVID-19 outcomes in the United States. Conservative-leaning states and those with Republican leadership generally experienced higher infection rates and death counts, particularly after the initial outbreak phase (Rosenfeld, 2020; Krieger et al., 2022). This trend was observed at both state and congressional district levels, even when controlling for social and demographic factors (Krieger et al., 2022). Conservative political ideology was associated with delayed implementation of preventive measures and less adherence to public health guidelines (Rosenfeld, 2020; Geana et al., 2021). Accordingly, I expect that conservative-leaning states will have higher COVID-19 infections and deaths due to lower compliance with public health measures.

Comorbidities: Race and Ethnicity

As COVID-19 began to escalate in the United States, racial/ethnic and socioeconomic factors were found to be associated with exposure and vulnerability to the disease. Profound racial/ethnic disparities developed in mortality rates in 2020 during the height of the COVID-19 pandemic in the United States (Shiels et al., 2021). Studies have found that Black, Latino, and indigenous individuals were disproportionately more likely to become infected and die from COVID-19 than their white counterparts (Chowkwanyun & Reed, 2020; Denice et al., 2020; Elflein, 2021); although whites make up the majority of the total number of COVID-19 cases and deaths because they make up over 60 percent of the US population (Elflein, 2021). Dai et al. (2021) found that major healthcare disparities were evident, especially among Hispanics who tested positive at a higher rate, required excess hospitalization and mechanical ventilation at higher rates, and had higher odds of in-hospital mortality despite their younger age. Public health experts speculate that this disparity may be due to the increased likelihood of these non-white individuals working in service jobs where they are in close contact with others, inequities in access to quality healthcare, living and working in unhealthy environmental conditions, the higher probability of having an underlying medical condition, and sustained systemic discrimination both in society-at-large and within the healthcare establishment (Chowkwanyun & Reed, 2020). Racial and ethnic disparities in health outcomes have been well documented during the COVID-19 pandemic. States with a higher percentage of racial or ethnic minorities tend to experience higher infection and death rates due to structural inequalities in healthcare access, economic conditions, and preexisting health disparities. Based on these findings, I expect that states with higher percentage of racial or ethnic minorities will have higher levels of COVID-19 infections and deaths than states that are predominately white.

Comorbidity: Elderly Population

Beyond partisan support, the most apparent factors closely related to the effects of COVID-19 are age and underlying health conditions. As age increases, so do the odds of getting symptomatic and dying from COVID-19 (Wu et al., 2020), with people over the age of 60 being particularly vulnerable. Common underlying conditions, like diabetes and obesity, have been closely linked with vulnerability to COVID-19, regardless of age (Patel et al., 2020; Wu et al., 2020). Previous research has employed different benchmarks for the elderly population, considered a crucial indicator of population vulnerability. For instance, some researchers used measures of the percentage of a state's elderly population to be more than 60 years (Fowler et al., 2021), while others used 70 years (Adolph et al., 2021). Still, others used over 65 years old (Amuedo-Dorantes et al, 2021). Although the Centers for Disease Control (CDC) warns that anyone over age 65 is at increased risk from COVID-19 (CDC, 2020), since the CDC provides official US government recommendations, I utilize the percentage of the population aged 65 and older as one of the important indicators to infer a state population's overall susceptibility. Accordingly, states with a higher median age will have higher number of COVID-19 related infections and deaths compared to states with lower median ages.

Comorbidity: Population Size and Density

Some studies have indicated that areas with higher population density experienced earlier outbreaks and higher infection rates (Wong & Li, 2020; Loomba et al., 2020). However, other research has found no significant association between population density and case numbers after adjusting for other factors (Carozzi et al., 2020; Carozzi et al., 2022). Metropolitan population size has been identified as a significant predictor of infection and mortality rates (Hamidi et al., 2020a; Hamidi et al., 2020b). Additionally, connectivity between areas, airport traffic, and age demographics influenced the spread of COVID-19 (Roy & Ghosh, 2020; Carozzi et al., 2022). In line with this, I expect that states with higher population density and large population size are expected to experience higher COVID-19 weekly infections and deaths due to increased opportunities for virus transmission compared to states with lower density and smaller populations.

Control: Vaccine Availability

The COVID-19 pandemic caused significant global morbidity and mortality, undermining the economic and social well-being of individuals and communities. Thus, vaccine development efforts were accelerated in response to the devastating COVID-10 pandemic. Similar to the COVID-19 policy directives, states differed in rolling out the vaccines in their states. Tenforde et al., 2022 found that COVID-19 vaccination was associated with a 90% reduction in risk for severe COVID-19 outcomes, including invasive mechanical ventilation and in-hospital deaths. In addition, COVID-19 vaccines with 95% efficacy substantially reduce hospitalizations and deaths (Moghadas et al., 2021). Based on these findings, I expect the introduction of the vaccination in February and March of 2021 will lower COVID-19 infection and death counts compared to the weeks prior to its introduction.

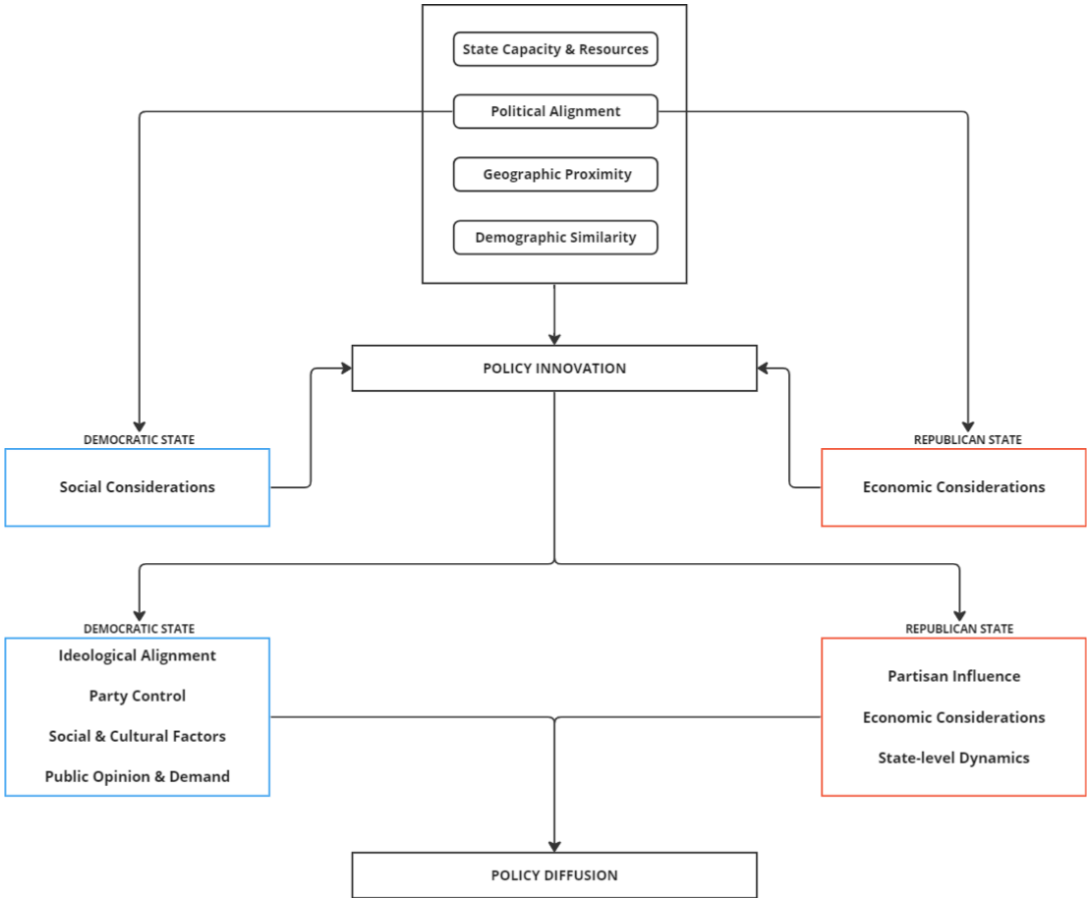

Fig 1: Research Model Used in the Analysis

Chapter 3: Research Design and Methodology

In my study, I employ the Policy Innovation and Diffusion model to investigate the underlying factors that contributed to the discrepancies in COVID-19 infection and mortality counts across various states. Using cross-sectional panel designs I examine the influence of state policy decisions on these variations in policy adoption and policy effectiveness. My study of policy adoption uses both the adoption of policies noted previously and the lifting of these policies, respectively, to explain both the folding out and the unfolding of COVID-19 NPIs using the PID framework. My study of the effectiveness of these NPIs centers on two key dependent variables, namely, the count of COVID-19 1) infections and 2) fatalities.

Sources of Data

The study utilizes variables and measures that correspond with the hypotheses presented in the literature section. This study's two dependent variables, namely the number of COVID-19 infections and deaths, are sourced from the Centers for Disease Control and Prevention (CDC) database from March 2020 through October 2021. The data covers COVID-19 infection cases, and death counts from every state.

The study focuses on four COVID-19 policy actions that are used both as dependent variables to explain policy innovation and diffusion and then as independent variables to gauge the impact of state actions in mitigating the pandemic. These actions are stay-at-home orders, mask mandates, travel restrictions, gathering restrictions, and school closures. Data for stay-at-home orders are drawn from the COVID-19 US State Policy database (CUSP) and the New York Times (2021), while the Ballotpedia database (ballotpedia.org, 2021) is utilized for the other four actions. I utilize the Oxford COVID-19 Government Response Tracker (OxCGRT) from the GitHub repository to analyze the variances in state government responses and their correlation with infection counts. This tool thoroughly examine the measures implemented by governments across different regions and their effectiveness in limiting the spread of the virus. By utilizing this comprehensive database, this study provides valuable insights into the most effective strategies for managing the pandemic.

Moreover, the study considers other variables that could impact the outcome, including the state's population count and density, income inequality, vaccine availability, governor's party affiliation, state's elite ideology, percentage of nonwhite population, median age, percentage of Trump vote in 2020, and state capacity. The Ballotpedia database (Ballotpedia.org, 2021) provides data for two additional political variables: governor party affiliation and ideology. This study utilizes the most recent census estimates to determine each state's total population count and density, as well as the median age of the state's population (U.S. Census Bureau, 2021). Race and ethnicity are measured by the percentage of non-Hispanic White residents in each state (American Community Survey, 2021).

The ideology of state governments is measured using Berry et al.'s ideology score (1998), which is a continuous variable with lower numbers indicating a more conservative ideology and higher numbers indicating a more liberal ideology. This variable allows for measuring the state's government ideological preference.

Partisanship is measured by the state governor's party affiliation (Ballotpedia.org, 2021) and the percentage of the two-party vote won by Donald Trump in 2020, according to the American Residency Project (2021).

When evaluating the economic condition of states, it is essential to consider income inequality. In this study, income inequality is measured using an estimated Gini Index, which is treated as a binary variable. A value of 1 indicates a region with relatively high-income inequality, while a value of 0 signifies lower income inequality, based on a specified threshold. This classification enables a simplified comparison of income distribution patterns across states. Furthermore, this study examines Gross State Product (GSP) for 2020 and 2021 as a measure of state capacity, indicating the overall economic resources available in each state (U.S. Bureau of Economic Analysis).

Finally, I utilize the CDC COVID Data Tracker to gather information on vaccination availability across states. This is captured as a binary variable coded as 1 beginning the week when vaccines became available to all states. To ensure accurate data, I lag these variables by a week since states cannot make judgments on COVID-19 infections, fatalities, or vaccination rates on the same day. Additionally, there may be delays in reporting infection cases and death counts, so these variables are also lagged by a week. The duration between the availability of data and the time taken by decision-makers to decide - known as decision lag time - is crucial in understanding the timing and factors that influence state policy choices in response to the pandemic. This lag time accounts for the time between the initial reporting of data and the time taken by decision-makers, such as governors, to decide on their response strategies. The reflect the reality that decision-makers cannot act on data on the same day it is reported and must contend with reporting delays. To improve model accuracy, the lag structure for each variable was selected based on which lag exhibited the strongest and most statistically significant relationship with the outcome variables during model testing. This data-driven approach to selecting lags enhances the model's ability to reflect the actual timing of policy decision-making accurately. By considering decision lag time, the models account for the lag between the reporting of COVID-19 data and the policy responses enacted by state leaders. This approach recognizes the real-world constraints faced in managing the pandemic.

Unit of Analysis

This research analyzes COVID-19 policy directives in each state from March 2020 to October 2021 (Mayer et al., 2022). The study period covers the pandemic's first and second waves, which varied by state. The dataset is a cross-sectional time-series dataset, with the unit of analysis being the state during each week during the study period. The study does not include the District of Columbia due to a lack of available data, and all trusts and territories are omitted as they are governed differently.

Policy Adoption and the PID Model(s)

The first part of the study analyzes the adoption of five COVID-19 NPIs: stay-at-home orders, mask mandates, travel restrictions, gathering restrictions, and school closures; the enforcement mechanisms associated with the adoption of these policies; and the timing of the subsequent lifting of these policies using the PID model.

The Policy Innovation and Diffusion (PID) model utilized in this study focuses on understanding policy adoption and partisan variations between Democrats and Republicans. The model considers various factors, such as political alignment, geographic proximity, and demographic similarity, to provide a comprehensive understanding of the complex policy landscape. The model emphasizes the impact of partisan dynamics, revealing the effect of party discipline at the state level, particularly in the context of COVID-19 vaccination policies.

Moreover, the PID model recognizes that political affiliation is just one aspect of the complex policy landscape and acknowledges the roles played by urbanization and demographic similarity. States with a higher urban population tend to be more innovative, irrespective of political affiliation. In contrast, factors such as income levels and the state's median age contribute to the likelihood of policy adoption. Additionally, the model introduces additional variables in the context of COVID-19 policy, including the influence of political variables, economic considerations, and state capacity. For instance, Democratic governors tend to prioritize public safety over unemployment concerns, influenced by liberal ideologies, while Republicans are more responsive to unemployment-related anxieties. Wealthier states are better positioned to prioritize safety, while economically disadvantaged states may face limitations. This comprehensive framework within the PID model reveals the intricate interplay of political ideologies, economic conditions, and public sentiments in shaping policy adoption across states, particularly in the COVID-19 pandemic.

Part of my study will also examine the lifting of policies, or the innovation of removing policies. A reverse diffusion process appears to be at play, where states that were late to adopt a policy are early to lift it, potentially due to changes in public opinion, shifts in political dynamics, or the evaluation of policy effectiveness. The lifting of policies, therefore, reflects a dynamic process influenced by the timing of adoption and the subsequent decisions of late adopters to remove the policy. I assess lifting of NPIs through analyzing the longevity of implementation. States that were laggards and/or lifted their NPIs more swiftly, will have a shorter number of weeks that their NPIs were in effect.

A growing body of research underscores the evolving nature of policy diffusion. A study by DellaVigna and Kim (2022) also found that the recent patterns of policy diffusion have shown an increasing importance of political similarity and party influence on state policy adoption (p. 21). This suggests that the lifting of policies may also be influenced by the emerging party discipline at the state level, with political similarity playing a significant role in shaping the decisions to remove policies. Additionally, the study highlights the impact of geographic and demographic proximity on policy diffusion, with these factors being more influential in earlier decades but giving way to the rising importance of political variables in recent years (DellaVigna & Kim, 2022, 3-4).

In other words, the lifting of policies follows a dynamic process influenced by the timing of adoption, the decisions of late adopters, and the increasing importance of political similarity and party influence on state policy adoption. These factors, along with geographic and demographic proximity, shape the patterns of policy diffusion and the subsequent decisions to remove policies.

This study acknowledges the evolving dynamics surrounding the issue and adopts Walker's (1969) concept of proximity, which defines peer states based on their shared geographic borders. This choice is intentional and aligns with the nature of the policy issue—COVID-19, a communicable disease. Since my research focuses on the diffusion of policies aimed at curbing the transmission of this infectious disease, states that physically border one another provide the most relevant reference group in this context. Policies implemented in one state are more likely to influence neighboring states due to shared media markets and the potential for cross-border virus transmission.

In contrast, DellaVigna and Kim's alternative approach—selecting the closest one-third of states based on distance—may be more appropriate in situations where physical proximity is less significant, such as when states adopt economic policies. However, given the urgency of public health concerns and the transmission-based nature of COVID-19, this study utilizes Walker's proximity measure, which focuses on bordering states to more accurately capture the pathways through which policy diffusion occurred during the pandemic.

To analyze the adoption of COVID-19 policies, I use a discrete-time history model, which is one form of an event history cross-sectional time series model, also referred to as a hazards model. A state that has not adopted a policy is coded 0, while states that adopt a policy are coded 1 on the week that it does. When a state adopts a policy, it is dropped from the analysis. States that never adopt a policy remain in the analysis through the entire timeframe.

After modifying the dataset in this manner, the discrete time events history regression is performed as a straightforward logit model. This hazards model can be written as:

$$logit(h_{ti}) = log\left(\frac{h_{ti}}{1-h_{ti}}\right) = \alpha(t) + B'x_{ti}$$

Assuming that hazard is approximately linear, then a linear function of $\alpha(t) = \alpha_0 + \alpha_1 t$ is fitted with the addition of t, t^2, and t^3 essentially as a control for the confounding effects of time (Steele, 2005). With this model, each COVID-19 policy variable is treated as a separate dependent variable. Independent variables such as political affiliation, ideology, unemployment rate, state capacity, and public support are used to predict the sequence in which a state adopts a policy or alternatively lifts it.

A state's political affiliation is expressed using a binary variable, which indicates whether its governor is a Democrat or a Republican. This variable can help measure political party affiliation's influence on policy adoption. Given the tendency of Democratic governors to prioritize public safety, they are expected to significantly impact the early adoption of COVID-19 policies, and to be the last to lift these policies.

Late adopters are those states that tend to be slow in implementing changes or adopting new policies compared to their counterparts. This study predicts that these late adopters are the first to lift COVID-19 restrictions. To gauge this phenomenon, this study uses a unique metric - the difference in weeks between the earliest adopter of a policy and the week in which all the other states decided to adopt the restriction. This method quantifies the time difference between states that implemented restrictions early on and those that followed later. I assume that the greater difference in the number of weeks, the higher the likelihood that a state lifts the restriction. By considering late adopters in this analytical framework, this study uncovers patterns that shed light on the factors influencing states' decisions in navigating the challenges posed by the pandemic.

Measuring the extent of a state's liberal ideology using a scale provides a reliable indicator of the influence of ideological orientation on policy adoption. States with a more liberal ideology tend to be early adopter specific COVID-19 policies, and to be the slowest to lift them.

The Gini Index is an indicator used to assess economic conditions, particularly income inequality. It is widely recognized that higher levels of inequality can affect the adoption of policies. It is hypothesized that Republican leaders tend to respond more to economic pressures, such as rising unemployment, often supporting less restrictive policies to boost economic activity. In contrast, Democratic leaders are more likely to prioritize public health and social welfare, even if it means implementing stricter COVID-19 policies.

State capacity is effectively assessed by measures of state wealth or fiscal capacity, which likely influences policy prioritization and adoption of COVID-19 policies. It is hypothesized that richer states have the capacity to prioritize safety measures, while poorer states may face constraints in doing so. This impacts the adoption of specific COVID-19 policies.

State wealth reflects a state's overall economic capacity, while the Gini Index assesses the level of income inequality within that wealth. This distinction is crucial because a state may exhibit high average wealth yet still have a significant portion of its population facing economic insecurity. Income inequality highlights the gap between higher- and lower-income groups—a gap that becomes particularly significant during crises like the COVID-19 pandemic. States characterized by greater inequality often have more residents in essential, in-person jobs, face crowded living conditions and experience limited access to healthcare or paid sick leave. These challenges can hinder individuals' ability to comply with public health policies. By incorporating both state wealth and income inequality, the model captures not only the resources available to a state but also the extent to which those resources are equitably distributed among its population—both of which can significantly influence the adoption and effectiveness of policies.

The prevalence of COVID-19 infections and deaths has played a crucial role in shaping governmental decisions concerning public opinion and policy adoption. The policy adoption model suggests that states dealing with high rates of COVID-19 infections and deaths may deviate from traditional political considerations and instead choose to implement strict pandemic-related policies. A study conducted by Morris et al. (2021) supports this hypothesis, indicating a strong correlation between the incidence of infections and deaths and the subsequent adoption of restrictive measures. As the number of infections and deaths from the pandemic increases, governors are forced to prioritize public health over political affiliations. Governor Kay Ivey, Republican governor of Alabama, is a notable example of this phenomenon. Despite political pressure not to adopt mask mandates, she responded to the rising number of infections and deaths by imposing a mask mandate as well as other restrictive policies. This observation underscores the pandemic's impact on policy decisions across party lines to safeguard public health.

Policy Effectiveness Model

The second part of this study analyzes two dependent variables: the total number of weekly COVID-19 infection cases and the total number of COVID-19-related deaths. Weekly infection counts represent all reported cases in a given state, while death counts reflect the total number of COVID-19 related fatalities reported in that state during the same week. To avoid confusion, I lag these variables by one week to allow for accurate reporting. Additionally, since there may be a delay in reporting infection cases and deaths, these variables are lagged by a week to ensure accuracy.

Predictor Variable(s)

Out of all the several actions states took to mitigate the COVID-19 pandemic, I utilize the four COVID-19 policy actions implemented by the states. These state policy actions include stay-at-home orders, mask mandates, travel restrictions, gathering restrictions, and school closures. These actions are scored 0 and 1, with 0 meaning that states took no action during that time period, and 1 indicates that states took strategic action to mitigate the COVID-19 pandemic.

This study considers various factors that may impact the results, such as the state's population count and density, median age, the ideology of the state government, race and ethnicity, the political party affiliation of the governor, the percentage of votes won by Donald Trump in 2020, income inequality, state capacity, and vaccine availability.

A comprehensive understanding of the underlying analysis is critical for accurately assessing the effectiveness of COVID-19 vaccines in reducing infection and death counts. To assess the influence of vaccine distribution on COVID-19 outcomes, this study includes a dummy variable that indicates vaccine availability across different states. This variable is coded as 1 for all weeks after COVID-19 vaccines became widely accessible to the general public. By March 2021, all U.S. states had made vaccines available to their residents, and the dummy variable reflects this change. This method allows for a distinction between pre-vaccine and post-vaccine periods and evaluate the effect of vaccine availability on infection and death counts during the pandemic.

Table ***Error! No text of specified style in document.*** *.1 Summary of Operationalized Independent Variables*

Variable	**Operationalization**	**Hypothesis & Direction (+/-)**
Shelter in place orders	Dichotomous variable for each week a policy is in place	H1 (-)
Mask mandates	Dichotomous indicator for each week a policy is in place	H2 (-)
Travel restrictions	Dichotomous indicator for each week a policy is in place	H3 (-)
Gathering Restrictions	Dichotomous indicator for each week a policy is in place	H4(-)
School Closures	Dichotomous indicator for each week a policy is in place	H5(-)
Party affiliation of the governor	If Democratic party has full state control = 1 If Republican party has full state control = 0	H6 Dem (-) Rep (+)

Trump Support in 2020	Percentage of the nonwhite population	H7 (+)
State Elite Ideology	More positive value indicate more conservative states; more negative values indicate more liberal states	H8a (+) H8b (-)
Race and Ethnicity	Percentage of racial/ethnic minorities	H9 (+)
Median Age	Higher median age indicate more health disparities	H10 (+)
Vaccine	Higher vaccine availability indicate lower infections/deaths	H11 (-)
Population Density	Higher population density indicate higher deaths Lower population density indicate lower deaths	H12a (+) H12b (-)
State Capacity	Continuous variable measured using Gross State Product (GSP) in millions of dollars; higher GSP indicates greater fiscal capacity	H13 (+)
GINI Index	Dichotomous variable: 1= high income inequality, 0= low-income inequality	H14 (-)

Analytical Strategy

In the following sections of my study, I apply a consistent analytical method to assess the impact of state policy directives on the number of infections and deaths. The panel data analysis may present two challenges: autocorrelation (or serial correlation) and heteroskedasticity, which result from deviations from the time series assumption. Panel data encompasses observations from the same cross-sectional unit over time, which can result in imprecise parameter estimates, less accurate standard errors, and flawed hypothesis tests if there is any correlation among observations. Hence, it is critical to consider autocorrelation when conducting estimations.

Heteroskedasticity is a statistical phenomenon in which the variance of the error term in a regression model varies across different observations, potentially due to systematic changes in the dispersion or spread of the error with one or more independent variables. Addressing this issue is critical for obtaining reliable and efficient parameter estimates in regression analysis.

To overcome the challenges posed by TSCS data, researchers often apply methods such as clustering standard errors and including fixed effects in the regression model (Wooldridge, 2013, p. 412). In this study, I incorporate cluster-robust standard errors at the state level to account for heteroskedasticity and potential correlation within clusters.

This study analyzes weekly COVID-19 infections and deaths, which are count data exhibiting overdispersion. To address this, I employ a mixed-effects negative binomial cross-sectional time-series regression model. Since the focus is on the variations among states over time, a fixed-effects approach is not suitable. Instead, I employ a random-effects specification to account for unobserved differences across states. To ensure robust inference, clustered standard errors are calculated at the state level. The hypotheses tested in this study are summarized in Table 3.1, which outlines the operationalization of each variable and its expected directional influence across models. The mixed-effects negative binomial regression model is formulated as follows:

$$\log(Yi) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + u_i$$

where Y_i represents the number of infection cases or deaths in state i, X_{1i}, X_{2i},…, X_{ki} are the independent variables, β_0 is the intercept, β_1, β_2 , … , $\beta_k$are the coefficients of the independent variables, and μ_i is the error term.

Chapter 4: Empirical Analysis of COVID-19 Policies Adoption and Enforcement Mechanisms

This chapter presents an overview of the adoption of five major non-pharmaceutical interventions (NPIs) implemented by U.S. states during the COVID-19 pandemic. In the absence of a unified national strategy, state governments took the lead in addressing the public health crisis. Consequently, there was significant variation in both the timing and duration of these interventions across different states.

The purpose of this chapter is to examine the adoption patterns of five specific interventions that were implemented across states during the COVID-19 pandemic. I begin by introducing each policy, outlining its intended purpose, and summarizing the existing research on its effectiveness. I then describe the policy adoption sequence, identifying the states that were the earliest adopters, as well as those that adopted it last, and highlighting those states that never adopted the policy. In addition, I examine the longevity or duration of each policy by highlighting the states that sustained it the longest and those states that repealed it very quickly. These descriptive patterns illustrate how and when state governments responded to the COVID-19 crisis.

The chapter discusses five key policies that were pivotal in mitigating the spread of COVID-19 such as mask mandates, stay-at-home orders, school closures, travel restrictions, and gathering restrictions. Each of these interventions were implemented to reduce interpersonal contact and lower transmission rates, especially during the early stages of the pandemic when vaccines were unavailable. Although the public health rationale for these policies was widely supported by epidemiological research, their implementation varied considerably due to a mixture of political, demographic, and institutional factors.

Mask mandates were introduced as public health measures aimed at reducing the transmission of COVID-19 by requiring individuals to wear face coverings in public settings, particularly indoors. These mandates were established through executive orders issued by state governors or directives from state health departments. The mandates varied significantly across states, ranging from broad requirements for all indoor public spaces to more specific restrictions in settings, such as retail stores or public transportation. Nonetheless, the main objective remained the same: to mitigate the airborne transmission of the virus in high-contact settings.

Stay-at-home orders (SIPO), also known as shelter-in-place directives, were among the most comprehensive non-pharmaceutical interventions implemented during the initial phase of the COVID-19 pandemic. These policies required residents to remain at home except for essential activities such as obtaining food, seeking medical care, or performing work deemed critical to the functioning of society. In the spring of 2020, state governors issued mandates that were effective for a specific period of time. Some states subsequently adjusted these mandates or applied them only to certain regions. The primary goal was to slow the spread of the virus by limiting people's movement and their interactions with others. These regulations were essential in the early efforts to manage the pandemic.

School closure policies mandated K-12 public schools to suspend in-person instruction to prevent the spread of COVID-19 among students, teachers, and staff. Nearly all states implemented some form of school closures during the early phases of the pandemic in spring 2020. However, the duration and approach to closures varied across states. Some states resumed in-person instruction earlier or implemented hybrid models that combined in-person and remote learning, depending on local case numbers and public health recommendations. Overall, school closures served as a critical early intervention to help limit the spread of the virus within communities.

Travel restrictions were implemented to limit the movement of individuals across state borders or from regions identified as high-risk due to rising COVID-19 case numbers. These policies required travelers to either quarantine upon arrival or present evidence of a recent negative COVID-19 test. Although fewer states implemented formal travel restrictions compared to other NPIs, the measures that were enacted typically targeted individuals coming from states with high transmission rates or from international locations. These restrictions aimed to prevent the spread of the virus across different jurisdictions, especially during times of rising community transmission.

Gathering restrictions were put in place to limit the size and nature of social, religious, and recreational gatherings in an effort to reduce the risk of COVID-19 transmission. The scope and strictness of these policies also varied by state. For instance, some states imposed strict limits of prohibiting gathering of more than 10 to 15 individuals for both indoor and outdoor gatherings, while other adopted more lenient approaches or delayed implementation altogether. These differences often reflected each state's public health conditions, political environment, and ability to effectively enforce laws.

While Chapter 2 discusses the effectiveness of these policies in detail, previous studies indicate that these interventions helped slow COVID-19 transmission. Research shows that mask mandates significantly reduced infections, with states enforcing these mandates seeing greater declines (Huang et al., 2020; Lyu & Wehby, 2020). SIPOs also played a crucial role in lowering cases, hospitalizations, and deaths in the U.S. (Courtemanche et al., 2020; Dave et al., 2020b, 2021; Fowler et al., 2020; Friedson et al., 2020; Lyu & Wehby, 2020; Siedner et al., 2020). Early school closures effectively reduced COVID-19 cases and deaths, though they highlighted social disparities (Auger et al., 2020; Rauscher, 2020; Zviedrite et al., 2024). Early travel restrictions were shown to limit the virus's spread, both internationally and in certain states (Chinazzi et al., 2020; Linka et al., 2020). Restrictions on gatherings reduced the rising cases (Ahlers et al., 2021). Indoor dining bans helped protect vulnerable communities (Page-Tan & Corbin, 2021), but reopening businesses led to more COVID-19 infections (Bruckhaus et al., 2021).

Table 4.1 summarizes the week-by-week adoption of five key COVID-19 policy interventions. States are categorized as early adopters, late adopters, or non-adopters based on when they implemented each action. The states are organized chronologically by the week they adopted each policy, offering a comparative baseline for the more detailed timelines discussed in the following sections.

Table ***Error! No text of specified style in document.****.2 Chronological Summary of State Policy Adoption Timing*

Policy	Early Adopters	Late Adopters	Non-Adopters
Mask Mandates	NJ, CO, NY, MD, HI, RI, AK, CT, VT, PA	NV, KS, TX, OR, MT, SC, WI, NH, IA, OK	FL, ID, MO, SD, TN
Stay-at-Home Orders	CA, IL, NJ, IN, RI, MT, LA, OH, MN, DE	AL, FL, NV, TX, MD, AZ, TN, MS, MO, SC	AR, CT, IA, KY, MA, NE, NM, ND, OK, SD, UT
School Closures	UT, DE, AK, AL, WA, LA, WV, OR, OH, WI	NY, MN, MA, IN, FL, GA, CT, RI	None
Travel Restrictions	AK, HI, KS, RI, WV, FL, SC, OK, VT, TX	UT, ID, AR, CT, NJ, NY, MA, CA, PA, MD	AL, CO, GA, IL, IN, IA, LA, MI, MN, MS, MO, NE, NV, NH, NC, OH, OR, SD, TN, VA, WA, WI
Gathering Restrictions	NJ, MN, TN, WA, NC, NM, RI, CT, CO, NV	MO, NE, KS, MS, SD, FL, GA, AR, AZ, ND	None

Policy Adoption Timeline: Mask Mandates

Earliest Adopters

The first states to implement statewide mask mandates were primarily in the Northeast and West, where high infection rates were reported early in the pandemic. New Jersey was the leader in Week 6, followed closely by Colorado, New York, Maryland, Hawaii, and Rhode Island in Week 7. By Week 8, additional states such as Alaska, Connecticut, Vermont, and Pennsylvania had also put mask mandates in place.

Late Adopters

Several states delayed adopting mask mandates until well into the pandemic. Oklahoma was the last state to implement a statewide mandate, doing so in Week 38. Other late adopters included Iowa (Week 25), New Hampshire (Week 24), South Carolina and Wisconsin (Week 22), Montana (Week 20), Oregon (Week 19), Kansas and Texas (Week 18), and Nevada (Week 17).

Non-Adopters

Five states, Florida, Idaho, Missouri, South Dakota, and Tennessee, never adopted a statewide mask mandate during the study period. The absence of a uniform policy highlights the decentralized nature of the U.S. response to the pandemic and the significant role of political discretion in shaping state-level actions.

Policy Adoption Timeline: Stay-at-Home Orders

Earliest Adopters

States such as California, Illinois, and New Jersey were the first to implement statewide stay-at-home orders during Week 3 in response to early outbreaks or projected risks. A second wave of adopters followed in Week 4, including Indiana, Rhode Island, Montana, Louisiana, Ohio, Minnesota, and Delaware.

Late Adopters

States like Missouri and South Carolina were among the last to issue stay-at-home orders, doing so in Week 6. Others, including Alabama, Florida, Nevada, Texas, Maryland, Arizona, Tennessee, and Mississippi, adopted the policy in Week 5.

Non-Adopters

Eleven states—Arkansas, Connecticut, Iowa, Kentucky, Massachusetts, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, and Utah—did not issue statewide stay-at-home orders during the study period. Like mask-mandates, the absence of uniform directives with stay-at-home orders underscores the decentralized nature of public health decision-making and the diversity of state-level responses during the pandemic.

Policy Adoption Timeline: School Closures

Early Adopters

Several states acted quickly to close schools in the early stages of the COVID-19 pandemic. By the second week, ten states had already implemented statewide school closures: Utah, Delaware, Alaska, Alabama, Washington, Louisiana, West Virginia, Oregon, Ohio, and Wisconsin.

Late Adopters

While most states responded swiftly, a few delayed school closures by a week or more. Missouri and Idaho were the last to implement statewide closures during the fourth week. Others, including New York, Minnesota, Massachusetts, Indiana, Florida, Georgia, Connecticut, and Rhode Island, adopted the policy slightly earlier in the third week.

Nationwide Implementation

Ultimately, all 50 states enacted statewide school closures during the observation period. This universal adoption highlights a rare moment of consensus among state leaders, who recognized the urgent need to suspend in-person instruction to reduce transmission risk. Unlike other pandemic policies, which were often marked by political or regional divides, school closures were broadly accepted and rapidly implemented across the country.

Policy Adoption Timeline: Travel Restrictions

Early Adopters

Some states acted quickly to implement travel restrictions in the early stages of the pandemic, particularly those facing unique geographic challenges or high tourist traffic. Alaska was the first state to impose such restrictions in Week 2, likely due to its remote location and reliance on air travel. Hawaii and Kansas followed suit in Week 3. By Week 4, several additional states—Rhode Island, West Virginia, Florida, South Carolina, Oklahoma, Vermont, and Texas—had also adopted travel restrictions.

Late Adopters

While some states moved promptly to implement travel restrictions, others significantly delayed their adoption. Utah and Idaho introduced restrictions in Weeks 6 and 7, followed by Arkansas in Week 11. Connecticut, New Jersey, and New York did not act until Week 17, despite being among the states most affected in the initial outbreak. Massachusetts followed in Week 23, while California and Pennsylvania delayed their implementation until Weeks 37 and 38, respectively. Maryland was the last state to adopt travel restrictions, doing so in Week 42.

Non-Adopters

Twenty-two states did not implement any statewide travel restrictions during the study period. These states included Alabama, Colorado, Georgia, Illinois, Indiana, Iowa, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, North Carolina, Ohio, Oregon, South Dakota, Tennessee, Virginia, Washington, and Wisconsin.

Policy Adoption Timeline: Gathering Restrictions

Early Adopters

Several states acted quickly to introduce gathering restrictions as part of their early response to the pandemic. By Week 2, New Jersey, Minnesota, Tennessee, Washington, North Carolina, New Mexico, Rhode Island, Connecticut, Colorado, and Nevada had already imposed limits on public and private gatherings. These proactive measures were often implemented alongside school closures and stay-at-home orders.

Late Adopters

While many states moved swiftly, others delayed the implementation of gathering restrictions. Missouri, Nebraska, and Kansas adopted these policies in Week 3, while Mississippi, South Dakota, Florida, Georgia, and Arkansas followed suit in Week 4. Arizona enacted restrictions in Week 5, and North Dakota was the last state to implement them, doing so in Week 37.

Non-Adopters

Ultimately, all fifty states adopted some form of gathering restrictions during the study period. This widespread action underscores the importance placed on limiting social contact to curb the spread of COVID-19—especially during the early and peak months of the pandemic.

These timelines illustrate general patterns in policy adoption. However, the second half of this chapter develops a more systematic approach to explain the factors influencing policy adoption behavior. In that section, I uses a hazards model to examine how political, demographic, and institutional factors affect the timing of state-level decisions.

Table 4.2 summarizes the longest durations and the quickest repeals of five key COVID-19 policy interventions implemented across U.S. states. States are categorized based on how many weeks each policy was in effect and are listed in ascending order of duration within each category. This overview examines the variation between states that maintained public health measures over time and those that repealed them more quickly. It also serves as a foundation for the detailed analysis of policy duration and repeal presented in the following sections.

Table ***Error! No text of specified style in document.****.3 Chronological Summary of State Policy Duration and Repeal Timing*

Policy	Longest Duration States	Earliest Repealing States
Mask Mandates	NY, CT, NC, IL, OR, NV, CO, CA, WA, MA	AK, NE, ND, OK, IA
Stay-at-Home Orders	DE, WA, HI, MI, NH, OR, NJ, NC, OH, CA	GA, AK, MS, AL, MT, TN, MO, TX, SC, CO
School Closures	ND, AR, VT, HI, RI, NC, KY, NM, WV, CA	MT, SD, KS, IA, NV, MS, ID, WI, IL, IN
Travel Restrictions	CT, NY, NM, NJ, AK, HI, ME, VT, RI, KS	AR, SC, AZ, ND, ID, KY, CA, TX, WV, DE
Gathering Restrictions	NJ, MS, MI, AL, OR, DE, NY, NM, IL, OH	ND, AK, SD, KS, MO, NH, HI, MT, FL, ID

Policy Duration and Repeal: Mask Mandates

Longest Duration

Several states maintained mask mandates for an extended period, reflecting a cautious and sustained public health strategy. Washington and Massachusetts had the longest durations at 78 weeks, followed by California at 75 weeks and Colorado at 73 weeks. Nevada kept its mandate for 71 weeks, while Oregon and Illinois had them in place for 69 weeks. North Carolina followed closely at 68 weeks, with Connecticut at 66 weeks and New York at 65 weeks. These states were early adopters of mask mandates and continued them until vaccination rates improved or case numbers declined significantly.

Quickest De-Adopters

In contrast, some states that implemented mask mandates quickly repealed them. Alaska had the shortest duration, maintaining its mandate for only 5 weeks, followed by Nebraska at 13 weeks, North Dakota at 15 weeks, Oklahoma at 17 weeks, and Iowa at 25 weeks. These brief durations reflect rapid policy shifts, often influenced by political, cultural, and regional attitudes toward pandemic measures.

Policy Duration and Repeal: Stay-at-Home Orders

Longest Duration

While most states implemented stay-at-home orders for limited periods during the initial wave of the pandemic, a few states maintained these orders for significantly longer durations. California had the longest stay-at-home order, lasting 33 weeks, followed by Ohio at 22 weeks and North Carolina at 20 weeks. States such as New Jersey, Oregon, New Hampshire, Michigan, Hawaii, Washington, and Delaware sustained their orders for 11 to 13 weeks. These extended durations reflect a continued commitment to limiting the spread of the virus during times of high case counts or delays in vaccine rollout.

Quickest De-Adopters

Several states that issued statewide stay-at-home orders lifted them quickly. Georgia, Alaska, Mississippi, Alabama, Montana, Tennessee, Missouri, Texas, and South Carolina each maintained their orders for only 5 weeks, while Colorado ended its order after 6 weeks. These brief durations indicate a swift return to normal mobility, likely influenced by economic concerns, political factors, or a lower perceived risk to public health.

Policy Duration and Repeal: School Closures

Longest Duration

The duration of school closures varied across states. California had the longest statewide school closures, lasting 86 weeks. This extended closure reflected a strong emphasis on limiting in-person instruction to reduce the spread of COVID-19. Other states with significant closures included West Virginia (49 weeks), New Mexico (43 weeks), and Kentucky (37 weeks). Additionally, states such as North Carolina (31 weeks), Hawaii and Rhode Island (27 weeks), Vermont (26 weeks), Arkansas (25 weeks), and North Dakota (24 weeks) also kept schools closed for prolonged periods. These extended closures often suggest a cautious approach to reopening, influenced by local case numbers, involvement from teacher unions, or concerns for the safety of students and staff.

Quickest De-Adopters

Some states reopened schools sooner, resulting in shorter closures. Montana and South Dakota experienced the briefest closures at just 8 weeks. Kansas had closures of 11 weeks, Iowa 12 weeks, and Nevada 13 weeks. Mississippi followed with closures lasting 15 weeks, while Idaho, Wisconsin, Illinois, and Indiana each had closures of around 16 weeks. These shorter durations may reflect political preferences, pressure from families to resume in-person learning, or different assessments of the risks associated with keeping schools closed.

Policy Duration and Repeal: Travel Restrictions

Longest Duration

Among the states that implemented travel restrictions, the duration of enforcement varied significantly. Kansas maintained its restrictions for the longest period—74 weeks—followed by Rhode Island at 67 weeks and Vermont at 59 weeks. Other states with extended durations included Maine (57 weeks), Hawaii (50 weeks), Alaska (49 weeks), New Jersey (47 weeks), New Mexico (46 weeks), New York (40 weeks), and Connecticut (39 weeks). These prolonged restrictions reflect a sustained commitment to limiting cross-border transmission, particularly in states with high population density, geographic isolation, or constrained healthcare infrastructure.

Quickest De-Adopters

Conversely, some states rescinded their travel restrictions shortly after implementation, indicating a desire to minimize disruptions to mobility and economic activity. Arkansas, South Carolina, Arizona, North Dakota, and Idaho maintained their restrictions for only 5 weeks, while Kentucky lifted its policy after 6 weeks. California followed with 7 weeks, and both Texas and West Virginia ended their restrictions after 8 weeks. Delaware maintained its policy for 9 weeks. These brief durations may reflect early reassessments of policy efficacy or growing political and economic pressures to reopen travel.

Policy Duration and Repeal: Gathering Restrictions

Longest Duration

Some states maintained gathering restrictions for an extended period. Ohio had the longest duration, keeping these restrictions in place for 81 weeks. Illinois and New Mexico followed with 77 weeks each, while New York upheld the policy for 70 weeks. Delaware, Oregon, Alabama, and Michigan each enforced the restrictions for 69 weeks. Mississippi and New Jersey maintained them for 67 weeks. These longer durations suggest a more cautious approach to reopening, likely influenced by factors such as higher case numbers, population density, or greater concern for public health safety.

Quickest De-Adopters

Several states lifted gathering restrictions relatively quickly after implementing them. North Dakota had the shortest duration, maintaining the policy for just 5 weeks. Alaska followed with 9 weeks, South Dakota with 11 weeks, Kansas with 13 weeks, and Missouri with 14 weeks. Other states, like New Hampshire (16 weeks), Hawaii (17 weeks), and Montana (21 weeks), also lifted restrictions fairly swiftly. While Florida (33 weeks) and Idaho (42 weeks) kept restrictions a bit longer, they were still among the shorter durations in the country. These early moves to reopen may reflect political preferences, economic concerns, or a lower perception of public health risk.

Descriptive Statistics

Table 4.3 provides a comprehensive overview of the variables used in the analysis of policy adoption and its duration. The dataset encompasses weekly data from all 50 U.S. states, covering the period from March 2020 to October 2021 (Mayer et al., 2022). It specifically focuses on five key NPIs: mask mandates, stay-at-home orders, school closures, travel restrictions, and gathering restrictions.

To analyze both the timing of policy adoption and the duration of these measures post adoption, the study employs two types of models: standard survival model and duration model. Each model incorporates a consistent set of political, demographic, structural, and epidemiological variables. These variables include gubernatorial party affiliation, Trump vote share in the 2020 election, state ideology, population size and density, median age, income inequality, state administrative capacity, percentage of nonwhite residents, as well as weekly infection and death rates. Furthermore, policy diffusion variables are included to capture the influence of neighboring states. These policy diffusion variables are measured as the proportion of neighboring states that have adopted a specific intervention. I provided the specific operationalization details in Chapter 3.

Table ***Error! No text of specified style in document.****.4 Descriptive Statistics of Variables Used in Policy Adoption and Duration Models*

Variable Name	Obs	Mean	Std. Dev.	Min	Max
Proportion of neighboring states with mask mandates	4,089	0.54	0.39	0	1.25
Proportion of neighboring states with SIPOs	4,089	0.07	0.21	0	1.33
Proportion of neighboring states with school closures	4,089	0.24	0.38	0	1.33
Proportion of neighboring states with travel restrictions	4,089	0.12	0.24	0	1
Proportion of neighboring states with gathering restrictions	4,089	0.61	0.39	0	1.33
Infection rate per million	4,263	1587.98	1657.76	0	12182.10
Mortality rate per million	4,263	23.39	26.34	0	215.20
Pop 2020	4,263	6738426	7385778	643077	3.95e+07
Pop density	4,263	210.60	273.42	1.3	1263
Gop gov	4,263	0.52	0.49	0	1
Percent Trump vote 2020	4,263	0.50	0.10	0.30	0.69
Percent nonwhite 2020	4,263	23.02	12.75	5.4	74.90
State ideology	4,263	-0.10	1.76	-3.61	2.93
State capacity	4,263	444798.80	562661.10	33435	3373241
Median age	4,263	38.90	2.26	31.10	44.80
GINI index	4,263	0.04	0.19	0	1

Analysis and Results

I begin with the COVID-19 policy adoption model. To analyze the timing of COVID-19 policy adoption, I use a discrete-time event history model—also known as a hazards model—where each state is observed weekly until it adopts a specific policy. A state that has not adopted a policy is coded 0, while states that adopt a policy are coded 1 on the week that it does. When a state adopts a policy, it is dropped from the analysis. States that never adopt a policy remain in the analysis through the entire timeframe.

After modifying the dataset in this manner, the discrete-time event history regression is performed as a straightforward logit model. This hazards model can be written as:

$$logit(h_{ti}) = log\left(\frac{h_{ti}}{1-h_{ti}}\right) = \alpha(t) + B'x_{ti}$$

Assuming that hazard is approximately linear, then a linear function of $\alpha(t) = \alpha_0 + \alpha_1 t$ is fitted with the addition of t, t^2, and t^3 essentially as a control for the confounding effects of time (Steele, 2005). With this model, each COVID-19 policy variable is treated as a separate dependent variable. Independent variables such as political affiliation, ideology, unemployment rate, state capacity, and public support are used to predict the sequence in which a state adopts a policy or alternatively lifts it.

Table 4.4 presents the results of five separate regression models, each examining the factors associated with the adoption of a specific non-pharmaceutical intervention (NPI): mask mandates (Model 1), stay-at-home orders or SIPOs (Model 2), school closures (Model 3), travel restrictions (Model 4), and gathering restrictions (Model 5). Each model includes a key policy diffusion variable, which captures the proportion of neighboring states that have adopted the same intervention, as well as a consistent set of political, demographic, and epidemiological controls. This set of hazards analyses, which focuses on the timing of policy adoption (with states exiting the risk set once they adopt the policy), reveals that political and geographic factors played inconsistent roles across all five NPIs. The only NPI where political and geographic diffusion both played a role is mask mandates. This may seem surprising at first glance, but as my discussion of early and late adopters notes, almost all states uniformly adopted school closures and gathering restrictions. Thus, there is not that much policy adoption variation to be explained with some of these NPIs.

Model 1, which focuses on mask mandates, indicates a strong and statistically significant diffusion effect. States were more likely to adopt mask mandates if their neighboring states had already done so. Additionally, states led by Republican governors were significantly less likely to adopt this policy, reflecting the broader pattern of partisan divergence during the pandemic on this issue. Both the infection rate (which had a negative relationship) and the death rate (which had a positive relationship) were statistically significant, suggesting that states responded more readily to rising mortality rates than to increasing infection counts when implementing mask mandates.

Model 2, examining SIPOs, similarly reveals a large and statistically significant diffusion effects. States were more likely to implement SIPOs when neighboring states had already done so. However, in contrast to Model 1, none of the political or demographic controls reached statistical significance, indicating that regional peer pressure may have been the primary driver of adoption in this case.

Model 3 analyzes school closures and presents an unexpected finding, as the coefficient for neighboring states with school closures is negative and significant. This suggests that rather than merely imitating the action of neighboring states, some states may have intentionally chosen a distinct approach based on their unique state-specific conditions in the implementation of school closures. Moreover, while the coefficient for Republican governor is negative and not significant, the Gini index was negatively and significantly associated with the adoption of school closures. The negative and significant coefficient for the Gini index suggests that states with higher income inequality are generally slower to adopt school closure policies.

Model 4, which focuses on travel restrictions, shows a strong and statistically significant diffusion effect, with neighboring state adoptions positively associated with a state's own policy response. The Gini index is also positively and significantly associated with travel restrictions, suggesting that states with greater income inequality were more likely to quickly adopt these measures. Interestingly, the death rate is negatively and significantly associated with adoption, reflecting states with a larger number of COVID-19-related deaths did not adopt travel restrictions. This may reflect the positive effect that travel restrictions had on retarding COVID-19 deaths. That is, in states that did not adopt this policy, COVID-19 deaths went up.

Model 5 evaluates gathering restrictions, and unlike the previous models, the diffusion variable is not statistically significant. This suggests that states may have made these decisions more independently, without being influenced by neighboring states. Nonetheless, Republican governor status remains a significant negative predictor, indicating that Republican-led states were less likely to implement gathering restrictions. Additionally, median age is positively and significantly associated with policy adoption, suggesting that states with older populations were more inclined to enforce restrictions on social gatherings.

Overall, these findings underscore the critical role of policy diffusion in shaping state-level responses to the pandemic, particularly for mask mandates, SIPOs, school closures, and travel restrictions. While political partisanship—specifically gubernatorial affiliation—consistently influenced policy adoption across several models, demographic and epidemiological factors showed varied effects, with variables like median age and income inequality reaching significance in certain contexts. The analysis highlights the complex interplay between regional influences, political leadership, and contextual factors in shaping the adoption of public health interventions during the COVID-19 pandemic.

Table ***Error! No text of specified style in document.****.5 Regression Results for Policy Adoption Models*

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
GOP Governor	-1.31*	-0.38	-0.51	-0.09	-0.86*
	(0.43)	(0.51)	(0.39)	0.57	(0.32)
Percent Trump Vote 2020	-0.27	0.21	-0.26	-1.46	-0.34
	(1.84)	(1.85)	(2.52)	(2.30)	(1.93)
State Ideology	-0.20	0.02	0.05	-0.04	-0.19
	(0.19)	(0.18)	(0.29)	(0.27)	(0.14)
State Capacity	-7.83e-07	1.35e-06	9.18e-07	-3.81e-06	-1.31e-06
	(2.35e-06)	(2.05e-06)	(3.14e-06)	(2.95e-06)	(1.66e-06)
Median Age	-0.20	0.13	0.10	-0.15	0.21*
	(0.13)	(0.13)	(0.14)	(0.17)	(0.10)
Population 2020	3.75e-08	-1.41e-08	-5.92e-09	2.75e-07	1.23e-07
	(1.65e-07)	(1.37e-07)	(2.07e-07)	(2.06e-07)	(1.16e-07)
Population Density	0.00	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percent Non-White 2020	0.00	-0.02	-0.01	0.00	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
GINI Index	-1.26	-1.10	-0.62*	1.22*	-0.35
	(0.97)	(1.21)	(0.31)	(0.59)	(0.27)
Infection Rate (per million)	-0.00*	-0.00*	-0.00	-0.00	-7.33e-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Death Rate (per million)	0.02*	-0.00	0.10	-0.03*	-0.02
	(0.00)	(0.01)	(0.11)	(0.01)	(0.01)
Proportion Neighbor Mask Mandates	1.12*	—	—	—	—
	(0.44)	—	—	—	—
Proportion Neighbor Stay-at-home Orders	—	3.45*	—	—	—
	—	(0.37)	—	—	—
Proportion Neighbor School Closures	—	—	-3.02*	—	—
	—	—	(0.63)	—	—
Proportion Neighbor Travel Restrictions	—	—	—	3.04*	—
	—	—	—	(1.09)	—
Proportion Neighbor Gathering Restrictions	—	—	—	—	0.80
	—	—	—	—	(0.44)
Constant	3.81	-8.44	-11.34	2.89	-10.33*
	(4.81)	(4.61)	(5.97)	(6.06)	(4.70)
Number of Observations	967	1,116	126	2,195	155
Log Pseudolikelihood	-150.62	-95.89	-21.73	-112.58	-82.58
Wald Chi2 (12)	98.41	193.65	92.96	41.38	142.22
Prob>Chi2	0.0000	0.0000	0.0000	0.0000	0.0000

After analyzing the initial adoption of COVID-19 policies in Table 4.2a, I now transition to a more dynamic assessment presented in Table 4.2b. This table examines both the adoption and duration of each NPI across states over time. Unlike the previous model, which removed states from the analysis after they adopted a policy, this model retains states in the analysis even after adoption. This approach allows me to assess how long each policy was in effect. By incorporating policy duration, the model provides a more comprehensive understanding of not only which states implemented specific interventions, but also how long these measures were sustained. This framework provides valuable insights into states' commitment to public health responses and examines whether similar political, demographic, or epidemiological factors influenced the longevity of these interventions following their initial implementation.

Table 4.5 presents five regression models that analyze the adoption and duration of NPIs implemented by U.S. states during the COVID-19 pandemic: mask mandates (Model 1), stay-at-home orders (Model 2), school closures (Model 3), travel restrictions (Model 4), and gathering restrictions (Model 5).

Model 1, which analyzes the duration of mask mandates, demonstrates a strong and statistically significant diffusion effect, as states that are surrounded by a greater proportion of neighbors with mask mandates are more likely to adopt and maintain such policies themselves. Political variables play a crucial role in this context; for instance, Republican governors are significantly less likely to uphold mask mandates, and a higher percentage of Trump votes in 2020 is positively associated with the duration of these policies. This seemingly counterintuitive result may reflect political dynamics at the state level or local pressures that lead to longer mandates in Republican-leaning areas during high-risk periods.

Additionally, state capacity and the median age of the population are both negatively associated with the duration of mask mandates. This suggests that older populations and wealthier states tended to lift mandates earlier. Conversely, states with larger populations and greater racial diversity (measured by the percentage of non-white residents) are associated with longer durations of mask mandates. Infection rates negatively impact the length of policy enforcement, while when death rates were higher, states kept the policy in place for a longer period of time. This indicates that mortality rates, rather than just the number of infection cases, are what prompted sustained public health responses.

In Model 2, which analyzes stay-at-home order, policy diffusion emerges as the most consistent predictor. The presence of stay-at-home orders in neighboring states is positively and significantly associated with a state's own adoption and continuation of this NPI. Interestingly, none of the political, demographic, or structural variables reach statistical significance. This suggests that stay-at-home orders were largely influenced by regional patterns rather than internal political or demographic pressures. This may be due to the urgency of the early pandemic response and the lack of clear partisan framing during the initial weeks.

Model 3 illustrates a significant positive diffusion effect, where states tend to imitate the school closure behavior of their neighbors. Although political variables do not show significance in the duration of school closures, structural and demographic factors play a crucial role. State capacity is positively linked to the duration of school closures, indicating that wealthier states may have had more flexibility to maintain these closures. In contrast, states with high income inequality (as measured by GINI index) were less likely to sustain school closures for a long time. This may be due to resource disparities or political resistance to prolonged disruptions in low-income communities. Additionally, population size is negatively and significantly correlated with policy duration, implying that more populous states ended school closures sooner. Moreover, higher infection rates tend to shorten policy duration, while higher death rates tend to keep the policy for a longer period of time, indicating a pattern of reactive policymaking in response to rising threats rather than through proactive policymaking.

The duration of travel restrictions is analyzed in Model 4. Policy diffusion is again identified as a statistically significant predictor. States are more likely to adopt and maintain travel restrictions if neighboring states have implemented these measures. While political and ideological factors do not show statistical significance, population size emerges as a strong positive predictor, as larger states tend to maintain travel restrictions for longer periods. Furthermore, state capacity and infection rates demonstrate negative associations, indicating that better-resourced states and those with higher case counts tend to lift restrictions more quickly. Furthermore, higher death rates are linked to prolonged travel restrictions, indicating that rising deaths prompted states to maintain these policies longer.

Model 5, which analyzes gathering restriction, indicates that the diffusion of policies among states remains significant, as states were more likely to adopt and maintain gathering restrictions if neighboring states had already implemented similar measures. Political factors, such as having a GOP governor and Trump vote share, did not show statistical significance. However, several structural and demographic predictors did. State capacity and median age were found to have a negative association with the duration of these policies, suggesting that older populations and wealthier states lifted gathering restrictions sooner. In contrast, both population size and the percentage of non-white residents were positively and significantly associated with the longevity of these policies. Furthermore, as observed in other models, infection rates were negatively correlated with policy duration. This finding likely reflects political and social pressure to ease restrictions in response to pandemic fatigue, even as infection numbers continued to rise.

Overall, across all five models examined, policy diffusion becomes evident as a strong and statistically significant predictor of both the adoption and duration of state-level NPIs. This finding strengthens the idea that states are influenced by the actions of neighboring state governments during uncertain times. In contrast, political variables—such as the presence of a

Republican governor and Trump vote shares—only significantly affect the duration of policies in the case of mask mandates.

Structural and demographic factors illustrate more consistent effects. State capacity, population size, and income inequality significantly impact the duration of policies, underscoring the importance of administrative resources and demographic dynamics. Moreover, epidemiological variables, including infection and death rates, play a crucial role, as higher infection rates are often associated with shorter policy durations, while increased death rates often lead to prolonged enforcement of policies.

In summary, while initial policy adoption may have been driven by political alignment and policy diffusion, the duration of public health interventions was shaped by a complex interplay of regional factors, demographic characteristics, and evolving public health conditions over time.

Table ***Error! No text of specified style in document.****.6 Regression Results for Policy Duration Models*

Variable	**Mask Mandates**	**Stay-at-Home Orders**	**School Closures**	**Travel Restrictions**	**Gathering Restrictions**
GOP Governor	-0.46*	-0.16	-0.15	-0.41	-0.14
	(0.21)	(0.38)	(0.19)	0.50	(0.17)
Percent Trump Vote 2020	1.57*	2.23	-0.22	-0.64	1.04
	(0.73)	(1.46)	(0.91)	(2.52)	(0.74)
State Ideology	-0.15	-0.03	0.16	-0.47	-0.14
	(0.10)	(0.14)	(0.11)	(0.24)	(0.08)
State Capacity	-2.33e-06*	-1.09e-06	2.67e-06*	-5.70e-06*	-2.45e-06*
	(8.98e-07)	(1.43e-06)	(8.98e-07)	(2.49e-06)	(7.22e-07)

Median Age	-0.19*	-0.06	-0.02	-0.17	-0.16*
	(0.05)	(0.08)	(0.07)	(0.11)	(0.05)
Population 2020	1.58e-07*	1.20e-07	-1.65e-07*	3.96e-07*	1.61e-07*
	(7.03e-08)	(1.05e-07)	(6.17e-08)	(1.86e-07)	(5.02e-08)
Population Density	-0.00	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percent Non-White 2020	0.01*	0.00	0.00	0.02	0.01*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
GINI Index	0.19	-0.07	-0.85*	-0.16	0.22
	(0.23)	(0.63)	(0.20)	(0.57)	(0.30)
Infection Rate (per million)	-0.00*	-0.00	-0.00*	-0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Death Rate (per million)	0.00*	-0.00	0.01*	0.00*	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Proportion Neighbor Mask Mandates	2.44*	—	—	—	—
	(0.30)	—	—	—	—
Proportion Neighbor Stay-at-home Orders	—	5.77*	—	—	—
	—	(0.47)	—	—	—
Proportion Neighbor School Closures	—	—	5.87*	—	—
	—	—	(0.22)	—	—
Proportion Neighbor Travel Restrictions	—	—	—	3.06*	—
	—	—	—	(0.61)	—
Proportion Neighbor Gathering Restrictions	—	—	—	—	2.86*

	—	—	—	—	(0.28)
Constant	-4.48*	-7.65*	-10.06*	-1.54	-3.32
	(1.92)	(3.37)	(2.70)	(4.22)	(1.69)
Number of Observations	4,089	4,089	4,089	4,089	4,089
Log Pseudolikelihood	-10640.44	-1664.55	-4205.87	-3669.96	-11778.72
Wald Chi2 (12)	205.52	678.85	909.54	250.42	228.68
Prob>Chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Discussion

This chapter discusses how states responded to an unprecedented public health crisis by examining the political factors that led to the adoption of policies and the challenges in maintaining them. It shows that sustaining public health measures often takes more than just political support at the start. The findings in this chapter provides valuable insights into the factors that influenced not just the adoption, but also the duration of NPIs across U.S. states during the COVID-19 pandemic. By using a framework that considers both when states adopted policies and how long they kept them in place, this chapter captures the evolving nature of state-level decision-making under uncertain conditions.

One of the most notable and consistent patterns observed across all the models is the strong influence of policy diffusion. In nearly every model, the actions of neighboring states significantly increased the likelihood that a state would adopt and sustain a particular policy intervention. This finding aligns with policy diffusion theory, which suggests that during times of crisis, states often look to their regional peers for guidance, reassurance, and examples of action. The effects of diffusion were especially evident for mask mandates, stay-at-home orders, school closures, and travel restrictions, indicating that states did not operate in isolation but instead responded to the regional policy environment when determining their own course of action.

This result closely aligns with the earlier research by Walker (1969) and Berry and Berry (1990), which showed the importance of policy diffusion in influencing state policy decisions. However, this study's findings differ from those of DellaVigna & Kim (2021), who emphasized that partisanship strongly influences state-level responses to the COVID-19 pandemic. Political factors such as the governor's party affiliation and the percentage of Trump voters in a state influenced the implementation of mask mandates. However, these factors did not consistently affect the duration of other policies. This is surprising, considering the highly polarized political climate during the pandemic. One might expect conservative states to resist and repeal certain policies more quickly than liberal states. Instead, the findings indicate that the longevity of these policies was more affected by factors such as institutional capacity, the severity of public health issues, and policy diffusion, rather than by partisanship alone.

This distinction reflects how different types of policies may vary in their political relevance. For example, mask mandates became emblematic of broader ideological debates about individual liberty and government control, while policies such as school closures and travel restrictions were likely viewed as more practical actions and less overtly political.

Structural and demographic factors such as state capacity, population size, income inequality, and median age were more consistent predictors of how long policies stayed in place across the models. States with greater administrative capacity were often quicker to lift restrictions, likely because they had more resources and infrastructure to adapt policies quickly. Similarly, states with larger populations or greater income inequality may have faced different challenges that affected how long they could keep policies in place. These findings harken back to the old policy determinants literature promoted in the 1970s (Dye, 1972).

Epidemiological factors also played a significant role in shaping public health policies. While one might expect higher infection rates would result in longer-lasting measures, the analysis actually shows the opposite trend. This counterintuitive finding may reflect the challenges of maintaining public compliance amid pandemic fatigue as well as the political and economic pressures to reopen. In contrast, higher death rates were consistently linked to longer durations, suggesting that more visible and severe consequences of the virus triggered states to maintain public health measures for extended periods. This reactive pattern demonstrates that states generally responded to the seriousness of public health outcomes when determining the duration of the policies.

In conclusion, these findings indicate that while initial policy decisions were mostly shaped by political orientation and the behavior of neighboring states, the sustainability of those policies were more heavily influenced by structural capacity, demographic pressures, and ongoing public health conditions. The limited impact of partisanship on policy duration goes against common expectations and highlights the complexity of state-level decision-making during a public health crisis. These findings demonstrate that pandemic policymaking is dynamic and influenced by context. They also emphasize the necessity to enhance state-level public health and administrative systems, improving responsiveness and resilience in future crises.

Chapter 5: Empirical Analysis of COVID-19 policies Impact on Health Outcomes

This chapter evaluates the effectiveness of state-level COVID-19 policies in curbing the spread of the virus and reducing mortality. Before conducting the statistical analysis, a series of preliminary analyses, including descriptive statistics and tests for model appropriateness are conducted. The analysis specifically evaluates the impact of certain NPIs such as mask mandates stay-at-home orders, travel restrictions, gathering restrictions, and school closures on infections and deaths. A detailed discussion of the findings is presented following the analytical results.

Descriptive Statistics

The analysis includes state-level COVID-19 data from March 2020 to October 2021(Mayer et al., 2022), covering both the pre-vaccine and post-vaccine rollout phases of the pandemic. To evaluate the effectiveness of NPIs, the analysis focuses on two key outcomes: weekly state-level infections and deaths. These count-based dependent variables are appropriate because the study is interested in the number of occurrences of an event—in this case, infections and deaths—within a fixed domain of time (King 1988). Unlike other studies that use daily growth rates of COVID-19 cases (e.g., Lyu & Wehby, 2020; Courtemanche et al., 2020), this study uses weekly raw counts to examine the effectiveness of various NPIs over an extended period while accounting for key confounding variables. A time-series cross-sectional dataset is created, including 49 U.S. states—excluding Wyoming due to data reporting irregularities[1] and drawing on weekly infection and death data from the CDC, originally compiled by Mayer et al. (2022).

[1] Wyoming was excluded from the analysis due to inconsistent or missing weekly COVID-19 case and death data reported to the CDC, making the state unsuitable for inclusion in a consistent time-series cross-sectional study.

The dependent variables are analyzed using a mixed-effects negative binomial regression model. Two models are estimated using the full dataset: one with infections as the dependent variable, and one with deaths. These models include policy interventions such as mask mandates, travel restrictions, stay-at-home orders, gathering restrictions, and school closures, as well as key demographic and political variables, such as population count and density, median age, state capacity, income inequality, percentage of nonwhite residents, percentage of Trump voters in 2020, state ideology, and gubernatorial party affiliation. I discussed the data for these analyses in chapter 3 and the hypotheses in chapter 2.

Descriptive statistics for the variables used in the analysis are presented in Tables 5.1 and 5.2. As a robustness check, this study also estimated the models using infections and deaths per 1,000 population as dependent variables. The direction of the coefficients remained consistent with those in the count-based models (Models 1 and 2), and no substantial differences were observed in the significance of the key policy variables. These supplementary results reinforce the reliability of the main findings in this chapter. Detailed descriptions of the variables are discussed below.

Table ***Error! No text of specified style in document.****.7 Summary of Variables*

Variable	Obs	Mean	Std. Dev.	Min	Max
Infections	4,263	10,341.34	18,693.37	0	286,550
Stay-at-home (L3)	4,116	0.08	0.27	0	1
Travel restrictions (L2)	4,165	0.17	0.38	0	1
School closures (L1)	4,214	0.25	0.43	0	1
Mask mandates (L1)	4,214	0.55	0.49	0	1
Gathering restrictions (L7)	3,920	0.65	0.47	0	1
Pop 2020	4,263	6,738,426	7,385,778	643,077	3.95e+07
Gop gov	4,263	0.52	0.49	0	1
Median age	4,263	38.90	2.26	31.10	44.80
Pop density	4,263	210.60	273.42	1.3	1,263
Vaccine (L4)	4,067	0.50	0.50	0	1

Percent Trump vote 2020	4,263	0.50	0.10	0.307	0.699
Percent nonwhite 2020	4,263	0.23	0.12	0.05	0.74
State ideology	4,263	-0.10	1.76	-3.61	2.93
State capacity	4,263	444,798.80	562,661.10	33,435	3,373,241
GINI index	4,263	0.04	0.19	0	1

Table ***Error! No text of specified style in document.****.8 Summary of Variables*

Variable	Observations	Mean	Std. Dev.	Min	Max
Deaths	4,263	163.00	296.49	0	3,779
Stay-at-home (L9)	3,822	0.09	0.28	0	1
Travel restrictions (L3)	4,116	0.17	0.38	0	1
School closures (L3)	4,116	0.25	0.43	0	1
Mask mandates (L6)	3,969	0.57	0.49	0	1
Gathering restrictions (L9)	3,822	0.66	0.47	0	1
Pop 2020	4,263	6,738,426	7,385,778	643,077	3.95e+07
Gop gov	4,263	0.52	0.49	0	1
Median age	4,263	38.90	2.26	31.10	44.80
Pop density	4,263	210.60	273.42	1.30	1,263
Vaccine (L7)	3,920	0.48	0.49	0	1
Percent Trump vote 2020	4,263	0.50	0.10	0.30	0.69
Percent nonwhite 2020	4,263	0.23	0.12	0.05	0.74
State ideology	4,263	-0.10	1.76	-3.61	2.93
State capacity	4,263	444,798.80	562,661.10	33,435	3,373,241
GINI index	4,263	0.04	0.19	0	1

Table 5.1 and 5.2 present a comprehensive summary of the variables utilized in the analysis of weekly state-level infections and deaths, respectively, over an 86-week period spanning from March 2020 to October 2021. Table 5.1 focuses on infections as the dependent variable, while Table 5.2 examines deaths. Both analyses incorporate Non-Pharmaceutical Interventions (NPIs) as key independent variables, including stay-at-home orders, travel restrictions, school closures, gathering restrictions, and mask mandates.

To accurately capture the timing of policy impacts, these models incorporate the lagged versions of these NPIs. The choice of lag structures for each NPI is informed by theoretical expectations and empirical evidence, recognizing that the effect of different interventions unfold in different timeframes. For instance, I found that mask mandates are best modeled with lag 1 in Table 5.1 to account for their immediate influence on individual behavior and infection trends, while lag 6 is employed in Table 5.2 which reflects the delayed impact on mortality outcomes. School closures are commonly associated with immediate effects, as they are typically implemented uniformly across a state, resulting in the sudden suspension of in-person interactions among students, teachers, and staff. This disruption decreases the potential for exposure in a large, centralized environment, making the policy's impact on disease transmission more immediate and observable. Consequently, shorter time lags are utilized when modeling their effect on infections, while longer time lags are applied to capture the subsequent effects on mortality. These lagged effects reflect how school closures reduce transmissions not only within schools but also across households and communities over time.

In contrast, interventions such as stay-at-home orders and gathering restrictions often rely on voluntary compliance, which makes them more challenging to monitor and enforce consistently. Public adherence to these measures can vary widely, and their impact may be delayed as individuals gradually adjust their behavior. For example, during the pandemic, social media frequently highlighted instances of people continuing to gather in bars and restaurants despite the existence of such policies. As a result, these types of NPIs typically require more extended time frames to show their effects, reflecting the slower pace of behavioral change and the subsequent delayed effects on COVID-19 outcomes. This varied lagged approach ensures the temporal dynamics of each intervention are properly reflected, allowing for a more precise assessment of their effects.

In addition to the NPIs, the analyses includes a range of control variables to account for state-level demographic, political, and contextual differences. The control variables remain consistent across both models, including the total state population in 2020, vaccine administration (lagged appropriately to account for delayed effects), population density, median age, the party affiliation of the governor, the percentage of Trump voters in the 2020 election, the proportion of nonwhite residents, state ideology, state capacity and income equality. These variables are included to account for potential confounding factors that may have influence both policy adoption and COVID-19 outcomes. By incorporating these controls, the analysis aims to isolate the effects of NPIs on infection and death counts across states during the pandemic. This method enhances our understanding of how state-level characteristics can influence the effectiveness of public health interventions.

As noted earlier, this study analyzes weekly COVID-19 infections and deaths, which are count data that demonstrate overdispersion. To address this, I use a mixed-effects negative binomial cross-sectional time-series regression model. Since the focus is on variations among states over time, a fixed-effects approach is not appropriate. Instead, we adopt a random-effects specification to account for unobserved differences across states. To ensure robust inference, jackknife standard errors are calculated and clustered by state. We anticipate negative coefficients for each of the five COVID-19 policy directives implemented in response to the pandemic. The mixed-effects negative binomial regression model is formulated as:

$$\log(\mathrm{Yi}) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + u_i$$

where Y_i represents the number of infection cases or deaths in state i, X_{1i}, X_{2i},…, X_{ki} are the independent variables, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the independent variables, and μ_i is the error term.

Analysis and Results

Table 5.3 presents the results from two mixed-effects negative binomial regression models. Model 1 assesses the impact of NPIs on weekly COVID-19 infections, while Model 2 analyzes their effect on weekly COVID-19 deaths. These findings serve as the foundation for the discussion that follows.

Table ***Error! No text of specified style in document.****.9 Negative Binomial Regression Results for COVID-19 Infections (Model 1) and Deaths (Model 2)*

Variable	**Model 1**	**Model 2**
Stay-at-home	-0.35*	-0.31*
	(0.17)	(0.13)
Travel Restrictions	0.08	-0.04
	(0.14)	(0.14)
School Closures	-1.00*	-0.46*
	(0.11)	(0.10)
Mask Mandates	0.22*	-0.05
	(0.08)	(0.11)
Gathering Restrictions	-0.39*	-0.30*
	(0.08)	(0.11)
Population 2020	5.36e-08	-2.40e-08
	(3.00e-08)	(4.11e-08)
GOP Governor	0.09	0.36
	(0.33)	(0.40)
Median Age	0.02	0.23*

	(0.06)	(0.08)
Population Density	0.00*	0.00*
	(0.00)	(0.00)
Vaccine	-0.43*	-0.85*
	(0.07)	(0.08)
% Trump Vote 2020	-0.41	-1.08
	(0.84)	(1.16)
% Non-White 2020	-0.91	-2.20
	(0.70)	(1.22)
State Elite Ideology	0.28*	0.41*
	(0.08)	(0.11)
State Capacity	1.07e-06*	2.36e-06*
	(3.64e-07)	(5.66e-07)
Gini Index	-0.28	-0.43
	(0.31)	(0.40)
_cons	7.61*	-4.08
	(2.17)	(3.12)
Number of Obs.	3,920	3,822
Integration Points	7	7
Number of Groups	49	49
Group Variable	state	state
Log Pseudolikelihood	-38258.56	-21050.19
Wald Chi2 (15)	516.43	273.03

Prob>Chi2	0.0000	0.0000

Note: Standard errors are parenthesized. Asterisk indicates statistical significance p≤0.05 and is considered statistically significant.

The results from the mixed-effects negative binomial regression models are presented together in Table 5.3 to facilitate direct comparisons across the models. Each column corresponds to a different specification based on the outcomes analyzed. Model 1 uses infections as the dependent variable, while models 2 focuses on deaths. This combined presentation of the regression results underscores the effectiveness of NPIs in reducing COVID-19 infections and deaths, while also demonstrating the robustness of the findings across both models.

Model 1 examines the impact of several NPIs on infection counts using the full dataset (March 2020-October 2021). The findings from the mixed-effects negative binomial regression model analyzing infections show significant variations in the effectiveness of NPIs and related contextual factors. Stay-at-home orders, lagged by three weeks, has a statistically significant negative relationship with infection counts ($\beta = -0.36$, $p < 0.05$), indicating their effectiveness in reducing transmission. The primary reason for this decline seems to be the reduction in people's mobility and fewer social interactions during that time. Travel restrictions, lagged by two weeks, did not show a statistically significant association with infections ($\beta = 0.07$, $p > 0.05$). This lack of significance may be attributed to the difficulty of enforcing travel restrictions in a country where travel between states and across states is difficult if not impossible to control. School closures, lagged by one week, led to a significant reduction in infections ($\beta = -0.99$, $p < 0.05$). This highlights their crucial role in reducing in-person interactions and breaking transmission chains, especially during the pre-vaccine phase of the pandemic. Mask mandates, when lagged by one week, shows a positive and statistically significant relationship with infections ($\beta = 0.21$, $p < 0.05$). This counterintuitive finding may be explained by several factors. For instance, it could reflect poor compliance, weak enforcement, variability in the quality and usage of masks, improper or inconsistent use of masks, or compensatory behaviors such as decreased adherence with the other health interventions (Huber 2021; Näher et al., 2024). Moreover, the positive association might suggest a reverse causality, where mandates were introduced in response to rising infection rates.

In contrast to mask mandates, gathering restrictions, lagged by seven weeks, has a statistically significant negative association with infection cases ($\beta = -0.39$, $p < 0.05$). This finding indicates that restricting large gatherings effectively reduced the spread of COVID-19 during the observed period. By minimizing opportunities for close contact in crowded settings, these restrictions likely interrupted the transmission chain of the virus. The observed lag period indicates that these measures took time to produce measurable effects on infection rates, possibly due to delays in behavior changes and the incubation period of the virus.

Among the demographic variables, the total state population shows a positive relationship with infection counts ($\beta = 5.36e-08$, $p > 0.05$). However, this relationship did not achieve statistical significance at the conventional level. While the effect aligns with expectations, the findings provide only limited evidence to support the notion that larger state populations contributed to higher infection counts. On the other hand, population density displays a positive and statistically significant relationship with infection counts ($\beta = 0.00$, $p < 0.05$), underscoring the role of urbanization in facilitating viral transmission. This finding aligned with the expectation that higher population densities increase contact rates, thereby enhancing the spread of infectious diseases in densely populated areas.

The median age shows a slight positive correlation with infection rates ($\beta = 0.02$, $p > 0.05$). However, this relationship is not statistically significant, indicating that age distribution alone may not significantly explain variations in infection counts across states. Similarly, the percentage of the nonwhite population in 2020 is negatively associated with infection rates ($\beta = -0.91$, $p > 0.05$). Again, this effect did not achieve statistical significance. Given the concerns about racial disparities associated with the pandemic, this finding is welcomed.

In addition to demographic characteristics of the state, the analysis also incorporates structural and institutional factors that may influence COVID-19 outcomes across states. State capacity shows a positive and statistically significant association with infection cases ($\beta = 1.07e\text{-}06$, $p < 0.05$). This finding suggests that states with greater wealth and capacity tended to have higher infection counts. This could be due to more robust testing infrastructure or more comprehensive surveillance and reporting systems. In contrast, GINI index, which measures income inequality, shows a negative but insignificant association with infection cases ($\beta = -0.28$, $p > 0.05$).

Conversely, vaccination administration, lagged by four weeks, is negatively associated with infection cases ($\beta = -0.43$, $p < 0.05$). This result reinforced the critical role of widespread vaccination in mitigating infection risks and reducing transmission. The four-week lag effect reflected the time required for vaccinations to take full effect at the population level, thereby emphasizing the importance of sustained vaccination efforts in controlling the pandemic.

The analysis of political and regional variables revealed a mix of significant and non-significant results. One notable finding was that state ideology exhibits a significant positive association with infection counts ($\beta = 0.28$, $p < 0.05$). Since more conservative states are coded higher on the state ideology scale, this result suggests that conservative-leaning states experienced higher infection cases. This outcome may reflect a range of factors, such as lower adherence to public health guidelines, delayed policy implementation, or greater resistance to mandates in more conservative regions. States like Florida and Texas, for example, often adopted less restrictive approaches during key phases of the pandemic, which may have contributed to elevated case numbers. In contrast, other variables, such as having a GOP governor ($\beta = 0.09$, $p > 0.05$), the percentage of Trump votes in 2020 ($\beta = -0.41$, $p > 0.05$), do not show statistical significance. This lack of significance suggests that these factors may not have directly influenced infection cases, or that their effects were moderated by other variables such as population density.

While Model 1 assessed the effect of NPIs on infection counts, Model 2 evaluates their impact on COVID-19 mortality, providing a complementary perspective on the effectiveness of these policies. Infections are not included as an independent variable in the model with deaths as the outcome, as they would absorb much of the variance that policy interventions might otherwise explain. Since infections are a necessary precursor to death, their inclusion would make it difficult to isolate the direct effects of NPIs on mortality. Specifically, this model examines the influence of various NPIs on COVID-19 deaths using the full dataset (March 2020 to October 2021). The findings from the mixed-effects negative binomial regression model reveal important variations in the effectiveness of these NPIs and the influence of contextual factors. Stay-at-home orders, lagged by 9 weeks, show a statistically significant negative relationship with COVID-19 deaths ($\beta = -0.31$, $p < 0.05$). This indicates that these measures contributed to a reduction in mortality. This finding is in line with Model 1's finding that SIPOs have a negative effect on infections.

On the other hand, travel restrictions, three weeks post-implementation, do not display a statistically significant association with mortality ($\beta = -0.04$, $p > 0.05$). This finding is consistent with Model 1 analyzing infections. School closures, which were implemented with a lag of three weeks, appears to have been a highly effective intervention, demonstrating a significant negative impact on mortality ($\beta = -0.46$, $p < 0.05$). This finding is in line with Model 1's result that school closures have a strong negative effect on infections. In contrast, mask mandates, lagged by six weeks, do not show a statistically significant association with mortality ($\beta = -0.05$, $p > 0.05$). Even though this contrasts with Model 1's finding that mask mandates are positively associated with infections, both findings underscore that mask mandates did not work. Gathering restrictions, with their effects becoming evident approximately nine weeks later, show a statistically significant negative relationship with deaths ($\beta = -0.30$, $p < 0.05$). This finding is consistent with Model 1's result that gathering restrictions significantly reduce infections.

Among the demographic variables, total state population displays a negative association with COVID-19 deaths ($\beta = -2.40e-08$, $p > 0.05$), although this relationship is not statistically significant, but population density is positively and significantly associated with COVID-10-related deaths ($\beta = 0.00$, $p < 0.05$). This finding when combined with Model 1, shows that states with higher population density tend to report more infections and deaths suggesting that there is an increased risk of transmission due to the challenges of maintaining physical distancing in densely populated areas. These findings indicate that population size alone is not a meaningful predictor of infections or deaths; it is essential to consider how people are distributed within that population, as indicated by population density.

The median age of a state's population is positively and significantly associated with the number of COVID-19-related deaths ($\beta = 0.23$, $p < 0.05$). This indicates that states with older populations tend to report higher death counts, which aligns with the understanding that older individuals are more vulnerable to severe outcomes from COVID-19. Similar to Model 1, the percentage of the nonwhite population shows a negative and insignificant relationship with COVID-19-related deaths ($\beta = -2.20$, $p > 0.05$).

Among the structural/institutional factors, state capacity shows a positive and statistically significant association with COVID-19-related deaths ($\beta = 2.36e-06$, $p < 0.05$), a result that is consistent with Model 1. In contrast, the GINI index has a negative but statistically insignificant relationship with COVID-19-related deaths ($\beta = -0.43$, $p > 0.05$).

The vaccination variable, with a seven-week lag, shows a statistically significant negative relationship with mortality ($\beta = -0.85$, $p < 0.05$). This indicates that the administration of the vaccine is significantly associated with a reduction in COVID-19 deaths. This finding aligns with expectations, as vaccines are known to lower hospitalization rates and prevent illness. The seven-week lag accounts for the time needed for immunity to develop and for the effects of policies to take effect. This finding is consistent with Model 1's result that vaccination coverage has a significant effect on infections.

The analysis of political and regional variables yielded both significant and non-significant results. State ideology shows a significant positive relationship with the dependent variable ($\beta = 0.41$, $p < 0.05$). This suggests that states with more conservative political orientations suffered more COVID-19 deaths. This effect may be due to lower adherence to NPIs, or delays in implementing public health measures in more conservative states. For example, such states were generally less likely to enforce measures such as mask mandates, gathering restrictions, or early lockdowns, which may have contributed to increased deaths. Additionally, greater vaccine hesitancy and reduced access to healthcare in some conservative-leaning states may have further intensified the impact of the pandemic. This finding aligns with

Model 1's result showing that more conservative states experienced higher infection cases, indicating a consistent trend across both infection and mortality outcomes.

Other political and demographic variables did not show statistical significance. For example, the percentage of Trump votes in 2020 shows a negative but statistically insignificant association with COVID-19 deaths ($\beta = -1.08$, $p > 0.05$), indicating no meaningful relationship in this model.

Discussion

In this chapter, the results from the two models provide a comprehensive assessment of the effectiveness of NPIs in reducing COVID-19 infections and deaths. The findings highlight variations in their impact across different outcomes. Overall, the analysis underscores the inconsistent effects of mask mandates and travel restrictions. Additionally, political and demographic factors influenced pandemic outcomes differently, with state ideology having a more significant impact than the other political variables. A key takeaway from the analysis is the effectiveness of stay-at-home orders in decreasing both infections and deaths. Their impact became statistically significant within three to nine weeks, depending on the measured outcome. This aligns with expectations, as reduced mobility and social interactions likely played a crucial role in limiting virus transmission. However, variations in compliance and enforcement across states may have affected the magnitude of these results. The analysis also indicates that school closures were among the most effective NPIs, consistently showing a significant negative association with both infections and deaths. This reinforces the argument that minimizing in-person interactions in schools was an essential strategy for curbing virus spread, especially before vaccines became widely available.

Gathering restrictions emerged as a highly effective measure, demonstrating a delayed but statistically significant impact on both infections and deaths. The observed lag in their effectiveness indicates that behavioral changes and compliance with policies took time to materialize. In contrast, the effectiveness of mask mandates were clearly either negative or insignificant. This suggests potential issues related to compliance, improper mask usage, or compensatory risk behaviors, where individuals may have engaged in riskier interactions due to a false sense of security from wearing masks. Additionally, the possibility of reverse causality—where mask mandates were introduced in response to rising case numbers—may help explain these findings. The lack of statistical significance regarding mortality further suggests that mask mandates alone may not have been effective in preventing severe COVID-19 outcomes. The findings indicate that travel restrictions generally did not significantly reduce COVID-19 infections or deaths. This lack of effectiveness may be attributed to the varying ways in which different states implemented these restrictions. Additionally, essential workers were still permitted to travel, which meant that the restrictions did not completely halt movement. Furthermore, the majority of COVID-19 cases were transmitted within local communities; thus, limiting travel between states likely had minimal impact on curbing the spread of the virus.

Demographic and regional factors played a significant role in shaping infection and mortality patterns during the pandemic. The size of a state's population shows varied effects across the infection and death models, suggesting that total population alone may not reliably predict COVID-19 outcomes. In contrast, population density is positively and significantly associated with both infection and death counts. This finding reinforces the notion that densely populated areas facilitate the transmission of the virus and contribute to higher mortalities. The strong negative correlation between vaccination rates and COVID-19 outcomes across different models underscores the critical role of vaccines in mitigating the pandemic's impact, noting a lag period that represents the time needed for immunity to develop. Political and ideological factors showed mixed effects. State ideology consistently demonstrated a significant positive relationship with both infections and deaths, suggesting that conservative-leaning states faced worse outcomes during the pandemic. In contrast, other political indicators, such as having a GOP governor or the percentage of Trump votes in 2020, did not show statistically significant effects. This implies that ideological positioning at the state level may have influenced policy responses and public compliance more directly than gubernatorial party affiliation or voter preferences. These findings provide valuable insights into the effectiveness of NPIs while also highlighting the complexities of policy implementation and public compliance. The results suggest that NPIs like stay-at-home orders, school closures, and gathering restrictions were among the most effective measures in reducing infections and deaths. In contrast, mask mandates and travel restrictions showed inconsistent effects. The influence of political ideology on pandemic outcomes further emphasizes the impact of state-level decision-making on public health responses.

Chapter 6: Discussion and Conclusion

This study examines the differences in how NPIs were adopted and their effectiveness across various states in the United States during the COVID-19 pandemic, from March 2020 to October 2021. Using the Policy Innovation and Diffusion (PID) framework, the study has two main objectives: (1) to identify the political, demographic, and regional factors that influenced the timing and likelihood of policy adoption in different states, and (2) to assess the effectiveness of these adopted policies in reducing COVID-19 infections and deaths. By employing a multi-method quantitative approach that includes event history modeling for policy adoption and negative binomial regression for evaluating policy effectiveness, this study provides a comprehensive and empirical analysis of the factors that shaped state responses to an unprecedented public health crisis.

Chapter 4 focused on understanding the timing and duration of state adoption of five major NPIs: mask mandates, stay-at-home orders, school closures, travel restrictions, and gathering restrictions. The findings from this chapter indicate that the policy adoption process was influenced by both political and regional factors. Policy diffusion emerged as one of the strongest and most consistent predictors across all models. The actions of neighboring states significantly increased the likelihood that a state would adopt and sustain a specific intervention, confirming the importance of regional peer influence in crisis policymaking.

While political factors, such as the governor's party affiliation and the percentage of Trump voters, influenced the adoption of certain policies (particularly mask mandates), these political variables had limited impact on the duration of most policies. In contrast, structural conditions—such as state capacity, population size, income inequality, and median age—were more reliable predictors of how long policies remained in effect in different states.

Interestingly, epidemiological indicators affected the duration of policies in unexpected ways. Higher infection numbers were not associated with longer policy durations and, in some cases, correlated with shorter durations, likely due to pandemic fatigue and pressure to reopen. In contrast, higher death counts led to longer policy durations, suggesting that states reacted more strongly to visible mortality than to rising case numbers. These findings reveal the complexity of maintaining public health measures and indicate that sustaining interventions requires more than just initial political will; it heavily depends on state's institutional capacity and the evolving severity of public health conditions.

Chapter 5 evaluated the effectiveness of various policies after their adoption, utilizing a random-effects negative binomial regression model with lagged predictors. The results indicated that stay-at-home orders significantly reduced both infections and deaths, especially after a delay of three to nine weeks. School closures emerged as one of the most effective NPIs, consistently demonstrating a negative association with both infections and fatalities. Gathering restrictions also proved effective, though their impact was delayed, highlighting the time needed for public behavior changes to take effect. In contrast, the effects of mask mandates were inconsistent. In most models, mask mandates did not lead to significant reductions in infections or deaths, and in some instances, they were associated with worse outcomes. This inconsistency may be due to factors like reverse causality, low compliance, inconsistent enforcement, or compensatory risk behavior, where individuals adopt less cautious behavior because they feel protected by wearing masks. Travel restrictions similarly showed minimal effects, likely due to inconsistent implementation across states, ongoing movement of essential workers, and the prevalence of local transmission both within and between states.

Demographic and regional factors also influenced pandemic outcomes. Population density, rather than total population size, was a stronger predictor of infections and deaths, reinforcing the risks associated with urban environments. Vaccine availability demonstrated a strong negative correlation with COVID-19 outcomes in all models, underscoring their crucial role in mitigating the pandemic. Political and ideological factors presented mixed effects; while gubernatorial partisanship and the percentage of Trump votes were generally insignificant, state ideology—particularly conservative leanings—was linked to higher rates of infections and deaths. This suggests that the ideological culture at the state level may impact both policy decisions and public compliance more significantly than specific electoral outcomes.

This study's findings confirm that the political context and regional dynamics play a crucial role in shaping both the adoption and effectiveness of pandemic policies. Political ideology was a significant factor in early policy responses, particularly regarding mask mandates. However, the ongoing implementation of these policies seemed to depend more on administrative capacity and the severity of public health issues than on partisanship alone. Additionally, the consistent influence of policy diffusion highlights the importance of state-to-state learning, especially in an environment characterized by high uncertainty and limited federal coordination.

Not all NPIs were found to be equally effective. Stay-at-home orders, school closures, and gathering restrictions emerged as the most successful measures for reducing infections and deaths, although their effects were often delayed. These policies were most effective when implemented early and maintained long enough to influence public behavior. In contrast, mask mandates and travel restrictions showed mixed results. The limited effectiveness of these interventions highlights a gap between policy design and real-world execution, which could be affected by factors such as the governor's decision-making, timing, communication, and public resistance.

This study presents several significant contributions. First, it integrates the timing of policy adoption and the duration of policies within a diffusion framework, which provides a more comprehensive understanding of the policymaking process during a crisis. Second, the inclusion of lagged policy variables in the effectiveness models improves causal interpretation by recognizing the delay between intervention and observable outcomes. Third, by examining the duration of policies as a dependent variable, this study offers a clearer understanding of state responsiveness. It extends the analysis beyond initial policy adoption to include how long states maintained public health interventions. Finally, by incorporating political, structural, and epidemiological dimensions, this study provides a thorough understanding of the various factors that drive state-level policy decisions and their public health outcomes.

Implications for Policy and Practice

The findings of the study have several important implications for public health policymaking. First, an effective public health response depends on both early and sustained interventions, rather than just initial implementation. The demonstrated effectiveness of NPIs such as school closures and stay-at-home orders highlights the importance of early, decisive, and sustained actions in reducing COVID-19 mortality. Policymakers should prioritize maintaining institutional capacity and fostering public trust to ensure continued compliance over time. In addition, timely adoption of measures that limit high-contact environments and maintaining them long enough to observe their meaningful effects should remain a priority. Second, regional collaboration and coordinated policies can enhance both the speed and consistency of responses, especially since states often look to neighboring jurisdictions when forming their own policies. Third, it is crucial to improve public health messaging and addressing any ideological resistance, especially for policies such as mask mandates that require collective behavioral changes and widespread compliance. As the findings suggest, public compliance, enforcement capacity, and the broader political context are crucial factors influencing the effectiveness of these measures.

Additionally, the findings indicate that strengthening state capacity—through investments in public health infrastructure and improving administrative efficiency—can enhance the policies more sustainable and effective.

Limitations and Future Research

This study offers a thorough analysis of pandemic policies at the state level, but several limitations need to be noted. First, focusing on state-level data masks the differences that may exist within states, as policies can vary significantly between counties or cities. Second, due to data limitations, it is impossible to directly measure compliance and enforcement, which likely affected the effectiveness of these policies. Third, the timeframe of the study, from March 2020 through October 2021, does not encompass later phases of the pandemic, such as the emergence of variants and the rollout of booster campaigns.

Future research should examine variations at the local level, differentiate between symbolic gestures and substantive or enforceable policy actions. It should also evaluate the effectiveness of public communication strategies in fostering compliance and building trust. Furthermore, researchers could explore how state-level responses during COVID-19 contributed to institutional learning and preparedness for future public health emergencies. Although this study does not directly address certain factors, it is reasonable to assume that public trust in government and vaccine uptake significantly influence policy effectiveness. These issues are crucial and warrant further exploration to gain a deeper understanding of how institutional credibility and public attitudes affect the success of policy interventions during public health crises.

Conclusion

The study provides a detailed analysis of how various U.S. states adopted, maintained, and implemented pandemic policies during COVID-19. It highlights the influence of political ideology, regional factors, institutional capacity, and the severity of public health situations on both policymaking and outcomes. The findings indicate that certain interventions, such as school closures and stay-at-home orders, were consistently effective. In contrast, other policy actions such as mask mandates and travel restrictions showed more limited and inconsistent results.

Overall, this study underscores the need for adaptable, well-resourced, and state-specific policy responses. It stresses the importance of state capacity, effective communication strategies, and collaboration among states in developing effective public health interventions. These insights can serve as valuable insights for policymakers seeking to develop more equitable, effective, and sustainable policy actions for future public health crises.

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