

THE IMPACT OF FULL NURSE PRACTITIONER SCOPE OF PRACTICE POLICY ON
ACCESS TO CARE IN THE PRIVATELY INSURANCE

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ABSTRACT

Esita Patel: The Impact of Full Nurse Practitioner Scope of Practice Policy on Access to Care in the privately insured
(Under the direction of Barbara Mark)

A greater understanding of how state-level nurse practitioner (NP) scope of practice (SOP) policies shape access to care is needed in the context of today's rapidly expanding NP workforce. Prior work suggests a positive association between NP SOP and access to preventive services, however most studies fail to inform how implementing full NP SOP policy affects access over time. This study uses a difference-in-difference (DD) analysis to examine changes in access-related outcomes in states before and after implementation of full NP SOP policy ("intervention group") compared to states with unchanged restricted NP SOP or unchanged full NP SOP policies ("comparison groups").

A retrospective analysis claims data from 2006-2015 was conducted using Truven Health MarketScan® Commercial Claims and Encounters Databases. Linear probability DD models were used to evaluate the effects of implementing full NP SOP on whether adults received an outpatient follow-up visit after hospitalization, an annual wellness exam, hyperlipidemia screening, or diabetes screening, as well as the impacts of full NP SOP implementation on all-cause emergency department encounters, all-cause hospitalizations, all-cause 30-day hospital readmissions, or hospitalizations for an acute ambulatory care sensitive condition in a one year period. Individual level covariates of age, gender, employment, rurality, and comorbidity were controlled for using a doubly robust propensity score strategy. Propensity score weighting was

used to balance characteristics between treatment and control groups in the pre- and post- policy periods. Robust standard errors clustered at the state-level were used to adjust for heteroscedasticity and within-state correlation. Year and state fixed effects were used to adjust for time- and group- invariant confounders.

The findings of this research indicated that in a commercially insured population, implementing full NP SOP does not consistently improve patients' access to care outcomes compared to states with unchanged full or unchanged restricted NP SOP. Overall, the main analysis did not find a significant change in outpatient follow-up within 14 days of hospitalization or utilization of acute care services. The main model suggested a 3.0 percentage point increase in diabetes screenings ($p < 0.05$) and a 4.0 percentage point decrease in annual wellness exams ($p < 0.01$) following full NP SOP policy implementation compared to states with unchanged full and unchanged restrictive NP SOP, respectively. Moreover, there was variability in changes in outcomes following full NP SOP policy implementation by state. Although prior work suggested a positive association between NP SOP and access, this work consisted largely of cross-sectional comparisons between states with restricted versus full NP SOP. The results of this study highlight the importance of using longitudinal quasi-experimental approaches in future work to assess the relationship between NP SOP policy and access to care. The results of this study compared to previous work also suggests that NP SOP may have differential impacts on those who arguably already have adequate access to care, such as the commercially insured, versus underserved populations who do not.

To Bhavesh Patel and Puja Shah

My husband and my sister, who believed in my journey so boldly, they gave me a stethoscope and laptop before I was accepted into any BSN or PhD program. Thank you for your unwavering vote of confidence, encouragement, and patience.

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LIST OF ABBREVIATIONS

AANP – American Association of Nurse Practitioners

ACSC – Ambulatory Care Sensitive Condition

AHRQ – Agency for Healthcare Research and Quality

AL – Alabama

AK – Alaska

AZ – Arizona

AR – Arkansas

CA – California

CO – Colorado

CT – Connecticut

DE – Delaware

FL – Florida

GA – Georgia

HI – Hawaii

ID – Idaho

IL – Illinois

IN – Indiana

IA – Iowa

KS – Kansas

KY – Kentucky

LA – Louisiana

ME – Maine

MD – Maryland
MA – Massachusetts
MI – Michigan
MN – Minnesota
MS – Mississippi
MO – Missouri
MT – Montana
NE – Nebraska
NV – Nevada
NH – New Hampshire
NJ – New Jersey
NM – New Mexico
NY – New York
NC – North Carolina
ND – North Dakota
OH – Ohio
OK – Oklahoma
OR – Oregon
PA – Pennsylvania
RI – Rhode Island
SC – South Carolina
SD – South Dakota
TN – Tennessee

TX – Texas

UT – Utah

VT – Vermont

VA – Virginia

WA – Washington

WV – West Virginia

WI – Wisconsin

WY – Wyoming

APRN – Advanced Practice Registered Nurse

ARF – Area Resource Files

CARA – Comprehensive Addiction and Recovery Act

CDC – Centers for Disease Control

CPT – Current Procedural Terminology

DD – Difference in Difference

DHHS – Department of Health and Human Services

ED – Emergency Department

FFS – Fee-for-Service

HCPCS – Healthcare Common Procedure Coding System

HRSA – Health Resources and Services Administration

HSA – Health Service Area

ICD – International Classification of Diseases

MCBS – Medicare Current Beneficiaries Survey

MD – Medical Doctor

MEPS – Medical Expenditure Panel Survey

MSA – Metropolitan Statistical Area

NAMCS – National Ambulatory Medicare Care Survey

NI – Not Included

NP – Nurse Practitioner

PA – Physician Assistant

PC – Primary Care

SES – Socioeconomic Status

SOP – Scope of Practice

US – United States

VA – Veterans Administration

CHAPTER I: INTRODUCTION

Access to Primary Care and Nurse Practitioner Scope of Practice Policy

In 2016, 1 in 10 people in the United States (U.S.) had difficulty accessing care when needed, with 13.6% unable to regularly schedule routine appointments (Agency for Healthcare Research and Quality [AHRQ], 2018). Access to health care is a multifaceted concept that is discussed in depth in the next chapter, but can be defined simply as *the use of health services to achieve desired health outcomes*. Access to care involves not only the availability, but also the ease and efficiency of gaining entry to healthcare sites, services, and providers that optimizes one's health (Begley, Lairson, Morgan, Rowan, & Balkrishnan, 2013). Access to primary care is vital to population health. Without adequate access to care, individuals cannot receive health services that prevent or reduce individual, societal, and economic disease burden, such as vaccinations, sexually transmitted infection screenings, or chronic disease management (AHRQ, 2017). Lack of access to primary care contributes to an increase in avoidable suffering and wasted dollars, as people are forced to seek expensive emergency care or hospitalization after often preventable health conditions are too advanced to ignore (Rosano et al., 2013; Shi, 2012).

Given the important link between access to care and population health coupled with the startling number of people who have inadequate access to care, it is no surprise that improving access to care is a national U.S. priority. Objective 1.3 of the U.S. Department of Health and Human Services (DHHS) 2018-2022 Strategic Plan aims to “improve Americans’ access to healthcare and expand choices of care and service options.” National efforts to increase access to

primary care in the U.S. include increasing the number of primary care providers, increasing insurance coverage for preventive services, redistributing primary care services, and restructuring the delivery of primary care (DHHS, 2018).

Improving access to care will, in part, require understanding how to optimize the use of a diverse primary care workforce to most effectively, efficiently, and equitably deliver care. More than 1 in 10 U.S. residents reside in a county with fewer than 1 primary care physician per 2,000 people, and the demand for primary care will increase as the population grows and ages, chronic conditions increase, and insurance coverage expands (UnitedHealth, 2018). However, providers other than physicians, namely nurse practitioners, are increasingly providing primary care. Between 2010-2016, the physician workforce grew by 1.1% while the nurse practitioner (NP) workforce grew by 9.4%; these trends are projected to continue through 2030, with the availability of advanced practice providers predicted to outstrip the availability of physicians in primary care (Auerbach, Staiger, Buerhaus, 2018). Moreover, between 2008-2016, the fraction of providers that were NPs in primary care practices grew by over 40%, while the fraction of providers that were physicians in these settings dropped by 12% (Barnes, Richards, McHugh, & Martsolf, 2018).

The NP workforce is primed to affect access to primary care, since NPs are the fastest growing primary care provider type and are more likely to provide care for underserved populations than other provider types (Bodenheimer & Bauer, 2016; Buerhaus, DesRoches, Dittus, & Donelan, 2015; Martsolf, Auerbach, & Arifkhanova, 2015). As NPs continue to make up a greater proportion of the primary care workforce, it becomes increasingly important to understand how best to utilize this segment of the workforce to increase access to care. This

includes gaining a better understanding of how regulatory policies for NPs influence access to care.

Currently, varied state-level NP scope of practice (SOP) policies govern the extent to which an NP can function as an independent primary care provider within a state. State-level NP SOP is a form of regulatory policy. These laws define the level of physician supervision required for an NP to provide care and also the types of care an NP can deliver within a state. States with full NP SOP policy allow NPs to prescribe and practice as an independent provider without physician supervision.

Allowing NP's full state-level SOP has been debated as a strategy to increase access to care since the establishment of the NP role in 1965 (Keeling, 1996). NP SOP laws are commonly categorized as "full," "reduced," or "restricted." While there are granular differences within each of these categories, the American Association of Nurse Practitioners (AANP) (2018) defines these categories as:

Full NP SOP

State practice and licensure laws permit all NPs to evaluate patients; diagnose, order and interpret diagnostic tests; and initiate and manage treatments, including prescribing medications and controlled substances, under the exclusive licensure authority of the state board of nursing. This is the model recommended by the National Academy of Medicine, formerly called the Institute of Medicine, and the National Council of State Boards of Nursing (AANP, 2018, paragraph 2).

Reduced NP SOP:

State practice and licensure laws reduce the ability of NPs to engage in at least one element of NP practice. State law requires a career-long regulated collaborative agreement with another health provider in order for the NP to provide patient care, or it limits the setting of one or more elements of NP practice (American Association of Nurse Practitioners, 2018 (AANP, 2018, paragraph 3).


Restricted NP SOP:

State practice and licensure laws restrict the ability of NPs to engage in at least one element of NP practice. State law requires career-long supervision, delegation or team management by another health provider in order for the NP to provide patient care. (AANP, 2018, paragraph 3).

The main difference between these SOP categories is the degree of physician supervision required for a NP to perform patient care activities. Although physician supervision requirements vary by state, they can take the form of activities such as chart reviews of NP care documentation by physicians, physicians being located within an established mile radius of the practicing NP, or completing annual paper work that must be signed off by a NP and supervising physician. According to the AANP (2018), twenty-four states with “full” NP SOP, the least restrictive policy, enable NPs to manage all aspects of patient care, including practicing and prescribing medications, without physician supervision. Common NP practice activities include physical exams, preventive care, patient counseling and education, and coordinating patients’ acute and chronic illnesses (Allers, 2014). Full NP prescription authority includes prescribing medications such as antibiotics and contraceptives as well as highly regulated Schedule II-V substances (Phillips, 2018). After training, NPs function as independent providers in states with full NP SOP

policies. Sixteen states have “reduced” NP SOP policy, which requires physician supervision to provide select practices, or prescriptive activities. Eleven states with “restrictive” NP SOP policies require physician supervision for all practice and prescription activities (Figure 1.1).

Figure 1.1: Overview of State-level Regulations of NP SOP as of 2018

State-level regulation of NP SOP	Categories	States	Definition
Least restrictive NP SOP  Most restrictive NP SOP	Full (n=24)	MT AK OR NH NM WY DC IA ME AZ WA ID CO MD HI ND VT NV CT RI MN NE OK SD	NPs manage all aspects of patient care, practicing and prescribing without physician supervision.
	Reduced (n=16)	AL AR DE IL IN KS KY LA MS NJ NY OH PA UT WV WI	Physician supervision is required for an NP to engage in some aspects of patient care but not others.
	Restricted (n=11)	CA FL GA MA MI MO NC SC TN TX VA	Physician supervision is required for all patient care activities performed by an NP.

As detailed in the previous section, NPs are primed to affect access to care as they increasingly deliver primary care and often care for underserved populations (Bodenheimer & Bauer, 2016; Buerhaus, et al., 2015; Martsolf et al., 2015). As NPs increasingly provide significant portions of primary care, it is conceivable that policies regulating NP scope of practice may influence access to primary care as well. However, arguments in support of full NP SOP typically do not address access to care (Buerhaus et al., 2015; Cassidy, 2012; Hain & Fleck, 2014; Isaacs & Jellinek, 2012). McMichael (2017b) found that a state’s decision about implementation of full NP SOP was related to hospital interest group spending while a state’s decision not to implement full NP SOP was related to physician group spending. This finding suggests that politics, instead of evidence on access to care needs, are drivers in a state’s decision to implement full NP SOP.

The rationale for restrictive NP SOP policies frequently invokes the differential training of NPs and physicians, and the assertion that NPs cannot independently provide the same quality of care as physicians (Isaacs & Jellinek, 2012). This is an argument commonly used by physician associations, such as the American Medical Association, to lobby against full NP SOP (Iglehart, 2013). However, restrictive SOP has not been found to improve various outcomes, including chronic disease management, cancer screening, or hospitalization for ambulatory care sensitive outcomes (Xue, Ye, Brewer, Spetz, 2016; Perloff, Clarke, DesRoches, O'Reilly-Jacob, & Buerhaus, 2017). Furthermore, substantial evidence, including numerous randomized controlled trials, conclude consistently that the quality of and patient satisfaction with NP-delivered care is equal to physician delivered care in similar care settings (Horrocks, Anderson, & Salisbury, 2002; Lenz, Mundinger, Kane, Hopkins, & Lin, 2004; Newhouse et al., 2011; Stanik-Hutt et al., 2013; Swan, Ferguson, Chang, Larson, & Smaldone, 2015).

Purpose of Dissertation

This chapter describes access to care and state-level NP SOP policy. However, as further detailed in Chapters II and III of this dissertation, there are few empirical examinations of how a state's implementation of full NP SOP affects outcomes related to access to primary care. This information is critical to help stakeholders make research, practice, and policy decisions surrounding NP SOP. Therefore the purpose of this dissertation is to measure the effects of states implementing full NP SOP at the state level on patients' access to care. The specific aims and hypotheses are as follows:

Specific Aim 1: Compare the impact on characteristics of the health delivery system, operationalized as time to outpatient follow-up within fourteen days of initial hospitalization,

between states implementing full state-level NP SOP and states with unchanged full or unchanged restricted NP SOP policy.

- Hypothesis 1: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater increase in individuals receiving outpatient follow-up within fourteen days after hospitalization.

Specific Aim 2: Compare the impact on realized access to care between states implementing full state-level NP SOP and states with unchanged full or unchanged restricted NP SOP policy.

Realized access will be operationalized by the following:

- Aim 2a: Utilization of preventive services, as measured by annual wellness visit, hyperlipidemia screening, and diabetes screening
 - Hypothesis 2a: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater increase in individuals utilizing preventive services.
- Aim 2b: Utilization of acute care services, as measured by all-cause emergency department encounters, all-cause hospitalizations, all-cause 30-day readmissions, and hospitalizations for acute ambulatory care sensitive conditions.
 - Hypothesis 2b: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater decrease in individuals utilizing acute care services.

Organization of the Dissertation

This chapter described access to care and state-level NP SOP policy, and concluded with the aims and corresponding hypotheses for the dissertation. The remaining chapters of this dissertation are organized as follows: Chapter II examines Aday and Andersen's Framework for

the Study of Access to Medical Care (1974). This theoretical framework is used to describe the relationship between a state-level health policy -- NP SOP -- and the multifaceted components of access to care. This framework is further used to define the parts of access to care this study addressed, and consider mechanisms by which NP SOP policy may exert an effect on access to care. Chapter II concludes with a discussion of the theoretical framework for this study that contextualizes how the specific aims and outcomes for this study were selected. Chapter III presents a review of literature on the relationship between NP SOP and access. This review identifies research gaps in the study of the relationship between NP SOP and access to care and informs the development of methods used in this dissertation. Chapter IV outlines the methods used in this study, including rationale for the research design, data, study sample, variables, and statistical analyses used in this study. Chapter V presents the results of this dissertation, beginning with descriptive statistics of the study sample, followed by the main results for Aims 1 and 2, and concludes with sensitivity and subgroup analyses. Chapter VI synthesizes the findings of the dissertation, considers the limitations of the study's design, discusses policy implications, and proposes recommendations for future research.

CHAPTER II: THEORETICAL FOUNDATION

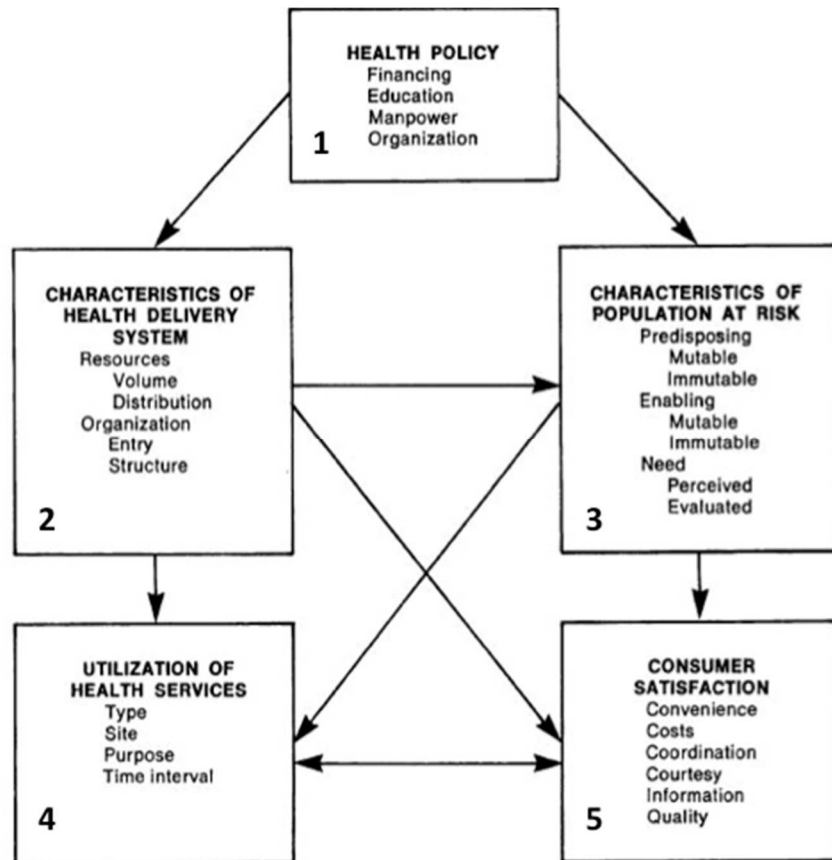
Access to care is a broad concept. An understanding of the constructs that contribute to the broad concept of “access to care” is imperative to our ability to measure and evaluate the impact of initiatives aimed at improving access to health care services. Using a theoretical framework that operationalizes the concept of access to care can further help improve abilities to evaluate policies, interventions, and research on access to care. This dissertation uses Aday and Andersen’s Framework for the Study of Access to Medical Care (1974) to define and contextualize how the outcomes assessed in this study are nested within the broader context of access to care.

Aday and Andersen’s Framework for the Study of Access to Medical Care (1974) was developed to define aspects of access to care and suggest how these aspects may be empirically measured. Although this widely used framework has undergone adaptations since it was first published, the five access concepts in this framework have remained in iterations of the model over time. This framework operationalizes access by delineating how (1) health policy can influence processes of care, including (2) characteristics of the health delivery system and (3) characteristics of the population at risk. These characteristics, in turn, can elicit changes in the outcomes of consumer (4) utilization of health services and (5) satisfaction with health services. Consumer utilization of and satisfaction with health services were later grouped into the single outcome of “realized access” (Figure 2.1) by Begley et al. in 2013.

In the simplest view, this framework describes how health policy directly affects characteristics of the health system and population, which, then, both directly affect realized

access to care, or the utilization of health services and consumer satisfaction. Subsequently, a health policy can then be thought of as indirectly affecting realized access to care, with this relationship mediated by the changes a health policy generates in the health delivery system or in the population at risk. The framework also suggests there is a direct relationship between the characteristics of the health delivery system and the characteristics of the population; this suggests that in addition to characteristics of the health system directly affecting realized access, health system characteristics can also indirectly affect realized access by a relationship mediated through the health system's effect on population characteristics. Lastly, there is a bidirectional relationship between the patient outcomes of utilization of health services and consumer satisfaction, meaning that as a consumer uses a health system, their satisfaction with the system is affected, which, in turn, influences their likelihood of future service use.

Figure 2.1: Aday and Andersen’s Framework for the Study of Access to Medical Care



Proposed Mechanisms of Increased Access based on NP SOP

This dissertation uses Aday and Andersen’s framework (1974) to consider mechanisms by which NP SOP policy effects access to care, with specific attention to how NP SOP influences the characteristics of the health delivery system and utilization of health services components of the framework. According to this framework, a health policy’s effect on a population’s realized access to care is partially mediated through the policy’s ability to change the characteristics of the health delivery system. Hence, these intermediary changes in characteristics of the health delivery system are mechanisms by which the policy ultimately affects realized access to care. Possible mechanisms that may explain how NP SOP affects

realized access to care include primary care provider productive capacity and primary care provider competition.

Primary Care Provider Productive Capacity

Martsof and Kandrack (2016) define productive capacity as the quantity, types, and quality of services that a provider can possibly produce, controlling for all other sources of service production, such as other providers or health information technology. Productive capacity includes how many patients a provider can see and how efficiently they can see them. NP SOP regulations may affect primary care provider capacity by increasing administrative burden on both NPs and physicians, and by increasing the costs associated with NP practice.

Restrictive SOP policies require physicians to supervise NPs for certain care activities. The increased administrative task burden associated with supervision may reduce the efficiency of care provision for both the physician and NPs by increasing time spent on administrative activities such as paperwork. Increased time spent on administrative activities takes away from time available to provide care and health services to patients. This additional time requirement may ultimately detract from the number of patients a single provider can serve. One study found that granting full NP SOP actually decreases physicians' administrative time by 45 minutes, increases the time physicians have for patient care by 3%, and increases the availability of appointments for patients by 5% (Traczynski & Udalova, 2018).

Although administrative tasks associated with physician supervision vary state to state, they can take the form of physicians having to be on-site when the NP is performing patient care, having to review and sign off on medical records the NP completes, or having to cross-consult on a proportion of the NP's patients. The physician is legally responsible for all medical acts outlined by the state-level NP SOP policy that require physician supervision. Notably, the degree

or quality of physician supervision is not consistent across practice sites or states, making it difficult to discern the value of physician supervision. Many states, like North Carolina, do not restrict the number of NPs a physician can supervise (North Carolina Board of Nursing, 2016). One study found that in Florida, some inexperienced NPs have no direct physician oversight while other NPs with 20 years of experience had extensive oversight (Rudner & Kung, 2017). For physicians, time spent supervising NPs decreases time available for patient care.

Similarly, for an NP, administrative tasks associated with physician supervision can detract from resources available for patient care. Administrative tasks for NPs include searching for a supervising physician within a given mile radius and having to wait for physician approval to perform select practice activities. In North Carolina, for example, the NP is required to file applications to the board of nursing and/or medicine for approval of the supervising physician each time the NP changes jobs or their previous supervisor decides to no longer supervise them. The NP cannot perform any patient care activities until this application is approved (North Carolina Board of Nursing, 2016). In a qualitative study of primary care providers in a state with restrictive NP SOP, NPs cited arbitrary or burdensome laws as barriers to practice (Kraus & DuBois, 2017). In areas with the worst physician shortages, NPs face heightened difficulty finding a physician to supervise them. This can lead to delays in NP provision of services in areas that are already facing increased needs for health care (Westat, 2015). One study found that implementing less restrictive NP SOP increased the supply of NPs the most in areas with the greatest physician shortages, with the size of the effect decreasing in areas with more physicians (McMichael, 2017b). Lastly, it is notable that in some states, NP SOP regulations prohibit NPs from performing certain care activities at all, regardless of physician supervision.

NP SOP may also influence primary care productive capacity by increasing the costs associated with NP practice. The increased administrative burden for NPs and physicians related to restrictive NP SOP regulations may pose additional administrative costs for an organization, taking away from capital that could be used to improve patient care (Martsolf & Kandrack, 2016). If a physician unexpectedly terminates supervision of an NP, the NP faces a gap in productive capacity to provide patient care and generate revenue until they find a new supervising physician (Westat, 2015). Also, physicians may require NPs to compensate them financially for their supervision, making it more difficult for an NP-led practices to remain financially viable or to care for publically insured or uninsured patients (Hain & Fleck, 2014).

Primary Care Provider Competition

By implementing full NP SOP policy, NPs have a pathway to become independent primary care providers, increasing provider competition between primary care NPs and primary care physicians. Increased provider competition in healthcare means there are a greater number of providers competing for business from a finite pool of consumers. This increased competition incentivizes providers to develop strategies to improve the quality and efficiency of their services so they can deliver higher quality care at lower costs (Dash & Meredith, 2010). Because restrictive SOP policies can serve as an anticompetitive barrier for primary care providers, removal of such policies may result in increased access to care. States with full NP SOP may have a more efficiently functioning primary care labor market that allows employers the opportunity to better optimize the most cost-effective and productive mix of providers, resulting in gains in increased output of primary care at lower costs of production (Markowitz & Adams, 2018).

Using the theory of economic regulation, occupational restrictions, such as restrictive SOP policies, have been hypothesized to protect the interest of a prevailing guild profession, like medicine, rather than the public (Blair & Durrance, 2015; Kleiner, 2015; Stigler, 1971). For example, one study found that less restrictive NP SOP policies resulted in lower prices of well-child visits, a perceivably positive outcome for population health, but also resulted in decreases in physician wages, a perceivably negative outcome for physicians (Kleiner, Marier, Park, & Wing, 2016). Similarly, another study found that increased task-specific occupational regulations for dental hygienists increased prices of basic dental services (Wing & Marier, 2014).

Because health delivery systems that are organized to maximize provider competition may expand choice, healthcare quality, efficiency, and costs, there is national attention on increasing competition in healthcare (Barros, Brouwer, Thomson, & Varkevisser, 2016; Bhattacharya, Hyde, & Tu, 2013; Dash & Meredith 2010; DHHS, 2018). The DHHS strategic objective 1.3 aims to improve the cost of care, availability of services, and culturally competent care by allowing individuals greater choice of how they access care. A key strategy to achieve this objective is to expand competition among health providers (DHHS, 2018). Similarly, the Federal Trade Commission also has a vested interest in targeting anticompetitive marketplaces for health providers (Iglehart, 2013).

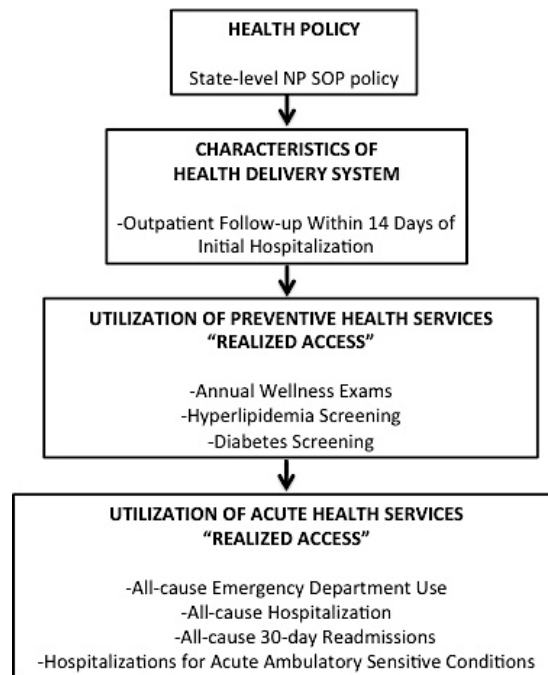
The relationship between NP SOP and provider competition has not been explicitly tested. However, given the evidence surrounding the benefits of provider completion, researchers have reflected on the implications of provider competition and NP SOP policy. Some propose that NP SOP policies may enable anticompetitive behavior, promoting barriers to entry, monopoly rents, and market division, resulting in decreased access (Kurtzman, Barnow, Johnson, Simmens, Infeld, & Mullan, 2017). Others theorize that full NP SOP may increase competition

between NPs and primary care physicians, possibly leading to the increased provision of primary care service when states implemented full NP SOP observed in their study (Tracynski & Udalova, 2018).

Theoretical Model for Proposed Study and Corresponding Hypotheses

The previous section of this chapter presented a limited portion of Andersen and Aday’s framework (1974) to consider how NP SOP affects the characteristics of the health delivery system and realized access to care. This model is further used to guide variable selection for Aim 1 and Aim 2. This dissertation measures characteristics of the health delivery system by assessing if individuals received an outpatient visit within fourteen days of their initial hospitalization. This dissertation measures realized access to care through utilization of the preventive services of annual wellness exams, hyperlipidemia screenings, and diabetes screenings (Figure 2.2).

Figure 2.2: Theoretical Framework for Proposed Study



The effect of a health policy on realized access can occur through changes in the characteristics of the health delivery system (Aday & Andersen, 1974). To explore this potential mechanism through which NP SOP may influence realized access to care, receipt of an outpatient visit within fourteen days of a hospitalization is used as a proxy for the characteristics of the health delivery system. If NP SOP policy affects the characteristics of the health delivery system by increasing primary care provider capacity and primary care provider competition, then outpatient care providers should increasingly be able to see patients for follow-up within two weeks of their hospitalization. Hence, this study assesses the effect of implementing full NP SOP on this characteristic of the health delivery system through Aim 1 and its corresponding hypothesis.

If implementing full NP SOP improves the characteristics of the health care system, then this improvement should contribute to changes in an individual's realized access to care as well (Aday & Andersen, 1974). The effect of a health policy on realized access may be captured by increased patient use of beneficial health services, like preventive services such as annual wellness exams and preventive screenings. If individuals increasingly receive preventive services in outpatient settings, the use of acute care services that often stem from poor primary care should decrease. Hence, the effect of a health policy on realized access may also be captured by a decrease use of acute care services, such as all-cause emergency department use, all-cause hospitalization, all-cause 30-day readmissions, and hospitalizations for ambulatory care sensitive conditions. Hence, this study assesses the impact of implementing full NP SOP on realized access to care through Aim 2 and its corresponding hypotheses.

Chapter Summary

This dissertation uses Andersen and Aday's framework (1974) to contextualize how the outcomes measured in this study are nested within the broader context of access to care. In this chapter, a widely used access to care theory is presented and used to delineate the multifaceted components of access to care. Furthermore, mechanisms through which NP SOP policy may affect access to care are considered. Ultimately, the access to care framework and potential mechanisms are used to develop the theoretical framework used to guide the aims of this study. In chapter 3, a systematic review of the literature assessing the relationship between NP SOP policy and access to care, categorized by Aday and Andersen's framework (1974) is presented.

CHAPTER III: REVIEW OF LITERATURE

Overview of Systematic Review on Effect of NP SOP and Access to Care

Despite the heated debate surrounding implementation of full NP SOP policy in all U.S. states to increase access to care, a synthesis of studies assessing the relationship between NP SOP and access is not available to guide research, practice, and policy decisions. To date, the only systematic review that examines the effect of NP SOP policy on various aspects of care, including access, identified a single article as addressing access to care, possibly due to a restrictive definition of access to care (Xue et al., 2016). A more substantive understanding of the relationship between state-level NP SOP policy and access to care is needed. To begin addressing this need, a systematic review of empirical studies assessing the relationship between NP SOP and access to care, operationalized by Aday and Andersen’s Framework for the Study of Access (1974), was conducted in August 2017 (Table 3.1) (Patel, Petermann, Mark, 2018). This framework was also used to map components of access that relate to NP SOP policy through concepts and relationships identified in the review.

Table 3.1: Operationalizing Aday and Andersen’s Access Concepts for use in this Review

Access to Care Concept	Operational Definition: <i>How the health policy of state-level NP SOP has implications on:</i>	
Characteristics of Health Delivery System	Processes of care	Workforce resources and the organization of these resources.
Characteristics of Population at Risk		Specific populations, especially traditionally underserved populations.
Utilization of Health Services	Patient- (or population-) level outcomes of care	The level and pattern of patient use of health care services.
Consumer Satisfaction		Patient reported satisfaction with available health services, including convenience, costs, coordination, courtesy, information, and quality.

The results of the systematic review revealed that less restrictive state-level NP SOP was associated with greater access to care compared to states with more restrictive NP SOP policies. The review also revealed that, to date, the majority of studies that evaluated the impact of state-level NP SOP restriction on access use retrospective cross-sectional designs by comparing states with and without NP SOP restrictions. These studies failed to estimate the causal relationship between NP SOP policy and access and were biased by difficulties controlling for the differences between states and changes in access over time. Furthermore, most previous studies do not use theory to address the multifaceted components of access to care.

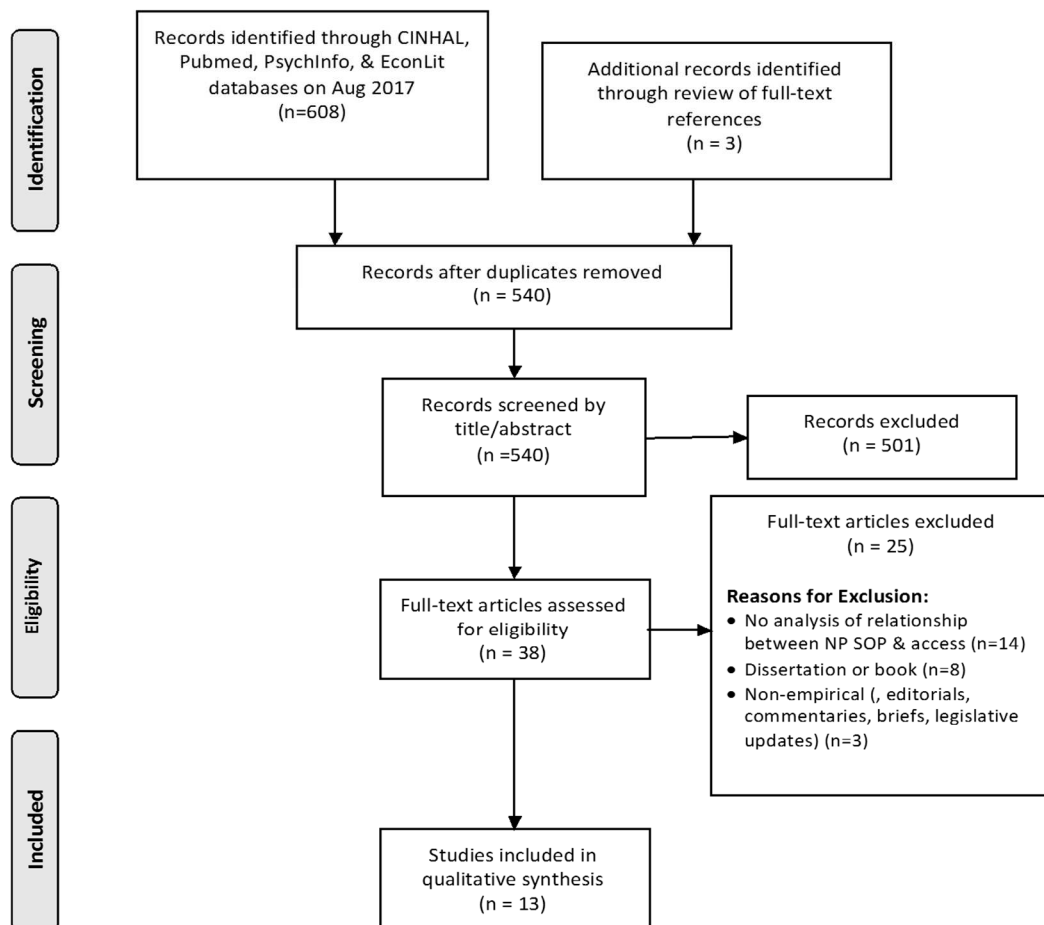
Systematic Review Methods

A systematic literature review was conducted following the seven steps for research synthesis outlined by Cooper (2016). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was followed for analysis and presentation of data from all stages of review (Moher, Liberati, Tetzlaff, & Altman, 2009).

Our research purpose was formulated through a preliminary review of the literature and other reports, and through round table discussion with researchers with experience studying the healthcare workforce and access to care. A health sciences librarian was consulted to strengthen our search strategy. We searched the electronic databases The Cumulative Index to Nursing & Allied Health Literature (CINAHL), Pubmed, PsychInfo, and EconLit for all empirical studies published from database conception – August 2017 using the following keywords search strategy: ("advanced practice registered nurse" or "advanced practice nurs*" or "nurse practitioner" or "aprn" or "apn" or "np") AND ("scope of practice" or "legislat*" or "regulat*" or "policy") AND ("access*"). Peer reviewed quantitative and qualitative studies that reported empirical findings related to NP SOP policy and any of the access concepts, as defined by Aday

and Andersen’s Framework (1974), and were written in English were included for full review. The references of selected articles were scanned for additional relevant articles. Articles that did not explicitly address the relationship between NP SOP policy and access to care were excluded. Studies conducted outside of the U.S. were also excluded since the state-level NP SOP policies being assessed are unique to U.S. healthcare regulation. Two authors blindly and independently screened all studies for eligibility at both the title/abstract and full text review stage using Covidence systematic review software (Melborne, Australia). Disagreements in screening were resolved by consensus. Our search strategy is presented in Figure 3.1.

Figure 3.1: PRISMA flow diagram



A standardized data extraction template was used to collect data on the research purpose, theoretical framework, study design, setting, demographics, methods, data collection, results, and quality. The quality of studies was considered based on select criteria from quality appraisal guidelines from the National Institute of Health, including: participant sampling criteria, sample size justification, effect size calculation, study design, and loss to follow-up (National Heart Lunch and Blood Institute, 2014). Studies were not excluded a priori based on quality in this review due to a limited number of studies conducted that addressed our purpose. Two authors independently extracted 15% of articles to reach consensus on types and depth of information extracted. A single author extracted the remainder of articles with secondary approval of information extracted from another author. Disagreements were resolved by consensus. After all data were extracted, results were collectively analyzed, categorized, and presented by common themes and conclusions, guided by access concepts outlined in Aday & Andersen's Framework (1974).

Results of Systematic Review

Characteristics of Studies Included in Review

The search yielded 608 studies, of which 38 full-text articles were reviewed, and 13 articles met all inclusion criteria for this review. Study characteristics and measures of NP SOP policy and access to care are described in Table 3.2. All studies used retrospective cross-sectional study designs. Three studies assessed repeated cross-sections over time (Kurtzman et al, 2017; Kuo, Loresto, Rounds, & Goodwin, 2013; Stange, 2014). All studies used secondary data, except one that analyzed primary data collected through a survey (Poghosyan, Shang, Liu, Poghosyan, Liu, & Berkowitz, 2015). In nine articles, a framework was used to guide the study. However, only three of these studies used a theoretical framework to specifically conceptualize

access to care (Cross & Kelly, 2015; Sonenberg, Knepper, & Pulcini, 2015; Sonenberg & Knepper, 2017).

The unit of analysis in studies ranged from insurance beneficiaries, providers, practices, provider-patient visits, and health service areas. Participants from five studies were Medicare and/or Medicaid beneficiaries (Cross & Kelly, 2015; DesRoches, Gaudet, Perloff, Donelan, Iezzoni, & Buerhaus, 2013; Mobley, Subramanian, Tangka, Hoover, Wang, Hall, & Singh, 2016; Reagan & Salsberry, 2013; Kuo et al, 2013). A national sample was used in nine studies. Ten studies examined access to primary care services, while others implied examination of primary care services (Oliver, Pennington, Revelle, & Rantz, 2014), examined community health centers (Kurtzman et al., 2017), or examined facilities with mammography services (Mobley et al., 2016).

Table 3.2: Characteristics of Studies From Systematic Review

Study	Theoretical Framework	Study Design & Participants	Geographic & Practice Setting	Measure for APRN SOP & Data Source	Measure for Access to Care & Data Source
1. Barnes et al. (2016)	Author defined framework of NP SOP and NP Medicaid reimbursement policies impacting NP PC practice	Retrospective, Cross-sectional 252,657 practices	National PC & specialty care	<ul style="list-style-type: none"> • Full NP SOP (least restrictive states) • Without full NP SOP (restrictive to most restrictive states combined) <p>Kuo et al., 2013 categories</p>	<ul style="list-style-type: none"> • Odds that an individual NP works in PC vs. specialty practice • Whether the practice accepts Medicaid <p>SK&A physician and NP/PA files</p>
2. Cross & Kelly (2015)	Aday and Andersen's Theoretical Framework for Measuring Access to Medical Care (1974)	Retrospective, Cross-sectional 15,027 Medicare beneficiaries	National PC	<ul style="list-style-type: none"> • Full • Reduced • Restricted <p>AANP</p>	<p>Patient-reported:</p> <ul style="list-style-type: none"> • Usual source of care • Appointment wait times • Difficulties with access and cost <p>MCBS</p>
3. Des-Roches et al. (2013)	NI	Retrospective, Cross-sectional 959,848 Medicare FFS beneficiaries	National PC	<ul style="list-style-type: none"> • SOP based on various dimensions including physician oversight and prescribing (<i>specific categories NI</i>) <p>2012 Pearson Report</p>	<ul style="list-style-type: none"> • Geographic distribution of NPs <p>Medicare administrative claims</p>
4. Graves et al. (2016)	NI	Retrospective, Cross-sectional 149,784 MDs, 149,784 NPs, 94,209 PAs, & 1,336 CNMs	National PC	<ul style="list-style-type: none"> • Full • Reduced • Restricted <p>Institute of Medicine and National Council of State Boards of Nursing</p>	<ul style="list-style-type: none"> • % of population in low-, medium-, and high-accessibility areas • Number of geographically accessible PC MDs, NPs, and PAs per 100,000 population • Number of uninsured by provider type <p>ARF, US Census Bureau County</p>
5. Kuo et al. (2013)	NI	Retrospective, Cross-sectional time series 5% sample of Medicare beneficiaries	National PC	<ul style="list-style-type: none"> • Most analyses divided into: 1. Independent practice and prescription authority 2. Independent practice but requiring supervision for prescription, or 3. Requiring physician supervision for practice and prescription <p>Some analyses divided into 5 levels defined by experts</p>	<ul style="list-style-type: none"> • Odds of having an NP as the PC provider • Estimated number of NPs per 100,000 state residents <p>Medicare beneficiary claims</p>
6. Kurtzman et	Economic Theory	Retrospective, Repeated cross-	National	<ul style="list-style-type: none"> • Full practice independence vs. not full practice independence 	<ul style="list-style-type: none"> • Quality Indicators: (smoking, depression, hyperlipidemia)

al. (2017)		sectional 6,498 NP-patient visit units	Community Health Centers	<ul style="list-style-type: none"> • Full prescriptive independence vs. not full prescriptive independence <p>The Nurse Practitioner Journal</p>	<p>management)</p> <ul style="list-style-type: none"> • Service Utilization: (Physical exam, education and counseling, imaging, medication) • Referral Patterns: (return visits, referral to MD)
7. Mobley et al. (2016)	Author created framework of multilevel modeling of person, county, and state-level factors	Retrospective Cross-sectional 2,450,527 Medicaid enrollees	25 States with adequate data Mammography facilities	<ul style="list-style-type: none"> • Expanded • Restrictive <p>The National Conference of State Legislatures</p>	<p>NAMCS Community Health Center</p> <ul style="list-style-type: none"> • Mammography use in a 3 year period <p>Medicaid FFS and managed care claims from 25 states</p>
8. Poghosyan et al. (2014)	Katner's Theory of Structural Power (1976)	Retrospective, Cross-sectional survey 291 NPs from MA; 278 NPs from NY	Massachusetts (MA) & New York (NY) PC	<ul style="list-style-type: none"> • MA – NPs can independently treat and diagnose, but physician collaborative agreement required to prescribe • NY– Physician collaborative agreement required for NP treatment, diagnosis, and prescription 	<p>Primary data on practice environment and characteristics collected using the Nurse Practitioner Primary Care Organizational Climate Questionnaire</p>
9. Oliver et al. (2014)	NI	Retrospective, Cross-sectional Medicare-Medicaid beneficiaries – <i>total number NI</i>	National <i>Implies PC, but NI</i>	<p>The Pearson Report</p> <ul style="list-style-type: none"> • Full • Reduced • Restricted <p>AANP</p>	<ul style="list-style-type: none"> • Avoidable hospitalizations • Readmission rates after inpatient rehabilitation • Nursing home resident hospitalizations • State overall health outcomes
10. Reagan & Salsberry (2013)	Economic Theory	Retrospective, Cross-sectional 715 health service areas	National PC	<ul style="list-style-type: none"> • No restriction • Intermediate restrictions • Most restrictive practices <p>Pearson Report 2008</p>	<p>4 previously collected sets of data</p> <ul style="list-style-type: none"> • Number of NPs per 100,000 population • Change in numbers of NPs between 2001 and 2008 • Growth rate in NPs for those HSAs that had a positive number of NPs
					ARF and Pearson Report

11. Sonenberg et al. (2015)	Aday, Begley, Lairson, and Slater Framework of Structure, Process, Outcomes (1998)	Retrospective Cross-sectional 50 states – <i>number of individuals/state NI</i>	National PC	<ul style="list-style-type: none"> State practice act language, prescription supervision, primary care case management, workers compensation, diagnosis and treatment, Modified Sekscensky Index 	<ul style="list-style-type: none"> Number of NPs licensed to practice per 100,000 population Health Outcomes: obese, diabetic, heart disease deaths per 100,000, hypertension
12. Sonenberg et al. (2017)	Social Ecology Theory (1947), Theory of Fundamental Causes (2010), Linking Social Capital Theory (2004), and Triple aim (2008).	Retrospective Cross-sectional 4 states – <i>number of individuals/state NI</i>	Alabama (AL), Colorado (CO), Mississippi (MI), Utah (UT) PC	<ul style="list-style-type: none"> AANP, Pearson Report, National Center for Health Workforce Analysis, Kaiser State Health Facts Least restrictive NP SOP laws: CO, UT Most restrictive NP SOP laws: AL, MS <p>American Journal of Nurse Practitioners</p>	<p>AANP, CDC Prevalence and Data Trends, National Vital Statistics Report</p> <ul style="list-style-type: none"> Select measures include: Population demographics, health professional shortage areas, number of NPs per 100,000 residents, number of NPs per 100,000 uninsured residents
13. Stange (2014)	Economic Theory	Retrospective Cross-sectional time series 803,200 Office-based visits; 293,100 person sample	23 (1996) - 35 (2008) U.S. states based on availability of data PC & specialty care	<ul style="list-style-type: none"> Practice index based on practice environment for NPs and PAs in 2000 and index ranks of physician oversight, prescriptive authority, and reimbursement policies. 2004 HRSA files 	<p>HRSA ARF</p> <p>Provider supply on:</p> <ul style="list-style-type: none"> Usual source of care Number of office based visits Use of preventative services <p>Dataset assembled by author; includes state licensing records, ARF, and MEPS</p>

Abbreviations: AANP American Association of Nurse Practitioners; APRN advanced practice registered nurse; ARF Area resource files; CDC Centers for Disease Control; FFS fee-for-service; HRSA Health Resources and Services Administration; HSA health service area; MCBS Medicare Current Beneficiaries Survey; MEPS Medical Expenditure Panel Survey; NAMCS National Ambulatory Medicare Care Survey; NI not included; NP nurse practitioner; PC primary care; SOP scope of practice

Since all but one study used a retrospective cross-sectional design, study quality was appraised and discussed based on applicable criteria from the *Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies* (National Heart Lung and Blood Institute, 2014). Studies were considered of higher quality if they had a national sample, provided a justification for sample size, calculated sample size, calculated effect size, analyzed data at multiple time points, and had a missing data rate of <50% (Table 3.3). Two studies did not use a national sample because they limited their sample to states based on state-level quality of data or data availability (Mobley et al., 2016; Stange, 2014). Two other studies did not use a national sample and focused on comparisons between two and four states, respectively (Poghosyan, Shang, Liu, Poghosyan, Liu, & Berkowitz, 2014; Sonenberg et al., 2017). All studies contained contextual description of their sample, but only one study provided calculations of effect size or sample size (Poghosyan et al., 2015). All studies used cross-sectional designs, but three used a repeated cross-sectional time series design in which data at multiple time points were considered (Stange, 2014; Kuo et al., 2013; Kurtzman et al., 2017). One study had significant amounts of data missing, with results based on only 3% of participants providing data on usual source of care and 1% of participants providing data on wait times (Cross & Kelly, 2015). Three studies were conceptually weighted less heavily when synthesizing conclusions about relationships between state-level NP SOP and access due to assessment of four or less states (Poghosyan et al., 2015; Sonenberg et al., 2017) and concerns about missing data (Cross & Kelly, 2015).

Table 3.3: Quality of Studies in Systematic Review*

Study	National Sample	Justification for Sample Size	Calculation of Effect Size	Data at Multiple Time Points	Lack of Significant Missing Data
Barnes et al. (2016)	Yes	Yes	No	No	Yes
Cross & Kelly (2015)	Yes	Yes	No	No	No
DesRoches et al. (2013)	Yes	Yes	No	No	Yes
Graves et al. (2016)	Yes	Yes	No	No	Yes
Kuo et al. (2013)	Yes	Yes	No	Yes	Yes
Kurtzman et al. (2017)	Yes	Yes	No	Yes	Yes
Mobley et al. (2016)	No	Yes	No	No	Yes
Poghosyan et al. (2014)	No	Yes	Yes	No	Yes
Oliver et al. (2014)	Yes	Yes	No	No	Yes
Reagan & Salsberry (2013)	Yes	Yes	No	No	Yes
Sonenberg et al. (2015)	Yes	Yes	No	No	Yes
Sonenberg et al. (2017)	No	Yes	No	No	Yes
Stange (2014)	No	Yes	No	Yes	Yes

*Appraised from NHLBI National Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies

The results were categorized into four access to care themes based on Aday and Andersen's Framework (1974): (1) characteristics of the health delivery system, (2) characteristics of the population at risk, and patient level outcomes of (3) utilization of health services and (4) consumer satisfaction with health services. Study results are detailed in Table 3.4. Since categorization of NP SOP varied throughout studies in this review, we standardized reporting and discussing NP SOP categories as least to most restrictive (Figure 1.1).

Table 3.4: Systematic Review Results by Access to Care Theme

Study	Significance: p-value * <0.05 ** <0.01 , *** <0.001 , **** <0.0001			
	Results: characteristics of health delivery system (n=8)	Results: characteristics of population at risk (n=5)	Results: utilization of services (n=4)	Results: patient satisfaction with care (n=2)
1. Barnes et al. (2016)	<ul style="list-style-type: none"> • More NPs working in PC vs. specialty care in states that had policies for both full NP SOP & 100% NP Medicaid reimbursement * • Fewer NPs working in PC vs. specialty care in states without policies for 100% NP Medicaid reimbursement* or policies for both full NP SOP and 100% NP Medicaid reimbursement** • No difference in number of NPs working in PC vs. specialty care in states with full NP SOP policy but not 100% Medicaid reimbursement policy 	<ul style="list-style-type: none"> • Practices were more likely to accept Medicaid if an NP was present and had either or both full NP SOP or 100% Medicaid reimbursement policies*** 		
2. Cross & Kelly (2015)				<ul style="list-style-type: none"> • Usual source of care not affected by SOP • Wait times higher in states with full vs. reduced or restricted NP SOP** • More difficulties accessing care in states with full vs. reduced SOP* • Fewer difficulties with cost in full vs. reduced or restricted NP SOP states*
3. DesRoches et al. (2013)	<ul style="list-style-type: none"> • Higher ratios of NPs billing Medicare for fee-for-service beneficiaries in states with least restrictive SOP† 			
4. Graves et al. (2016)	<ul style="list-style-type: none"> • Greater PC NPs per 100,000 population in states with full vs. restrictive SOP* • Greater PC NPs per 100,000 population in rural counties in states with full vs. restrictive SOP 	<ul style="list-style-type: none"> • States with less restrictive SOP had up to 40% more PCNPs in some areas, but no significant difference in the share of overall population in low-accessibility areas across SOP categories • PC NPs and PAs were the largest shares of the PC workforce in rural areas of states with full NP SOP and the smallest share in urban areas of states with reduced and restricted NP 		

SOP

5. **Kuo et al. (2013)**
- Greatest increase in number of NPs per 100,000 residents was in states with least restrictive SOP requirements*
 - Patients in states with the least restrictive SOP had a greater odds of having an NP as their PC provider*

6. **Kurtzman et al. (2017)**
- Independent prescription associated with increased likelihood of NP-visits including health education and medication use*, and MD-visits including health education**
 - Independent practice associated with increased incidence of MD-visits including depression treatment**, and likelihood of NP-visits resulting in physician referral**

7. **Mobley et al. (2016)**
- Patients in states with expanded vs. restrictive SOP had enhanced odds of mammography use in both urban and rural areas*

8. **Poghosyan et al. (2014)**
- NPs in MA vs. NY reported better practice environments*
 - More NPs in MA vs. NY worked in community health centers ***
 - More NPs in MA vs NY worked in rural locations***

9. **Oliver et al. (2014)**
- Decreased rates of avoidable hospitalization and readmission within 30 days of discharge for beneficiaries in states with full vs. without full NP SOP ***
 - Decreased rates of annual hospitalization for beneficiaries in nursing homes in states with full vs. without full NP SOP .

10. **Reagan & Salsberry (2013)**
- More NPs per 100,000 population and greater growth rate of NPs in states with least vs. most restrictive SOP***
 - More per capital NPs in states with least vs. most restrictive SOP****
 - No difference in number of NPs between states with intermediate vs. most
 - % of population in poverty not affected by SOP
 - Lower uninsurance rates in states with least vs. most restrictive SOP***

	restrictive SOP • Growth in number of NPs (2001-2008) was > 100% no SOP restrictions, 92% in intermediate SOP, and 73% restrictive SOP states†		
11. Sonenberg et al. (2015)	• No association between SOP and number of NPs licensed to practice per 100,000 population		
12. Sonenberg et al. (2017)	• Fewer NPs per 100,000 residents and uninsured residents in CO & UT vs. MS† • Greater ratio of funding to number of rural health clinics in CO & UT vs. AL & MS† • Fewer practitioners needed to remove health professional shortage area designations in CO & UT vs. AL & MS†	• Lower % of population in rural settings, <200% of poverty limit, unemployed, uninsured, have Medicaid, and have Medicare in CO & UT vs. AL & MS † • Higher % of population that is a minority in CO & UT vs. AL & MS†	• Lower % of adults reporting not seeing a doctor due to costs in CO & UT vs. AL & MS†
13. Stange (2014)			• Greater supply of NPs alone did not affect health care utilization • PC utilization was responsive to NP provider supply in areas that grant non-physician clinicians the least restrictive SOP ** • Expansions in NP prescriptive authority was associated with increases in patient care utilization**

Table 3.4: NP SOP results in this table are presented in context of how NP SOP was measured in parent study, but were standardized and discussed as least versus most restrictive in the results section of this review.

Abbreviations: AANP American Association of Nurse Practitioners; ARF Area resource files; HRSA Health Resources and Services Administration NI not included; MD medical doctor; NP nurse practitioner; PA physician assistant; PC primary care; SOP scope of practice – *refers specifically to state-level NP SOP policy*; Vs. versus; † Statistical significance not assessed

† Statistical significance not assessed

Relationship Between NP SOP and Characteristics of the Health System

Eight studies addressed the relationships between NP SOP policy and the characteristics of the health delivery system by addressing characteristics of the NP workforce (Barnes, Maier, Altares, Sarik, Germack, Aiken, & McHugh, 2016; Desroches et al., 2013; Graves, Mishra, Dittus, Parikh, Perloff, & Buerhaus, 2016; Kuo et al., 2013; Poghosyan et al., 2015; Reagan & Salsberry, 2013; Sonenberg et al., 2015; Sonenberg et al., 2017). NPs were more likely to work in primary care, bill Medicare, or practice in states with the least restrictive NP SOP policies (Barnes et al., 2016; DesRoches et al., 2013; Graves et al., 2016; Reagan & Salsberry, 2013; Kuo et al., 2013). Furthermore, there was more growth in the number of NPs in states with the least restrictive SOP policies (Reagan & Salsberry, 2013; Kuo et al., 2013). Lastly, patients in states with the least restrictive NP SOP policies were more likely to have an NP as their primary care provider (Kuo et al., 2013). The results of most studies showed a positive association between less restrictive NP SOP policy and NP workforce capacity. However, Sonenberg et al. (2015) reported no significant association between NP SOP policy and number of NPs licensed to practice per 100,000 population. And, Sonenberg et al. (2017) reported more NPs per 100,000 residents in a state with more restrictive NP SOP policies compared to two states with less restrictive NP SOP policies.

Other studies examined relationships between state-level NP SOP policy and the characteristics of the NP workforce including the relative balance of specialty and primary care provided by NPs and variations in NP reported practice environments by state NP SOP policy. One study examined the impact of NP SOP policy on the NP workforce for primary care versus specialty care. This study reported that NPs were more likely to work in primary care versus specialty care in states with both full NP SOP and 100% Medicaid reimbursement policies;

however, this difference did not hold in states with full NP SOP but without 100% Medicaid reimbursement policies (Barnes et al., 2016). Finally, when comparing two states with differing NP SOP policies, NPs in the state with the less restrictive NP SOP policy reported better practice environments (Poghosyan et al., 2015).

Relationship Between NP SOP and Characteristics of the Population at Risk

Five studies addressed the relationships between NP SOP policy and the characteristics of the population at risk, including the underserved populations of Medicaid beneficiaries and patients living in rural and high-poverty locations (Barnes et al., 2016; Graves et al., 2016, Poghosyan et al., 2015; Reagan & Salsberry, 2013; Sonenberg et al., 2017). Some studies report that in states with the least restrictive NP SOP policies, NPs were more likely to work in primary care, provide care in rural and high-poverty areas, and accept Medicaid (Barnes et al., 2016; Graves et al., 2016). Another study reports that a state with a less restrictive NP SOP policy has more NPs working in community health centers and in rural locations (Poghosyan et al., 2015) than a comparison state with a more restrictive NP SOP policy. Another study reported there was a lower percent of the population that was <200% of the federal poverty limit, unemployed, uninsured, publically insured, or living in a rural setting, in two states with less restrictive versus two states with more restrictive NP SOP policies (Sonenberg et al., 2017). In contrast, one study found that although states with less restrictive SOP had up to 40% more primary care NPs in some areas, there was no significant difference in the share of overall population in low-accessibility areas across SOP categories. The authors suggested that this may be due to the socioeconomic environment negatively impacting provider reimbursement (Reagan & Salsberry, 2013).

Relationship Between NP SOP and Utilization of Health Services

Four studies addressed the relationships between NP SOP policy and the patient- or population-level outcomes of utilization of health services. Utilization was assessed by proportion of patients receiving a referral to another provider, receiving health education services, receiving preventive services, and avoiding hospitalizations and 30-day readmissions (Kurtzman et al., 2017; Mobley et al., 2016; Oliver et al., 2014; Stange, 2014). There was greater use of preventive services and decreased rates of avoidable hospitalizations, hospital readmissions within 30 days discharge from rehabilitation, and hospitalizations of nursing home patients in states with the least restrictive NP SOP policies (Mobley et al., 2016; Oliver et al., 2014; Stange, 2014). One study reported that only some components of full NP SOP policy were associated with increased likelihood of a patient visit to an NP including health education services and prescription of a medication. This study also reported an increased likelihood of patients receiving a referral to a physician from an NP at Community Health Centers in states with SOP policies that allow NPs to practice without physician supervision (Kurtzman et al., 2017). Finally, Stange (2014) reported that a larger supply of NPs, without considering other state and patient level factors, did not significantly affect healthcare utilization.

Relationship Between NP SOP and Patient Satisfaction with Care

Two studies in this review assessed patient satisfaction with care as indicated by patient reported usual source of care, wait times, difficulties accessing care, and difficulties with cost of care (Cross & Kelly, 2015; Sonenberg et al., 2017). While one study reported a smaller percentage of the population not seeking care due to costs in two states with less restrictive versus two other states most restrictive NP SOP policies (Sonenberg et al., 2017), contradictory findings from another study reported increased patient difficulties with cost in states with the

least restrictive NP SOP policies (Cross & Kelly, 2015). This study also found that patient satisfaction with usual source of care and wait times was worse in states with the least restrictive NP SOP policies (Cross & Kelly, 2015).

Results of Review Conceptualized by Aday and Andersen's Framework (1974)

Aday and Andersen's Framework (1974) was used as a novel approach to map components of access to care that may relate to NP SOP policy through concepts and relationships identified in this review (Figure 3.2). The components of access to care related to NP SOP policy were determined through the results of this review. Possible relationships between these components of access were considered through the original relationships between concepts in Aday and Andersen's framework (1974). The relationships between the components of access to care were conceptual and not necessarily tested by the studies in this review. Figure 1.5 applies the review findings to Aday and Andersen's Framework (1974) to map components of access to care related to NP SOP policy. By considering what components of access to care relate to NP SOP policy and the relationships between these components, future work can begin assessing the underlying mechanism for how state-level NP SOP policy affects access to care.

Figure 3.2: Results of Review Conceptualized by Aday and Andersen’s Framework for the Study of Access to Medical Care (1974)

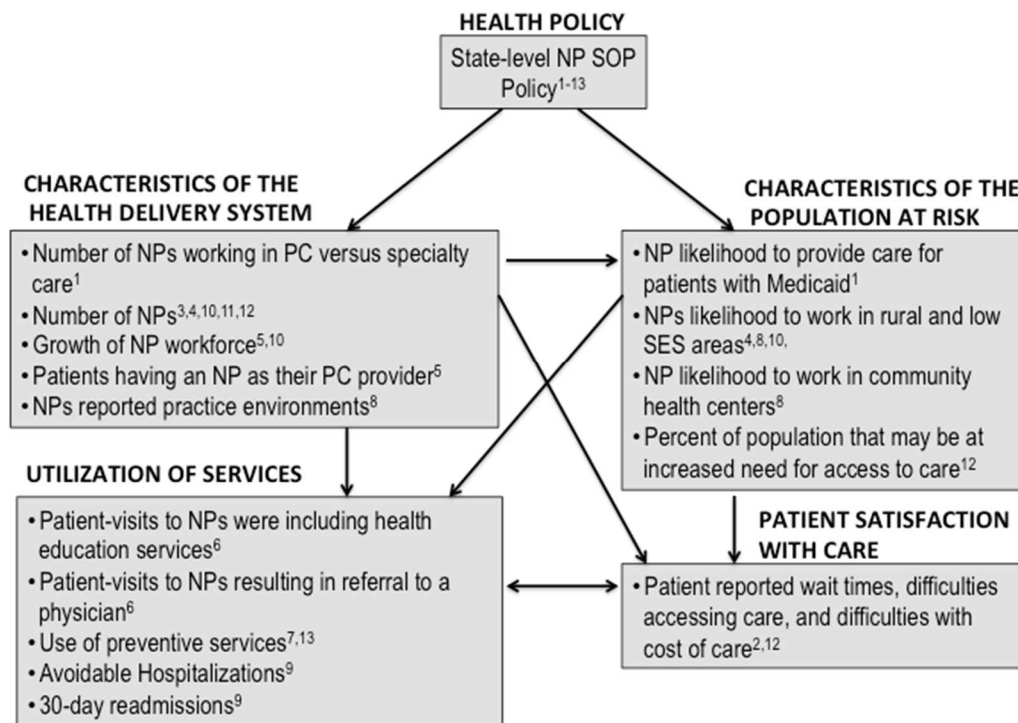


Figure 3.2: Bullets represent variables found from review of literature that aligned with concepts in this framework were mapped accordingly. 1. Barnes et al. (2016) 2. Cross & Kelly (2015) 3. DesRoches et al. (2013) 4. Graves et al. (2016) 5. Kuo et al. (2013) 6. Kurtzman et al. (2017) 7. Mobely et al. (2016) 8. Poghosyan et al. (2015) 9. Oliver et al. (2014) 10. Reagan & Salsberry (2013) 11. Sonenberg et al. (2015) 12. Sonenberg et al. (2017) 13. Stange (2014)

Abbreviations: NP nurse practitioner; PC primary care; SES socioeconomic; SOP scope of practice

All components of Aday & Andersen’s Framework (1974) are addressed by the studies in this literature review, suggesting that this body of research is capturing the multifaceted definition of access. Further analyzing the results jointly through the framework demonstrated that although there are 13 studies assessing the impact of NP SOP policy on access to care, these studies individually addressed different concepts of access. Although eight studies assessed the impact of NP SOP policy on characteristics of the health delivery system, the impact of NP SOP policy on patient satisfaction with care was largely understudied. Future work should place emphasis on assessing the more understudied aspects of access to care.

Lastly, the relationships between components of access to care outlined in Aday and Andersen's framework (1974), offer an opportunity to consider relationships between multiple components of access to care in future studies. For example, future work may consider the "characteristics of population at risk" as a moderator between the impacts of health policy on patient utilization of health services. Since NPs may be more likely to care for traditionally underserved population, the impact of increasing the NP workforce may have a greater effect on access to care for these populations than for others.

Discussion of Systematic Review

This review is the first to review to assess the relationship between state-level NP SOP policy and access to care and to use Aday and Andersen's Framework (1974) to broadly conceptualize and apply a multifaceted definition of access. This review adds to the understanding of how NP SOP policy is associated with access to care and can be used to guide further research and policy efforts surrounding state-level NP SOP policy.

The relationship between NP SOP policy and the characteristics of the health delivery system, primarily the NP workforce, was the aspect of access to care most studied in this review. Most studies that assessed the impact of NP SOP policy on the NP workforce found that less restrictive NP SOP policy was associated with a greater number of NPs or growth of NPs (Barnes et al., 2016; DesRoches et al., 2013; Graves et al., 2016; Kuo et al., 2013; Reagan & Salsberry, 2013). This may perhaps be due to NPs reporting better practice environments in states with less restrictive NP SOP policies (Poghosyan et al., 2014). Studies that did not support this association acknowledged that their study design was limited by using a state-level unit of analysis (Sonenberg et al., 2015) or that their study was not generalizable because they compared four select states (Sonenberg et al., 2017). Collectively, studies assessing the impact of NP SOP

policy on the NP workforce provide evidence that less restrictive NP SOP is positively associated with characteristics of the health delivery system related to the NP workforce.

A recent review on factors that affect the NP workforce's potential in reducing health disparities supports that restrictive state-level NP SOP policy may limit an NP's contribution to reducing health disparities (Poghosyan & Carthon, 2017). Unfortunately, there were few studies that addressed whether NP SOP policy is related to the characteristics of the population at risk, and some studies had conflicting results. The difference in results may be attributed to greater statistical power to detect differences in studies with more micro- versus macro-level unit of analyses due to differences in sample size and standard deviations (Li & Dai, 2013). For example, Reagan & Salsberry (2013) examined health service areas as their unit of study, while Barnes et al. (2016) and Graves et al. (2016) examined practice sites and providers, respectively.

One study reported fewer socioeconomic and health disparities in two states with less versus two states with more restrictive NP SOP policies (Sonenberg et al., 2017). Although it is possible that the socioeconomic and health differences in states with and without full NP SOP policy are related to the policy itself, it is also possible that states with fewer disparities were more likely to allow full NP SOP policy. If the former is correct, it builds a case for less restrictive NP SOP policies to reduce socioeconomic and health disparities. If the latter is correct, future work should assess why states that had better socioeconomic and health outcomes were the ones choosing to have full NP SOP in their state. Ultimately, there is insufficient evidence from this review on the impact of NP SOP policy on care for underserved populations, highlighting a need for additional studies that examine this relationship.

Utilization of primary care services was greater (Kurtzman et al., 2017; Mobely et al., 2016; Stange, 2014), and utilization of acute health services was lower in states with less restrictive NP SOP policies (Oliver et al., 2014), providing some evidence of a relationship between less restrictive NP SOP policies and utilization of health services. These findings are consistent with evidence that suggests that increased market competition is associated with higher quality over time (Rivers & Glover, 2008). The relationship between increased competition and improved quality could explain why Kurtzman et al. (2017) found that some aspects of physician-delivered care in Community Health Centers, like depression treatment, was better in states with less restrictive NP SOP policies. Furthermore, these findings may be a result of decreased administrative burden on physicians in states with less restrictive NP SOP policy, increasing time available for patient care (Traczynski & Udalova, 2018).

A critique of removing NP physician supervision requirements is that it may result in increased utilization of patient referrals to MDs by NPs (Isaacs & Jellinek, 2013). Kurtzman et al. (2017) found that patient-visits to NPs in in states with less restrictive NP SOP were more likely to result in referrals to physicians; they suggest this may be due to NPs in full NP SOP states having fewer resources and therefore relying more heavily on referral networks, NP uncertainty when physician supervision is unavailable, or NP fear of liability or malpractice. It is also possible that the increase in referrals to MDs is a necessary secondary outcome of NPs caring for more complex patients in states with full NP SOP policies. Ultimately, the rationale for why there may be increased referrals to MDs, and whether this reflects inefficacies versus necessities in care delivery, remains unclear and merits further investigation.

Although other studies report high patient satisfaction with care delivered by NPs (Stanik-Hutt et al., 2013), there was insufficient evidence available from this review on the

relationship between NP SOP policy and patient satisfaction with convenience, coordination, and cost of care. Patient satisfaction with care was the least studied aspect of access to care found in this review and the two studies that addressed this relationship were considered lower quality because they contained significant amounts of missing data and only assessed two states, respectively (Cross & Kelly, 2015; Sonenberg et al., 2017). The results of these studies also contradicted one another. For these reasons, additional evidence is needed to make conclusions on if NP SOP is related to patient satisfaction with care.

Although the results of this study generally support that less restrictive NP SOP is positively associated with select aspects of access to care, additional evidence is required. We were unable to make conclusions of effect of NP SOP policy on access to care since most studies in this review evaluated associative, not causal relationships. A greater use of longitudinal and natural experimental designs, understanding of the mechanism by which NP SOP policy affects access, and use of access theories to broadly study NP SOP's effect on multiple aspects of access are needed to enhance conclusions about the relationship between NP SOP and access.

This review is limited by lack of inclusion of the so-called “grey” literature and lack of assessment of patient health outcomes. Although we found relevant white papers, dissertations, or reports from organizations like Westat and The RAND Corporation that contained informative data on the relationship between NP SOP and access, we did not include these sources because they were not published in a peer-reviewed journal (Martsolf & Kandrack, 2016; Westat, 2015). Furthermore, studies assessing the impact of NP SOP on access have been published since this systematic review was conducted (Tracysnki & Udalova, 2018; Xue et al., 2018). Although these sources were not included to uphold the methodological robustness of a systematic review, they should be considered in addition to the results of review to inform policy decisions surrounding

NP SOP. This review also did not assess patient health outcomes. Since this review was based on access to care as defined by Aday & Andersen Framework (1974), we did not purposefully search for or report patient health outcomes related to NP SOP. However, we acknowledge that the goal of improved access to care is to ultimately improve patient outcomes, which this should be considered in future studies. These limitations should be acknowledged when using the results of this review to guide future research and policy on NP SOP.

Conclusion from Systematic Review

In conclusion, the results of review provide preliminary evidence that NP SOP policy is associated with select aspects of access to care, but warrants further investigation of these relationships. Additional evidence is required to assess the relationship between NP SOP policy and the characteristics of the population at risk and consumer satisfaction with care. This positive association between NP SOP and the characteristics of the health delivery system related to the NP workforce and consumer utilization of health services suggest that NP SOP can be further assessed as a policy lever to improve access to care. Ultimately, however, further research is required before policy efforts to remove or maintain NP SOP regulation based on its effect on access to care can be substantiated.

Seminal Study Assessing Impact of NP SOP Policy Change

Following the completion of the systematic review, Traczynski & Udalova (2018) published the results of a study that measured the effect of granting full NP SOP on various components of access to care using data from the Medical Expenditure Panel Survey (MEPS) from 1999-2012. MEPS is a survey that provides nationally representative estimates of healthcare utilization, expenditures, accessibility and quality of care for the majority of the US, including people with private or public insurance and the uninsured (MEPS, 2018). Instead of the

cross-sectional approach taken by most studies in the systematic review, this study used a design that leveraged state level change to full NP SOP using a difference-in-difference (DD) analysis. By comparing changes in access in states that changed NP SOP from restricted to full with states that did not change NP SOP, exogenous variation due to changes in things such as federal policies, could be teased out and the effect of NP SOP on access could be estimated (Dimick & Ryan, 2014; Dunning, 2008). Traczynski & Udalova (2018) were the first to use such a design to test and report that selected measures of access significantly improved when states granted full independence compared to states that had unchanged restricted NP SOP.

The measures of access to care assessed in this study can be categorized using the concepts outlined by Aday and Andersen's framework (1974). Traczynski & Udalova (2018) found that granting full NP SOP affected the "characteristics of the health delivery system" by decreasing physician administrative time and increasing patient care time for providers. These changes in the health delivery system are possible mechanisms by which the changes in realized access occurred when states granted full NP SOP. Traczynski & Udalova (2018) also reported that granting full NP SOP affected realized access by increasing consumer utilization of routine checkups by 3.3 percentage points, availability of appointments when wanted by 5%, and adults rating their health care as excellent by 8.6%. Adults reporting their care as excellent increased by 30% for individuals who had an NP as their primary care provider. Furthermore, utilization of undesirable care, as measured by emergency room visits related to ambulatory care sensitive conditions, decreased by 11.6%. The findings from this study suggest that removing NP SOP restrictions should be further considered as a policy lever to improve access to care in 24 U.S. states.

Chapter Summary

In this chapter, a synthesis of the literature assessing the impact of NP SOP on access to care is presented. This systematic review is followed by a brief discussion of a recent study. The next chapter outlines how this dissertation builds on this past literature and details the study design and methodology that will be used to achieve the study aims.

CHAPTER IV: STUDY DESIGN AND METHODS

This study uses a pre-post quasi-experimental research design to assess preventive service utilization before and after states implement full NP SOP laws (“intervention group”) compared to states with unchanged restricted NP SOP or unchanged full NP SOP (“comparison groups”) between 2006-2015. A retrospective analysis of commercial claims data is conducted using Truven Health MarketScan Databases (MarketScan, 2018). Linear probability difference-in-differences (DD) models are used to evaluate the effect of the independent variable of implementation of full NP SOP laws on receipt of each of the following outcomes in eligible adults in a one year period: outpatient follow-up within 14 days after hospitalization, annual wellness exams, hyperlipidemia screening, diabetes screening, all-cause emergency department encounters, all-cause hospitalization, all-cause 30-day readmission, or a hospitalization for an acute ambulatory care sensitive condition. Individual level covariates of age, gender, employment, rurality, and comorbidity are controlled for using a doubly robust propensity score strategy. Propensity score weighting is used to balance characteristics between the pre-policy intervention group with the post-policy intervention, pre-policy comparison, and post-policy comparison groups. Robust standard errors clustered at the state-level are used to adjust for heteroscedasticity and within-state correlation. Year and state fixed effects are used to adjust for time- and group- invariant confounders.

The guiding research question in this study is: what is the effect on access to care of a state implementing full SOP policy compared to states that do not change NP SOP policy? The specific aims and hypotheses in this study are as follows:

Specific Aim 1: Compare the impact on characteristics of the health delivery system, operationalized as time to outpatient follow-up within fourteen days of initial hospitalization, between states implementing full state-level NP SOP and states with unchanged full or unchanged restricted NP SOP policy.

- Hypothesis 1: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater increase in individuals receiving outpatient follow-up within fourteen days after hospitalization.

Specific Aim 2: Compare the impact on realized access to care between states implementing full state-level NP SOP and states with unchanged full or unchanged restricted NP SOP policy.

Realized access will be operationalized by the following:

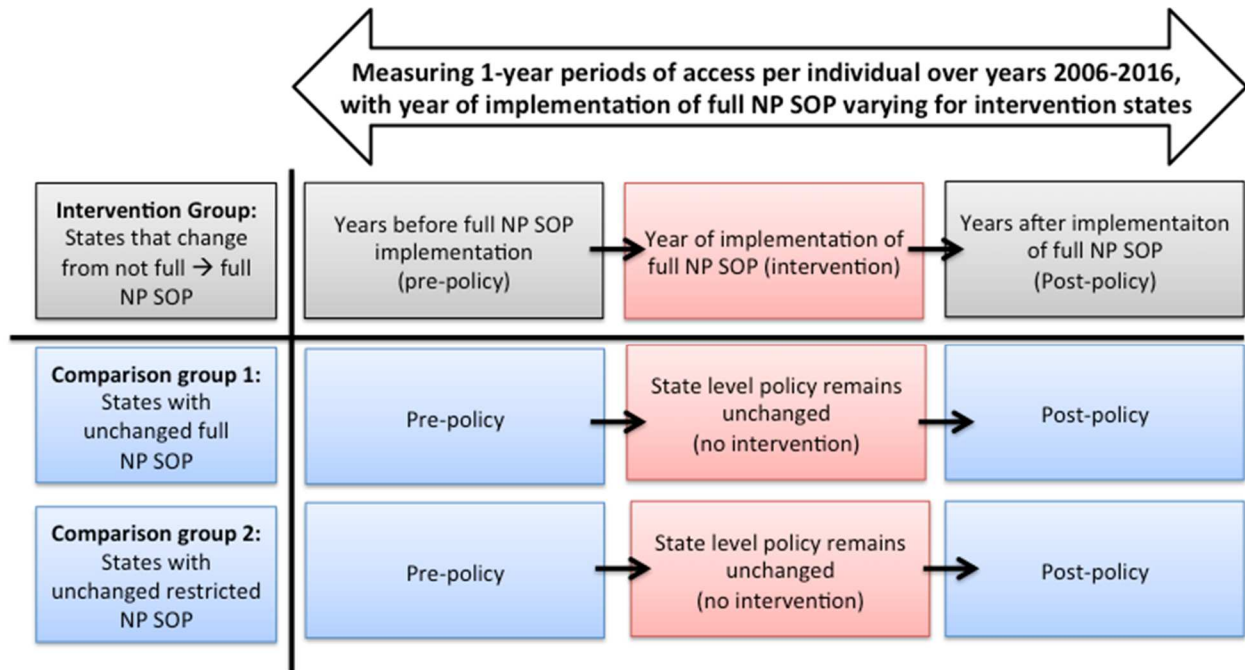
- Aim 2a: Utilization of preventive services, as measured by annual wellness visit, hyperlipidemia screening, and diabetes screening
 - Hypothesis 2a: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater increase in individuals utilizing preventive services.
- Aim 2b: Utilization of acute care services, as measured by all-cause emergency department encounters, all-cause hospitalizations, all-cause 30-day readmissions, and hospitalizations for acute ambulatory care sensitive conditions.
 - Hypothesis 2b: Compared to states with unchanged full or unchanged restricted NP SOP, states that implement full NP SOP will have a greater decrease in individuals utilizing acute care services.

Research Design

Although the gold standard for generating evidence to inform causal inference between an intervention and an outcome is a randomized controlled trial, this design is often not feasible with a state-level policy. A natural experiment is a quasi-experimental approach and is often used when a randomized controlled trail is not feasible. In a natural experiment, the “intervention” is a phenomenon that occurred without investigator control, such as a policy that was implemented in some states and not others. This approach assumes “as if random” assignment into naturally occurring intervention (also referred to as experimental or treatment) groups versus control (also referred to as comparison) groups. For a state-level policy that is implemented in some states but not others, this approach assesses variation in outcomes over time between individuals in states that implement a policy versus states that do not implement the policy. Since true randomization into intervention versus control groups is not plausible in many cases of state legislation, a natural experiment is often as close as researchers can get to a design that informs causal inference. However, the main limitation of this approach is it is not a true “experiment,” and the researcher cannot control the environment and assignment of the individuals to groups. This threat to validity of causal inference must be considered when generating conclusions based on a natural experimental design (Dunning, 2008).

This dissertation reports the results from leveraging a natural experiment that is conducted through a retrospective analysis of commercial insurance claims data from 2006-2015. It uses pre-test post-test design with an intervention and two control groups (Figure 4.1).

Figure 4.1: Pre-post Design of Intervention versus Comparison States over Time



This design allows for comparison of the average change in outcomes over time in intervention versus comparison groups to determine the impact of implementing full NP SOP on key access to care measures. The intervention group is adults living in states that implemented full NP SOP during the study period. The two comparison groups are adults living in states with unchanged full NP SOP (comparison group 1) and individuals living in states with unchanged restricted NP SOP (comparison group 2). The three study groups are further broken down into three study periods, the pre-policy period, policy implementation period, and post-policy period. The pre-test period is any 12-month period before the year of full NP SOP implementation or during the year of implementation of full NP SOP. The implementation period is the 12-month period following the date a state implements full NP SOP. The post-test period is any 12-month period after a state's implementation of full NP SOP. States in the intervention group implement full NP SOP in varying years. Each state has pre- and post- period data of at least two or more

years. A pre- post- period of at least two years was selected based on prior work indicating the full effect of full NP SOP implementation is realized in a two year period (Traczynski & Udalova, 2018). The study longitudinally assesses changes in access over time through repeated cross-sections of 12-month periods per individual. The effect of the independent variable of full NP SOP on the dependent variables (measures of access to care) is evaluated by comparing the average change in each dependent variable in the intervention versus comparison groups over time.

Data

The study uses commercial claims data from Truven Health MarketScan Databases. The Truven Health MarketScan® Research Database contains data on individual patient utilization, expenditures, and enrollment across inpatient, outpatient, and prescription drug services from approximately 350 payers. This database is constructed from privately insured claims by employers and health plans with business relationships with Truven Health. MarketScan generally represents working-aged adults who are insured through employer-sponsored or private health plans. This means that enrollees may be somewhat younger and healthier than the general population (e.g., excludes people who are disabled due to illness and older adults enrolled in the federal Medicare program), live in urban geographic areas, and work for medium and large employers. Furthermore, since all individuals in this database have insurance, they likely have greater access to care than uninsured populations in the U.S. (National Center for Health Statistics, 2017). Furthermore, the South Eastern U.S. is over-represented in this data source. This is because MarketScan relies on voluntary employer participation for data collection.

The MarketScan database was selected after consideration of several other data sources, including the Medical Expenditure Panel Survey (MEPS, 2018), National Ambulatory Medical

Care Survey (NAMCS, 2018), The Behavioral Risk Factor Surveillance (BRFSS, 2018), and the National Sample Survey of Nurse Practitioners (NSSNP, 2016). Publically available MEPS data does not include state-level data. Furthermore, since Traczynski and Udalova (2018) used MEPS data to assess multiple aspects of access to care, other data sources were further considered to allow cross-examination of their results in a different population using different data. Publically available NAMCS data also does not contain state-level data for all years, and, based on year 2012 which contained state-level data, likely has inadequate sample size for the intervention states in this study. Furthermore, the sampling frame for NAMCS data is based on a selection of physician offices from the American Medical Association, so NP care is likely underrepresented. BRFSS was also considered, since it contains data on all 50 states. However, all states are required to ask only 4 access related questions annually. Further, these access questions only consider physician delivered care, so NP care is likely underrepresented or totally absent in this data source as well. Lastly, the NSSNP database was considered, but it is cross-sectional and would not allow for the proposed study design. Ultimately, the MarketScan database was selected because it contains readily available national state-level longitudinal data, variables to approximate access, and a large enough sample to conduct this study and assess subgroups within the study.

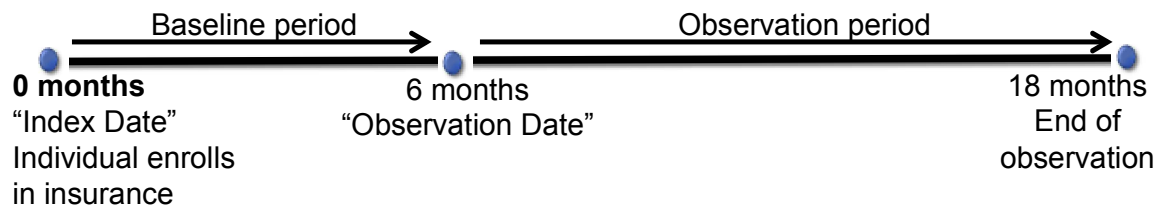
Although this study of commercially insured adults is not generalizable to uninsured adults or those with other sources of insurance, the effect of implementing full NP SOP on access in a commercially insured population has not been assessed prior to this study. Employer sponsored insurance is the largest form of health coverage in the U.S. (Kaiser Family Foundation, 2017). Furthermore, Traczynski and Udalova (2018) found no heterogeneity in results based on insurance status, gender, living inside or outside MSAs, rural or urban counties,

age, or education status, helping build the case for conducting this study in this commercially insured population.

Study Sample and Time Frame

This study sample consists of repeated cross-sections of unique individuals aged 18-64 years old residing in an intervention or comparison state between years 2006-2015. Individuals are included in the study if they have 18 months of continuous enrollment in the MarketScan database. The date of first enrollment is considered the index date. The first 6 months after enrollment are the baseline period and are used to capture baseline comorbidities of the individual. The following 12 months after the baseline period are the observation period and are used to capture the dependent variables of access related outcomes of the individual (Figure 4.2).

Figure 4.2: Defining Baseline and Observation Periods for Individuals



Individuals are included for only one 18-month period and are thereafter excluded from observation. Not allowing individuals to be re-sampled in the study reduces sample size. However, it also decreases bias from repeated measures on the same individual. If this study allowed individuals to contribute data to the study for multiple 18-month periods, some individuals would be assessed more than once while others would not, depending on how long the individual is continuously enrolled in their health insurance. Repeated measures of the same individual can cause bias, such as learning effects where the individual learns how to better

utilize their insurance benefits over time, or carry-over effects where an individual's previous level of access related outcomes influence the subsequent level of these outcomes (Singh, Rana, & Singhal, 2013). Hence, only unique individuals are included in this study.

It is also possible that select individuals are not uniquely represented in the dataset. If an individual switches employer sponsored insurance plans in years following their initial inclusion in this study, this would lead to a different insurance enrollment identification being generated for this person. It is not feasible to differentiate them from a truly unique individual based on insurance enrollment numbers and this non-unique individual could therefore inadvertently be included in the study as a unique individual. Since it is not possible to identify these individuals, it is not possible to estimate how frequently this occurs and is a limitation of this data source.

All available pre- and post-policy data on individuals are used in each state. Since states change NP SOP in different years, the pre- and post- measurement periods for access outcomes differ by state. Individuals are categorized in the intervention versus comparison groups based on their state and categorized in the pre- versus post- policy group based on their observation date (date the 12-month observation period begins). Individuals whose observation period overlaps over 50% (6 months) with the NP SOP policy implementation year are excluded from the study. If an individual is not excluded from the study, and their observation date month-year is less than the month-year of full NP SOP policy implementation, they are categorized into the pre-policy group. If an individual is not excluded from the study, and their observation date month/year is greater than the month/year of full NP SOP policy implementation, they are categorized into the post-policy group. For example, if an individual lives in Colorado, which implemented full NP SOP policy in July 2010, they are classified as belonging to the intervention group. They are excluded from the study if their observation period date began anytime between January 2010 to

January 2011, because these observation dates make greater than half of their observation period overlap with the NP SOP policy implementation period. If their observation date is December 2009 or earlier, they are classified into the pre-policy group, and if it is February 2011 or later, they are classified into the post-policy group (Table 4.1).

Table 4.1: Example of Classification into Pre- versus Post- Policy Groups for Colorado

Observation start (month-year)	Number of months observation period overlaps with policy implementation year	Inclusion, group if included
Dec-09	5	yes, pre-policy group
Jan-10	6	no
Feb-10	7	no
Mar-10	8	no
Apr-10	9	no
May-10	10	no
Jun-10	11	no
Jul-10	12 (Policy implementation month/year)	no
Aug-10	11	no
Sep-10	10	no
Oct-10	9	no
Nov-10	8	no
Dec-10	7	no
Jan-11	6	no
Feb-11	5	yes, post-policy group

This classification scheme is similar for individuals in comparison groups, but they are classified into the restricted or full comparison group instead of the intervention groups and the pre- and post- policy years are based on synthetically assigned pre- post- periods instead of actual policy implementation periods (further detailed in the following section of this dissertation). Access outcomes are observed at least two years pre- and post- full NP SOP policy

implementation, since Traczynski and Udalova (2018) reported that the effects of NP SOP policy were realized within 2 years of policy implementation.

The intervention group, individuals in states that implement full NP SOP during the month-years in parenthesis, include Rhode Island (July 2008), Maryland (Oct 2010), Colorado (July 2010), Vermont (June 2011), Hawaii (January 2011), North Dakota (October 2011), and Nevada (July 2013). Comparison group 1, individuals in states with unchanged full NP SOP policy, include Montana, Arkansas, Oregon, New Hampshire, Minnesota, Wyoming, Washington D.C., Iowa, Main, and Arizona. Comparison group 2, individuals in states with unchanged restricted NP SOP policy, include California, Florida, Georgia, Massachusetts, Michigan, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia.

It should be noted that these classifications are ambiguous. Different organizations and researchers have defined full versus restricted NP SOP policy differently. For example, Traczynski & Udalova (2018) classify Maryland as implementing full NP SOP in 2010 while another study does not classify Maryland as implenting full NP SOP in 2010 (Xue et al., 2018). In these cases, researchers varied in their definitions of Full NP SOP. Full NP SOP can be operationalized as the absence of a formal collaborative physician practice agreement, the absence of physician supervision required for NP practice or prescription, or include more granular details like an NP's right to sign a death certificate (Barton and Associates, 2018).

This dissertation categorizes SOP by the degree of physician supervision, not the presence or absence of a collaborative practice agreement. Data on NP SOP policies by state are collected through assessment of state-level legislation on NP SOP, and compared against data from multiple sources. To reduce bias from erroneous categorization of when a state implemented full NP SOP in this study, multiple sources were consulted to verify when states

implemented full NP SOP. These sources include the State Law Fact Sheet outlined by the Centers for Disease Control (2016), the State Law Chart for Nurse Practitioner Prescriptive Authority by the American Medical Association (2017b), the State Law Chart for Nurse Practitioner Practice Authority by the American Medical Association (2017a), the State Practice Environment by the American Association of Nurse Practitioners (2018), and SOP dates outlined in previous studies (Gadbois, Miller, Tyler, & Intrator, 2015; Traczynski & Udalova, 2018).

SOP categories and dates used in this study are consistent across sources, with the exception of Rhode Island and Maryland. Some sources indicate Rhode Island implemented full NP SOP in 2008 while others indicate this occurring in 2013. Rhode Island allowed full NP SOP for NPs in 2008, and further expanded this policy to allow full NP SOP for all advanced practice registered nurses in 2013 (Doyle & Gallo, 2012; Betness, 2009). Therefore, this study classifies Rhode Island as implementing full NP SOP for NPs in 2008. Some sources indicate Maryland implemented full NP SOP in 2010 while others indicate this occurring in 2015. Maryland changed NP SOP laws to remove all physician collaborative practice requirements in 2010, while still requiring the NP to name a physician they could consult with per their discretion. This attestation was removed in 2015 (Maryland Board of Nursing, 2017). The Director of Legislation, Shirley Devaris, at the Maryland Board of Nursing was further consulted on October 2018 via e-mail and telephone interview to confirm SOP categorization for Maryland.

Simulation of Synthetic Pre-Post periods for Comparison Groups

Since intervention states implement full NP SOP in varying years, there are multiple pre- and post-policy time periods in this dissertation. Therefore, there is not a clear delineation for which years to specify as pre-policy versus post-policy for the comparison groups. DD models with variation in treatment timing have recently been proposed (Goodman-Bacon, 2018;

Callaway & Sant' Anna, 2018). However, these approaches do not allow for the propensity score weighting method used in this study. Therefore, in order to define the pre-policy and post-policy periods for the comparison groups, pre- and post- policy years were synthetically assigned to match the pre- and post- policy groups in the intervention states by year and sample size.

The approach of synthetic assignment of pre- and post- policy periods in this dissertation is adapted from synthetic control methods. Synthetic control methods were developed to evaluate the effect of a policy that occurs at an aggregate level, like a state policy, and has a smaller number of affected units than available control units (Abadie, Diamond, & Hainmueller, 2003). Synthetic controls are purposely selected to serve as comparators for the treatment group by assigning weights to the control groups to mirror the observable characteristics of the treatment group as closely as possible over time. In a true synthetic control design, the synthetic control is the time-invariant weight average of all control units (Kreif et al, 2016). In the approach used in this dissertation, the synthetic pre- and post- periods for control groups are selected to mirror when intervention groups implement full NP SOP, but weights are assigned using a propensity score method specific for use with this study design instead of synthetic control weighting methods. This propensity score weighting approach is further discussed in the statistical analysis section of this chapter.

To verify that the year of synthetic pre- post- period assignment for comparison groups does not largely drive the results, ten variations of synthetically assigned pre- and post- periods are assessed. The main model is run using each variation of pre- post- periods. The sign, magnitude, and significance of the DD estimator across variations of pre- post- periods are similar, supporting that the year of assignment of pre- post- periods for comparison groups is not

driving the results in this study (Appendix 1). Therefore, the first set of synthetically assigned pre-post-periods are applied to both comparison groups.

Variables and Measurements

Table 4.2 outlines the variables, measures, and data sources for the independent, dependent, and individual level control variables used for aims 1 and 2 of this dissertation. Table 4.3 describes how each dependent variable was identified using MarketScan data tables, including relevant healthcare common procedure coding system (HCPCS), current procedural terminology (CPT), or international classification of disease (ICD) -9 or -10 codes. The analytic dataset is constructed using SAS 9.3 (Cary, NC).

Table 4.2: Independent, Dependent, and Individual Level Control Variables

Variable	Measure	Type	Data Source
Independent Variables			
Treatment	1 if individual is in an intervention state 0 if an individual is in a comparison state	Binary	Data on SOP categories and year of full NP SOP implementation obtained through assessment of multiple sources, including previous studies, state-level legislation on NP SOP, and conversations with a state Board of Nursing. Pre- and post- policy group assignment for comparison groups developed through simulations of synthetically assigned pre- post- periods
Time	1 if in post-policy group, 0 if in pre-policy or year of policy implementation	Binary	
DD Estimator	(Treatment*Time)	Interaction term	
Dependent Variables			
Outpatient follow-up within 14 days of initial hospitalization <i>for individuals who have at least 1 hospitalization only</i>	1 if outcome occurred during year of observation 0 if outcome did not occur during year of observation	Binary	MarketScan

Receipt of Annual Wellness Exam			
Receipt of hyperlipidemia screening <i>for individuals ≥ 45 years old only</i>			
Receipt of diabetes screening <i>for individuals ≥ 45 years old only</i>			
All-cause hospitalization			
All-cause ED-admission			
All-cause 30-day readmission <i>for individuals with at least 1 hospitalization only</i>			
Hospitalization for an acute ambulatory care sensitive condition (Bacterial pneumonia, urinary tract infection, dehydration)			
Individual level Control Variables			
Age	Age of individual at beginning of baseline observation period	Continuous	MarketScan
Gender	1 if male 0 if female	Binary	
Comorbidity Index	Charlson comorbidity index (CCI)	Categorical	
Residence in a Metropolitan statistical area (MSA)	1 if living in an MSA 0 if not living in an MSA	Binary	
Employment Status	1 if Active Full Time 0 if Other (part time, seasonal, retiree, COBRA continuee, Disability, unknown)	Binary	

Table 4.3: Description of Dependent Variable Construction

Dependent Variable	Description of how variable was constructed in MarketScan
Outpatient follow-up within 14 days of initial hospitalization <i>for individuals who have at least 1 hospitalization only</i>	Any outpatient service encounter date less than or equal to 14 days + date of first hospitalization

Receipt of Annual Wellness Exam	Any outpatient service with a HCPCS/CPT code for wellness exam ('99385', '99386', '99387', '99395', '99396', '99397', 'G0438', 'G0439')
Receipt of hyperlipidemia screening <i>for individuals ≥ 45 years old only</i>	Any outpatient service with a HCPCS/CPT code for a standard lipid panel ('80061')
Receipt of diabetes screening <i>for individuals ≥ 45 years old only</i>	Any outpatient service with a HCPCS/CPT code for a diabetes screening ('82947', '82950', '82951', '83036')
All-cause hospitalization	Any inpatient encounter
All-cause ED-admission	Any inpatient or outpatient encounter with the standard place of service as 23 (emergency room) or service sub-category code ending in 20 (specifies type of emergency room)
All-cause 30-day readmission <i>for individuals with at least 1 hospitalization only</i>	Any emergency department encounter date less than or equal to 30 days + date of any hospital discharge
Hospitalization for an acute ambulatory care sensitive condition (Bacterial pneumonia, urinary tract infection, dehydration)	Any inpatient encounter with diagnoses 1-5 containing an ICD-9 or ICD-10 code for bacterial pneumonia, urinary tract infection, or dehydration ('27650', '27651', '27652', '2760', '00861', '00862', '00863', '00864', '00865', '00866', '00867', '00869', '0088', '0090', '0091', '0092', '0093', '5589', '5845', '5846', '5847', '5848', '5849', '586', '9975', '481', '4822', '48230', '48231', '48232', '48239', '48241', '48242', '4829', '4830', '4831', '4838', '485', '486', '59010', '59011', '5902', '5903', '59080', '59081', '5909', '5950', '5959', '5990', 'E860', 'E861', 'E869', 'E870', 'A080', 'A0811', 'A0819', 'A082', 'A0831', 'A0832', 'A0839', 'A084', 'A088', 'A09', 'K5289', 'K529', 'N170', 'N171', 'N172', 'N178', 'N179', 'N19', 'N990', 'J13', 'J14', 'J15211', 'J15212', 'J153', 'J154', 'J157', 'J159', 'J160', 'J168', 'J180', 'J181', 'J188', 'J189', 'N10', 'N119', 'N12', 'N151', 'N159', 'N16', 'N2884', 'N2885', 'N2886', 'N3000', 'N3001', 'N3090', 'N3091', 'N390')

Independent Variables

A standard difference-in-difference framework guides the specification of independent variables in this dissertation (Wing, Simon, & Bellow-Gomez, 2018). The variable “treatment” is a binary variable that is equal to 1 if an individual is in an intervention state that implements full NP SOP over the study period and 0 otherwise. The variable “time” is a binary variable that is equal to 1 if the start of the observation year for an individual is classified as being in the post-policy period and 0 otherwise. The DD estimator is the variable of interest, and is an interaction term generated by multiplying “treatment” by “time.” The DD estimator represents the average

treatment effect of implementing full NP SOP comparing the pre-policy and post-policy treatment differences between the intervention and comparison groups.

Dependent Variables

Access is operationalized by using the characteristics of the health delivery system and realized access to care components of Aday and Andersen's framework (1974). This dissertation uses outpatient follow-up within 14 days of initial hospitalization as a proxy for a characteristic of the health delivery system. If full NP SOP increases the health system's capacity to provide patient care, more patients may be able to follow-up with an outpatient provider after being hospitalized (Traczynski & Udalova, 2018). Receiving outpatient follow-up after hospital discharge is associated with reduced post-discharge hospital readmissions, emergency department use, and mortality, with individuals receiving follow-up earlier having better outcomes and the impact greatest for individuals with the most comorbidities (Health Quality Ontario, 2017; Jackson et al., 2015). The recommendations for how soon a patient should receive an outpatient follow-up after hospital discharge vary by reason for hospitalization. The fourteen-day timeframe used in this study was guided by Medicare payment incentives to encourage outpatient follow-up appointments with 14 days of discharge as a strategy to reduce readmission (Jackson, Shahsahebi, Wedlake, & DuBard, 2015).

Realized access is operationalized by measuring utilization of preventive services that require access to primary care (Aim 2a) and acute care services that can result from lack of access to primary care (Aim 2b). Individuals ideally engage with primary care and a healthcare provider to receive many preventive services, like annual wellness exams or screenings for diseases (AHRQ, 2017). Preventive services assessed in this study are those that are billable and recorded in administrative claims and include: annual wellness exam, hyperlipidemia screening, and diabetes screening. Because the U.S. Preventive Task Force (2016) recommends universal

lipid screening for all adults aged 40-70 and the American Diabetes Association recommends screening for diabetes in all individuals greater than 45 years of age (Pippit, Li, & Gurgle, 2016) we restricted our sample for these two outcomes to include only health plan enrollees who were 45 years of age or older at the time of their index enrollment date.

Lack of access to primary care services can lead to increased utilization of acute care services, like emergency care or hospitalization (Rosano et al., 2013; Shi, 2012). Furthermore, acute care services may be the only form of available care for individuals in areas where primary care services are sparse (Tang, Stein, Hsia, Maselli, & Gonzales, 2010). Therefore, this dissertation also measures realized access to care through utilization of acute care services. Utilization of acute care is measured by all-cause acute hospitalizations, ED-admissions without hospitalization, 30-day hospital readmissions, and hospitalization for acute ambulatory care sensitive conditions, measures that are often used to compare the quality of healthcare across states (National Quality Forum, 2014) and for evaluating models for the organization of primary care (Rosenthal, Abrams, & Bitton, 2012).

To specifically assess utilization of acute care services that are avoidable through high-quality primary care, this study uses an AHRQ Prevention Quality Indicator developed by the Centers for Medicare and Medicaid (CMS, 2015). This measure is called the acute ambulatory care sensitive condition (ACSC) composite and was developed to capture hospitalization for rapid onset conditions that are often preventable through access to high quality primary care, including bacterial pneumonia, urinary tract infection, and dehydration. Although a chronic ACSC composite also exists, the acute ACSC composite was selected over the chronic composite because observable changes in the chronic care composite outcomes take longer to realize and may not be captured in the period of the study (AHRQ, 2001, 2006, 2017).

Individual-level Control Variables

This dissertation includes the individual level characteristics of age, gender, residence in a metropolitan statistical area, employment status, and comorbidity status. These characteristics are included as covariates in the regression and are also used to generate propensity score weights for each individual in the model. Ideally, all variables that impact the outcome or that are confounders of the intervention and outcome relationship should be included to maximize the precision of the estimated effect (Brookhart et al., 2006). The individual level covariates in this study are selected because they are related to access to care and unrelated to a state's implementation of full NP SOP. Furthermore, these variables are available using MarketScan claims data. Aday and Andersen (1974) describe how age, gender, rurality, income (related to employment status), and comorbidity status are characteristics of the population at risk that affect the likelihood of an individual to utilize health services. Due to limitations associated with using claims data, several individual level covariates that also affect access and are unrelated to NP SOP, such as an individual's education status or race are not included as an individual-level covariate, limiting bias reduction in this study (Pan & Bai, 2016). Concerns over covariate control are mitigated by the use of a DD model for analysis, since DD model compares within group changes over time.

The Charlson comorbidity index is used to measure comorbidity in this study. This comorbidity measure is a widely used weighted index that captures individuals' number and acuity of comorbid conditions. Although commonly used to approximate medical comorbidity in claims based studies, this index was originally intended to capture an individual's probability of death and must be used cautiously. The Charlson comorbidity score weights conditions by severity and assigns a weight of 1 for myocardial infarction, congestive heart failure, peripheral

vascular disease, cerebrovascular disease, dementia, chronic pulmonary disease, connective tissue disease, ulcer disease, liver disease, and diabetes; a weight of 2 for: hemiplegia, renal disease, diabetes with end organ damage, and malignancy; a weight of 3 for moderate or severe liver disease; and a weight of 6 for metastatic solid tumors or AIDS (Charlson, Mary Szatrowski, Ted Peterson, 1994). The presence or absence of each comorbidity in the index is assessed by ICD-9 and ICD-10 diagnosis codes in outpatient and inpatient utilization files in a 6-month baseline period prior to the 1-year observation period. Although there is debate about inclusion of each comorbidity as an individual binary variable rather than as an index, this dissertation uses the index because there is evidence that models that include each individual comorbidity as an individual binary variable have similar performance as models that use the index (Austin, Wong, Uzzo, Beck, & Egleston, 2016; Leiffers, Baracos, Winget, & Fassbender, 2010).

Doubly robust estimation combines two approaches for measuring the effect of an intervention on an outcome. Doubly robust estimation is used in this dissertation because it generally outperforms using only one method (Funk et al. 2011). The doubly robust estimation strategy used in this dissertation combines controlling for individual level covariates in a regression framework with balancing group differences in these individual level covariates using propensity score weighting.

Statistical Analysis

Descriptive statistics are used to summarize dependent and control variables by group. Bivariate analyses are used to assess unadjusted differences between individuals in states that implement full NP SOP versus comparison states with unchanged full NP SOP and also with unchanged restricted NP SOP. Group differences in the mean of each variable are analyzed using two-tailed t-tests assuming unequal variances between groups. Furthermore, the average of each

outcome in intervention versus comparison groups is plotted overtime centered by years pre- and post- policy implementation and by year.

The statistical analysis for the main results for Aim 1 and Aim 2 in this dissertation occurs in three phases. In the first phase, three options for model specifications are considered: a logit model, a modified Poisson regression model, and a linear probability model. Literature surrounding model specification for binary dependent variables in DD models is evaluated to guide which type of model is used in this dissertation (Wooldridge, 2016). In the second phase, the propensity score weighting strategy is developed using multinomial logistic regression (Stuart et al., 2014). In the third phase, the DD regression models are analyzed for each dependent variable, using the model type specified in phase one and the propensity score weighting strategy developed in phase two. Statistical significance is set at $\alpha=0.05$ for all analyses. All analyses are conducted using Stata version 13.1 (College Station, Texas).

Model Specification

Logit models are a class of nonlinear models widely used for statistical analysis of the effect of a set of explanatory variables on a binary outcome (Cramer & Ridder, 1988). They are a form of a probability model, describing the dependence of the probability of the presence or absence of a binary outcome based on a set of independent variables. Results are often interpreted as odds ratios (Woodridge, 2016). However, interaction terms in a logit model are not readily interpretable, requiring adjustments to the DD estimator not commonly found in statistical packages (Karaca-Mandic, Norton, & Dowd, 2012). The magnitude of the interaction term in a nonlinear model is often wrongly interpreted as a marginal effect. However, the magnitude, sign, and significance of the interaction term require adjustments that can lead to the actual effect being of different magnitude, sign, and significance (Ai & Norton, 2003).

Furthermore, using a nonlinear functional form in a DD model leads to a violation of an underlying assumption of DD models, the common trends assumption. A DD model can tease out unobservable confounding between groups if the trends in outcomes over time are the same between intervention and comparison groups in the pre-policy period. By nature of a nonlinear model, this is often not true (Lechner, 2010).

Poisson regressions are most often used for the statistical analysis of the effect of a set of explanatory variables on an outcome that is a count variable (Coxe, West, & Aiken, 2009). A modified Poisson regression approach has been developed specifically for use in models with binary outcomes. The development of this approach was largely driven by the desire to estimate relative risk, instead of odds ratios as produced by logistic regression models (Zou, 2004). This approach is especially relevant in segmented regression analyses that measure the impact of an intervention using interrupted time series data (Wagner, Soumerai, Zhang, & Ross-Degnan, 2002). However, as with logit models, an interaction term, like a DD estimator, in a Poisson model is not readily interpretable due to it being a type of nonlinear model (Shang, Nesson, & Fan, 2016).

Linear probability models are another type of model commonly used for statistical analysis of the effect of a set of explanatory variables on a binary dependent variable (Lien & Rearden, 1990). Linear probability models use an ordinary least squares estimation framework to derive this effect and results are generally interpreted as percentage point differences (Wooldridge, 2016). Because the dependent variable in a linear probability model can only take on two forms, the error term is also limited to two values conditional on the dependent variables. This leads to all LPM models being heteroscedastic by nature, which can increase the odds of making a type I error. However, there are multiple options to correct for heteroscedasticity.

Furthermore, linear probability models can lead to predicted probabilities of outcomes not falling within the range of zero to one, which does not make theoretical sense for many binary outcomes (Horrace & Oaxaca, 2005). In the context of DD, linear probability models are often a parsimonious option for analysis of a binary outcome, generate a DD estimator that is readily interpretable, and have options to adjust for heteroscedasticity (Caudill, 1988; Lechner, 2010; Bertrand, Duflo, & Mullainathan, 2004).

Most literature presented in this section favors use of a linear probability model for DD with a binary outcome. Therefore, linear probability models are selected for use in the DD analyses in this dissertation because they are the simplest model choice, do not violate assumptions of DD, and produce DD estimators that are readily interpretable. To adjust for the inherent heteroscedasticity associated with this type of regression, a cluster-robust variance estimator is applied to all regression models in this study (Cameron & Miller, 2015).

Propensity Score Weighting

Propensity score methods were developed to reduce selection bias in observational studies by making characteristics of the treatment and control groups more similar, since randomization to treatment groups is not possible in observational designs. A propensity score is the conditional probability of an individual being assigned to a specific group, given a set of observed characteristics that are used to build the propensity score (Rosenbaum & Rubin, 1983). It is important to note that propensity score estimation models are the strongest at reducing selection bias between groups when all potential observed covariates are included in the model (Pan & Bai, 2016). If there is an unmeasured confounder uncorrelated with the observed characteristics that significantly affects access, this limits the ability of propensity score methods to balance groups and reduce bias. In this dissertation, several individual level covariates of this

nature, such as an individual's education status or race could not be included in the model because they were unavailable in the claims data source.

Stuart et al. (2014) developed a propensity score weighting strategy for use with difference-in-difference models that is especially applicable to studies that use repeated cross-sectional data, as does this dissertation. DD models that use repeated cross-sectional data are susceptible to selection bias across time and across groups. Selection bias across time occurs due to confounding from changes in-group composition over time. Selection bias across groups occurs when the individuals with higher-than-average outcomes are more likely to be in the intervention versus the comparison group, and this difference in outcomes trends differently between groups over time. Using matching methods to balance the intervention and comparison groups can result in more accurate estimates (Ryan, Burgess, & Dimick, 2014).

To minimize bias in this study from differences between intervention versus comparison groups, this study applies the four-group propensity score weighting strategy outlined by Stuart et al. (2014). When comparing the intervention group to the unchanged full comparison group, the four groups (pre-policy intervention, post-policy intervention, pre-policy unchanged full comparison group, and post-policy unchanged full comparison group) are weighted to be similar to the pre-policy intervention group, which receives a weight of "1". This process is repeated separately for comparing the intervention group to the unchanged restricted comparison group. The characteristics of age, gender, residence in a metropolitan statistical area, employment status, and Charlson comorbidity index score are used to balance the groups.

To generate the propensity score weight, a multinomial logistic regression is used to predict the probability of being in the pre-policy intervention group based on the above characteristics. To assess if propensity score weighting successfully balanced characteristics

between groups, the reduction in standardized difference between the pre-policy intervention group versus other groups (post-policy intervention, pre-policy control, post-policy control) is assessed for each covariate. Standardized differences, or the difference in means of the covariate divided by the standard deviation, are often used to compare group similarly (Stuart et al., 2016). Consistent with the approach outlined by Stuart et al. (2016), a standardized difference greater than 0.10 is used to indicate substantial difference in covariates between groups and standardized difference closer to 0.00 is used to indicate balance in covariates between groups. After assessing if propensity score weighting adequately balances covariates between groups, the inverse of the propensity score weights are applied to the DD model.

Difference-in-difference Model

A propensity score weighted linear probability DD model, with a state and a time fixed effect, and robust standard errors clustered at the state-level is used for analysis of the eight dependent variables in Aim 1 and Aim 2. The following general form of the regression model is used for the primary analysis for each outcome, comparing the intervention group to comparison group 1 (unchanged full NP SOP). Analyses are then specified comparing the intervention group and comparison group 2 (unchanged restricted NP SOP). Therefore, a total of 16 regressions are conducted for the main analyses:

Equation 1: Difference-in-difference Regression with State and Time Fixed Effects, controlling for Individual-level Covariates

$$\begin{aligned}
 & AccessOutcome_{ist} \\
 & = \beta_0 + \beta_1 time_{ist} + \beta_2 treatment * time_{ist} + \delta X_{ist} + \alpha_t + \alpha_s + \varepsilon_{ist}
 \end{aligned}$$

Where “i” indicates variables that vary by individual, “s” indicates variables that vary by state, and “t,” indicates variables that vary by time. The variable “treatment” is a dummy variable equal to 1 if an individual is in an intervention state and 0 if an individual lives in a comparison state. Since treatment group assignment is constant within states, the variable “treatment” would be collinear with the state fixed effect, and therefore is not included in the regression model. The variable “time” is a dummy variable equal to 1 if an individual is in the post-policy period and 0 if an individual is in the pre-policy or policy-implementation period. The coefficient β_1 is the measure of the difference in access outcomes between the pre-policy and post-policy periods. This coefficient provides information on if the access outcomes in the pre-policy versus post-policy period are different, without considering differences between the intervention and comparison group. The coefficient β_2 is the DD estimator of interest. β_2 is an interaction term between the “treatment” and “time” variables, and represents the average treatment effect of a state implementing full NP SOP relative to the comparison group.

The δ represents coefficients on all control variables included in the model, which are the same as the individual level covariates included in the propensity score for the main models. The α_t and α_s refer to the year and state fixed effects to account for group- and time- invariant confounding, respectively. The state fixed effect is a set of dummy variables for each state in the analysis. State fixed effects capture unobserved heterogeneity across states that are fixed over time. The time fixed effect is a set of dummy variables for each year in the analysis. Year fixed effects capture unobserved variation over time that is not attributed to the independent variables in the model (Wooldridge, 2016).

If the p-value associated with the DD-estimator is significant at $\alpha=0.05$, this suggests that implementing full NP SOP is associated with the outcome being analyzed. However, due to the

large number of individuals in this study, it is likely that some results are statistically significant but have little practical importance. Therefore, the clinical significance of each result is also considered when discussing the implications of the results in Chapter VI.

Linear probability models are inherently heteroskedastic, leading to standard errors that are falsely too small and increase the likelihood of making a Type I error (Harrace & Oaxaca, 2005). Furthermore, when assessing the impact of an intervention at the state level, the data are often cluster-correlated, since individuals within states are likely to share more characteristics than between states (Wing, Simon & Bellow-Gomez, 2018). Cluster-correlated data violate the assumption of independence of observations, which leads to underestimation of the true variance and also increases the likelihood of making a Type I error (Cameron & Miller, 2015). The robust variance estimation for cluster-correlated data is widely used to correct the variance in a model to improve statistical hypothesis testing (Williams, 2000). Although other alternatives for accounting for cluster correlation exist, there is not consensus on which option is the best practice. Furthermore, all options are increasingly limited when a study has a small number of clusters (Wing et al., 2018 Strumph, Harper, & Kaufman, 2017). This dissertation uses robust standard errors clustered at the state-level to adjust for heteroscedasticity and within-state correlation.

The assumptions for DD analysis of parallel trends and common shocks are considered prior to conducting the study. A DD model rests on the parallel trends assumption that the dependent variables in the intervention and control group change at similar rates over time. Traczynski & Udalova (2018) explicitly tested the parallel trends assumption by comparing access related outcomes between states that eventually changed NP SOP policy to those that did not change NP SOP and found no differential trends in outcomes between these groups,

supporting the parallel trends assumption. However, the inability to evaluate the common shocks assumption directly, in which events unrelated to the policy during or after policy implementation equally effect the treatment and comparison groups, are likely be a limitation of this study (Dimick & Ryan, 2014). Other state-specific policy changes, such as Medicaid expansion, that differentially impact access in intervention and control states also violate this assumption. Although this dissertation attempts to address this type of confounding by controlling for these types of state-level confounders using state-level fixed effects and a sensitivity analysis controlling for individuals state-level factors, it is possible that some factors are not captured.

Sensitivity and Subgroup Analyses

Parameterized State Effects Model

This dissertation compares the state fixed effects approach in the main model by examining whether the sign, magnitude, and significance of the DD estimators are similar in a parameterized state effects model that controls for specific state level covariates, holding all other factors constant. If the results are consistent between models, it supports the robustness of the results in the main model. State fixed effects, or a set of dummy variables for each state, are used in the main model in equation one. In equation two, parameterized state effects, or specific state-level covariates, are used in place of the state fixed effects approach in the main model.

The parameterized state effects model is a sensitivity analysis comparing the parameterized state effects approach in equation 2 to the state fixed effects approach from the main model in equation 1. Including a state and year fixed effect adjusts for effects that are time or group- invariant (Wing et al., 2018). Although this approach captures many sources of confounding, it does not adjust for effects that vary by both state and year. A variable such as

Medicaid expansion, which affects access, varies by state, and in addition varies by year, is an example of such a variable (Kaiser Family Foundation, 2018).

The regression for this analysis is similar to the regression in equation 1 for the main model. However, this regression does not include α_s , the state fixed effect, and instead includes a set of baseline state level covariates in addition to the individual level covariates captured by the coefficient δ . The state level covariates include population, Medicaid expansion status by year, primary care health professional area score, number of primary care physicians, number of nurse practitioners, percent of population in poverty, median income, and gross domestic product (Table 4.4). The following regression is used for this analysis:

Equation 2: Difference-in-difference Regression with Time Fixed Effects, Controlling for Individual- and State- level Covariates

$$AccessOutcome_{ist} = \beta_o + \beta_1 time_{ist} + \beta_2 treatment * time_{ist} + \delta X_{ist} + \alpha_t + \varepsilon_{ist}$$

Table 4.4: State Level Control Variables for Parameterized State Effects Model

Variable	Measure	Type	Data Source
Population	Number of people in state in 2006	Continuous	(United States Census Bureau, 2008)
Medicaid Expansion	1 if state expanded Medicaid during or after year of observation for an individual 0 otherwise	Binary	(Kaiser Family Foundation, 2018)
Primary Care HPSA Score	Average primary care Health Professional Shortage Area (HPSA) score for all primary care HPSAs designated within a state in 2006	Categorical	(Human Resources Service Administration, 2018)

	Score between 0-25 calculated based on population-to-provider ratio, percent of population below 100% federal poverty limit, infant health index, and travel time to nearest source of care		
Primary Care Physicians	Number of primary care physicians in 2006	Continuous	(Centers for Disease Control, 2015)
Number of registered nurses with a master's/doctorate	Number of nurse practitioners in 2008	Continuous	(Human Resources Service Administration, 2008)
Poverty	Percent of population in poverty in a state in 2006	Continuous	(United States Census Bureau, 2011)
Median income	Median income in a state in 2006	Continuous	(United States Census Bureau, 2018)
GDP	State Gross Domestic Product (GDP) in 2006	Continuous	(Bureau of Economic Analysis, 2008)

Assessment of Trends for Individuals in Rural Locations

Rural populations often face greater barriers in access to care leading to negative health outcomes than non-rural ones (Douthit, Dwolatzky, & Biswas, 2015). Additional evidence is needed to assess if full NP SOP policy can be leveraged as a means to improve rural health. A systematic review of the relationship between NP SOP and access to care found mixed evidence surrounding the impact of NP SOP and access to care for rural populations (Patel et al., 2018). Traczynski and Udalova (2018) found no heterogeneity in the effect of implementing full NP SOP based on living inside or outside of metropolitan statistical areas. However, recent literature suggests that full NP SOP is associated with increased access to care in rural settings (Neff et al., 2018; Spetz, Skillman, & Andrilla, 2017; Xue et al., 2018). Given the conflicting evidence

surrounding the impact of NP SOP on access to care for rural populations, and the heightened need to increased access to care for rural populations, this dissertation specifically assesses the impact of implementing full NP SOP for individuals in rural settings through a subgroup analysis. The effect of implementing full NP SOP on access is analyzed for individuals in rural locations by restricting the regression analysis in equation 1 to individuals not in a metropolitan statistical area. Each outcome in Aims 1 and 2 is analyzed.

Assessment of Trends by State

The effect of implementing full NP SOP on access is analyzed for homogeneity across states by individually assessing each outcome in Aims 1 and 2 in each intervention state. The regression outlined in equation 1 restricted to each state is used to generate state specific estimates. This analysis assesses if trends in some intervention states differ from trends in the other intervention states by assessing the sign, magnitude, and significance of the DD estimator between states. For trends that are heterogeneous across states, possible post-hoc analyses and contextualization of factors differentially contributing to access within those states are discussed in Chapter VI.

Chapter Summary

This chapter describes the methodology used to achieve the aims of this study. First, the research design, data, sample, and timeframe are outlined. The definitions and data sources for the independent, dependent, and propensity score variables are then described. Next, the steps for statistical analysis of the main models in this study are presented, including the process used to select the model type, the propensity score weighting approach, and the difference-in-difference model. The statistical analysis section is followed by a description of sensitivity and subgroup analyses conducted in this study. In the next chapter, the results of the study are presented.

CHAPTER V: RESULTS

Description of Sample

After synthetic pre-post periods for comparison groups were applied, the final study sample consisted of 2,339,184 individuals in the intervention group (7 states), with 1,701,330 in the pre-policy period and 637,854 in the post-policy period. There were 3,747,506 individuals in comparison group 1 (unchanged full SOP, 10 states), with 2,315,840 in the pre-policy period and 1,431,666 in the post-policy period. There were 21,890,886 individuals in comparison group 2 (unchanged restricted, 11 states), with 12,833,551 in the pre-policy period and 9,057,335 in the post-policy period (Table 5.1).

Table 5.1 Summary of Intervention and Comparison Pre- and Post- Policy Groups, 2006-2015

Group	Total Number of Individuals	Number of Individuals in pre-policy period	Number of Individuals in post-policy period	States (change year for states that changed policy)
Intervention group (implementing full NP SOP)	n= 2,339,184	n= 1,701,330	n= 637,854	RI (2008), MD (2010), CO (2010), HI (2011), VT (2011), ND (2011), NV (2013)
Comparison group 1 (unchanged full NP SOP)	n= 3,747,506	n= 2,315,840	n= 1,431,666	MT, AK, OR, NH, MN, WY, DC, IA, ME, AZ
Comparison group 2 (unchanged restricted NP SOP)	n=21,890,886	n=12,833,551	n= 9,057,335	CA, FL, GA, MA, MI, MO, NC, SC, TN, TX, VA

Table 5.2 presents the number of individuals in each intervention state by state and by year for this study, marking the NP SOP policy implementation year for each state. The number of individuals in intervention states varied by state, with the most individuals residing in Maryland (n=1,256,306) and the least individuals in Hawaii (n=9,373). The number of individuals in intervention states also varied by year, with the greatest number of individuals represented in years 2008 (n= 935,623), and the least number of individuals in years 2010 (n=78,140).

Table 5.2: Number of Individuals in each Intervention State and Year

Year	Colorado	Hawaii	Maryland	Nevada	North Dakota	Rhode Island	Vermont	Year Total
2006	111,342	2,229	101,366	112,386	12,266	22,344	8,563	370,496
2007	36,674	302	21,203	32,046	2,313	4,500	2,034	99,072
2008	59,497	1,412	830,937	30,989	6,910	295*	5,583	935,623
2009	41,078	360	99,255	26,116	2,649	10,931	1,775	182,164
2010	1,623*	1,961	8,175*	42,178	4,414	12,072	7,717	78,140
2011	79,454	751*	46,807	29,193	651*	17,589	147*	174,592
2012	78,624	687	32,111	27,309	4,537	7,985	4,223	155,476
2013	69,762	775	47,333	1,685*	2,807	6,754	3,008	132,124
2014	45,135	174	25,001	20,853	1,891	3,380	1,164	97,598
2015	43,905	722	44,118	16,226	1,786	5,952	1,190	113,899
State Total	567,094	9,373	1,256,306	338,981	40,224	91,802	35,404	2,339,184

*denotes year of full NP SOP policy implementation

Table 5.3 presents the sample size, mean, and standard deviation for independent variables, dependent variables, individual-level control variables, and state-level control variables for the intervention group, full NP SOP comparison group 1, and restricted NP SOP comparison group 2. Two-tailed t-tests assuming unequal variances between the intervention group versus full NP SOP comparison group 1 and the intervention group versus the restricted NP SOP comparison group 2 revealed that all variables are significantly different between

groups at a statistical significance level of $\alpha=0.001$. The significance was likely related to the large sample size of this study. Since all variables were significantly different between groups at the same level of significance, the results of the t-tests were not displayed in Table 5.3. Select differences included individuals in the full NP SOP comparison group having, on average, fewer hospitalizations for ambulatory care sensitive conditions, more outpatient follow-up after hospitalizations within 14 days, a larger proportion of individuals residing in rural locations, lower average Charlson Comorbidity Index scores compared to individuals in states in the intervention or restricted NP SOP comparison group. Furthermore, states in the full NP SOP comparison group had, on average, a smaller population, higher primary care health professionals shortage area scores, fewer primary care physicians, and fewer nurses with a masters or doctorate than states that in the intervention or restricted NP SOP comparison group.

Table 5.3: Summary Statistics of Study Variables for Intervention and Control Groups from 2006-2015†

Variable	<u>Full NP SOP Comparison Group</u>			<u>Intervention Group</u>			<u>Restricted NP SOP Comparison Group</u>		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Independent Variables									
Time (post-policy)	3,747,506	0.38	0.48	2,339,184	0.27	0.45	21,890,886	0.41	0.49
DD Estimator (treatment*time)	3,747,506	0	0	2,339,184	0.27	0.44	21,890,886	0	0
Outcome Variables									
Outpatient Visit Follow-up within 14 days of Initial Hospitalization (%)	193,203	58.0%	0.49	128,715	57.0%	0.5	1,173,507	56.0%	0.5
Annual Wellness Exam (%)	3,747,506	30.0%	0.46	2,339,184	30.0%	0.46	21,890,886	27.0%	0.44
Diabetes Screening (for ages ≥45) (%)	1,579,004	18.0%	0.39	1,021,146	18.0%	0.38	8,963,841	20.0%	0.4
Lipid Screen (for ages ≥45) (%)	1,579,004	43.0%	0.49	1,021,146	44.0%	0.5	8,963,841	44.0%	0.5
All Cause ED Utilization (%)	3,747,506	14.0%	0.35	2,339,184	15.0%	0.36	21,890,886	15.0%	0.35
All Cause Hospitalization (%)	3,747,506	5.0%	0.22	2,339,184	6.0%	0.23	21,890,886	5.0%	0.23
All Cause 30 day Readmission after any Hospitalization (%)	193,203	7.0%	0.25	128,715	7.0%	0.26	1,173,507	7.0%	0.25
Hospitalization for acute ACSC (%)	3,747,506	0.5%	0.07	2,339,184	0.6%	0.08	21,890,886	0.6%	0.07
Individual-level Control Variables									
Age of Patient (years)	3,747,506	40.6	12.67	2,339,184	41.21	12.57	21,890,886	40.39	12.54
Sex (male) %	3,747,506	48.0%	0.5	2,339,184	47.0%	0.5	21,890,886	47.0%	0.5
Residence in a Metropolitan Statistical Area %	3,747,506	71.0%	0.45	2,339,184	91.0%	0.28	21,890,886	88.0%	0.32
Active Full Time Employee %	3,747,506	43.0%	0.5	2,339,184	40.0%	0.49	21,890,886	47.0%	0.5

Charlson Comorbidity Index	3,747,506	0.15	0.58	2,339,184	0.19	0.68	21,890,886	0.17	0.64
State Level Control Variables									
Population (number)	3,747,506	3353159	1754615	2,339,184	4597477	1498266	21,890,886	18240818	11156588
Primary Care Health Professions Shortage Area Score	3,747,506	9.01	1.91	2,339,184	8.92	1.7	21,890,886	8.99	1.6
Primary Care Physicians (number)	3,747,506	2224	1220	2,339,184	3679	1539	21,890,886	10945	7207
Nurses with a Masters or Doctorate (number)	3,747,506	3944	2124	2,339,184	6469	2452	21,890,886	17583	10553
Poverty (%)	3,747,506	12.45%	2.63	2,339,184	9.42%	1.82	21,890,886	14.38%	2.1
Income (dollars)	3,747,506	48308	6043	2,339,184	59117	5316	21,890,886	47278	5789
Gross Domestic Product (dollars)	3,747,506	37371	15079	2,339,184	39441	1555	21,890,886	36764	4150
Medicare Expansion (%)	3,747,506	7%	0.25	2,339,184	9%	0.28	21,890,886	3%	0.17

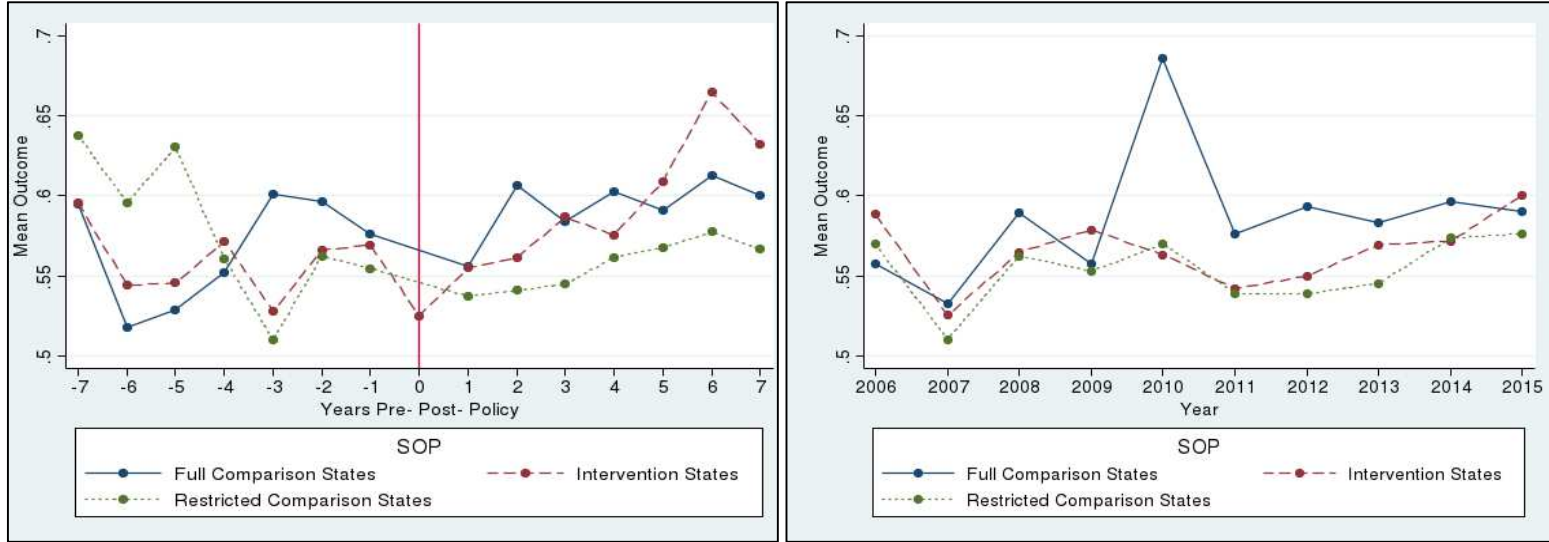
† All variables are significantly different between groups at a significance level of at $\alpha=0.001$.

Figures 5.1 through 5.8 chart the raw averages of each outcome over time in intervention and comparison groups centered by years pre- and post- policy implementation, and also by year.

Visual assessment of outcomes centered by years pre- and post- policy implementation period revealed that the trends in the pre-policy period for outcomes were relatively parallel, with greater parallelism in trends at years closer to the policy implementation year. There were generally larger differences in the average of each outcome between intervention and comparison groups at years 6 and 7 pre- and post- policy implementation than in years closer to the policy implementation year. This was likely due to fewer states contributing to averages in pre- and post- policy years 6 and 7, because only states that had policy implementation years of 2008 or 2013 were included in these averages.

Visual assessment of outcomes over time by year revealed a lack of notable change in the average number of individuals who had outpatient follow-up within 14 days of initial hospitalization or used the emergency department in intervention or comparison states. There was an increase over time in the average number of individuals who received an annual wellness exam, diabetes screening, or lipid screening in intervention and comparison states. There was a decrease over time in the average number of individuals who experienced an all-cause hospitalization, thirty-day readmission, or hospitalization for an acute ambulatory care sensitive condition (ACSC) in intervention and comparison states.

Figure 5.1: Average Receipt of Outpatient Follow-up Within 14 Days of Hospitalization by Years Pre- Post- Policy and Year



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Figure 5.2: Average Receipt of Annual Wellness Exam by Years Pre- Post- Policy and Year

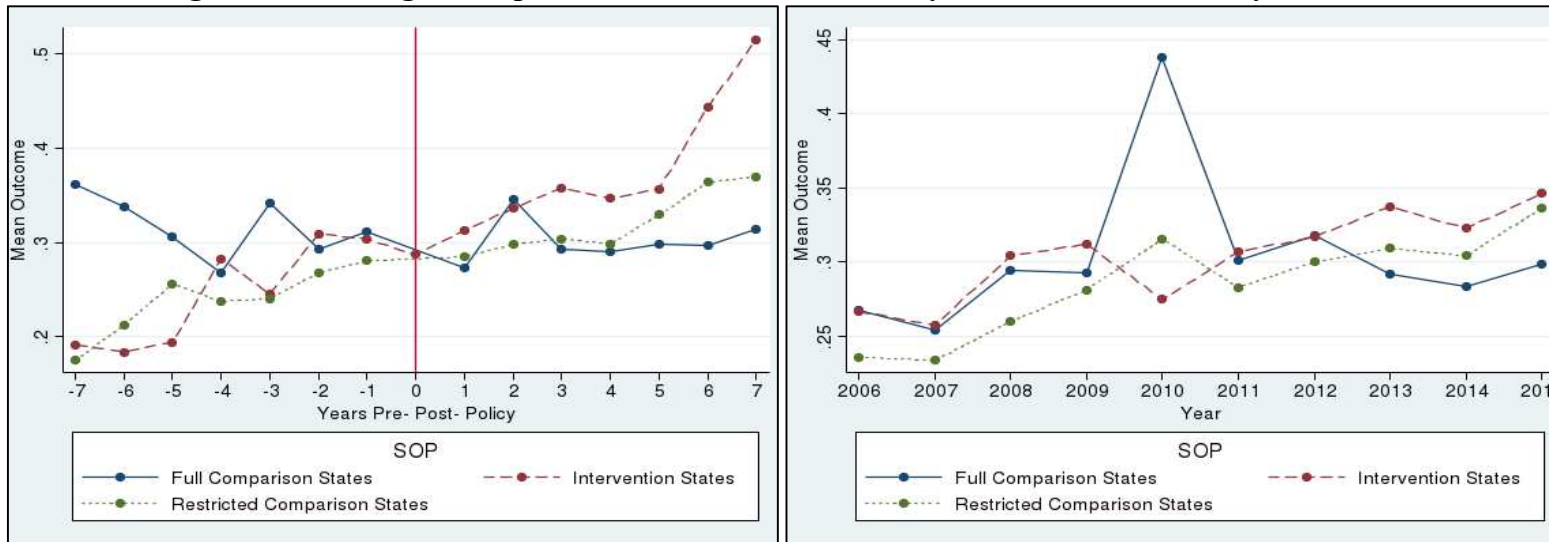


Figure 5.3: Average Receipt of Diabetes Screening by Years Pre- Post- Policy and Year

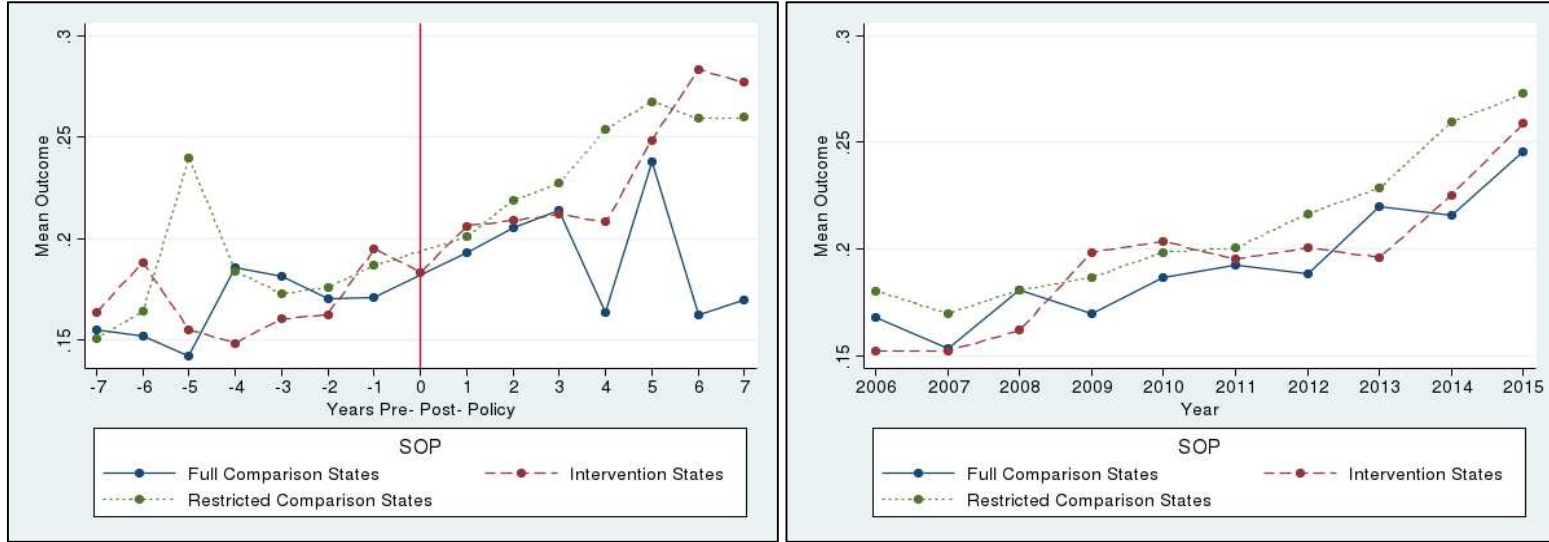


Figure 5.4: Average Receipt of Lipid Screening by Years Pre- Post- Policy and Year

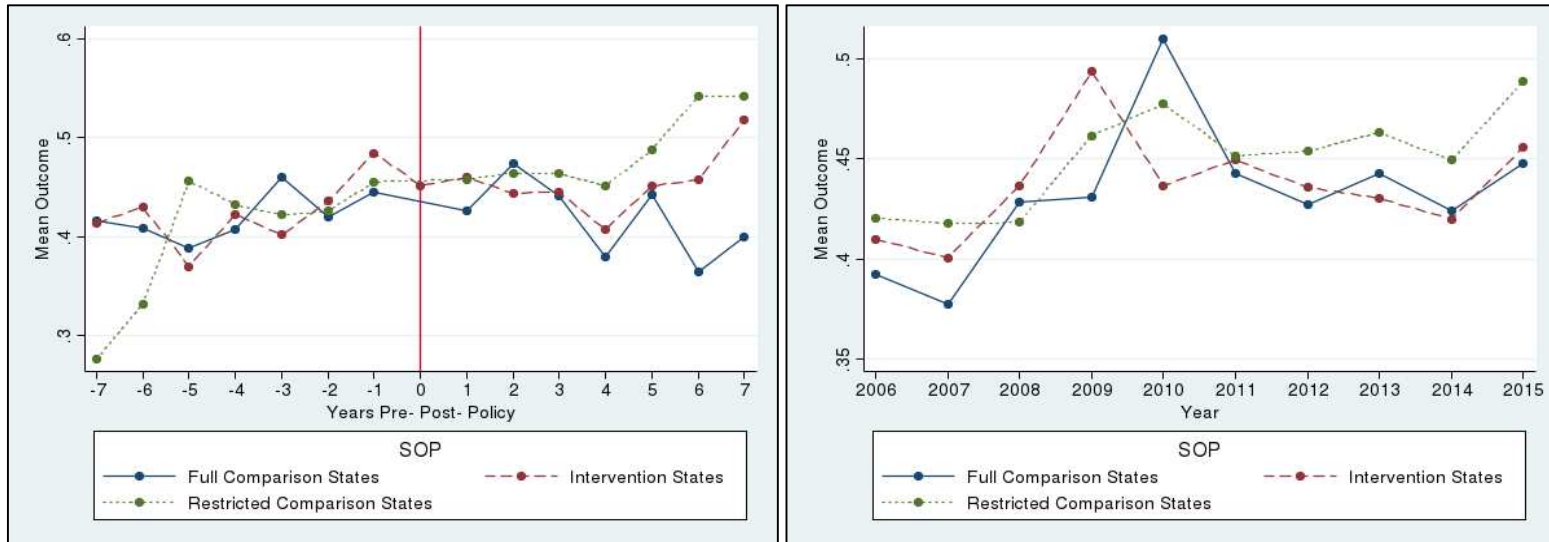


Figure 5.5: Average All-cause Hospitalizations by Years Pre- Post- Policy and Year

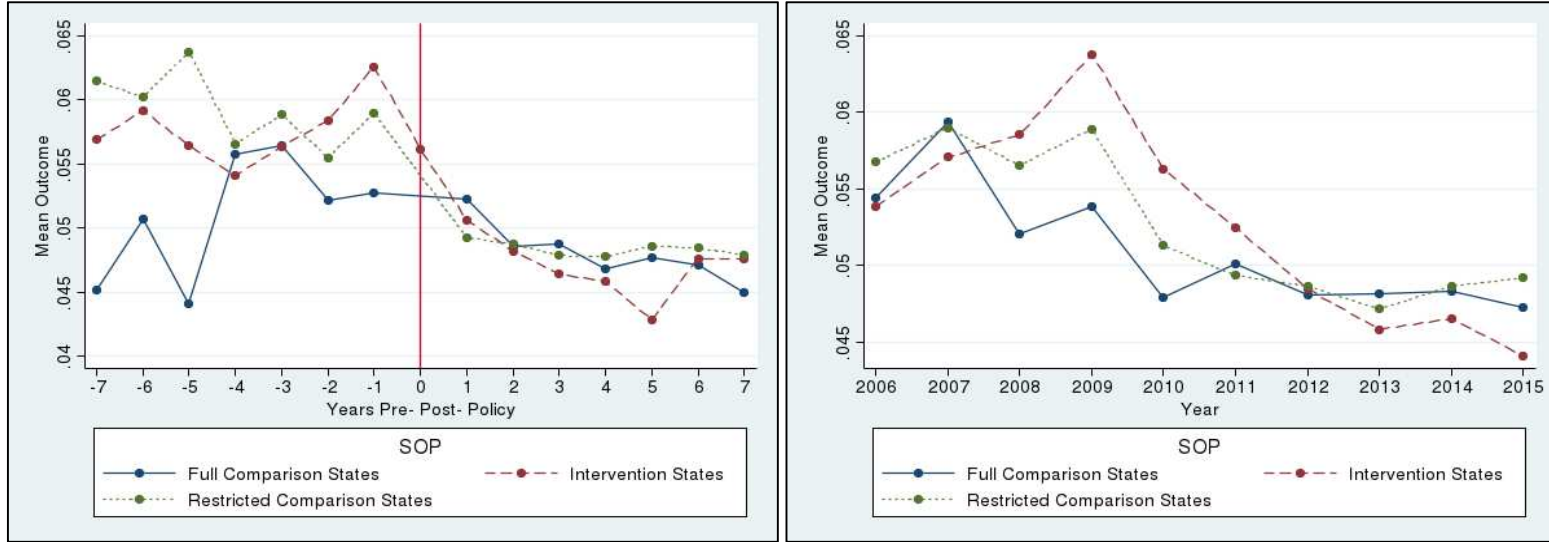


Figure 5.6: Average Emergency Department Utilizations by Years Pre- Post- Policy and Year

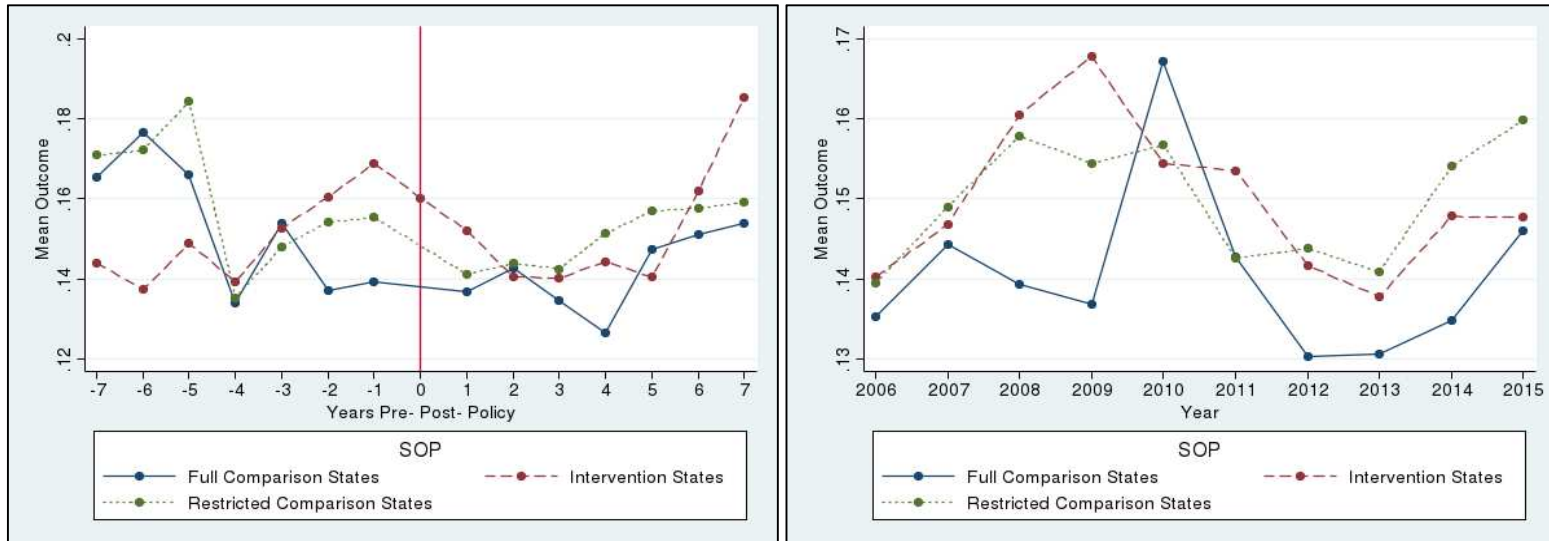
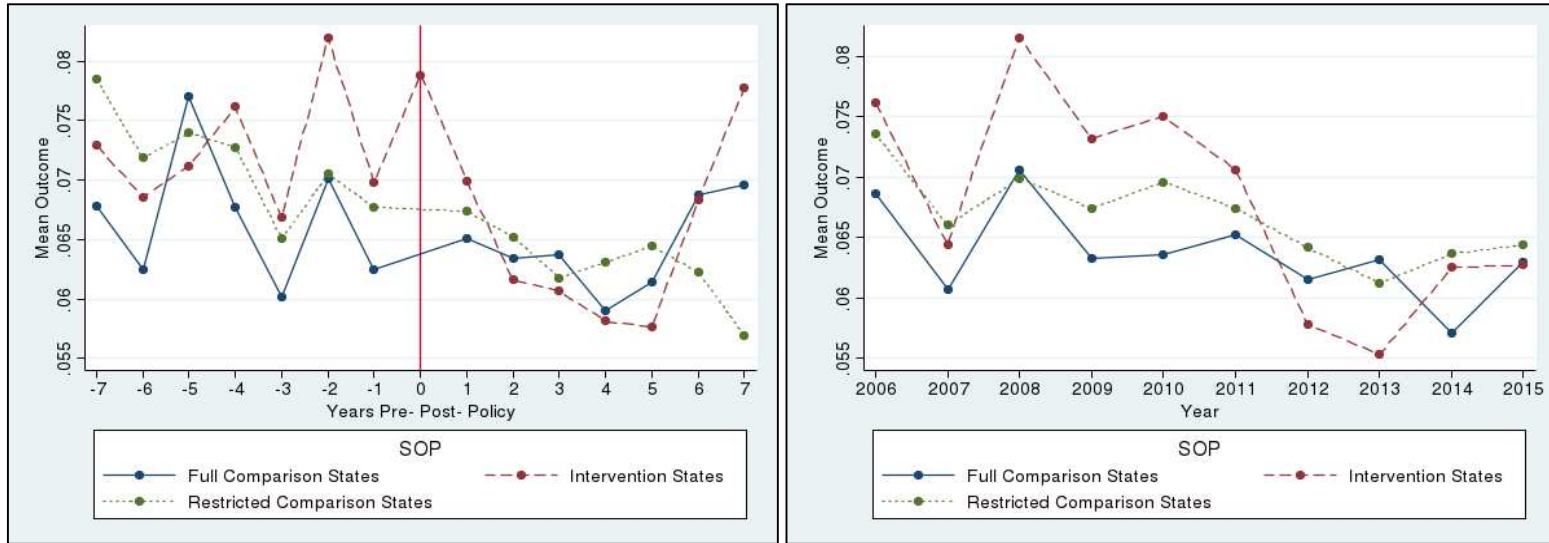
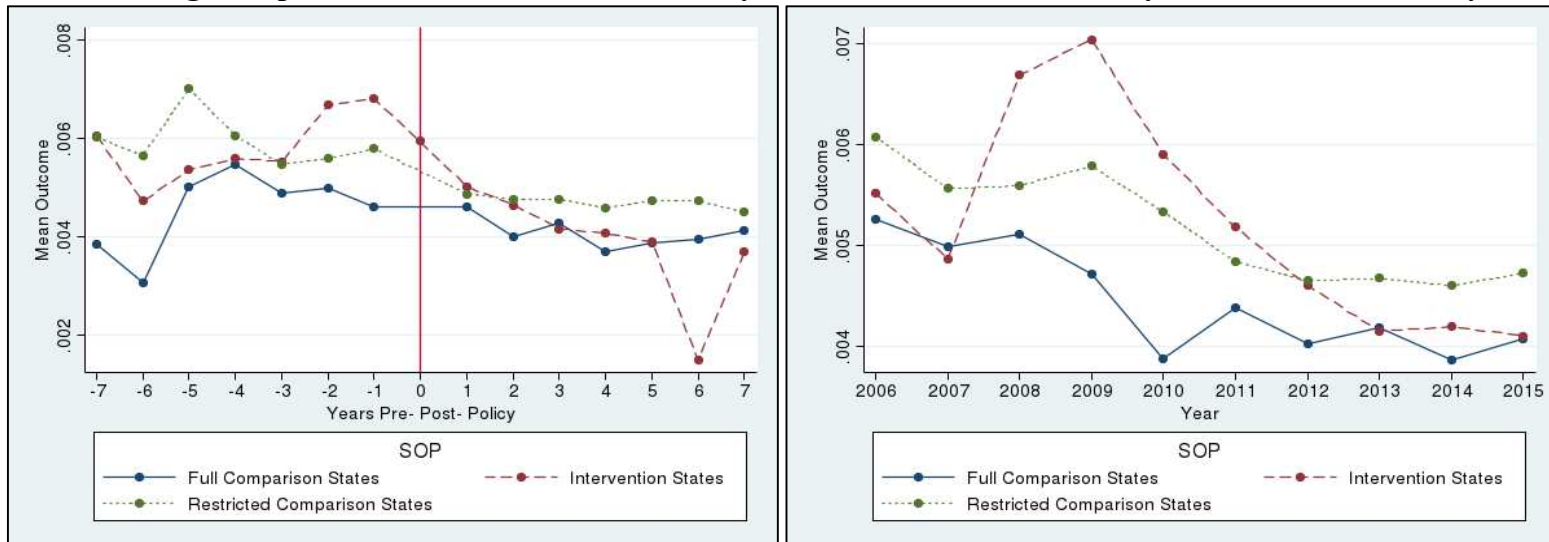


Figure 5.7: Average Thirty-Day Hospital Readmissions by Years Pre- Post- Policy and Year



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Figure 5.8: Average Hospitalizations for Acute Ambulatory Care Sensitive Conditions by Years Pre- Post- Policy and Year



Propensity Score Weighting

Table 5.4 displays the characteristics of individuals in intervention and full comparison states in the pre- and post- policy periods before and after propensity score weighting. Table 5.5 displays the characteristics of individuals in intervention and restricted comparison states in the pre- and post- policy periods before and after propensity score weighting. Prior to propensity score weighting, several covariates had a standardized difference in means greater than 0.1, representing substantial difference between groups. After propensity score weighting, the standardized difference in means for all covariates was less than 0.01, suggesting that propensity score weighting was successful in removing covariate differences between groups.

Table 5.4: Characteristics of Individuals in Intervention and Full Comparison States in Pre and Post Periods Before and After Propensity Score Weighting

Pre- versus Post- Policy Intervention Group					
Covariate	Pre-policy intervention (Mean)	<u>Unweighted</u>		<u>Weighted</u>	
		Post-policy intervention group (Mean)	Standardized Difference	Post-policy intervention group (Mean)	Standardized Difference
Age (years)	41.96	39.23	0.217	41.97	-0.001
Gender (male)	0.47	0.49	-0.034	0.47	-0.008
Residence in a MSA	0.91	0.92	-0.038	0.91	-0.012
Full time Employee	0.31	0.65	-0.708	0.31	-0.001
Charlson Comorbidity Index	0.2	0.15	0.075	0.19	0.01
Pre-policy Intervention Group versus Pre-policy Full NP SOP Comparison Group					
Covariate	Pre-policy intervention (Mean)	<u>Unweighted</u>		<u>Weighted</u>	
		Pre-policy Full Comparison (Mean)	Standardized Difference	Pre-policy Full Comparison (Mean)	Standardized Difference
Age (years)	41.96	41.4	0.045	41.92	0.003
Gender (male)	0.47	0.48	-0.02	0.47	-0.001
Residence in a MSA	0.91	0.69	0.577	0.91	0.001
Full time Employee	0.31	0.38	-0.153	0.31	-0.006
Charlson Comorbidity Index	0.2	0.15	0.07	0.2	-0.002

Pre-policy Intervention Group versus Post-policy Full NP SOP Comparison Group					
Covariate	Pre-policy intervention (Mean)	Unweighted		Weighted	
		Post-policy Full Comparison (Mean)	Standardized Difference	Post-policy Full Comparison (Mean)	Standardized Difference
Age (years)	41.96	39.29	0.211	42.05	-0.007
Gender (male)	0.47	0.49	-0.037	0.47	-0.004
Residence in a MSA	0.91	0.74	0.461	0.91	0.01
Full time Employee	0.31	0.5	-0.394	0.32	-0.011
Charlson Comorbidity Index	0.2	0.14	0.089	0.19	0.008

Table 5.5: Characteristics of Individuals in Intervention and Restricted Control States in Pre and Post Periods before and after Propensity Score Weighting

Pre- versus Post- Policy Intervention Group					
Covariate	Pre-policy intervention (Mean)	Unweighted		Weighted	
		Post-policy intervention (Mean)	Standardized Difference	Post-policy intervention (Mean)	Standardized Difference
Age (years)	41.96	39.23	0.217	42.25	-0.023
Gender (male)	0.47	0.49	-0.034	0.47	0.001
Residence in a MSA	0.91	0.92	-0.038	0.91	0.009
Full time Employee	0.31	0.65	-0.708	0.32	-0.026
Charlson Comorbidity Index	0.2	0.15	0.075	0.2	0.003

Pre-policy Intervention Group versus Pre-policy Restricted NP SOP Comparison Group					
Covariate	Pre-policy Intervention (Mean)	Unweighted		Weighted	
		Pre-policy Restricted Comparison (Mean)	Standardized Difference	Pre-policy Restricted Comparison (Mean)	Standardized Difference
Age (years)	41.96	41.49	0.037	42.01	-0.004
Gender (male)	0.47	0.47	0.006	0.47	0.003
Residence in a MSA	0.91	0.87	0.133	0.90	0.027
Full time Employee	0.31	0.47	-0.318	0.36	-0.11
Charlson Comorbidity Index	0.2	0.18	0.031	0.2	-0.001

Pre-policy Intervention Group versus Post-policy Restricted NP SOP Comparison Group					
Covariate	Pre-policy Intervention group (Mean)	Unweighted		Weighted	
		Post-policy Restricted Comparison (Mean)	Standardized Difference	Post-policy Restricted Comparison (Mean)	Standardized Difference
Age (years)	41.96	38.83	0.25	42.01	-0.004
Gender (male)	0.47	0.48	-0.018	0.47	-0.005
Residence in a MSA	0.91	0.9	0.037	0.91	0.008
Full time Employee	0.31	0.48	-0.349	0.31	0.007
Charlson Comorbidity Index	0.2	0.16	0.062	0.2	0.007

Main Results

Table 5.6 describes the results of the main model, a doubly robust propensity score weighted linear probability model difference-in-difference (DD) analysis with state and year fixed effects and cluster-robust standard errors, by presenting the coefficient for the difference-in-difference estimator, robust standard error, and significance level associated with each outcome.

Effect of NP SOP on Receipt of Outpatient Follow-up within 14 Days of Hospitalization

Hypothesis 1 stated that compared to states with unchanged full or unchanged restricted NP SOP, states that implemented full NP SOP would have a greater increase in individuals receiving outpatient follow-up within fourteen days after hospitalization. Hypothesis 1 was not supported by the results of this study. DD analysis showed that implementation of full NP SOP policies has no effect on whether an individual received outpatient follow-up after hospitalization within 14 days compared to individuals in states with unchanged full NP SOP policies or in states with unchanged restricted NP SOP policies.

Effect of NP SOP on Preventive Service Use

Hypothesis 2a stated that compared to states with unchanged full or unchanged restricted NP SOP, states that implemented full NP SOP would have a greater increase in individuals utilizing the preventive services of annual wellness exams, diabetes screenings, and lipid screenings. Hypothesis 2a was unsupported by the main results of this study, with the exception of diabetes screening. Although DD analysis showed that implementation of full NP SOP policies results in a 3.0 percentage point increase in diabetes screenings ($p < 0.05$), analysis also showed that there is no effect on receipt of an annual wellness exam or lipid screening compared to individuals in states with unchanged full NP SOP policies. DD analysis also indicated that implementation of full NP SOP policies resulted in a 4.0 percentage point decrease in annual wellness exams ($p < 0.01$) and had no effect on receipt of a diabetes screening or lipid screening compared to individuals in states with unchanged restricted NP SOP policies.

Effect of NP SOP on All Cause Utilization of Acute Care

Hypothesis 2b stated that compared to states with unchanged full or unchanged restricted NP SOP, states that implemented full NP SOP would have a greater decrease in individuals utilizing acute care services. Hypothesis 2b also was not supported by the main results of this study. DD analysis showed that implementation of full NP SOP policies had no effect on whether an individual had an all-cause hospitalization, all-cause emergency department utilization, all-cause 30-day readmission, or hospitalization for an acute ambulatory care sensitive condition (ACSC).

Table 5.6: Difference-in-Difference Estimators for Outcomes Estimated by Main model

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0090	0.0089	0.0297*	0.0214	-0.0019	0.0047	-0.0007	0.0002
Robust SE	(0.0094)	(0.0115)	(0.0140)	(0.0114)	(0.0023)	(0.0058)	(0.0035)	(0.0003)
N	321918	6086690	2600150	2600150	6086690	6086690	321918	6086690
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	0.0019	-0.0397**	0.0184	-0.0100	-0.0002	-0.0002	-0.0016	0.0001
Robust SE	(0.0072)	(0.0104)	(0.0124)	(0.0172)	(0.0017)	(0.0054)	(0.0026)	(0.0002)
N	1302222	24230070	9984987	9984987	24230070	24230070	1302222	24230070

*p<0.05; **p<0.01; ***p<0.001

Results of Sensitivity and Subgroup Analyses

In addition to the main models (presented as “overall” in following Tables and Figures), three additional sets of sensitivity and subgroup analyses were conducted for each outcome in this dissertation: 1. a parameterized state effects model which controlled for select state level covariates in lieu of a state fixed effect (presented as “stcov” in following Tables and Figures); 2. a model that only included individuals in rural locations (presented as “rural” in following Tables and Figures); and 3. six models that only included individual intervention states (presented as CO Colorado, HI Hawaii, MD Maryland, NV Nevada, ND North Dakota, RI Rhode Island, VT Vermont in following Tables and Figures).

The results of the sensitivity and subgroup analyses are presented in three ways. First, the coefficient for the difference-in-difference (DD) estimator, robust standard error, and significance level associated with each outcome are presented for each model. Next, to compare

results across models, a “color map” indicating changes for each outcome in each model is presented. The color map was used for visual assessment of the sign and significance of trends in the effects of implementing full NP SOP policy across outcomes and models. Lastly, forest plots with the point estimates and 95% confidence intervals associated with DD estimators for each model are presented separately for each outcome. The forest plots provided greater detail than the color map by allowing a visual assessment of magnitude, in addition to the sign and significance, of the effect to implementing full NP SOP policy.

Parameterized State Effects Model

Table 5.7 describes the results of the parameterized state effects model, a doubly robust propensity score weighted linear probability model DD with year fixed effects and cluster-robust standard errors, by presenting the coefficient for the difference-in-difference estimator, robust standard error, and significance level associated with each outcome.

Table 5.7: Difference-in-Difference Estimators for Outcomes Estimated by Parameterized State Effects Model

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All- Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0330*	-0.0178	-0.0023	-0.0138	0.0004	-0.0064	0.0009	0.0004
Robust SE	(0.0134)	(0.0144)	(0.0151)	(0.0132)	(0.0017)	(0.0085)	(0.0036)	(0.0004)
N	321918	6086690	2600150	2600150	6086690	6086690	321918	6086690
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	0.0162	-0.0319	-0.0009	-0.0477*	0.0013	-0.0080	-0.0028	-0.0003
Robust SE	(0.0105)	(0.0217)	(0.0168)	(0.0195)	(0.0012)	(0.0056)	(0.0024)	(0.0002)
N	1302222	24230070	9984987	9984987	24230070	24230070	1302222	24230070

*p<0.05; **p<0.01; ***p<0.001

Trends for Individuals Living in Rural Locations

Table 5.8 describes the results of the main model applied to individuals that did not live in a metropolitan statistical area by presenting the coefficient for the difference-in-difference estimator, robust standard error, and significance level associated with each outcome.

Table 5.8: Difference-in-Difference Estimators for Outcomes for Individuals in Rural Areas

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0274	-0.0052	0.0240	0.0268	0.0008	-0.0031	-0.0003	0.0007
Robust SE	(0.0184)	(0.0143)	(0.0149)	(0.0311)	(0.0019)	(0.0082)	(0.0065)	(0.0004)
N	68621	1295801	615861	615861	1295801	1295801	68621	1295801
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	-0.0100	-0.0422**	0.0078	0.0038	0.0044*	-0.0049	-0.0061	0.0009*
Robust SE	(0.0220)	(0.0109)	(0.0136)	(0.0269)	(0.0018)	(0.0073)	(0.0060)	(0.0004)
N	166174	2795385	1300338	1300338	2795385	2795385	166174	2795385

*p<0.05; **p<0.01; ***p<0.001

Trends by State

Tables 5.9-5.15 describe the results of the main model for each state by presenting the coefficient for the difference-in-difference estimator, robust standard error, and significance level associated with each outcome.

Table 5.9: Difference-in-Difference Estimators for Outcomes for Individuals in Colorado

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0230**	0.0015	0.0074	-0.0040	0.0009	-0.0010	-0.0051	0.0005
Robust SE	(0.0057)	(0.0081)	(0.0109)	(0.0098)	(0.0018)	(0.0039)	(0.0031)	(0.0003)
N	220470	4314600	1797842	1797842	4314600	4314600	220470	4314600
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	-0.0043	-0.0431***	-0.0016	-0.0277*	0.0022*	-0.0065	-0.0052**	0.0003*
Robust SE	(0.0062)	(0.0083)	(0.0109)	(0.0126)	(0.0008)	(0.0046)	(0.0013)	(0.0001)
N	1200774	22457980	9182679	9182679	22457980	22457980	1200774	22457980

*p<0.05; **p<0.01; ***p<0.001

Table 5.10: Difference-in-Difference Estimators for Outcomes for Individuals in Hawaii

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	0.0200*	0.0304**	0.0661***	0.0018	0.0064*	-0.0026	-0.0095*	0.0012**
Robust SE	(0.0085)	(0.0076)	(0.0106)	(0.0069)	(0.0020)	(0.0047)	(0.0032)	(0.0003)
N	193602	3756879	1584639	1584639	3756879	3756879	193602	3756879
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	0.0178*	-0.0313**	0.0527***	0.0515**	0.0069***	-0.0044	-0.0088***	0.0009***
Robust SE	(0.0070)	(0.0091)	(0.0110)	(0.0127)	(0.0009)	(0.0058)	(0.0015)	(0.0002)
N	1173906	21900259	8969476	8969476	21900259	21900259	1173906	21900259

*p<0.05; **p<0.01; ***p<0.001

Table 5.11: Difference-in-Difference Estimators for Outcomes for Individuals in Maryland

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	0.0006	-0.0026	0.0341*	0.0169	-0.0052**	0.0037	0.0012	-0.0001
Robust SE	(0.0109)	(0.0099)	(0.0132)	(0.0140)	(0.0015)	(0.0070)	(0.0030)	(0.0003)
N	266347	5003812	2166478	2166478	5003812	5003812	266347	5003812
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	0.0060	-0.0546***	0.0208	-0.0211	-0.0030*	0.0006	-0.0004	-0.0001
Robust SE	(0.0088)	(0.0072)	(0.0112)	(0.0210)	(0.0013)	(0.0059)	(0.0017)	(0.0002)
N	1246651	23147192	9551315	9551315	23147192	23147192	1246651	23147192

*p<0.05; **p<0.01; ***p<0.001

Table 5.12: Difference-in-Difference Estimators for Outcomes for Individuals in Nevada

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0293	0.0975***	0.0694***	0.0628***	-0.0031	0.0173**	0.0139***	0.0007
Robust SE	(0.0145)	(0.0103)	(0.0143)	(0.0123)	(0.0020)	(0.0054)	(0.0024)	(0.0004)
N	212679	4086487	1718406	1718406	4086487	4086487	212679	4086487
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	-0.0106*	0.0297*	0.0390***	0.0185	-0.0027*	0.0058	0.0139***	0.0005
Robust SE	(0.0045)	(0.0098)	(0.0080)	(0.0110)	(0.0010)	(0.0061)	(0.0012)	(0.0002)
N	1192983	22229867	9103243	9103243	22229867	22229867	1192983	22229867

*p<0.05; **p<0.01; ***p<0.001

Table 5.13: Difference-in-Difference Estimators for Outcomes for Individuals in North Dakota

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator Robust SE	0.0022 (0.0093)	0.0264* (0.0089)	-0.0015 (0.0101)	0.0208* (0.0080)	-0.0038 (0.0017)	0.0200** (0.0049)	-0.0209*** (0.0027)	-0.0006* (0.0002)
N	195545	3787730	1593922	1593922	3787730	3787730	195545	3787730
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator Robust SE	0.0082 (0.0058)	-0.0327** (0.0095)	-0.0141 (0.0111)	-0.0186 (0.0123)	-0.0033*** (0.0007)	0.0129 (0.0061)	-0.0216*** (0.0014)	-0.0008*** (0.0001)
N	1175849	21931110	8978759	8978759	21931110	21931110	1175849	21931110

*p<0.05; **p<0.01; ***p<0.001

Table 5.14: Difference-in-Difference Estimators for Outcomes for Individuals in Rhode Island

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator Robust SE	-0.0011 (0.0085)	0.0329* (0.0113)	0.0522** (0.0136)	0.0683** (0.0202)	0.0050* (0.0020)	0.0186*** (0.0034)	-0.0039 (0.0027)	0.0010** (0.0003)
N	197869	3839308	1616452	1616452	3839308	3839308	197869	3839308
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator Robust SE	0.0243** (0.0073)	0.0040 (0.0101)	0.0523** (0.0133)	0.0623*** (0.0128)	0.0052*** (0.0006)	0.0119* (0.0043)	-0.0038* (0.0013)	0.0004** (0.0001)
N	1178173	21982688	9001289	9001289	21982688	21982688	1178173	21982688

*p<0.05; **p<0.01; ***p<0.001

Table 5.15: Difference-in-Difference Estimators for Outcomes for Individuals in Vermont

Effect of Implementing Full NP SOP compared to Full NP SOP Comparison group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	0.0836***	0.0588***	0.0549***	0.1495***	0.0057*	-0.0028	-0.0085*	0.0000
Robust SE	(0.0106)	(0.0092)	(0.0100)	(0.0057)	(0.0021)	(0.0048)	(0.0034)	(0.0003)
N	194624	3782910	1596435	1596435	3782910	3782910	194624	3782910
Effect of Implementing Full NP SOP compared to Restricted NP SOP Comparison Group								
DD estimator	0.0845***	-0.0022	0.0424**	0.0968***	0.0057***	-0.0086	-0.0070***	-0.0004*
Robust SE	(0.0075)	(0.0107)	(0.0113)	(0.0147)	(0.0009)	(0.0059)	(0.0014)	(0.0002)
N	1174928	21926290	8981272	8981272	21926290	21926290	1174928	21926290

*p<0.05; **p<0.01; ***p<0.001

Assessment of Trends Across Models

To assess how trends in the effects of implementing full NP SOP policy vary across states, a color map demonstrating whether there was a statistically significant increase, decrease, or no change in each outcome for each model and comparison group is presented in Figure 5.9. Improved outcomes were defined as an increase in outpatient follow-up within 14 days after hospitalization, annual wellness exams, diabetes screenings, lipid screens, and a decrease in all-cause hospitalizations, all-cause emergency department utilizations, all-cause 30-day readmissions, and acute ambulatory care sensitive condition hospitalizations. Worsened outcomes were defined as the opposite of improved outcomes.

Overall, the color map revealed heterogeneity in the effect of implementing NP SOP by model specification, rurality, and state. The conclusions drawn from the main model did not align with the parameterized state effects model in which state fixed effects are replaced by

specified state level covariates. Furthermore, the color map suggested that individuals in rural locations did not gain a greater improvement in access-related outcomes when full NP SOP is implemented compared to individuals in the overall main model.

There was also evidence from the color map that implementing full NP SOP improved access related outcomes for some states while worsening the same access related outcomes in other states. For example, there were fewer annual wellness exams over time in the intervention states of Colorado, Maryland and North Dakota compared to states with unchanged restricted SOP. This was also true for individuals in rural locations. However, there was an increase in annual wellness exams in the intervention state Nevada compared to states with unchanged full SOP and unchanged restricted SOP. Although there were differential impacts of full SOP on annual wellness exams between states, the overall model suggested that implementing full SOP resulted in fewer annual wellness exams overtime compared to states with unchanged restricted SOP.

The color map also suggested that implementing full NP SOP may improve some aspects of access to care more than other aspects of care. For example, individuals in three or more intervention states experienced a greater increase in preventive services like diabetes screenings and lipid screenings compared to states with unchanged full or unchanged restricted SOP. In contrast, no intervention states experienced a decrease in emergency department utilization compared to states with unchanged full or unchanged restricted SOP.

Lastly, the color map provided evidence that some states may realize more positive effects when implementing full SOP than others other states. Most outcomes in Vermont, for example, improved after full SOP is implemented. Individuals in Vermont experienced an improvement in out-patient follow-up within 14 days of initial hospitalization, diabetes

screening, lipid screenings, all-cause 30-day readmissions, and hospitalizations for acute ambulatory care sensitive conditions compared to states with unchanged full or unchanged restricted SOP. In contrast, individuals in Hawaii experienced an increase in all-cause hospitalizations and hospitalizations for acute ambulatory care sensitive conditions compared to states with unchanged full or unchanged restricted SOP.

Figure 5.9: Color Map of Outcomes by Model and Comparison Group

Legend†	
	Significantly improved outcome
	No significant change in outcome
	Significantly worsened outcome

Effect of Implementing Full SOP compared to Full SOP Comparison Group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All-Cause 30-day	Acute ACSC Hosp.
Overall								
StCov								
Rural								
CO								
HI								
MD								
NV								
ND								
RI								
VT								
Effect of Implementing Full SOP compared to Restricted SOP Comparison Group								
	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All-Cause Hosp.	All-Cause ED	All Cause 30-day	Acute ACSC Hosp.
Overall								
StCov								
Rural								
CO								
HI								
MD								
NV								
ND								
RI								
VT								

† Improved outcomes are defined as an increase in outpatient follow-up within 14 days after hospitalization, annual wellness exams, diabetes screenings, lipid screens, and a decrease in all-cause hospitalizations, all-cause emergency department utilizations, all-cause 30-day readmissions, and acute ambulatory care sensitive condition hospitalizations. Worsened outcomes are defined as the opposite of improved outcomes.

The forest plots (Figures 5.10-5.17) were used to further compare the sign, significance, and magnitude of the effect of implementing full SOP on outcomes across models. The point estimate from the DD estimator and the 95% confidence interval calculated from the robust standard error are displayed on the y-axis. The model is displayed on the x-axis. The results displayed by the forest plots reiterate the trends found in the color chart.

When assessing the outcomes for which the main model revealed a significant effect (diabetes screenings, annual wellness exams), the forest plots revealed consistency in the magnitude of the effect across models. The magnitude of the effect of full NP SOP policy implementation on annual wellness exams when using the unchanged restricted comparison group (Figure 5.11) is negative in all models except the subgroup analysis for Nevada and Rhode Island. Furthermore, the magnitude of the effect of full NP SOP policy implementation on diabetes screenings when using the unchanged full comparison group (Figure 5.12) is positive in all models except the model using parameterized state effects and the subgroup analysis for Nevada, both of which have point estimates close to 0.

Figure 5.10: Effect of Full NP SOP Policy Implementation on Outpatient Follow-up within 14 days after Initial Hospitalization

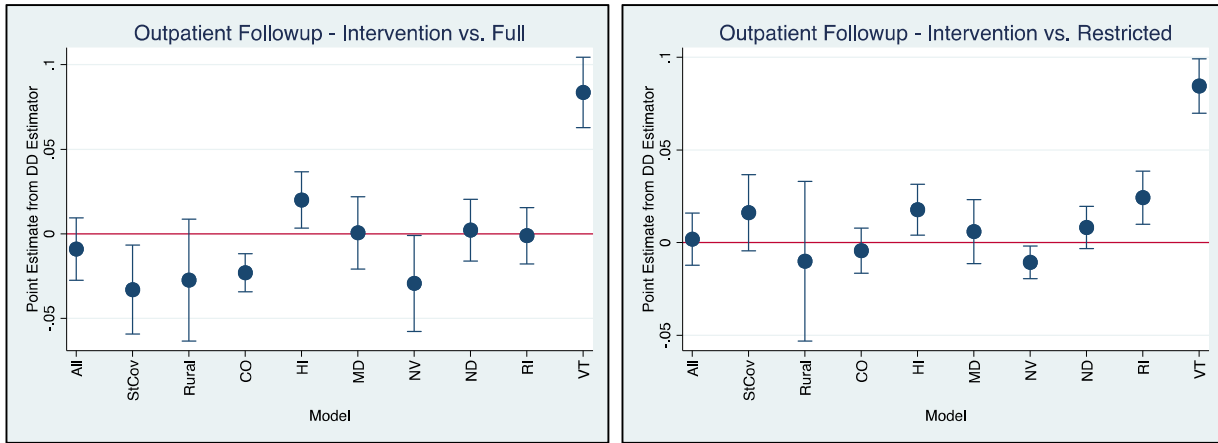


Figure 5.11: Effect of Full NP SOP Policy Implementation on Annual Wellness Exams

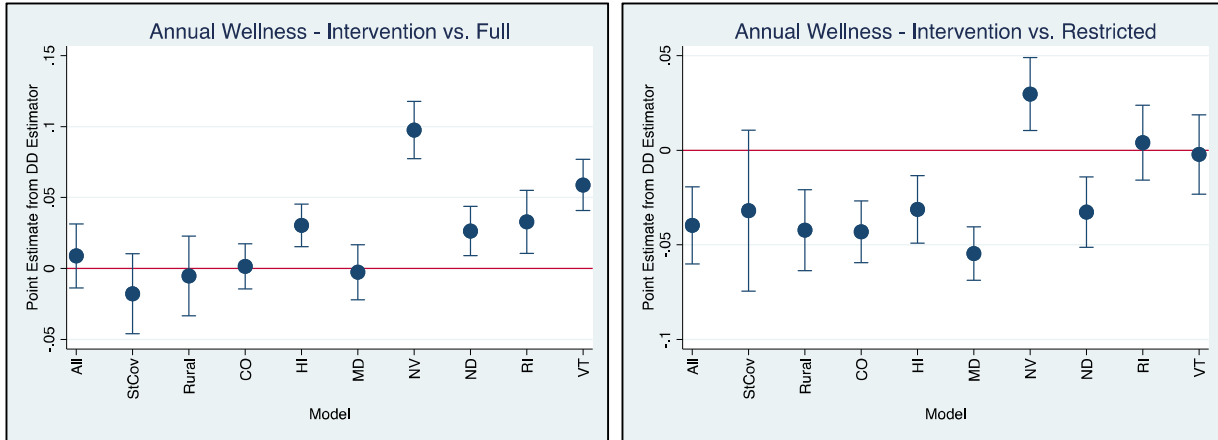


Figure 5.12: Effect of Full NP SOP Policy Implementation on Diabetes Screenings

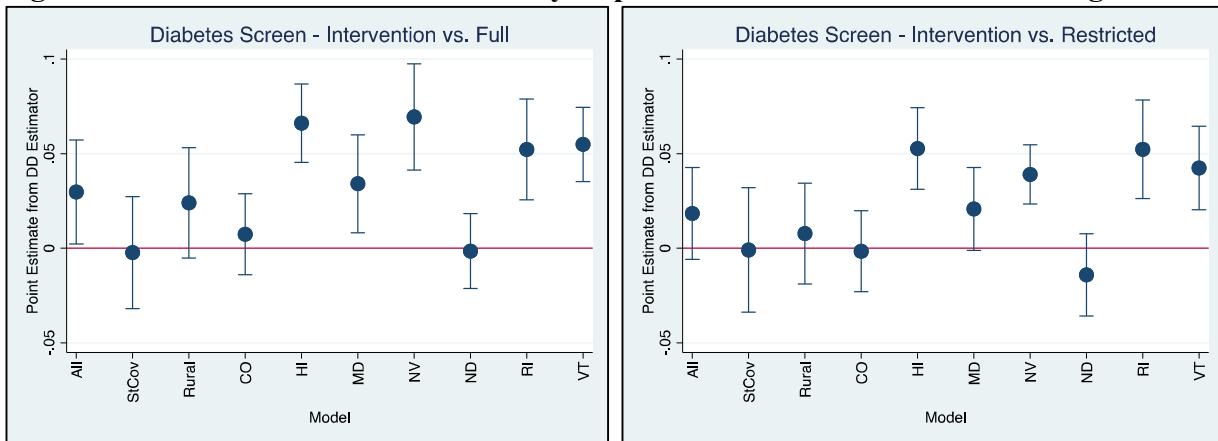


Figure 5.13: Effect of Full NP SOP Policy Implementation on Lipid Screenings

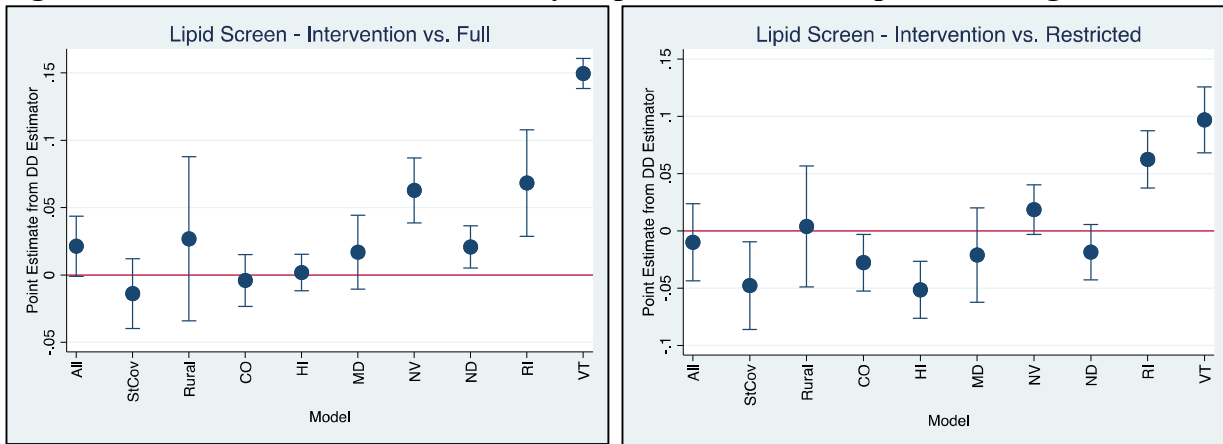


Figure 5.14: Effect of Full NP SOP Implementation on All-cause Hospitalization

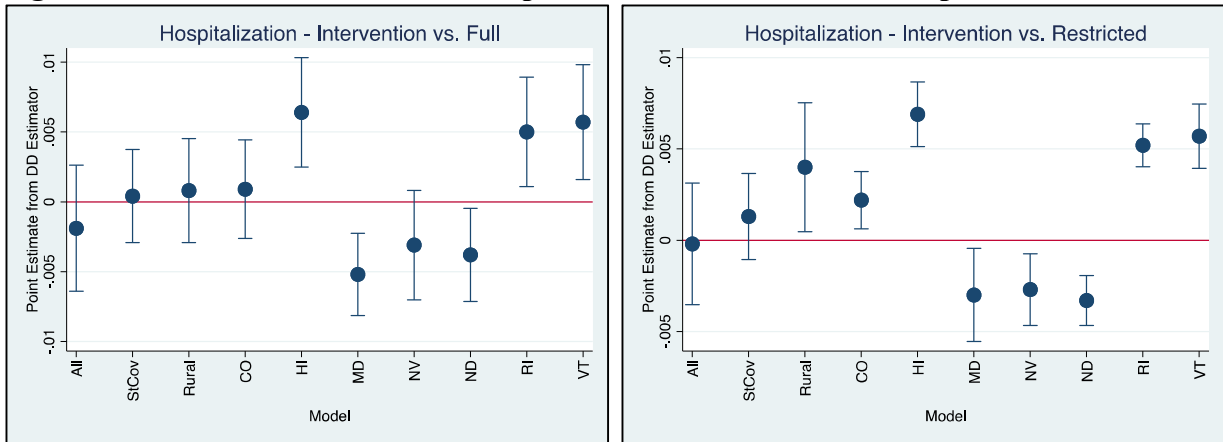


Figure 5.15: Effect of Full NP SOP Implementation on Emergency Department Use

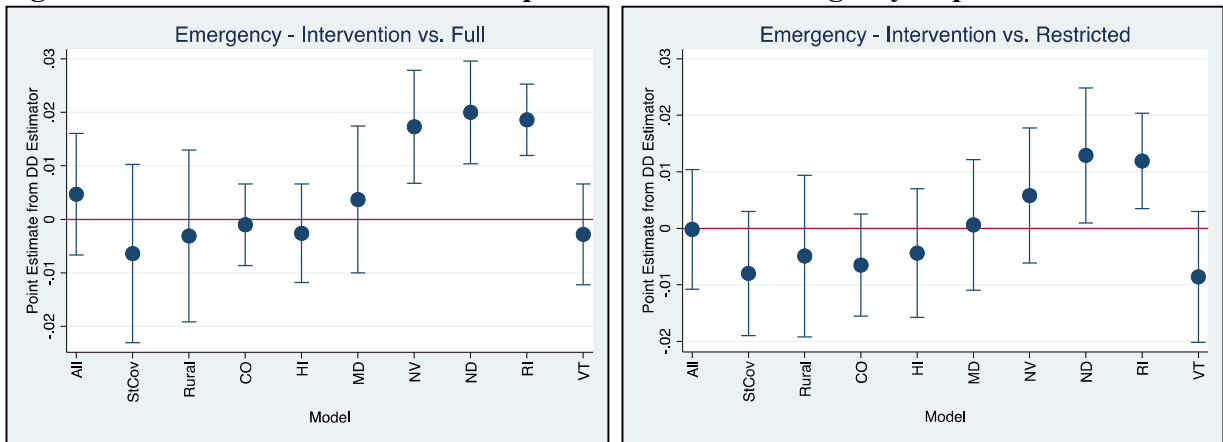


Figure 5.16: Effect of Full NP SOP Implementation on 30-day Hospital Readmissions

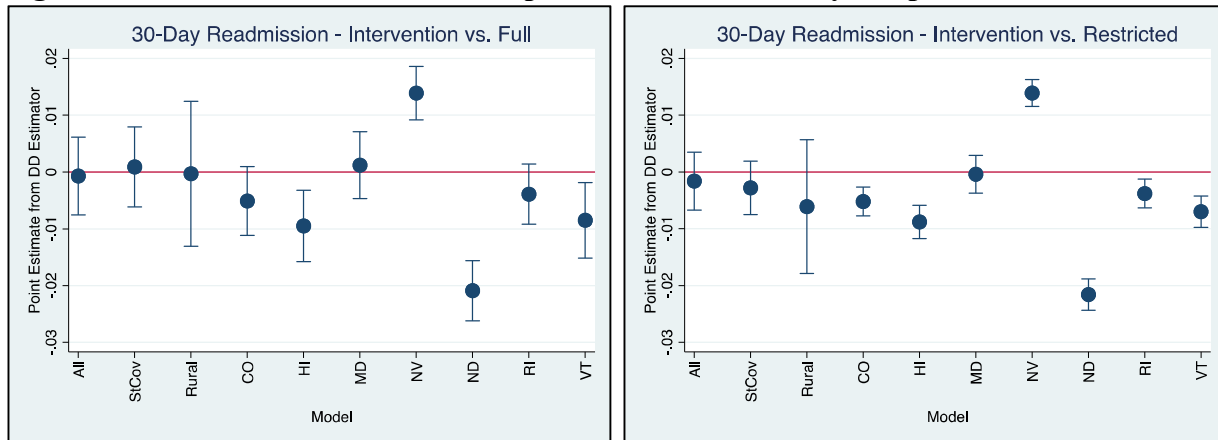
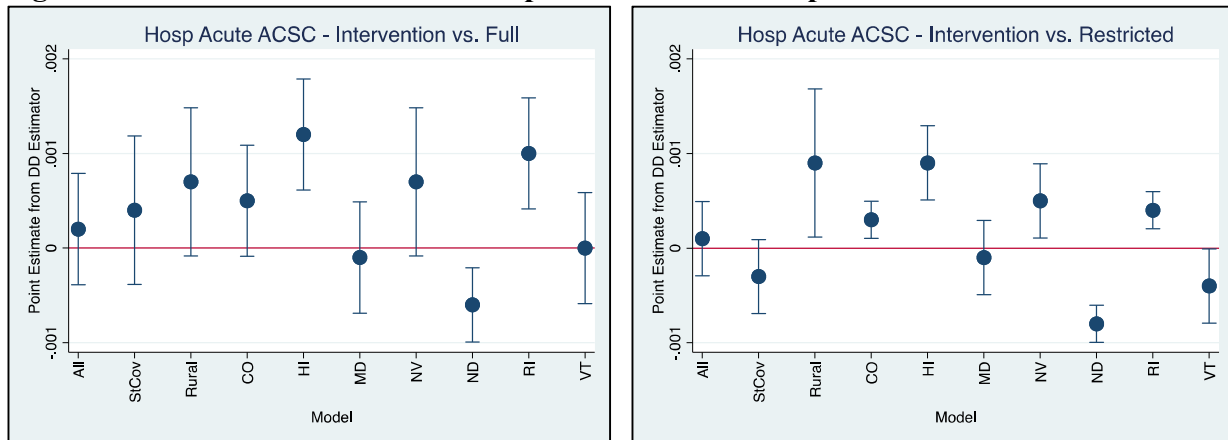


Figure 5.17: Effect of Full NP SOP Implementation on Hospitalization for Acute ACSC



Chapter Summary

This chapter described the findings of this dissertation. The main findings did not support hypothesis 1, 2a, or 2b; DD analysis indicated that, in a commercially insured population, implementing full NP SOP does not increase outpatient follow-up within 14 days after hospitalization, increase utilization of preventive services, or decrease utilization of acute care services. The results from the main model, which included a state fixed effect, did not align with a model had no state fixed effects but instead controlled for various state level covariates.

Last, when assessing effects for individuals in rural locations, and at individual states, there was substantial variation in the significance, sign, and magnitude of the effect of implementing full NP SOP on the access to care outcomes measured in this dissertation.

CHAPTER VI: DISCUSSION

This chapter begins with a discussion of how this study advances the body of knowledge about the effect of NP SOP policy on access to care. This is followed by a discussion of the main hypotheses and results, and a consideration of why these results did not align with previous work assessing NP SOP and access to care. The results of the sensitivity and subgroup analyses are then discussed. Next, the limitations of this study are presented. This chapter closes by presenting the implications for policy, suggestions for future research, and overall conclusions from this study.

Advancements over Prior Work

This dissertation is the first study to use claims data to assess the impact of implementing full NP SOP on access related outcomes in a commercially insured population and in individual states. It is also among the first to use a longitudinal and quasi-experimental approach to examine this relationship. A systematic review revealed that most studies that previously examined NP SOP and access to care did not use longitudinal or quasi-experimental designs (Patel et al., 2018). Only one study used a quasi-experimental approach to assess the effect of implementing full NP SOP policy on various access to care outcomes (Traczynski and Udalova, 2018). Like this dissertation, the Traczynski and Udalova's (2018) study used a difference-in-difference framework to analyze how implementing full NP SOP policy affects outcomes like annual wellness exams and emergency department utilization. Because of the similarities of this

dissertation and Traczynski and Udalova's (2018) work, the differences in methodological approaches are discussed below in greater detail.

Traczynski and Udalova's (2018) did not use a theoretical framework to guide their study. In contrast, this dissertation has a defined theoretical basis underlying the selection of outcomes measured by framing the measures of realized access to care within the widely used Aday and Andersen's Framework for the Study of Access to Medical Care (1974). This framework is useful in studies assessing the impact of a health policy on access to care because it delineates the various components of access to care and how they interact with one another. Ultimately, The Aday and Anderson's framework provided an informed means to guide development of the hypotheses tested in this dissertation with respect to the multifaceted and interacting components of access to care. This study assessed the effect of implementing full SOP on the characteristics of the health delivery system and utilization of health services access to care components of Aday and Anderson's framework. Although the relationships among access to care components were not tested, this framework was used to inform consider how other components of access to care, such as the characteristics of the population, influence the results of this study.

The theoretical basis for the measure of hospitalization for ambulatory care sensitive conditions in this study is also more concordant with the intended use of this measure. This measure was developed as a part of the Agency of Healthcare Quality's Prevalence Quality Indicators, which assess potentially avoidable hospitalizations for acute ambulatory care sensitive conditions. These measures were developed for use as proxies to assess access to high quality primary care (AHRQ, 2001, 2006, 2017). Traczynski and Udalova (2018) assessed patient reported ED-use for ambulatory care sensitive conditions. However, these measures were

developed and tested for hospitalizations, not patient reported ED-use. By using healthcare claims data, this dissertation captured all billed hospitalizations for acute ambulatory care sensitive conditions.

Although the use of claims data has its limitations (discussed in limitations section of this chapter), using claims data also has select advantages over the patient reported data used in the Traczynski and Udalova (2018) study. Claims data captures actual utilization of health services. Hence, data are less likely to be skewed by recall bias which can be problematic in patient reported data. MEPS data, specifically, underreports actual ED visits by one-third and office visits by one-fifth due to the nature of patient reported data, giving an inaccurate representation of utilization of services (Zuvekas & Olin, 2009). Since claims data includes all billed health services, MarketScan claims data may better capture actual utilization of emergency care.

The design of this dissertation, which separates comparison groups into those with unchanged full SOP and unchanged restricted SOP, allows the opportunity to assess how results differ depending on these comparison groups. The unchanged full SOP group serves as a positive control, because the policy was already implemented in these states, while the unchanged restricted SOP group serves as a negative control. Because the Traczynski and Udalova (2018) study combines both comparison groups in a single analysis, it is not possible to assess how results differ depending on which comparison group is used. Using separate comparison groups allows examination of whether, in a state implementing full NP SOP policy, access related outcomes within that state become more like the outcomes in states with unchanged full NP policy while also becoming less like the outcomes in states with unchanged restricted NP SOP policy.

Another methodological strength of this dissertation is its use of a propensity score weighting strategy specifically designed for use in DD models where the data are from repeated cross-sections (Stuart et al., 2014). DD models that use repeated cross-sectional data are prone to confounding by changes in-group composition over time. The model in Traczynski and Udalova's (2018) study may have been confounded by individuals in the NP SOP change states versus comparison states differing in ways that impacted their access outcomes over time, such as comorbidity status. By using the propensity score weighting approach in this dissertation, bias from this type of confounding is minimized.

NP SOP Policy and Access to Care

In this dissertation, access to care was operationalized into three categories according to Aday and Andersen's Framework for the Study of Access to Medical Care (1974), as detailed in Chapter II. The first access to care category was the characteristics of the health delivery system, measured by assessing if individuals who were hospitalized received outpatient care within 14 days of their hospitalization. The second access to care category was utilization of preventive services, measured by assessing if individuals received an annual wellness exam and if individuals over 45 years of age received a diabetes screening or a lipid panel screening within a one-year period. The third access to care category was utilization of acute care services, measured by assessing if individuals were hospitalized for any condition, used an emergency department, had a 30-day readmission, or were hospitalized for an acute ambulatory care sensitive condition within a one-year period. The following sections discuss the main hypotheses and results categorized by these three access to care categories examined in this dissertation. For the results from the main analyses that revealed a statistically significant effect, the effects in individual states were also presented to contextualize the main findings.

NP SOP Policy and Outpatient Follow-up within 14 days of Hospitalization

Hypothesis 1 stated that following implementation of full NP SOP policy, there would be a greater increase in the number of individuals receiving outpatient follow-up within fourteen days after hospitalization compared to comparison states. Hypothesis 1 was not supported by the results from the main models in this study. The magnitude of the effect of implementing full NP SOP on outpatient follow-up within 14 days of hospitalization was insignificant in the main models using the unchanged restricted NP SOP comparison group as well as the unchanged full NP SOP comparison group. The results from the main model indicated that implementing full NP SOP did not change an individual's likelihood of receiving outpatient follow-up within 14 days of hospitalization in a commercially insured population.

Although previous studies have not assessed this outcome specifically, Traczynski & Udalova (2018) found that implementing full NP SOP policy decreased administrative burden for providers while increasing appointment availability for patients (Traczynski & Udalova, 2018). Although not examined in this study, the increased availability of appointments observed in this previous study may apply to less urgent appointments, like routine wellness exams, instead of ones that raise more concern, like for patients who were hospitalized. If patients who are hospitalized receive priority for appointments in outpatient care settings, regardless of NP SOP policies, it could explain why this study did not find a significant association between implementing full NP SOP and outpatient follow-up after hospitalization. The proportion of patients who received outpatient follow-up after hospitalization within 14 days was stable over time, with over 50% of patients receiving outpatient follow-up in each group, lending preliminary support to this explanation (Figure 5.1). Further work is required to assess if less

urgent visits, instead of visits following hospitalization, are becoming increasingly available following full NP SOP policy implementation.

From a theoretical perspective, it is important to consider that the outpatient follow-up measure may not be able to detect the characteristics of the health delivery system that change in response to implementing full NP SOP. This measure was selected as a proxy for a characteristic of the health delivery system because more direct measures of other characteristics of the health delivery system, such as provider competition, were not measurable in an administrative claims dataset. The use of this measure was supported by its use as a Medicare payment incentive to prevent hospital readmissions. Guidelines for how soon a patient should receive an outpatient follow-up after hospital discharge vary by reason for hospitalization and patient readmission risk status (Jackson, Shahsahebi, Wedlake, & DuBard, 2015). Therefore, future studies that use this measure may consider refining it to assess outpatient follow-up after hospitalization for a specific diagnosis.

NP SOP Policy and Utilization of Preventive Services

Hypothesis 2a stated that following implementation of full NP SOP policy, there would be a larger increase in preventive screening utilization compared to comparison states. Hypothesis 2a was partially supported by a result from the main models in this study. Although the main model revealed an increase in diabetes screening in states following full NP SOP policy implementation compared to states with unchanged full SOP, it did not reveal a significant change in lipid screenings in states following full NP SOP implementation compared to comparison states. Furthermore, the results from the main model suggested that compared to individuals in states with unchanged restricted SOP, individuals in states that implemented full SOP experienced a decrease in annual wellness exams.

Diabetes Screenings.

The main model did not find an overall significant increase in diabetes screenings in states that implemented full NP SOP compared to states with unchanged restricted NP SOP. However, the main model revealed there was a significant increase in diabetes screenings in states that implemented full NP SOP compared to states with unchanged full NP SOP. Because of this significant effect, the trends in individual states were further examined to contextualize this finding. Examination of data from individual states revealed that several states realized a significant increase in diabetes screenings compared to both unchanged full and unchanged restricted NP SOP comparison groups. When looking at individual states, there was an increase in the number of individuals receiving an annual diabetes screening in Hawaii, Nevada, Rhode Island, and Vermont compared to individuals in either comparison groups, and there was also an increase in Maryland compared to individuals in the unchanged full SOP comparison group. There were no states for which the implementation of full SOP resulted in a significant decrease in rates of diabetes screenings over time compared to states in both comparison groups. Diabetes screening was the only study outcome for which all significant findings across models suggested an improvement in the outcome following full NP SOP implementation compared to both comparison groups.

The increase in diabetes screenings following full NP SOP implementation may be attributed to an increase in provider competition following full NP SOP implementation, although provider competition was not explicitly tested in this study. However, prior work suggests increased provider competition can result in gains through the increased output of primary care at higher quality and lower cost (Markotwitz & Adams, 2018; Dash & Meredith, 2010). Moreover, Traczynski and Udalova (2018) found an increase in patient reported quality of

care following full NP SOP implementation. Provider competition may play a larger role for types of care in which NPs and primary care physicians function similarly; NPs regularly manage diabetes related care in a manner similar to primary care physicians (Lutfiyya et al., 2017; Kuo et al., 2015). If there is increased provider competition due to NPs and physicians increasingly filling similar roles in diabetes management following full NP SOP implementation, it may improve diabetes care overall. Over 33.9% of the U.S. population has pre-diabetes diabetes, and the morbidity and mortality associated with diabetes can be lessened by prevention, glycemic control, and risk reductions strategies available through access to appropriate care, like diabetes screenings (Dagogo-Jack, 2002, Centers for Disease Control, 2017). The results of this dissertation suggest that implementing full NP SOP may increase diabetes screenings; by extension, increased diabetes screenings may decrease the development and overall prevalence of diabetes in the general population. However, additional work is necessary to understand the mechanism through which implementing full NP SOP may affect this disease.

Annual Wellness Exams.

The main model did not find an overall significant change in receipt of annual wellness exams when compared to states with unchanged full NP SOP. However, the main model revealed there was a significant decrease in individuals receiving annual wellness exams in states that implemented full NP SOP compared to states with unchanged restricted NP SOP policy. Because of this significant effect, the trends in individual states were further examined to contextualize this finding. The significance and sign of this finding aligned with results from the models comparing individuals in states with unchanged restricted SOP and individuals in Colorado, Hawaii, Maryland, or North Dakota. However, when compared to the other comparison group, states with unchanged full NP SOP, Hawaii, Nevada, North Dakota, Rhode

Island, and Vermont experienced a significant increase in receipt of annual wellness exams. The divergence in results by comparison group highlights the importance of selecting meaningful comparison groups and contextualizing findings accordingly when using difference-in-difference frameworks (further discussed in Discussion of Subgroup and Sensitivity Analyses Section).

The decrease in annual wellness exams following full NP SOP policy implementation compared to states with unchanged restricted NP SOP was surprising; a similar study found that the probability that an adult receiving a yearly checkup increased by 3.3 percentage points in the two years following full NP SOP policy implementation (Traczynski & Udalova, 2018).

However, Traczynski and Udalova's study (2018) used a different data source that did not rely on billing data. It is possible that the decrease in annual wellness exams observed in this study is due to care provided during outpatient care visits being billed as other types of care, even if the care provided actually included an annual wellness exam. One report found that some clinicians who clearly provided wellness visits do not bill for any wellness visits. They also found that when a problem-oriented visit and wellness visit occurred on the same day, the care related to the problem-oriented visit was more likely to be coded, possibly because problem-oriented visits are reimbursed at higher rates (Nicoletti, 2016).

It is possible that individuals in this study had more outpatient service encounters following full NP SOP implementation and the annual wellness exam occurred but not billed for. If this were the case, billing data may show a decrease in wellness exams when, in reality, annual wellness exams are occurring but being masked by billing for other outpatient service encounters. Results should also indicate a greater increase in the average number of outpatient visits during the study period for states that implement full NP SOP versus states with unchanged restricted NP SOP policies.

As a post-hoc exploratory assessment of this explanation, this study compared the percent change in the average number of outpatient visits in 6-months between years 2006 to 2015 between intervention and comparison groups. All groups experienced a decrease in the average number of annual outpatient service encounters over time. Individuals from the restricted NP SOP comparison group, full NP SOP implementation group, and full SOP comparison group experienced an average percent decrease in number of outpatient visits in a 6-month period of -1.84%, -1.50%, and -1.41%, respectively. The restricted NP SOP comparison group experienced the largest percent decrease in the average number of outpatient service encounters; this finding lends preliminary support that the decrease in annual wellness exams observed in this study may be related to differences in changes in outpatient service utilization between groups. Conclusions cannot be drawn from this cursory analysis, but warrant further investigation.

It is also important to consider the possibility that a decrease in annual wellness exams in this population may not necessarily be a negative health outcome or indicative of decreased access to care. Healthier people may choose not to have an annual wellness exam. There has been debate about the utility of the annual wellness exams for healthy individuals. Annual physical exams do not consistently reduce morbidity or mortality, and have been associated with increased harm from costly increased testing and false positives in otherwise healthy adults (Mehrotra & Prochazka, 2015). The population of people in the MarketScan database is somewhat younger and healthier than the general population and they work for medium and large employers. Because this is a commercial insurance-based dataset, it is less likely to include people disabled due to illness and older adults enrolled in the Medicare, who may realize more benefits from an annual wellness exam than the general population (Colburn & Nothelle, 2018).

It is possible that the annual wellness exam is not beneficial for the healthier and younger people in the MarketScan database.

Lipid Screenings.

The results from the main model indicated that implementing full NP SOP does not change an individual's likelihood of receiving lipid screening in a commercially insured population. The magnitude of the effect of implementing full NP SOP on lipid screenings was insignificant in the main models using the unchanged restricted NP SOP comparison group and the unchanged full NP SOP comparison group. It was interesting that the results from the main model found a significant increase in diabetes screenings but not a significant increase in lipid screenings compared to the full SOP comparison group. Both diabetes screenings and lipid screenings are conducted through lab tests in outpatient care settings for similar populations. It is possible that the differences in results is attributed to lipid screenings occurring at a higher level at baseline in the pre-policy period compared to diabetes screenings, allowing more room for growth over time for diabetes versus lipid screenings. Lending preliminary support for this possibility, there was a larger percent increase for diabetes screenings compared to lipid screenings between 2006 and 2015.

NP SOP Policy and Utilization of Acute Care Services

Hypothesis 2b, stated that following the implementation of full NP SOP policy, there would be a larger decrease in individuals who were hospitalized for any condition, used an emergency department, had a 30-day readmission, or were hospitalized for an acute ambulatory care sensitive condition compared to comparison states. Hypothesis 2b was not supported by the results from the main models in this study. The magnitude of the effect for each of the outcomes for utilization of acute care services was insignificant in the overall model using the unchanged

restricted NP SOP comparison group and the unchanged full NP SOP comparison group.

Overall, the results of the main model indicated that implementing full NP SOP does not change an individual's likelihood of utilizing acute care services in a commercially insured population.

Similar to the findings from this dissertation, Traczynski & Udalova (2018) found small and insignificant effects of implementing full NP SOP on overall emergency room visits.

Theoretically, this finding may be explained because all-cause acute care utilization captures medically necessary conditions that are less amenable to change through health policy, more so than preventable conditions. Aday and Andersen (1974) define the need for medical services as the level of illness and describe how there are conditions for which care is absolutely necessary, like acute appendicitis. Therefore, some level of acute care utilization is unavoidable and necessary for everyone. This may be why individuals with a usual source of care or insurance use the emergency room at least once in a 12-month period at similar rates to people without insurance or no usual source of care (Garcia, Bernstein, & Bush, 2010).

When assessing the effect of implementing full NP SOP policy on emergency room visits specifically for ambulatory care sensitive conditions, conditions that are often preventable through primary care, Traczynski & Udalova (2018) found a decrease in this outcome following full NP SOP implementation. In contrast, this dissertation assessed a related outcome, hospitalizations for acute care ambulatory care sensitive conditions, but did not find a significant change in this outcome following full NP SOP implementation. The differences in results may be attributed to differences in the regression model type used in this dissertation versus the Traczynski & Udalova (2018) study. These differences are further discussed in the following section.

Differences between Results of Dissertation and Previous Literature

Several of the findings from the main models of this dissertation were surprising based on previous literature about NP SOP policy and access to care. The literature review in Chapter III of this dissertation suggested a positive association between full NP SOP and access to care. However, the results from the main models of this dissertation do not consistently align with a positive association between implementation of full NP SOP and increased access to care. The difference in findings from the systematic review and this dissertation may be attributed to different study designs and data sources. Most studies included in the systematic review evaluated the impact of state level NP SOP regulation on access to care through cross-sectional designs, in which states with and without full NP SOP were compared at one point in time (Patel et al., 2018). In comparison, this dissertation evaluates the effect of implementing full NP SOP over time, compared to states with unchanged NP SOP.

The study design deployed in this dissertation is most similar to the design in the study conducted by Traczynski & Udalova (2018), which assessed the effect of implementing full NP SOP policy on multiple outcomes. They found that changing NP SOP laws to allow full NP SOP increased the likelihood that individuals received an annual wellness exam. They also found that implementing full NP SOP policy reduced emergency room use for conditions responsive to primary care. Lastly, they proposed that these changes were partially realized by changes in the organization of care delivery, as evidenced by their findings of reduced physician time on administrative tasks, increased physician patient care time, and increased patient reported of appointments when wanted following full NP SOP implementation. Because of the similarities of this dissertation and Traczynski and Udalova's (2018) work, the differences in results are discussed in greater detail.

Differences in specific findings between this dissertation and the Traczynski & Udalova (2018) study have been discussed earlier in this chapter. It is important to note design and methodological differences between the studies as possibly contributing to different findings. The difference in results between this study and the Traczynski & Udalova (2018) study may be attributed to this dissertation using a different data source and time frame. This study relied on billing data from a commercially insured population, whereas the Traczynski & Udalova (2018) study assessed MEPS data, which includes a more socioeconomically diverse population and was designed to gather information relevant to access to care. Their time frame also differed from the 2006-2015 time frame in this dissertation. Because they assessed years 1999-2012, the intervention states in their sample included Arizona, Idaho, and Washington, but excluded Nevada as it had not changed SOP during their timeframe.

The difference in results between this dissertation and the Traczynski & Udalova (2018) study may also be attributed to a difference in approach for statistical analysis. This dissertation used a propensity score weighting strategy to increase similarity in baseline characteristics between intervention and comparison groups in the pre- and post- policy periods, but a similar strategy was not deployed in the Traczynski & Udalova (2018) study. Furthermore, Traczynski & Udalova (2018) used a logistic regression model instead of a linear probability model for binary outcomes. Although linear probability models pose many strengths for use with difference-in-difference analysis, as described in Chapter IV of this dissertation, they are not well suited to assess outcome variables that are very rare or very common, such as the acute ambulatory care sensitive outcome which only occurred in 0.55% of individuals in this study. This outcome was relatively rare, so the linear probability model used in the analysis may not have been well suited to detect changes in this outcome.

Of note, Traczynski & Udalova (2018) also conducted a robustness check using a linear probability model and found the results to be qualitatively and quantitatively similar under the logistic versus linear probability model functional form specification. As a cursory model specification check, the outcomes from this study were run using the logistic regression approach outlined in Traczynski & Udalova (2018). The conclusions from the main models in this dissertation (Table 5.6) were similar to conclusions drawn from the model outlined by Traczynski & Udalova (2018) (Appendix table 1.5). When assessing the average marginal effects from the logistic regression model, there was a 1.4 percentage point increase in diabetes screenings ($p=0.02$). There was also a 2.4 percentage point decrease in annual wellness exams, although this decrease was not statistically significant at the 5% level.

Discussion of Subgroup and Sensitivity Analyses

The sensitivity and subgroup analyses revealed differences between the results of the main model and these sub-analyses. There was variation in the sign, significance, or magnitude of the effect for many outcomes by model type (main model with state fixed effects versus parameterized state effects model), rurality, comparison group, and by state.

The conclusions from the main models, which included a state fixed effect, were not equivalent to the parameterized state effects model that controlled for key state-level characteristics in place of the state fixed effect for outcomes in hypotheses 1 and 2a. In general, models with a fixed effect are better at controlling for omitted variable bias than models that control for covariates in the regression. This is because state fixed effects control for observable and unobservable predictors that can be difficult to otherwise capture (Wooldridge, 2016). Although several state-level characteristics were included in the parameterized state effects model, it is possible this model is still subject to omitted variable bias. On the other hand, the

ability of the state fixed effects to effectively control for unobserved factors relies on the assumption that these unobserved factors are time-invariant (Bell & Jones, 2015). A covariate such as Medicaid expansion, which was included in the parameterized state effects model and not the main model, violates this assumption because it varies by state and year. Therefore, both approaches have tradeoffs. Ultimately, this dissertation drew conclusions from the main state fixed effect models because there were likely many unobserved confounders that could not be captured by the parameterized state effects model.

This dissertation also assessed the effect of implementing full NP SOP on access related outcomes specifically for individuals in rural locations. The literature review in Chapter III presented conflicting evidence about the association between NP SOP and access for rural populations. Furthermore, Traczynski and Udalova (2018) found no heterogeneity in the effect of implementing full NP SOP based on residence inside or outside of metropolitan statistical areas. This dissertation found no effect of implementation of full SOP on access related outcomes compared to the unchanged full SOP comparison group when assessing individuals in rural locations. Compared to the unchanged restricted SOP comparison group, the results suggested a significant decrease in annual wellness exams, and an increase in all-cause and acute ambulatory care sensitive condition hospitalizations for individuals in rural locations. The results of this dissertation provide evidence that among a commercially insured population, implementing full NP SOP does not increasingly improve access to care for individuals in rural locations compared to the general population. It is possible that it takes longer than 2 years to realize an effect of implementing full NP SOP policy on access to care for rural locations.

The results relative to change in outcomes when implementing full NP SOP policy was partially dependent on which comparison group was used. For example, in the main model, there

was a significant increase in diabetes screenings when compared to the unchanged full NP SOP group, but no significant change when compared to the unchanged restricted NP SOP group. When examining the results from individual states, five of the seven states experienced increases for at least two preventive services (annual wellness exams, diabetes screenings, or lipid screenings) when compared to states with unchanged full NP SOP. Furthermore, there were no intervention states that had a significant decrease in preventive services when compared to states with unchanged full NP SOP. This trend was not as consistent when using the restricted SOP comparison group. The divergence in results by comparison group highlights the importance of contextualizing findings according to comparison groups. States in the unchanged full SOP and in the unchanged restricted SOP groups differed in many ways. States with unchanged full SOP functioned as positive controls, were less populous, and more likely to be Western states. Individuals in states with unchanged full SOP had the lowest average Charlson Comorbidity Index and highest percent of people in rural locations of the groups studied in this dissertation (Table 5.3).

Perhaps the most interesting finding of the sensitivity and subgroup analyses was the heterogeneity of the results by intervention state. These findings indicate that implementing full SOP was associated with select improved access related outcomes in some states while worsening select outcomes in others. These conflicting findings may be why the overall effect of NP SOP on the access related outcomes measured in this study was null for most outcomes. The type of DD analysis used in this study, in which intervention states are pooled into a single intervention group, works best for state-level policy analysis when a policy has standardization across states (Wing et al., 2018). This is because it is difficult to interpret results about a policy's general effectiveness if states operationalize the policy differently.

However, there is evidence that there is variation in what NP SOP laws means “on the ground” in one state compared with another. For example, although both Colorado and Vermont are considered full NP SOP states, Vermont requires 24 months and 2,400 hours of collaboration under an experienced physician or NP for an NP to transition to becoming an independent provider, while Colorado only requires 1,000 hours of mentorship. Similarly, although both North Carolina and Texas are considered restricted NP SOP states, North Carolina requires consultation with an NP’s supervisory physician monthly for the first 6 months of collaboration, while Texas requires this for the first 3 years of collaboration (Spetz, 2018). Because there is between state variation in the way NP SOP policy is operationalized, the single-state DD analyses may be more informative than the main analysis conducted in this study. These single-state analyses allowed an opportunity to assess which states benefitted most from full NP SOP implementation, like Rhode Island and Vermont, and subsequently explore what factors led to the successes in this state.

Study Limitations

Although this study better assesses if full NP SOP policy influences access to care than many previous cross-sectional comparisons, the ability to determine causal inference is limited because of the use of observational data not intended for the purposes of this study and due to the assumptions of difference-in-difference analysis. It is important to consider the results of this study in light of the following limitations.

Many of the limitations in this study are attributed to limitations in using claims data, which are collected for billing purposes instead of research. Some limitations associated with using claims data for research include lack of ability to study those without insurance, limited clinical information (i.e., absence of physiological measurements such as blood pressure), the

lack of direct access to care information (i.e., usual source of care), the under-coding of select variables (i.e. nurse practitioner specific visits), the inability to capture care not routinely billed to an insurer (i.e. patient education), and possible bias from billing code inconsistencies between different providers or organizations (Johnson & Nelson, 2013; Tyree & Lind, 2006). Despite the limitations in the MarketScan claims data source, it was used in this study because it offered several advantages over other data sources (previously discussed in Chapter IV).

This study was unable to assess a socioeconomically diverse population because the MarketScan claims data used only contains individuals with private health insurance. There may be a limit on how much access to care could change for individuals in this data source because they already have better access to care than other populations. Access needs may be more pronounced for individuals who are uninsured and have lower incomes compared to individuals in the MarketScan claims data. Therefore, changes in access to care following full NP SOP policy implementation may be more detectable for individuals without private health insurance and with lower incomes. The Traczynski and Udalova (2018) study used MEPS data, which includes uninsured and unemployed individuals. Although Traczynski and Udalova (2018) did not find heterogeneous effects of implementing full NP SOP by insurance status, they did not assess heterogeneity by income status. It is possible that individuals in MarketScan have higher incomes than individuals in MEPS, because individuals in MarketScan are more likely to be employed. MarketScan's sampling strategy includes employer sponsored insurance plans while MEPS includes sampling those who are unemployed (MEPS, 2019).

There were a number of variables of interest that could have influenced access to care, but were not included in the analysis due to unavailability in the claims data. These missing variables could bias parameter estimates presented in this dissertation. At the state level, there

were likely other variables, such as availability of transportation, which could influence access to care in that state, but were not included in the model (Arcury, Preisser, Gesler, & Powers, 2005). The use of state fixed effects in the main model helped control for time invariant variables of this nature. There were also several individual level covariates that affect access to care, such as an individual's education status or race, which could not be included in the model because they were unavailable in the claims data source. Although propensity score weighting was used to balance intervention and comparison groups in the pre- and post- policy periods, propensity score methods can only control for observed variables. Concerns over covariate control are mitigated by the use of a DD model for analysis, since DD model compares within group changes over time.

This dissertation did not assess NP-specific care due to reliance on claims data. The study sample is not limited to individuals receiving NP-specific care because provider type is not reliably coded in claims data due to “incident to billing”, in which NP services are billed under a physician (Pickard, 2014). However, Traczynski and Udalova (2018) report that the effect of NP independence was not limited to NP-specific care, but likely had spillover effects that changed physician delivered primary care as well due to a decrease in administrative burden of supervising NPs after states grant full NP SOP. The spillover effects may also be due to increased primary care provider competition after states grant full NP SOP (Barros et al., 2016).

Lastly, the ability to inform causal inference is also limited by the lack of testing of the assumptions of a DD analysis. Because Traczynski & Udalova (2018) explicitly tested the parallel trends assumption and found no differential trends in outcomes between states that implemented full SOP and states that did not, the parallel trends assumption was not explicitly tested in this dissertation. Instead, this study plotted the trends in outcomes over time between

groups to assess parallel trends visually. However, this dissertation revealed that many of the results in this study differed from the results in the Traczynski & Udalova (2018) study; in hindsight, it may have been useful to formally test the parallel trends assumption by assessing the interaction between time and policy exposure in the pre-policy period. Furthermore, the common shocks assumption of DD analysis, in which events unrelated to the policy during or after policy implementation equally effect the treatment and comparison group, was not evaluated due to difficulties in testing this assumption (Dimick & Ryan, 2014). Ideally, the only difference between exposures affecting the intervention and comparison groups would be the policy at hand. However, this assumption is often unrealistic when assessing state-level policies. By pooling multiple states together for each comparison groups, instead of using matched single-state comparison groups, comparison groups may be more likely to, on average, experience similar shocks to the intervention group.

Implications for Policy

As the NP workforce grows in number and provides larger shares of primary care it is increasingly important to understand how state-level NP SOP policies influence access to care. Although the results of the main model suggested little overall effect of implementing full NP SOP policy on access to care outcomes, further investigation revealed that the effect varied significantly by state. Policy evaluation at a state-by-state level can perhaps better inform how this policy affects access to care. Certain states, like Vermont and Rhode Island, realized an improvement in many access related outcomes following full NP SOP implementation. It is important to examine the contextual factors unique to these states that can moderate the policy's success (Damschroder et al., 2009). For example, Vermont's progressive healthcare environment facilitated this state to consider unique health policy solutions, like a single-payer health plan

(McDonough, 2015). Although the single payer health care system ultimately failed in this state, many other states have not even considered this type of health care coverage. Vermont's unique healthcare environment may have been key in the success of implementing full NP SOP policy. Ultimately, engaging with policy stakeholders in states where implementing full NP SOP resulted in improvements in access to care may help policy stakeholders in states considering full NP SOP implementation understand the barriers and facilitators to successful policy implementation.

When evaluating state level NP SOP policies to categorize them for this study, there was variation among states in the definition of full NP SOP and the date full NP SOP was implemented. There were also variations in the rules following full NP SOP implementation for the process in which NPs had to participate to become an independent provider, like the number of supervised hours prior to becoming an independent provider. Standardization in NP SOP policy may be necessary to draw conclusions about the effect of NP practice policies across states. Defining standardized versions of state laws can not only help states successfully implement a policy, but also allow researchers to study the overall effect of this policy through quasi-experimental designs. Often, policy organizations play a key role in standardization of state policies (Wing et al., 2018). The Advanced Practice Registered Nurse (APRN) Consensus Model from the National Council of State Boards of Nursing has begun some of this work. This model promotes consistent regulation of NP SOP across the U.S. to remove barriers to patient access to health professionals and care. Although this model is endorsed by over 48 nursing organizations, it is unclear if non-nursing organizations share the same level of buy-in and support (National Council of State Boards of Nursing, 2008). It may be necessary to engage in

interdisciplinary discussions and collaborations to achieve standardization of full NP SOP policies.

This dissertation sheds light on the problems associated with the failure to gather data on the NP workforce in national datasets. When exploring the use of other national data sources for this study, it was discovered that most did not distinctly capture NP delivered care; for example, The Medical Expenditures and Panel Survey combines registered nurses with NPs, and The National Ambulatory Medical Care Survey combines NPs with nurse midwives. Other data sources, like insurance claims data, often underestimate NP delivered care due to “incident to” billing. Without the data infrastructure to track how NPs practice throughout the U.S., it is difficult to fully understand how NPs contribute to access to care issues. Moving forward, national datasets should distinguish between NP delivered care and care from other providers.

Recommendations for Future Research

The findings of the subgroup analyses for individual states revealed variation in the effect of NP SOP by state. This finding highlights the importance of assessing more granular details in policy implementation when assessing the effects of a state level policy. A mixed methods approach that integrates quantitative and qualitative methods may be needed to understand why some states benefited from full SOP policy implementation while others did not realize many benefits (Madey, 1982). Mixed methods approaches are useful when quantitative data that measure the magnitude of an outcome cannot fully contextualize the real-life environment that facilitated the absence or presence of the effect (National Institute of Health, 2018). Relative to this study, qualitative interviews with NP SOP policy stakeholders at multiple levels, including legislators, healthcare organization administrators, clinicians, and patients, about the utility of

this policy and the barriers and facilitators to its implementation in various states may help explain why results differed by state.

Changes in access to care in a commercially insured population may be more difficult to detect than anticipated at the outset of this study. Andersen and Aday's Framework for the Study of Access to Medical Care (1974) describes how the relationship between a health policy and realized access to care can be mediated through the characteristics of the population at risk, which includes individual level characteristics like health insurance status. Because this population has private health insurance, they may not have as pronounced issues accessing care as individuals who are uninsured or publically insured (National Center for Health Statistics, 2017). NPs are more likely to care for underserved populations than other providers, building a case for assessing the impact of NP policies on underserved populations (Buerhaus et al., 2015). Furthermore, some populations may benefit from NP delivered care more than others. For example, researchers have reported that Medicare beneficiaries primarily cared for by NPs had fewer hospital admissions, readmissions, inappropriate emergency department use, and use of low-value imaging compared to beneficiaries attributed to physicians (Buerhaus, Perloff, Clarke, O'Reilly-Jacob, Zolotusky, DesRoches, 2018). Future work could evaluate the effects of NP SOP on populations with greater access to care needs, such as the uninsured. Future work could also evaluate how characteristics of the population influence the relationship between NP SOP policy and access to care.

Future work could continue to build on the difference-in-difference framework used in this study. Although Traczysnki and Udalova found that the effect of full NP SOP policy implementation was realized within 2 years, other studies can further examine this finding. For example, future studies can consider including a lagged treatment variable in their analysis to

assess if the effect of NP SOP policy varies over time (Wing et al., 2018). Additionally, future studies could consider different approaches to selecting comparison groups. DD studies rely on the assumption that trends in outcomes over time are parallel between intervention and comparison groups. Trends in outcomes are rarely perfectly parallel between states, making this assumption difficult to maintain.

An approach that may better support the common trends assumption of DD analysis is having within state control groups. In 2016, the Veterans Administration (VA) opted to allow NPs within their organization full SOP, regardless of state-level policies (Sofer, 2017). This health system level change creates the opportunity to compare the effect of implementing NP SOP policy in the VA with neighboring health organizations in the same state. Because these organizations are in the same state, they are influenced by a similar set of state-level factors and likely have greater parallel trends than organizations across different states. It is important to note although a study of NP SOP policy implementation in the VA versus neighboring organizations would improve issues from cross-state comparisons, the unique organizational characteristics of and population served by the VA would require additional considerations.

Future research should consider which policies, both nested within NP SOP policy and laws separate from NP SOP policy, have the greatest effect on improving access to care. For example, one study suggests that the relationship between NP SOP and access is amplified when other state-level healthcare policies are taken into account, such as 100% Medicaid reimbursement for NPs (Barnes et al., 2016). Considering the intersection between state-level NP SOP policy and federal policy can also guide future research efforts. The Comprehensive Addiction and Recovery Act (CARA) designed to combat opioid use disorders, for example, allows NPs to prescribe buprenorphine (National Association of State Alcohol and Drug Abuse

Disorders, 2018). It would be interesting to assess if the CARA law is differentially implemented in states with and without full NP SOP policies because NP SOP policies dictate the level of physician supervision required for NPs to provide patient care. Also, evaluating which parts of NP practice regulated by SOP policy have the greatest impact on access to care can guide future policy efforts. For example, studies could explore if physician supervision of NPs for medication prescribing only versus practice have a greater influence on NP care delivery.

Although this dissertation focused on state-level NP SOP policy, the intersection of this state-level policy with organizational policy should be considered. For example, organizational policies may circumvent or override state-level policies and allow the NPs to perform greater or reduced roles than the state-level NP SOP policy specifies. It would be interesting to assess how much various organizational policies moderate the effect of state-level NP SOP policy within a state. For example, future work could test if organizations supporting models of care that optimize the use of NP delivered care, such as nurse managed health clinics, realize greater benefits following full NP SOP policy implementation at the state level (Westat, 2015). Ultimately, the intersection of organization and state level NP SOP policy poses an interesting avenue for further research. This future research may be aided by Poghosyan, Boyd, and Clarke's (2016) conceptual model on full scope of practice for nurse practitioners, which outlines the relationships between scope of practice regulations, organizational policies, practice environment, NP workforce outcomes, and NP care and patient outcomes.

Conclusion

Although stakeholders agree that there is a need to improve U.S. access to high quality care, a greater understanding is needed of if and how policies aimed at improving access actually achieve this goal. The need is heightened when a policy is subject to deep-rooted political

contention between professional groups surrounding its effectiveness, as is policy change surrounding NP SOP. Despite political contention, it remains crucial to conduct, disseminate, and use objective but meaningful research to inform actionable policy change, especially when this type of policy research dwells in the “shadow of politics” (Peterson, 2018).

Prior work suggested a positive association between NP SOP and access. However, this work consisted largely of cross-sectional comparisons between states with versus without full NP SOP policies. This study leverages state level NP SOP policy changes as a natural experiment and finds that implementing full state-level NP SOP policy does not consistently improve individuals’ access to care related outcomes measured in this study. The results of this study highlight the importance of using conceptually and methodologically sophisticated research that moves away from cross-sectional comparisons of states with full versus restrictive SOP policies and towards quasi-experimental designs.

It is unrealistic to assume that any single health policy will, across the board, solve American’s multifaceted access to care problems. Contextualizing the populations for which a policy is most effective is important, especially considering the geographic, socioeconomic, and cultural diversity in this country. The results of this study suggest that implementing full state-level NP SOP policy may have little impact on those who arguably already have better access to care, such as the commercially insured; findings may be different in studies that examine access to care was examined in underserved populations who face greater barriers. Additionally, the results show that the effect of this policy is dependent on the state that is implementing it. Contextualizing the policy environment and how the policy was operationalized in states that experienced the most positive improvements in access to care after enacting full NP SOP laws may help guide other states make decisions about implementation of similar policies.

Appendix One

Appendix Table A.1: Synthetically Assigned Policy Implementation Year for Full NP SOP Comparison States

State	Sim Year 1	Sim Year 2	Sim Year 3	Sim Year 4	Sim Year 5	Sim Year 6	Sim Year 7	Sim Year 8	Sim Year 9	Sim Year 10
Maine	2008	2012	2013	2010	2010	2012	2010	2010	2010	2010
New Hampshire	2013	2010	2008	2010	2011	2008	2013	2013	2010	2013
Iowa	2010	2010	2008	2010	2010	2008	2010	2010	2010	2010
Minnesota	2010	2010	2010	2010	2010	2010	2008	2010	2008	2008
Washington DC	2013	2010	2008	2008	2008	2008	2010	2010	2013	2013
Arkansas	2010	2013	2010	2013	2008	2013	2010	2010	2010	2010
Arizona	2010	2008	2010	2010	2010	2010	2010	2010	2010	2010
Montana	2008	2011	2010	2008	2011	2011	2010	2008	2010	2010
Wyoming	2008	2008	2010	2012	2010	2010	2010	2010	2010	2010
Oregon	2010	2010	2010	2010	2010	2010	2010	2010	2012	2010

Appendix Table A.2: Synthetically Assigned Policy Implementation Year for Restricted NP SOP Comparison States

State	Sim Year 1	Sim Year 2	Sim Year 3	Sim Year 4	Sim Year 5	Sim Year 6	Sim Year 7	Sim Year 8	Sim Year 9	Sim Year 10
Massachusetts	2010	2013	2009	2010	2010	2010	2010	2010	2008	2010
Michigan	2013	2013	2010	2010	2010	2010	2010	2013	2010	2010
Missouri	2010	2013	2010	2010	2009	2010	2010	2010	2008	2008
Florida	2010	2010	2013	2010	2010	2010	2010	2010	2010	2010
Georgia	2010	2009	2010	2013	2013	2010	2013	2010	2010	2010
North Carolina	2008	2010	2010	2010	2008	2010	2010	2010	2013	2010
South Carolina	2010	2008	2008	2012	2010	2008	2010	2008	2010	2010
Virginia	2010	2010	2013	2012	2012	2010	2008	2010	2013	2010
Tennessee	2008	2012	2010	2010	2010	2009	2010	2008	2010	2010
Texas	2010	2010	2010	2010	2010	2010	2010	2010	2010	2010
California	2010	2010	2010	2008	2010	2011	2008	2010	2010	2010

Appendix Table A.3: Comparison of DD Estimators Across Simulations using Full NP SOP Comparison States

	Sim 1	Sim 2	Sim 3	Sim 4	Sim 5	Sim 6	Sim 7	Sim 8	Sim 9	Sim 10
	Outpatient Visit Follow-up within 14 days									
DD estimator	-0.0571	-0.1031*	-0.0806	-0.0804	-0.0849	-0.0608	-0.0890*	-0.0806	-0.0604	-0.0821
SE	(0.0399)	(0.0415)	(0.0399)	(0.0418)	(0.0436)	(0.0414)	(0.0405)	(0.0399)	(0.0406)	(0.0418)
N	3430	3430	3430	3430	3430	3430	3430	3430	3430	3430
	Annual Wellness Exam									
DD estimator	-0.0151	-0.0086	-0.0121	-0.0078	-0.0039	-0.0069	-0.0237	-0.0121	-0.0113	-0.0027
SE	(0.0144)	(0.0159)	(0.0170)	(0.0171)	(0.0147)	(0.0152)	(0.0163)	(0.0170)	(0.0154)	(0.0141)
N	64570	64570	64570	64570	64570	64570	64570	64570	64570	64570
	Diabetes Screen									
DD estimator	0.0066	0.0150	0.0239	0.0208	0.0182	0.0168	0.0121	0.0239	0.0057	0.0215
SE	(0.0156)	(0.0172)	(0.0178)	(0.0168)	(0.0192)	(0.0172)	(0.0156)	(0.0178)	(0.0147)	(0.0174)
N	27652	27652	27652	27652	27652	27652	27652	27652	27652	27652
	Lipid Screen									
DD estimator	-0.0065	0.0054	0.0012	0.0079	0.0033	-0.0002	-0.0148	0.0012	-0.0028	0.0047
SE	(0.0165)	(0.0207)	(0.0195)	(0.0174)	(0.0205)	(0.0177)	(0.0180)	(0.0195)	(0.0146)	(0.0178)
N	27652	27652	27652	27652	27652	27652	27652	27652	27652	27652
	All Cause Hospitalization									
DD estimator	0.0077	0.0071	0.0054	0.0062	0.0068	0.0099*	0.0054	0.0054	0.0079	0.0069
SE	(0.0048)	(0.0037)	(0.0048)	(0.0040)	(0.0046)	(0.0040)	(0.0044)	(0.0048)	(0.0041)	(0.0046)
N	64570	64570	64570	64570	64570	64570	64570	64570	64570	64570
	All Cause ED Utilization									
DD estimator	0.0206**	0.0109	0.0118	0.0046	0.0115	0.0163*	0.0160**	0.0118	0.0131	0.0099
SE	(0.0054)	(0.0059)	(0.0067)	(0.0073)	(0.0070)	(0.0069)	(0.0053)	(0.0067)	(0.0078)	(0.0067)
N	64570	64570	64570	64570	64570	64570	64570	64570	64570	64570
	All Cause 30 day Readmission									
DD estimator	0.0151	0.0114	0.0013	0.0075	0.0037	0.0140	0.0184	0.0013	0.0185	0.0149
SE	(0.0160)	(0.0142)	(0.0165)	(0.0112)	(0.0142)	(0.0176)	(0.0119)	(0.0165)	(0.0108)	(0.0201)
N	3430	3430	3430	3430	3430	3430	3430	3430	3430	3430

	Acute ambulatory care sensitive condition Hospitalization									
DD estimator	0.0021	0.0022	0.0026	0.0024*	0.0033	0.0023	0.0019	0.0026	0.0020	0.0024
SE	(0.0012)	(0.0011)	(0.0012)	(0.0011)	(0.0018)	(0.0012)	(0.0011)	(0.0012)	(0.0011)	(0.0013)
N	64570	64570	64570	64570	64570	64570	64570	64570	64570	64570

Appendix Table A.4: Comparison of DD Estimators Across Simulations using Restricted NP SOP Comparison States

	Sim 1	Sim 2	Sim 3	Sim 4	Sim 5	Sim 6	Sim 7	Sim 8	Sim 9	Sim 10
	Outpatient Visit Follow-up within 14 days									
DD estimator	-0.0499*	-0.0427	-0.0378	-0.0300	-0.0526*	-0.0421	-0.0533	-0.0391	-0.0500*	-0.0568*
SE	(0.0234)	(0.0264)	(0.0252)	(0.0238)	(0.0237)	(0.0257)	(0.0272)	(0.0261)	(0.0228)	(0.0230)
N	14354	14354	14354	14354	14354	14354	14354	14354	14354	14354
	Annual Wellness Exam									
DD estimator	-0.0508**	-0.0481**	-0.0484*	-0.0315*	-0.0538**	-0.0307*	-0.0467**	-0.0319*	-0.0501**	-0.0521**
SE	(0.0170)	(0.0165)	(0.0183)	(0.0138)	(0.0154)	(0.0133)	(0.0140)	(0.0139)	(0.0167)	(0.0179)
N	273315	273315	273315	273315	273315	273315	273315	273315	273315	273315
	Diabetes Screen									
DD estimator	0.0139	0.0135	0.0096	0.0211	0.0126	0.0228	0.0109	0.0223	0.0128	0.0130
SE	(0.0145)	(0.0145)	(0.0148)	(0.0160)	(0.0146)	(0.0159)	(0.0146)	(0.0156)	(0.0136)	(0.0137)
N	115063	115063	115063	115063	115063	115063	115063	115063	115063	115063
	Lipid Screen									
DD estimator	-0.0188	-0.0161	-0.0261	-0.0094	-0.0164	-0.0059	-0.0124	-0.0073	-0.0265	-0.0230
SE	(0.0217)	(0.0240)	(0.0209)	(0.0187)	(0.0207)	(0.0184)	(0.0209)	(0.0181)	(0.0203)	(0.0217)
N	115063	115063	115063	115063	115063	115063	115063	115063	115063	115063
	All Cause Hospitalization									
DD estimator	0.0028	0.0069	0.0036	0.0075*	0.0039	0.0062	0.0058	0.0056	0.0048	0.0047
SE	(0.0031)	(0.0037)	(0.0033)	(0.0035)	(0.0032)	(0.0035)	(0.0038)	(0.0034)	(0.0033)	(0.0035)
N	273315	273315	273315	273315	273315	273315	273315	273315	273315	273315

	All Cause ED Utilization									
DD estimator	-0.0037	0.0020	-0.0035	0.0047	-0.0027	0.0058	0.0008	0.0051	-0.0042	-0.0045
SE	(0.0067)	(0.0052)	(0.0064)	(0.0089)	(0.0062)	(0.0088)	(0.0047)	(0.0090)	(0.0059)	(0.0067)
N	273315	273315	273315	273315	273315	273315	273315	273315	273315	273315
	All Cause 30 day Readmission									
DD estimator	-0.0103	-0.0063	-0.0081	-0.0138	-0.0077	-0.0164	-0.0091	-0.0129	-0.0133	-0.0137
SE	(0.0106)	(0.0093)	(0.0113)	(0.0105)	(0.0106)	(0.0097)	(0.0109)	(0.0105)	(0.0107)	(0.0112)
N	14354	14354	14354	14354	14354	14354	14354	14354	14354	14354
	Acute ambulatory care sensitive condition Hospitalization									
DD estimator	0.0012	0.0018	0.0013	0.0015	0.0012	0.0012	0.0014	0.0014	0.0011	0.0012
SE	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0009)	(0.0010)
N	273315	273315	273315	273315	273315	273315	273315	273315	273315	273315

Appendix Table A.5 Effect of Implementing Full NP SOP using Logistic Regression DD

	Out-patient Follow-up 14 days	Annual Wellness Exam	Diabetes Screen	Lipid Screen	All- Cause Hosp.	All- Cause ED	All Cause 30 day	Acute ACSC Hosp.
DD estimator	-0.0084	-0.0234	0.0138*	-0.0086	0.0015	0.0027	-0.0035	0.0001
Robust SE	(0.0059)	(0.0157)	(0.0058)	(0.0147)	(0.0007)	(0.0030)	(0.0028)	(0.0001)
N	1723157	32772650	13639873	13639873	32772650	32772650	1723157	32772650

*p<0.05; **p<0.01; ***p<0.001

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