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Local Health Department Capacity to Improve Public Health - The Impact of Public Health Accreditation and Public Health Funding

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LOCAL HEALTH DEPARTMENT CAPACITY TO IMPROVE PUBLIC HEALTH:

THE IMPACT OF PUBLIC HEALTH ACCREDITATION & PUBLIC HEALTH FUNDING

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To: Dean Tomás R. Guilarte
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This dissertation, written by Nancy S. Elliott, and entitled Local Health Department Capacity to Improve Public Health: The Impact of Public Health Accreditation & Public Health Funding, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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DEDICATION

To my family, for your unwavering faith, your humor, and your support along the way. To my husband, for your love of the granular, your ability to question, and your commitment to science.

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ABSTRACT OF THE DISSERTATION

LOCAL HEALTH DEPARTMENT CAPACITY TO IMPROVE PUBLIC HEALTH: THE IMPACT OF PUBLIC HEALTH ACCREDITATION & PUBLIC HEALTH FUNDING

by

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Public health accreditation and public health funding have the potential to transform the way local health departments (LHDs) deliver public health, but it is unclear if they are having their intended impact. Since performance expectations are high and public health funding is scarce, LHD leadership will continually be interested in finding the most effective ways of improving public health. The purpose of this research is to examine whether LHDs are reaching their goal of public health improvement through public health accreditation and public health funding. Data from the National Association of County and City Health Officials Profile Surveys, Public Health Accreditation Board, County Health Rankings Annual Reports, and the National Longitudinal Survey of Public Health Systems were used to conduct three studies. The first study uses local level panel data and a difference-in-difference methodology to quantify the difference in the change in public health outcomes across counties in Florida and control states, before and after obtaining public health accreditation. Results reveal that public health accreditation was significantly associated with improvements to public health outcomes. This study suggests that accreditation can be a driver for health improvement and a catalyst to advance public health. The second study uses a quasi-experimental design with the use of a panel data difference-in-difference estimator to estimate the treatment effect of public health accreditation on the effectiveness of essential public health activities provided by LHDs. Results suggest that public health accreditation does not lead to the improved effectiveness of public health activities. Findings highlight that accreditation is one element that complements other performance improvement strategies to achieve a significant effect on the health system. The third study employs multivariate linear regression models with the use of local-level cross-sectional and panel data to examine whether increased LHD funding translates to public health benefits. Results suggest that increased LHD expenditures were not associated with any of the studied public health outcomes. The study highlights the need to control for omitted variable bias and reverse causation bias as other public health system components may influence the results, thus leading one to conclude that large expenditures explain better health outcomes. Public health accreditation and public health funding can be successful tools for public health practice when used as starting points to address public health problems.

KEYWORDS

Local health departments, public health accreditation, public health funding, performance, public health, health policy, local public health systems

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ABBREVIATIONS AND ACRONYMS

Average Treatment Effect	ATE
Body Mass Index	BMI
Centers for Disease Control and Prevention	CDC
Community Health Assessment	CHA
Community Health Improvement Plan	CHIP
Consumer Price Index	CPI
Emergency Preparedness	EP
Fixed Effects	FE
Federal Information Processing Standards	FIPS
Full-Time Equivalents	FTEs
Human Immunodeficiency Virus	HIV
Instrumental Variables	IV
Local Health Department	LHD
Missing Completely at Random	MCAR
Maternal and Child Health	MCH
National Association of City and County Health Officials	NACCHO
National Longitudinal Survey of Public Health Systems	NALSYS
Ordinary Least Squares	OLS
Public Health Accreditation Board	PHAB
Standard Deviation	SD
Sexually Transmitted Disease	STD
Strategic Plan	SP
United States	U.S.
World Health Organization	WHO

CHAPTER I

INTRODUCTION

1.1. Statement of the Problem

Local health departments (LHDs) have played a major role in the 10 great public health advances in the first decade of the 21st century: vaccine-preventable diseases, prevention and control of infectious diseases, tobacco control, maternal and infant health, motor vehicle safety, cardiovascular disease prevention, occupational safety, cancer prevention, childhood lead poisoning prevention, and public health preparedness and response (CDC, 2021a; Erwin & Brownson, 2017). Often referred to as the "boots on the ground," LHDs play a unique role in a complex health system by promoting and protecting the health of local communities.

In the 1988 report, The Future of Public Health, the Institute of Medicine concluded that public health is a vital function that is in trouble due in part to a public health system that is incapable of addressing current problems (Institute of Medicine, 1988). The report recommended that the public health system change from its traditional service-oriented perspective to a broader conceptualization involving three fundamental core functions of public health: Assessment, Policy Development, and Assurance (Derose et al., 2002). These recommendations influenced the national health objectives in the year 2000 calling for 90% of the population to be served by an LHD that effectively addresses the core functions of public health (Handler & Turnock, 1995).

It can be argued that the 2000 objective was ultimately reached with the growth of the public health accreditation program in the last decade. As of March 2022, over 90% of the United States (U.S.) population was covered by an accredited local or state health department (PHAB, 2021a). However, during this same time, funding for LHDs has grown increasingly scarce. From 2009 to 2012, over 40% of LHDs reported having a lower budget compared to the previous fiscal year (NACCHO, 2013). Average LHD expenditures per capita have decreased 30%, from $80 in 2008 to $56 in 2019 (NACCHO, 2020). As stewards of public resources and experts in the delivery of public health services, LHD officials are challenged to provide public health infrastructure and allocate limited resources to meet the public health needs in their communities (Baum, 2011). As such, a key goal of LHD efforts is public health improvement. Public health accreditation and public health funding have the potential to transform the way LHDs deliver public health, but it is unclear if they are having their intended impact. It is vital to know what impact these public health practice decisions are having on the public health system.

1.2. Rationale for Research

Significant events such as the Anthrax attack, Hurricane Katrina, and most recently, the Covid-19 pandemic brought the important role of LHDs in the public health system to the forefront of public attention and political discourse. Such events revealed that LHDs are underfunded and limited in their ability to effectively provide essential public health services to local communities. At a time of constrained resources in the United States, coupled with heightened expectations for the performance of local public health agencies in addressing emerging health threats, LHDs need to know how to manage their work for the most impact. LHD leadership will continually be interested in finding the most effective ways of improving public health. However, they have little evidence-based guidance on which to inform decision-making about the organization of responsibilities and the allocation of public health resources (Mays et al., 2010). More research is needed to improve our understanding of the context in which public health systems operate, and to determine if public health accreditation and public health funding can serve as successful tools for public health practice. Assessing the impacts of public health accreditation and funding can provide LHDs with the needed evidence to use limited resources wisely.

1.3. Gap in Literature

1.3.1. The Impact of Public Health Accreditation

Despite the growth of public health accreditation programs in the last decade, the literature on its impact on public health outcomes remains relatively limited with available studies primarily using observational designs (Joly et al., 2007). McCullough & Fenton (2011) postulate that public health accreditation influences LHD capacity by increasing infrastructure, ensuring the use of quality improvement procedures, and providing consistent service operations (McCullough & Fenton, 2011). Some studies assess the impact of accreditation on health outcomes but focus on the accreditation of other organizations in the healthcare system such as hospitals and social services organizations. The available literature suggest that public health accreditation may improve quality and accountability (Bender et al., 2010; Russo, 2007; Brewer et al., 2007), and may hold potential for promoting improvements in service delivery, operations, and outcomes in public health (Mays, 2004), but the direct link to outcome improvement is unclear.

A growing body of literature reports the positive impact on public health accreditation on performance measurement and improvement (Kronstadt et al., 2016; Beitsch et al., 2018; Ingram et al., 2018; Allen, 2019). Cross-sectional evidence reveals that accreditation may help stimulate LHD organizational supports for evidence-based decision making, and provide pathways to accountability, consistency, and a better fit between community needs and public health services (Allen, 2019; Shah et al., 2015). Employing a cross-sectional and longitudinal approach, one study points to accreditation serving as a key driver for the uptake of quality improvement and performance management (Beitsch, 2018). Another longitudinal study suggests that accreditation may help public health systems develop the public health system capital necessary to protect and promote public health (Ingram et al., 2018). A literature review on other service industries hints of accreditation's potential in improving service delivery, operations, and outcomes in public health (Mays, 2004). The available literature focused on public health accreditation tends to be descriptive in nature and sheds light on the perceived pros and cons to achieving accreditation (Chapman, 2018; Kronstadt et al., 2016; Mays, 2004; McCullough & Fenton, 2011; Siegfried et al., 2018; Riley et al., 2012). The observational nature of most of the public health accreditation literature limits its value in providing convincing conclusions on its impact (Hussein et al., 2021). Despite the increase in accredited LHDs across the U.S., the evidence base concerning the effectiveness of LHD activities and impact of accreditation programs remains sparse.

1.3.2. The Impact of Public Health Funding

Handler et al. (2001) proposes a conceptual framework linking public health systems inputs, outputs, and outcomes. This conceptual model pertaining to public health suggests that the organizational capacity of a public health agency plays an important role in its ability to improve internal processes and performance along with public health outcomes. The framework explicates the relationships among the various components of the public health system and suggests that an increase in funding and other resources result in increases to services and activities, leading to improved public health performance, and ultimately, produce improved community health status (Handler et al., 2001). Various studies attempt to link LHD activities, characteristics, or performance to public health outcomes in support of the conceptual model (Schenck et al., 1995; Kanarek et al., 2006; Kennedy, 2003; Mays et al., 2004). One study published in 2011 assessed the relationship between LHD inputs and health outcomes and concluded that changes in local public health funding were significantly associated with changes in infant mortality and deaths attributed to cancer, cardiovascular disease, and diabetes at the county level (Mays & Smith, 2011). Erwin (2012) concludes that LHD funding was not associated with improvements in infant mortality, while Nicholas et al. (2016) and Bernet et al. (2018) find that increases in public health funding is inversely and significantly related to reductions in infant mortality. Time-series studies examining the associations between expenditures for programs targeting sexually transmitted disease prevention, tobacco control, and HIV prevention and health outcomes found that disease incidence and risky behaviors declined as funding increased (Farrelly et al., 2008; Holtgrave & Kates, 2007; Chesson et al., 2005; Linas et al., 2006; Tauras et al., 2005).

Several national level studies have found weak and conflicting associations between funding and health outcomes (Filmer & Pritchett, 1999; Rivera, 2001; Ghobarah et al., 2004).

Using public health funding data from 1993 and 2005, Erwin et al. (2011) assessed the impact of changes in LHD resources on health outcomes by relying on state-level evidence. The authors observed a relationship between combined state-level LHD expenditures and infectious disease morbidity, providing further evidence in support of the conceptual model linking inputs, outputs, and outcomes. Significantly, the Erwin et al. (2011) study and several like it rely on state-level evidence and are limited by their cross-sectional research designs. Such studies are unable to infer a direct cause and effect relationship between public health funding and health outcomes. A better understanding as to whether increases in public health funding result in better performance and health requires a more granular approach that focuses on the important role of LHDs. Existing evidence is often conflicted and inconclusive about the extent to which public health funding improves health outcomes and the link between LHD inputs, outputs, and outcomes remains poorly understood (Chen, 2017; Taylor 1998). Given the complexities of the public health delivery system, it is not clear if greater investment in public health funding enables public health agencies to improve their internal processes and performance, thus resulting in better public health outcomes in the communities served.

1.4. Purpose Statement

The purpose of this research is to examine whether LHDs are reaching their goal of public health improvement through public health accreditation and public health funding. Many of the available studies on the impact of accreditation express the possibility of improvement, but the direct link to outcome improvement is uncertain. The observational nature of current literature limits its value in providing convincing conclusions on its impact.

In Chapter II, we addressed this literature gap by conducting a robust econometric study where we consider if LHD accreditation improves public health. A growing body of literature reports the positive impact on public health accreditation on performance measurement and improvement, but the evidence base concerning the impact of accreditation program on the effectiveness of LHD activities remains limited. In Chapter III, we consider if public health accreditation improves the effectiveness of public health activities by using a robust quasi-experimental design.

The current literature exploring that relationship funding and outcomes has often relied on state-level evidence and present conflicting associations. It is unclear if differences in public health funding contributes to differences in outcomes. This research sheds light on a local component of the public health delivery system by taking a more focused approach looking at the important role of local health departments. Based on the literature gap, in Chapter IV, we assess the impact of public health funding on public health on the local level with an observational research design.

By employing robust studies to address relevant research questions, this dissertation provides clarity on what impacts these public health practice decisions are having on the public health system. This research contributes to the field of Public Health Systems and Services Research which explores the relationship between public health resources and interventions.

1.5. Research Questions and Hypotheses

Three studies address key research questions on the impact of public health accreditation and public health funding.

Research Question #1	What is the impact of public health accreditation on public health outcomes?
Research Question #2	What is the impact of public health accreditation on the effectiveness of public health activities?
Research Question #3	What is the impact of LHD expenditures on public health outcomes?

The three studies aim to test three relevant hypotheses:

Hypothesis #1	Public health accreditation contributes to improved public health outcomes.
Hypothesis #2	Public health accreditation contributes to the increased effectiveness of public health activities.
Hypothesis #3	Increased LHD expenditures improve local level public health outcomes.

1.6. Public Health Significance

Exploring the impact of public health accreditation and public health funding is warranted to build the evidence base around effective public health practice. By investigating how LHD's accreditation and funding impact intended outcomes, this dissertation could guide policymakers and others in decisions about how these resources should be used wisely to protect and improve health most effectively. With the use of strong research designs, this study provides stronger causal inferences establishing the link between local governmental public health funding, performance, and the health of communities. The implications of these findings suggest that public health accreditation and public health funding can be successful tools for public health practice. This research can provide compelling and useful evidence for public health policy makers and practitioners interested in directing resources for maximum benefit.

1.7. Dissertation Overview

The remainder of this dissertation is structured as follows. Chapter II provides a background on the complex role of LHDs in the public health system. Chapter III delves into the research design and the data used for the analyses. Chapter IV presents a quasi-experimental study on the causal impact of public health accreditation on public health outcomes. Chapter V examines the causal impact of public health accreditation on the effectiveness of public health activities. Chapter VI addresses the methodology challenges when attempting to determine the impact of LHD funding on public health outcomes. Chapter VII summarizes the studies and provides the study implications.

CHAPTER II

BACKGROUND

2.1. Local Health Departments (LHDs) from A Health Systems Perspective

Local health systems are extensive and complex in that they require various factors to function and are composed of numerous interacting partners (Fowler et al., 2019). The complexity and multifaceted nature of a health system is illustrated when LHDs coordinate their work vertically with state and federal governmental agencies and horizontally with a network of partners that contribute to public health in a jurisdiction, including hospitals, schools, faith-based organizations, the media, and community-based partners (Fowler, et al., 2019; Thomas et al., 2015). Such complexity is also seen in other system and structural components of the public health infrastructure (Thomas et al., 2015). Assessing the impact of LHDs, and the relationship between public health accreditation, funding, performance, and outcomes, requires an adequate understanding of the complex health system in which they operate. This dissertation underscores how research on LHD-related accreditation and funding can be viewed from a systems perspective. This background review is structured around the World Health Organization (WHO) framework that describes health systems in terms of six core components: leadership and governance, health information technology, financing, health workforce, medical products and technologies, and service delivery (World Health Organization, 2010). These main “building blocks,” as defined by the WHO, contribute to the strengthening of health systems. Focusing on these components allows for a review of a broader array of factors to properly frame LHDs within the health system. A review of the literature on the impact of LHD funding on health outcomes reveals that questions about health expenditures and outcomes connect to each of these components, but it is particularly helpful to frame them within the contexts of leadership and governance, healthcare financing, health workforce, and service delivery.

2.2. Leadership and Governance

The role of leadership and governance in building a health system, according to WHO, is to ensure that strategic policy frameworks exist and are combined with effective oversight, coalition-building, regulation, attention to system design, and accountability (WHO, 2010). Leadership/governance provides the basis for the input components of financing and health workforce, and the output component of service delivery. Literature suggests that LHDs are an important service provider in the larger U.S. public health system and their mission, authority, governance, and accountability vary across communities.

2.2.1. Federal, State, & Local Government Public Health Infrastructure

In the U.S., governments at the federal, state, and local levels are responsible for protecting and promoting public health (Gostin, 2002). Under the U.S. Constitution, states and their local subdivisions retain the primary responsibility for improving public health (Institute of Medicine, 2002). State and local public health authorities engage in a variety of activities and services to fulfill this responsibility, such as assessing health status and needs, educating the public about health risks, and linking individuals to health and social services based on needs. State and local governmental public health agencies are also responsible for providing a safety net to all members of the communities they serve, ensuring that health services are available (Institute of Medicine, 2002). The federal government is responsible for six main areas related to public health: (1) policy making, (2) financing, (3) public health protection, (4) collecting and disseminating information about health and healthcare delivery systems, (5) capacity building for public health, and (6) direct management of services (Boufford & Lee, 2001).

2.2.2. Local Health Department's Role in the Health System

LHDs play a key role in the provision of public health services in the U.S. State and local governmental public health agencies are responsible for providing a safety net to guarantee that personal healthcare services are available to all members of the communities they serve (Institute of Medicine, 2002). More LHDs are competing with the private sector in providing safety-net clinical services (Klaiman et al., 2016; Hsuan & Rodriguez, 2014). Grott (2006) contends that in the absence of national health care reform, LHDs were prompted to provide more clinical services, in addition to core public health functions. LHDs form one part of a complex health system and they work with a variety of partners in their communities, including healthcare partners, government agencies, and community-based partners, to provide core public health activities (NACCHO, 2017a).

2.2.3. Jurisdictions Served by LHDs

There are approximately 2,800 LHDs in the U.S., and they serve different sized jurisdictions across the nation. Small LHDs are classified as those that serve populations of fewer than 50,000 people; medium LHDs serve populations between 50,000 and 500,000 people; and large LHDs serve populations of 500,000 or more people (NACCHO, 2017a). In 2016, only 6% of all LHDs were classified as large, yet they served about half of the U.S. population (51%) (NACCHO, 2017a). Although most LHDs (62%) were classified as small during that time, they served only 10% of the U.S. population (NACCHO, 2017a). The jurisdiction size and the rurality of LHDs are key factors influencing governmental activity at the local and state level (Meyerson, 2016).

2.2.4. Governance Structure of LHDs

LHDs have diverse governance structures. LHDs operating under a centralized governance structure may include multiple levels such as county units and multi-county regions or districts. Under this governance structure, the state agency has direct control and authority for the supervision of local public health agencies. In the U.S., the majority of LHDs are locally governed, and a small minority are units of the state health agency or have shared governance (NACCHO, 2017a). In most states with mixed governance, units of the state health agency serve most parts of the state, while a small number of large metropolitan areas have locally governed LHDs (NACCHO, 2017a). In other states, LHDs report directly to a state agency or a local board of health.

A recent LHD survey revealed that 19% of all LHDs were part of a combined Health and Human Services Agency, and three-quarters (76%) of all LHDs had a local board of health (NACCHO, 2017a).

2.3. Healthcare Financing

The WHO defines health financing as the function of a health system concerned with the mobilization, accumulation, and allocation of money to cover the health needs of the people, individually and collectively, in the health system (WHO, 2010). The purpose of health financing is to make funding available, ideally to ensure that all individuals have access to effective public health and personal health care. In the case of LHDs, various factors influence levels of financing.

2.3.1. Local, State and Federal Funding of Local Health Departments

State and local governments traditionally have had financial responsibility for basic governmental public health services, such as workforce training, development of information systems, disease surveillance, management of public health laboratories, and implementation of population-based prevention and health education programs, as well as other protections such as water and air quality management, waste disposal, and pest control. State and local governments share responsibilities with the federal government, which is mandated with supporting the public health infrastructure at the national, state, and local levels (Institute of Medicine, 2002).

2.3.2. Diversity in Funding Levels

There is great diversity in funding levels among LHDs serving jurisdictions of similar sizes. On average, LHDs serving the smallest populations (fewer than 25,000 people) have higher per capita revenues and expenditures than LHDs serving larger populations. LHDs with a shared governance structure receive and spend more on average than LHDs with exclusively local or state governance. Overall annual LHD expenditures per capita vary greatly by state with LHDs in Delaware spending less than $6 per person and LHDs in Alaska and New York spending more than $100 per person (NACCHO, 2017a). In 2016, annual LHD expenditures per capita were less than $30 in 10 states, $30 to $49 in 15 states, $50 to $69 in 10 states, and more than $70 in four states. Over time, average LHD expenditures per capita have decreased 25%, from $63 in 2008 to $48 in 2016 (NACCHO, 2017a). There is a wide variation in LHD funding levels, and a small, but significant relationship between LHD funding and public health need (Boeke et al., 2008).

LHDs with lower budgets than the previous fiscal year are more likely to reduce services than LHDs with higher or unchanging budgets. LHDs with higher budgets compared to the previous fiscal year are slightly more likely to expand and less likely to reduce services than LHDs with lower or unchanging budgets. Over time, average LHD expenditures per capita have decreased 30%, from $80 in 2008 to $56 in 2019 (NACCHO, 2020). From 2009 and 2012, between 41% and 45% of LHDs reported having a lower budget compared to the previous fiscal year.

In recent years, fewer LHDs have reported budget cuts with 15% of LHDs reporting having a lower budget in 2019 (NACCHO, 2020).

2.3.3. Sources of Revenue

LHDs receive funding from a variety of sources, including local, state, federal, and clinical sources. Just under one-third (30%) of LHD revenues come from local sources and 21% come from state sources (NACCHO, 2017a). Fifteen percent of LHD revenues are payments for clinical services (Medicare, Medicaid, private insurers, or patient personal fees) (NACCHO, 2017a; Mays & Mamaril, 2017). On average, small LHDs receive more per capita from local, state, and clinical sources than medium and large LHDs (NACCHO, 2017a). LHDs with shared governance receive more per capita from state, federal, and clinical sources than LHDs with exclusively local or state governance (Hsuan & Rodriguez, 2014). Locally governed LHDs receive more per capita from local sources than state governed LHDs or LHDs with shared governance (NACCHO, 2017a).

2.3.4. Funding Complexity

The Institute of Medicine (2012) describes funding for governmental public health as inadequate, unstable, and unsustainable due to the complex mix of LHD funding streams, purposes, and funding mechanisms. LHDs mesh federal, state, and local funding streams to cover their needs, and many LHDs are left without financing for key priorities or for needed cross-cutting capabilities (such as information systems and policy analysis) due to the dysfunction in how the public health infrastructure is funded. Assessing the funds and expenditures for the public health infrastructure at the local level is complex.

Data from NACCHO (2017a) illustrate some of this complexity. Total annual LHD expenditures range from less than $250,000 to more than $25 million, with 28% of LHDs reporting annual expenditures of less than $1 million and 3% reporting expenditures of $25 million or more. Since 2008, average per capita revenues from local, state, and clinical sources decreased. Notably, mean per capita LHD revenues from clinical sources decreased by one-third since 2008 (NACCHO, 2017a).

2.3.5. Resource Allocation Decision-Making

Several articles describe the local, state, and federal landscapes in which LHD funding is impacted (Bekemeier et al., 2014; Erwin et al., 2012). In recent times, events such as the passage of the Affordable Care Act, national budget crises, and fluctuating federal support for public health preparedness affected resource allocation decisions made by LHD officials. As stewards of public resources and experts in the delivery of public health services, LHD officials are challenged to allocate limited funds, staff time, and other resources to meet the public health needs in their communities (Baum, 2011; McCullough et al., 2015). Recent research suggests that a relatively small proportion of all local government spending goes toward public health and that several factors associated with fiscal allocation levels are amendable to LHD intervention compared to other factors such as size, governance, and jurisdiction type (McCullough et al., 2015).

2.4. Health Workforce

The WHO (2010) notes that the ability of an area to meet its health goals depends largely on the knowledge, skills, motivation, and deployment of the people responsible for organizing and delivering health services. An adequately sized and appropriately trained LHD workforce performing competently is an essential element of the public health infrastructure. Health professionals must be prepared to respond to an array of needs related to environmental safety. They must also be trained in the interpretation of scientific data that can influence health outcomes, and the clarification of vast amounts of highly technical information after a community emergency (WHO, 2010). Public health services, like others provided by LHDs, are dependent on a willing and able workforce.

2.4.1. Local Health Department Workforce Characteristics and Composition

LHD workforce characteristics and composition vary across jurisdictions. On average, LHDs employ 57 employees or 50 full-time equivalents (FTEs); however, these vary greatly by the size of the population served by the LHD (NACCHO, 2017a). Eighty percent of LHDs employ fewer than 50 FTEs, 37% employ fewer than 10 FTEs, and 42% employ between 10 and 50 FTEs (NACCHO, 2017a). Ten percent of LHDs employ 100 or more FTEs. While LHDs serving fewer than 10,000 people employ eight employees or six FTEs on average, LHDs serving over one million people employ 736 employees or 694 FTEs on average (NACCHO, 2017a). Half of LHDs employ fewer than 18 employees. Among all LHDs, the overall workforce capacity is 4.2 FTEs per 10,000 people (NACCHO, 2017a). LHDs serving smaller populations employ a greater number of FTEs per 10,000 people than LHDs serving larger populations. Over 70% of full-time employees are employed by LHDs serving metropolitan areas, compared to the less than 30% employed by LHDs serving rural or smaller areas (NACCHO, 2017a).

2.4.2. Job Losses and Gains

The current economic climate and fiscal constraints influenced drastic public health workforce job losses and reduced services in many communities (Klaiman et al., 2016). Since 2008, the estimated number of LHD employees decreased from 190,000 in 2008 to 147,000 in 2016, a decrease of 23% (NACCHO, 2017a). Similarly, the estimated number of FTEs employed by LHDs decreased from 166,000 in 2008 to 133,000 in 2016, a decrease of 20%. (NACCHO, 2017a). Overall, LHDs lost 21% of their workforce capacity since 2008. While 5.3 FTEs per 10,000 people were employed at LHDs in 2008, only 4.2 FTEs per 10,000 people were employed in 2016 (NACCHO, 2017a). Large LHDs have experienced a greater loss in workforce capacity since 2008 compared to medium or small LHDs.

2.4.3. Local Health Department Capacity to Perform Services

Staffing is viewed as a human resource influencing the capacity of LHDs to perform services. A study in 2015 suggested that reductions in infant mortality were associated with increased staffing and provision of prenatal and obstetric care, underscoring that those other aspects of LHD capacity, such as staffing, are expected to improve health outcomes (Schenck et al., 2015). Baum et al. (2011) argue that acute staffing shortages complicate the task of addressing public health needs and emergencies.

2.4.4. Workforce Issues and Challenges

Some of the most cited workforce needs identified by surveyed state health agencies and LHDs include strengthening epidemiology workforce capacity, adding administrative positions, and improving salaries to recruit and retain highly qualified employees (Beck et al., 2015; Klaiman et al., 2016). Some workforce challenges experienced by LHDs include an exodus of retirees, gaps in knowledge and skills due to technology changes, inadequate workforce diversity, and limited training opportunities (Beck, 2014; Bekemeier, 2015). Recent fiscal constraints and the current economic climate influenced drastic reductions to the public health workforce and services in many communities (Klaiman et al., 2016).

Since the Great Recession of 2008, the size of the public health workforce has declined by over 20%, with large-sized LHDs experiencing a greater loss in workforce capacity (Beck et al., 2014; Beck, et al., 2015). Between 2000 and 2013, LHDs reduced the size of the public health nurse workforce by over 20,000 and eliminated 56,630 jobs in key professions such as epidemiology and environmental health (Spratley et al., 2000; U.S. Department of Health and Human Services, 2010; NACCHO, 2018). In 2017 alone, LHDs reported an estimated 800 jobs lost with the majority because of layoffs (NACCHO, 2018). A shrinking LHD workforce is associated with threats to the public's health (Bekemeier et al., 2014). LHD officials are required to address these challenges amid a highly unstable public health environment with significant budget cuts and job losses limiting efforts to build an effective workforce. The available research highlights the need for a better-trained workforce capable of effective service delivery in a highly unstable public health environment.

2.5. Service Delivery

Health system inputs – health workforce, procurement and supplies, and financing – impact outputs, namely service delivery. Increased inputs should lead to improved service delivery and enhanced access to services (WHO, 2010). LHDs are tasked with ensuring the availability of health services that meet a minimum quality standard and with securing access to them. Public health services, like others provided by LHDs, vary in scale and type depending on available resources and a variety of other factors.

2.5.1. Clinical and Population-Based Services & Activities Provided by LHDs

LHDs provide many different types of clinical programs and services, including adult and child immunizations; screening and treatment for chronic and communicable diseases or conditions; and maternal and child health services. Likewise, LHDs provide many different types of population-based programs and services, including epidemiology and surveillance; primary prevention; regulation, inspection, or licensing; and environmental health services (Shah et al., 2014). Variation in commonly performed services can be due to certain services and activities being more sensitive to economies of scale, level of funding, infrastructural capacity, and priority of the needs in communities (Shah et al., 2014).

The Institute of Medicine's 1988 report, The Future of Public Health, recommended a change in the public health system from its traditional service-oriented perspective to a broader conceptualization involving three fundamental core functions of public health: Assessment, Policy Development, and Assurance (Derose et al., 2002). The report influenced the national health goals in the year 2000 calling for 90% of the population to be served by an LHD that effectively addresses the core functions of public health (Handler, 1995). It was assumed that when LHDs successfully carried out these core functions, the activities and services would meet the health needs of the local population (Derose et al., 2002).

In recent years, LHDs suffered significant cuts in the wake of the Great Recession and have remained challenged to recover. During 2012, nearly one-half (48%) of all LHDs reduced or eliminated services in at least one program area (NACCHO, 2013). Immunization, maternal and child health (MCH), and emergency preparedness (EP) services were most frequently affected (Mete et al., 2003). Twenty percent of LHDs reported cuts in immunization services, followed by 15% for both MCH and EP (NACCHO, 2013). In the six economic surveillance studies conducted since 2009 on LHDs, MCH was among the top three most frequently reduced programs. EP services was one of the top three most frequently reduced programs in four of the six surveys (NACCHO, 2013). These most affected services and activities connect to the Assessment Public Health Function.

2.5.2. Ten Essential Services of Public Health

The Ten Essential Services of Public Health serve as a framework describing the key public health activities that all communities should undertake (Table 1) (CDC, 2022a). The framework was developed in 1994 by a Steering Committee comprised of federal agencies and public health associations (CDC, 2022a).

Table 1. The 10 Essential Services of Public Health

Assessment	
Essential Service 1	Monitor Health to Identify and Solve Community Health Problems
Essential Service 2	Diagnose and Investigate Health Problems and Hazards in the Community
Policy Development	
Essential Service 3	Inform, Educate, and Empower People About Health Issues
Essential Service 4	Mobilize Community Partnerships to Identify and Solve Health Problems
Essential Service 5	Develop Policies and Plans That Support Individual and Community Health Efforts
Assurance	
Essential Service 6	Enforce Laws and Regulations That Protect Health and Ensure Safety
Essential Service 7	Link People to Needed Personal Health Services and Assure the Provision of Healthcare When Otherwise Unavailable
Essential Service 8	Assure a Competent Public and Personal Healthcare Workforce
Essential Service 9	Evaluate Effectiveness, Accessibility, and Quality of Personal and Population-Based Health Services
Essential Service 10	Research for New Insights and Innovative Solutions to Health Problems

Table 1. The table depicts the 10 Essential Public Health Services that all LHDs are expected to provide in their local communities. Source: Turnock BJ, Handler AS, and Miler CA. Core Function-Related Local Public Health Practice Effectiveness. J Public Health Manag Pract 1998; 4(5):26-32.

Since then, LHDs have organized their work around these services to protect and promote the health of the communities they serve. In 2020, the framework was revised to better align with emerging public health practice. The Essential Services Framework provides the structure for voluntary public health accreditation (PHAB, 2021a).

2.5.3. Local Health Department Accreditation

Roughly one decade after the development of the Ten Essential Services framework, the national public health community explored whether public health accreditation could serve to improve LHD performance. Between 2004-2006, organizations such as the CDC and the Robert Wood Johnson Foundation, and a Steering Committee intervened to plan the establishment of a voluntary national accreditation program (Bender et al., 2010; Canniff, 2018). In 2007, a nonprofit organization, the Public Health Accreditation Board (PHAB), was developed to administer the national public health accrediting body (Bender et al., 2010). The national accreditation for LHDs began in September 2011. PHAB (2022b) notes that as of March 2022, "a total of 40 state, 299 local, 5 Tribal, 1 statewide integrated local public health department system (Florida), and 2 Army Installation Departments of Public Health have achieved five-year initial accreditation or reaccreditation (PHAB, 2022b)." PHAB's mission is to promote and protect public health by advancing LHD quality and performance (PHAB, 2021d; Gerding et al., 2020).

Table 2. Domains for the Public Health Accreditation Board

Domain 1	Conducting assessments of public health and public health issues
Domain 2	Investigating health issues and hazards
Domain 3	Providing information on public health issues and functions
Domain 4	Engaging with the community to address health issues
Domain 5	Developing plans and policies for public health
Domain 6	Enforcing public health law
Domain 7	Promoting strategies for improved healthcare access
Domain 8	Ensuring a competent workforce
Domain 9	Evaluating and improving processes, programs, and interventions
Domain 10	Applying and contributing to evidence-based public health
Domain 11	Maintaining management and administrative capacity
Domain 12	Maintaining capacity to engage the jurisdiction's public health governmental entity

Table 2. The table shows the public health domains for accreditation. LHD applicants are evaluated on a set of published standards. Standards are organized into the 12 domains.

The PHAB accreditation process as demonstrated by the PHAB standards and domains (Table 2 and Table 3) assess an LHD's capacity to carry out the ten Essential Public Health Services (Kronstadt et al., 2018; Leider et al., 2021). Public health accreditation standardized the work of LHDs and is commonly used as a measurement of public health system performance.

Table 3. Public Health Accreditation Board Standards

	Measures and Standards
Domain 1	Conduct and disseminate assessments focused on public health status and public health issues facing the community • Standard 1.1: Participate in or Conduct a Collaborative Process Resulting in a Comprehensive Community Health Assessment • Standard 1.2: Collect and Maintain Reliable, Comparable, and Valid Data That Provide Information on Conditions of Public Health Importance and On the Health Status of the Population • Standard 1.3: Analyze Public Health Data to Identify Trends in Health Problems, Environmental Public Health Hazards, and Social and Economic Factors That Affect the Public's Health • Standard 1.4: Provide and Use the Results of Health Data Analysis to Develop Recommendations Regarding Public Health Policy, Processes, Programs, or Interventions
Domain 2	Investigate health problems and environmental public health hazards to protect the community • Standard 2.1: Conduct Timely Investigations of Health Problems and Environmental Public Health Hazards • Standard 2.2: Contain/Mitigate Health Problems and Environmental Public Health Hazards • Standard 2.3: Ensure Access to Laboratory and Epidemiologic/Environmental Public Health Expertise and Capacity to Investigate and Contain/Mitigate Public Health Problems and Environmental Public Health Hazards • Standard 2.4: Maintain a Plan with Policies and Procedures for Urgent and Non-Urgent Communications
Domain 3	Inform and educate about public health issues and functions • Standard 3.1: Provide Health Education and Health Promotion Policies, Programs, Processes, and Interventions to Support Prevention and Wellness • Standard 3.2: Provide Information on Public Health Issues and Public Health Functions Through Multiple Methods to a Variety of Audiences
Domain 4	Engage with the community to identify and address health problems • Standard 4.1: Engage with the Public Health System and the Community in Identifying and Addressing Health Problems Through Collaborative Processes • Standard 4.2: Promote the Community's Understanding of and Support for Policies and Strategies That will Improve the Public's Health

Domain 5	Develop public health policies and plans
	• Standard 5.1: Serve as a Primary and Expert Resource for Establishing and Maintaining Public Health Policies, Practices, and Capacity • Standard 5.2: Conduct a Comprehensive Planning Process Resulting in a Tribal/State/Community Health Improvement Plan • Standard 5.3: Develop and Implement a Health Department Organizational Strategic Plan • Standard 5.4: Maintain an All-Hazards Emergency Operations Plan
Domain 6	Enforce public health laws
	• Standard 6.1: Review Existing Laws and Work with Governing Entities and Elected/Appointed Officials to Update as Needed • Standard 6.2: Educate Individuals and Organizations On the Meaning, Purpose, and Benefit of Public Health Laws and How to Comply • Standard 6.3: Conduct and Monitor Public Health Enforcement Activities and Coordinate Notification of Violations among Appropriate Agencies
Domain 7	Promote strategies to improve access to healthcare services
	• Standard 7.1: Assess Healthcare Capacity and Access to Health Care Services • Standard 7.2: Identify and Implement Strategies to Improve Access to Healthcare Services
Domain 8	Maintain a competent public health workforce
	• Standard 8.1: Encourage the Development of a Sufficient Number of Qualified Public Health Workers • Standard 8.2: Assess Staff Competencies and Address Gaps by Enabling Organizational and Individual Training and Development
Domain 9	Evaluate and continuously improve processes, programs, and interventions

	• Standard 9.1: Use a Performance Management System to Monitor Achievement of Organizational Objectives • Standard 9.2: Develop and Implement Quality Improvement Processes Integrated into Organizational Practice, Programs, Processes, and Interventions
Domain 10	Contribute to and apply the evidence base of public health
	• Standard 10.1: Identify and Use the Best Available Evidence for Making Informed Public Health Practice Decisions • Standard 10.2: Promote Understanding and Use of Research Results, Evaluations, and Evidence-based Practices with Appropriate Audiences
Domain 11	Maintain administrative and management capacity
	• Standard 11.1: Develop and Maintain an Operational Infrastructure to Support the Performance of Public Health Functions • Standard 11.2: Establish Effective Financial Management Systems
Domain 12	Maintain capacity to engage the public health governing entity
	• Standard 12.1: Maintain Current Operational Definitions and Statements of the Public Health Roles, Responsibilities, and Authorities • Standard 12.2: Provide Information to the Governing Entity Regarding Public Health and the Official Responsibilities of the Health Department and of the Governing Entity • Standard 12.3: Encourage the Governing Entity's Engagement in the Public Health Department's Overall Obligations and Responsibilities

Table 3. The table presents the public health accreditation standards. Source: Public Health Accreditation Board. Public Health Accreditation Board Standards – An Overview. Version 1.0. 2011.

2.6. Background Summary

LHDs remain remarkably diverse in terms of their organizational structure, workforce capacity, funding, range of services, and communities served (NACCHO, 2017a; Teutsch & Fielding, 2016). The background review shows that the work of LHDs connects to multiple health system building blocks, as referenced by the WHO. By examining LHDs from the perspectives of leadership and governance, health financing, health workforce, and service delivery - four of the six components of a well-functioning health system - added insight is gained into their unique role within the U.S. health system. By employing a health systems approach and considering the health system through multiple lens, a deeper understanding of the importance of research on the impact of public health accreditation and public health funding is gained.

CHAPTER III

OVERVIEW

3.1. Research Design

In previous studies, limited conclusions can be drawn about the impacts of public health accreditation and public health funding. This chapter provides an overview of the research design and approach of the research studies which were chosen to mitigate some of the challenges of previous studies. With the use of strong research designs, these studies offer stronger causal inferences establishing the link between local governmental public health funding, performance, and the health of local communities.

3.1.1. Retrospective Observational Design

This research makes use of a retrospective observational design. Retrospective observational studies can provide credible evidence particularly if a randomized controlled experiment is not feasible. Observational studies lack random assignments. In this design, variables of interest are observed and relationships between them are measured. The data for these study designs have already been collected for other purposes. This analytic, observational study is employed in this dissertation particularly to mitigate some of the challenges that have been encountered in previous cross-sectional design studies. This design can address some issues such as the inability to determine whether exposure or outcome came first, and difficulty in interpreting results (Schenck et al., 1995; Kanarek et al., 2006; Kennedy, 2003; Mays et al., 2004c, 2004d). In a retrospective study, the outcome is measured after the exposure, and researchers can examine multiple effects for a single exposure and assess the strength of relationships between variables of interest (Kelsey et al., 1996). A retrospective cohort serves as a suitable study design to reliably answer one of the research questions in this study. Correspondingly, the available data allowed for the use of a retrospective observational design exploring the association between LHD expenditures and public health outcomes in Chapter VI.

3.1.2. Quasi-Experimental Design

This research also makes use of a quasi-experimental design. Quasi-experiments test descriptive causal hypotheses about manipulable causes to support a counterfactual inference about what would happen in the absence of a treatment (Shadish et al., 2002). Unlike a randomized control trial, quasi-experiments lack random assignments. Quasi-experiments are observational in nature, in that variables are observed rather than manipulated. However, in this design, randomness is introduced by the variation in individual/entity circumstances that make it appear "as if" a treatment is randomly assigned (Stock & Watson, 2011).

3.2. Setting and Sample

3.2.1. Sample Population

The study sample includes all U.S. public health agencies meeting the national definition of an LHD: "an administrative or service unit of local or state government that is concerned with health and carries out some responsibility for the health of a jurisdiction smaller than the state" (NACCHO, 2017a). There are approximately 2,800 agencies or units that met this definition in the U.S.

3.2.2. Sampling Method

One of the datasets used in Chapter V, the National Longitudinal Survey of Public Health Systems (NALSYS), uses a stratified random sample of the nation's largest local governmental public health agencies. The sampling method was selected to provide greater precision. LHDs were surveyed in 1998, 2006, 2012, 2014, 2016, and 2018 to ascertain the availability of 20 core public health activities within their jurisdictions. In each wave of the NALSYS, the survey was re-administered to the same stratified sample of agencies. Collectively, the agencies included in the analytic sample serve as the designated local public health authority for most of the total U.S. population in each survey year.

The National Association of County and City Health Officials (NACCHO) dataset used in Chapter VI uses a stratified random sampling without replacement, with strata defined by the size of the population served by the LHD (NACCHO, 2017a). In participating in the survey, all LHDs complete the Core Questionnaire, and a random set of LHDs receive supplemental modules to provide additional information. The sampling process is used to produce reliable estimates and determine which of the LHDs in the study population receive the supplemental modules (NACCHO, 2020).

3.2.3. Sample Size, Eligibility Criteria, and Characteristics of Selected Sample

The sample reflects the LHDs that responded to the NALSYS and NACCHO surveys. The sample size, including multiple observations per LHD, helps to increase statistical power. LHDs that responded to the surveys and had matching control variable data were included in this study. Observations are linked to multiple years of available data by using identifying information in the form of the Federal Information Processing Standard (FIPS) code on each public health agency.

3.3. Instrumentation

3.3.1. Description of Instrumentation Tool

The NACCHO Profile Studies, the NALSYS, County Health Rankings Annual Reports, and the Public Health Accreditation Board serve as the principal sources of data. All data in this research was obtained from secondary sources. The Institutional Review Board of Florida International University determined that this study was exempt.

3.3.2. National Association of County and City Health Officials Profile Survey

NACCHO collects expenditure data along with organizational and operational characteristics of local public health agencies through census surveys every 2-3 years. The NACCHO surveys collect jurisdiction population estimates which are used to construct the estimates of spending per capita. NACCHO uses a database of LHDs based on earlier Profile studies and consults with state health agencies and state associations of local health officials to identify LHDs for inclusion in the study population. All LHDs in the study population received the Core Web-based questionnaire. A randomly selected group of LHDs also received one of the two sets of supplemental questions. LHDs were selected to receive the Core questionnaire only or the Core plus one of the two modules using stratified random sampling, with strata defined by the size of the population served by the LHD (NACCHO, 2020). The module sampling process and the use of appropriate estimation weights are designed to produce national estimates for all LHDs, but not to produce state-level estimates. Special estimation weights were developed for some finance and workforce variables to account for non-response (NACCHO, 2017a). A data use agreement was established with NACCHO to use data for this research study.

3.3.3. National Longitudinal Survey of Public Health Systems

The National Longitudinal Survey of Public Health Systems (NALSYS) is used to classify the structural characteristics of local public health delivery systems and to examine variation in these characteristics over time across the U.S. The survey follows a nationally representative cohort of U.S. communities with no overlapping jurisdictions in the cohort. NALSYS uses the same study population as the NACCHO Profile Surveys, allowing the opportunity to merge the datasets. NALSYS uses a validated questionnaire administered to the director of the local governmental public health agency in each community to collect information on how many of the 20 core public health activities are being provided in the community. Table 4 lists the core public health activities conducted by LHDs. The 20 activities included in the survey can be categorized into the three core functions of public health: Assessment, Policy Development, and Assurance. These activities were identified based on public health professionals' expert opinion and their representation of common public health activities. Although not a comprehensive inventory of public health protections, these 20 activities serve as a valuable screening tool for characterizing the breadth of public health work performed within communities. The local public health official, serving as the designated respondent for each community, is asked to report information on all public health activities carried out in the community, regardless of which organizations perform them (Mays, 2012).

Table 4. List of Core Public Health Activities Conducted by LHDs

Assessment	
1.	Conduct periodic assessment of community health status and needs
2.	Survey community for behavioral risk factors
3.	Investigate adverse health events, outbreaks, and hazards
4.	Conduct laboratory testing to identify health hazards and risks
5.	Analyze data on community health status and health determinants
6.	Analyze data on preventive services use
Policy Development	
7.	Routinely provide community health information to elected officials
8.	Routinely provide community health information to the public
9.	Routinely provide community health information to the media
10.	Prioritize community health needs
11.	Engage community stakeholders in health improvement planning
12.	Develop a communitywide health improvement plan
Assurance	
13.	Identify and allocate resources based on community health plan
14.	Develop policies to address priorities in community health plan
15.	Maintain a communication network among health-related organizations
16.	Link people to needed health and social services
17.	Implement legally mandated public health activities
18.	Evaluate health programs and services in the community
19.	Evaluate local public health agency capacity and performance
20.	Monitor and improve implementation of health programs and policies

Table 4: The table depicts the public health activities expected to be conducted by LHDs. Source: Turnock BJ, Handler AS, and Miler CA. Core Function-Related Local Public Health Practice Effectiveness. J Public Health Manag Pract 1998; 4(5):26-32.

A data use agreement was established with the Systems for Action National Coordinating Center at the University of Colorado, Colorado School of Public Health, Health Systems, Management and Policy Department to use data for this research study.

3.3.4. County Health Rankings

County Health Rankings provide data on health outcomes, including mortality and morbidity measures, and health factors, including health behaviors, clinical care, social and economic factors, and the physical environment (Remington et al., 2015). The County Health Rankings use a model of community health which assesses health factors (determinants of health) and health outcomes (length and quality of life) (County Health Rankings, 2022). Data for most of the measures are available at the local (county) level and are assembled from several national sources, including the Behavioral Risk Factor Surveillance System, the National Center for Health Statistics, and the American Community Survey. Annual data is available for download on the County Health Rankings website.

The Annual Reports provide data over the previous years. Table 5 shows the years available for the annual reports and the years represented by the data. As an example, the 2012 Annual Report provided data on the 2008-2009 outcome variables. In Chapter IV and Chapter VI, single year outcome data in the County Health Ranking Annual Reports that best correspond with the study period is used.

Table 5. County Health Rankings Annual Reports Available Years

CHR Annual Reports	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Outcome Variables											
Obesity prevalence	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
STD	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Diabetes prevalence	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
HIV prevalence	2008	2009	2010	2010	2012	2013	2014	2015	2016	2018	2019
Control Variables											
Primary care	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Preventable hospitalization	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
High school	2008-2010	2009-2010	2010-2011	2011-2012	2012-2013	2014-2015	2014-2015	2016-2017	2017-2018	2015-2019	2018-2019
Unemployed	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Poverty	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Uninsured	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Median income	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Population	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Age	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Race	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Ethnicity	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020

Table 5. The County Health Rankings Annual Reports provide data over the previous years. The first column shows the available years in the Annual Reports. The columns that follow show which year is represented in each Annual Report. As an example, the 2012 Annual Report provided data on the 2008-2009 outcome variables. This study uses data in the Annual Reports that best correspond with the study periods

In Chapter IV, the Annual Reports for years 2016-2022 were used for the outcome variables: obesity prevalence, STD, diabetes prevalence, and HIV prevalence. The Annual Reports for years 2012-2022 were used for the control variables: primary care, preventable hospitalization, high school, unemployed, poverty, uninsured, population size, median household income, age, race, and ethnicity. In Chapter VI, the Annual Reports for years 2013-2022 were used for the outcome variables: obesity prevalence, STD, diabetes prevalence, and HIV prevalence. The Annual Reports for years 2009-2022 were used for the control variables: primary care, preventable hospitalization, high school, unemployed, poverty, uninsured, population size, median household income, age, race, and ethnicity.

3.3.5. Public Health Accreditation Board

The Public Health Accreditation Board (PHAB) collects and provides accreditation data on LHDs across the U.S. The PHAB is a nonprofit organization working to advance the quality and performance of LHDs through a national voluntary accreditation process (PHAB, 2011). The PHAB accreditation process generates the only set of peer-reviewed data about public health capacities (PHAB, 2022b). In 2011, PHAB developed a logic model and research agenda to help guide research and evaluation efforts related to accreditation. The logic model and research agenda have routinely been revised in 2013, 2017, and 2021 to reflect the evolving nature of the accreditation program. Data is available for download on the PHAB website.

3.3.6. Processes for Assessment of Reliability and Validity of the Instruments

While the NACCHO and NALSYS surveys are self-reported by LHD officials and reflect the perceptions and perspectives of the respondents, no evidence of systematic over-reporting or underreporting was found during extensive in-person site visits conducted in the jurisdictions of agencies participating in NALSYS and NACCHO survey instrument development and validation. Response rates for each wave of the surveys ranged from 68% to 73%, with no sign of systematic differences between responding and nonresponding agencies (Mays, 2012; NACCHO, 2017a).

Plausible threats to validity were ruled out. Conclusions can be logically drawn from the results produced by an appropriate methodology. An appropriate sample size is used to reduce the degree to which chance variability may account for the results observed in the study. A p-value of 0.05 and the confidence interval measure provide information about the role of chance in the study. Information bias and misclassification were minimized during the study design with the use of restriction (a method that imposes uniformity in the study base by limiting the type of individuals who may participate in the study) and the use of clear exclusion and inclusion criteria. The impact of confounding variables is minimized during the analysis phase of the study. Multivariate analyses allow for control of and the measure of multiple known confounders at the same time and allow for the interpretation of the effect of each confounder individually. The confounders considered in this study are listed in Section 3.4.3.

3.4. Description of Data

3.4.1. Cross-sectional Data

Cross-sectional data provides data on different entities or units for a single time-period (Stock & Watson, 2011). A cross-sectional design can use a large pool of data to compare differences between groups. It is favorable to use this data when a snapshot of the population at one point in time is needed (Wang & Cheng, 2020). Analyses using this data likely suffer from omitted variable bias or the bias that results when the effect of a missing variable is attributed to variables included in the model. Cross-sectional data cannot be used to make a casual inference. In Chapter VI, cross-sectional data is used to estimate the relationship between LHD expenditures and public health outcomes.

3.4.2. Panel Data

Panel data, also referred to as longitudinal data, are data for multiple entities at two or more time periods. (Stock & Watson, 2011). Panel data combined both cross-sectional and time series data and can be used to detect change over time. In a balanced panel dataset, each entity has the same number of observations. Compared to a cross-sectional design, a panel design can be used to better control for omitted variable bias. When multiple time points are included in a study sample, a time trend variable can be included in the model to control for systematic differences across time. In Chapter VI, panel data is used to estimate the relationship between LHD expenditures and public health outcomes.

3.4.3. Independent Variables

In Chapter IV and Chapter V, the exposure variable of interest is whether **public health accreditation** was obtained. Public health accreditation was expected to advance the quality and performance of governmental public health agencies. In 2011, the Public Health Accreditation Board launched the national, voluntary public health accreditation program as a strategy to advance the quality and performance of governmental public health departments, and in 2016, Florida achieved accreditation for the entire integrated local public health department system in the state. The focus of the study is Florida’s 67 counties: Alachua, Baker, Bay, Bradford, Brevard, Broward, Calhoun, Charlotte, Citrus, Clay, Collier, Columbia, DeSoto, Dixie, Duval, Escambia, Flagler, Franklin, Gadsden, Gilchrist, Glades, Gulf, Hamilton, Hardee, Hendry, Hernando, Highlands, Hillsborough, Holmes, Indian River, Jackson, Jefferson, Lafayette, Lake, Lee, Leon, Levy, Liberty, Madison, Manatee, Marion, Martin, Miami-Dade, Monroe, Nassau, Okaloosa, Okeechobee, Orange, Osceola, Palm Beach, Pasco, Pinellas, Polk, Putnam, Santa Rosa, Sarasota, Seminole, St. Johns, St. Lucie, Sumter, Suwannee, Taylor, Union, Volusia, Wakulla, Walton, and Washington.

In Chapter VI, the primary exposure variable of interest is **LHD expenditures** measured as per capita LHD expenditures (expended public health dollars divided by the population of LHDs’ jurisdiction). Data for the exposure variable is obtained from four waves of NACCHO profile data (2010, 2013, 2016, 2019).

3.4.4. Dependent Variables

In Chapter IV and Chapter VI, the main outcome variables include various public health outcomes available in the County Health Rankings. **Adult obesity** is the percentage of the adult population (age 20 and older) that reports a body mass index (BMI) greater than or equal to 30 kg/m2 provided by the CDC Diabetes Interactive Atlas. **Sexually transmitted infections** measure the number of newly diagnosed chlamydia cases per 100,000 population provided by the National Center for Hepatitis, HIV, STD, and TB Prevention. **Diabetes prevalence** is the percentage of adults aged 20 and above with diagnosed diabetes from the CDC Diabetes Interactive Atlas. **HIV prevalence** is the number of people aged 13 years and older living with a diagnosis of human immunodeficiency virus (HIV) infection per 100,000 population from the National Center for Hepatitis, HIV, STD, and TB Prevention. It is important to note that estimates for obesity prevalence and diabetes prevalence were produced by modeled data, which make it difficult to use for tracking progress in small geographic areas (County Health Rankings, 2021). Likewise, there are limits to modeled data in that they cannot incorporate the effects of local conditions, like unique population characteristics, into their estimates (County Health Rankings, 2021).

In Chapter V, the outcome variables are measures of **Effectiveness of Public Health Services** performed in each jurisdiction. The effectiveness of each activity is based on the LHD official's rating on a 5-point Likert scale ranging from "meets no needs" to "fully meets needs." The study also includes activity-specific measures combining the average measures of effectiveness for three public health functions: Assessment (activities 1 through 6 in Table 4), Policy Development (activities 7 through

15), and Assurance (activities 16 through 19). Data for these variables are obtained from five waves (2006, 2012, 2014, 2016, and 2018) of the NALSYS.

3.4.5. Control Variables

Control variables in the model included factors known to influence health at the local level available in the County Health Rankings Annual Reports. **Uninsured** adults measure the percentage of the population under age 65 without health insurance provided by the Small Area Health Insurance Estimates. **Primary care physicians** measure the ratio of population to primary care physicians from the Health Resources & Services Administration. **Preventable hospital stays** are the rate of hospital stays for ambulatory-care sensitive conditions per 100,000 Medicare enrollees from the Dartmouth Atlas of Health Care. **High school graduation** is the percentage of ninth-grade cohort that graduates in four years from the National Center for Education Statistics. **Unemployment** is the percentage of the population ages 16 and older unemployed, but seeking work, from the Bureau of Labor Statistics. **Children in poverty** is the percentage of people under age 18 in poverty provided by the Small Area Income and Poverty Estimates. **Population** is the total population size of the jurisdiction. **Age** is the percentage of the population that is 65 years and older. **Race** is the percentage of the population that is Non-Hispanic African American. **Ethnicity** is the percentage of the population that is Hispanic. Population, age, race, and ethnicity measures are provided by the Census Population Estimates. **Median household income** is the income where half of the households in a county earn more, and half of the households earn less, provided by the Small Area Income and Poverty Estimates. Total **full-time employees** for the LHD are included. Indicator variables for **jurisdiction** classification – city, city-county, county, multi-city, multi-county – are also represented. Data for the LHD full-time employees and jurisdiction variables are obtained from the NACCHO Profile Surveys. Based on a review of the literature and rationale for inclusion, additional data is obtained to further characterize the LHDs and community characteristics: the presence of a board of health (whether it existed, whether it had policymaking authority, and whether it was the governing board); staff full-time equivalents (FTEs) per capita; type of jurisdiction (centralized, mixed, or other); population size of the jurisdiction; and whether the jurisdiction was a metropolitan or a smaller, micropolitan area. Data for these measures are obtained from the NACCHO surveys.

3.5. Data Analysis

3.5.1. Level of Analysis and Measurement

The three studies use the LHD and the community it serves as the unit of analysis. This unit was selected to account for the factors at the level of the individual LHD that may impact the relationship between accreditation, funding, and outcomes.

3.5.2. Nature of the Scale for Key Variables

In Chapter IV and Chapter VI, two of the public health outcomes are rates. Results for the STD and HIV variables are interpreted as increases or reductions per 100,000 population in a county. The other public health outcomes, obesity prevalence and diabetes prevalence, are percentages. In Chapter V, the effectiveness of public health activities, the main outcome variables, are provided by the National Longitudinal Survey of Public Health Systems (NALSYS), a validated survey of local public health officials. The survey measures how effectively each public health activity is carried out in the community based on a 5-point Likert scale ranging from “meets no needs or 0%” to “fully meets needs or 100%.” Response sets used in the survey instrument were designed with numeric anchor points to support approximations to an interval scale (Mays & Hogg, 2015; Norman, 2010). Parametric statistics used with these types of measures are robust to violations of distributional assumptions that result from treating Likert variables as interval measures, particularly in relatively large samples. In Chapter VI, LHD expenditures per capita are adjusted to represent 2021 constant dollars by employing a model proposed by NACCHO where the weighted average of the general Consumer Price Index (CPI) is used. The value for per capita LHD expenditures is transformed via the natural logarithm to reduce skewness and outliers in the LHD expenditure measure, create a more normal distribution to improve model fit, and for ease in interpretation of results.

3.5.3. Hypotheses

In Chapter IV, the central hypothesis investigated whether public health accreditation results in positive changes to public health outcomes. It was hypothesized that there would be greater reductions in public health outcomes in Florida counties with accredited LHDs as indicated by negative difference-in-difference coefficients. In Chapter V, the central hypothesis investigated whether public health accreditation positively impacts the effectiveness of public health activities. It is postulated that there would be greater increases in effectiveness in Florida counties with accredited LHDs as indicated by positive difference-in-difference coefficients. In Chapter VI, the central hypothesis investigated whether increased LHD expenditures improve local-level public health outcomes. It is hypothesized that increased LHD expenditures improve public health outcomes as shown by decreases to the regression coefficients.

3.5.4. Ordinary Least Squares (OLS) Regression

Ordinary Least Squares (OLS) regression is used to test the hypotheses. Linear regression analysis is an econometric method used to make quantitative estimates of economic relationships (Studenmund, 2006). Regression results do not prove causality, but rather test the strength and direction of a quantitative relationship. A standard technique in regression analysis is the OLS technique which estimates the coefficients of econometric models (Studenmund, 2006). The OLS regression estimation method calculates the sample estimate of a true population value. The method minimizes the differences between the actual true population value and the estimated value produced by the regression. Under a set of assumptions, OLS produces an estimated regression equation that is as close as possible to the observed data. A multivariate OLS regression model can estimate the change in a dependent variable as a function of the change in more than one independent variable (Studenmund, 2006). In this analysis as further detailed in Chapter VI, a cross-sectional design is used, and an OLS regression model is tested by each year available in the data. OLS was performed using the regress command available with Stata statistical software. The pooled OLS regression model is commonly considered as a technique for panel data.

In a pooled OLS model, data on different units are combined or pooled together and there is no assumption on individual differences (Muck, 2018). A pooled OLS is tested in Chapter VI using the regress Stata command.

3.5.5. Fixed Effects and Random Effects Models

This research also makes use of panel data techniques. Using panel data requires the need to control for autocorrelation that exists between observations of the same public health systems over time. There are several alternative panel data estimation procedures tested to account for the autocorrelation. Random Effects models are used to determine the changes in outcomes that are associated with changes in the explanatory variable while controlling for a range of other factors that influence the outcomes. This model assumes that the agency-specific correlation coefficients are randomly distributed and uncorrelated with the other characteristics included in the model. A Fixed Effects specification is used to control for any time-invariant confounding factors that may have had an impact on the dependent variable and allows the agency-specific coefficients to be correlated with other covariates. The Fixed Effects model will not experience bias due to time-invariant omitted variables. Statistical analyses for these procedures are performed using the xtreg Stata command. A Hausman specification test can be performed to decide whether a Fixed Effects or Random Effects model should be used. The Hausman test examines whether there is a correlation between the time-invariant omitted and independent variables. If the regression coefficients under the Fixed Effects model and Random Effects models are statistically different, then the Fixed Effects model is preferred for model estimation.

3.5.6. Difference-in-Difference Approach

Chapter VI and Chapter V make use of a difference-in-difference methodology. The difference-in-difference design is a quasi-experimental approach often used to study causal relationships by comparing outcomes of groups exposed to different programs or policies at different times (Wing et al., 2018; Wooldridge, 2012a; Wooldridge, 2012b; Callaway & Sant'Anna, 2020). The approach relies on a natural experiment where there is a policy change that is expected to affect treatment for one group more than another. Other than the policy change, the two groups should not have different experiences. Under this approach, the natural experiment is exogenous or not affected by any other variables. Outcomes pre and post intervention are compared between the intervention group and the comparison group which allows for the controlling of the background changes in outcomes. Regression modeling is used for these studies to adjust for other factors that may differ between the groups and to estimate statistical significance of the association between the intervention and outcomes (Dimick & Ryan, 2014).

The main assumption of this design is that the outcomes are parallel for the control and treatment groups prior to the intervention or policy (Wooldridge, 2012a). Whether the parallel trends assumptions are met can be tested visually with the use of line graphs by plotting the means of the outcome over time. A parallel trends test can also be conducted. If the results of the test are not significant, there is not sufficient evidence to reject the null hypothesis of the parallel trends (Baker, 2020). A Granger causality test can then be conducted to determine if the control or treatment groups change their behavior in anticipation of the intervention or the policy (Wooldridge, 2012a; Baker, 2020). If the results of the test are not significant, there is not sufficient evidence to reject the null hypothesis of no behavior change prior to treatment. The assumptions being met ensure the average treatment effect on the treated (ATET) estimate is unbiased and accurate. The difference-in-difference technique controls for unobservable time and group characteristics that confound the effect of the treatment on the outcome (Stata, 2021).

The statistical analysis is performed using the xtreg and the xtdidregress commands available with Stata statistical software. If a small number of groups is included in the sample, alternative methods can be used with the analysis to make reliable inferences about the treatment effect. The Bell and McCaffrey (2002) degrees-of-freedom adjustment is a method that can employ bias-corrected standard errors (Stata, 2021; Bell & McCaffrey, 2002). The Donald and Lang (2007) is an aggregation method, and the wild-cluster bootstrap can be used to obtain p-values and confidence intervals (Donald & Lang, 2007; Stata, 2021).

3.5.7. Instrumental Variables Approach

In Chapter VI, an Instrumental Variables (IV) approach was originally tested. The IV approach is a strong quasi-experimental approach the exploitation of the variation in the treatment variable to be explained by instrumental variables which are exogenous – related to the treatment, but unrelated to the outcome, except via the treatment (Wooldridge, 2012a; Angrist & Pischke, 2008). This approach is used to address simultaneous or reverse causality where causality runs backward from the outcome variable to the explanatory variable as well as forward from the explanatory variable to the outcome variable. Reverse causality is ruled out in this approach as the instrumental variable's regression solves the problem of correlation between LHD expenditures and the error term. Instruments are identified and used to isolate the movements in the explanatory variable that are uncorrelated with the error term which in turn permit consistent estimation of regression coefficients.

An OLS regression is first employed to estimate the association between LHD expenditures and public health outcomes. The Durbin-Wu-Hausman test is then used to test the null hypothesis that LHD expenditures are exogenous in the public health outcomes regression. Rejecting the null hypothesis signifies that there is endogeneity, and instrumental variables estimation should be used rather than OLS. The model is re-estimated using an econometric technique known as instrumental variables with a two-stage least squares approach. At the first stage, the instrumental variable is used to predict LHD expenditures while adjusting for the other covariates in the model. In this step, the exogenous variation in LHD expenditures is effectively isolated. The first-stage regression with instrument Z, endogenous regressor W, and other regressors X is modeled as:

$$W\iota = \alpha 0 + \alpha 1 Z^{\iota} + X_{\iota}\Theta + \varepsilon\iota \quad (1)$$

The estimated coefficients from this model are used to predict W. At the second stage, the predicted variation in the LHD expenditures variable is used in place of the original formula in estimating the outcome. The empirical specification used is shown below. The coefficient β1 then gives the causal effect of interest (the effect of LHD expenditures on public health outcomes).

$$Y = \beta 0 + \beta 1 W^{i} + X_{\iota\gamma} + \grave{o} \tag{2}$$

To control for the potential endogeneity of public health funding, a natural experimental design was first leveraged in Chapter VI by relying on instrumental variables methods to study the relationship between LHD expenditures and the public health outcome measures. Like Mays (2016) and Smith (2015), several measures of public health governance and decision-making structures were used as instrumental variables. These measures include the existence of a local board of health with authority to adopt health policies and regulations and the existence of a local government authority to approve public health agency budgets independently of state government (Mays et al., 2016; Smith et al., 2015; Shah et al., 2019). Using a process that is unrelated to the outcome measures, these instrumental variables assign LHDs to different levels of public health spending. Theory posits that the instrumental variables influence LHD expenditures but have no alternative pathway of impact on public health outcomes. Prior research indicates that local health governing boards and decentralized fiscal authority generate enhanced community support for local health activities, thereby increasing LHD expenditures. As such, much like randomization in a controlled trial, the instrumental variables serve to place LHDs in different groups as the instrumental variables are significantly predictive of LHD expenditures, but not independently associated with public health outcomes.

Fixed Effects regression models with instrumental variables estimation were employed to determine the changes in public health outcomes that are associated with changes in LHD expenditures, while controlling for a range of other factors that influence local public health. The statistical analysis was performed using the xtivreg and the ivregress Stata commands. To determine if the conditions for instrument validity hold, standard validity tests were conducted including the nonzero average causal effect, overidentification, and weak identification tests. Results revealed that the conditions for instrument relevance and exogeneity were not satisfied. The selected instruments did not explain the variation in LHD expenditures (relevance), did not plausibly impact LHD expenditures, and directly impacted the health outcomes (exogeneity). Strong instruments were tested by checking if the f-statistic exceeded the rule of thumb of 10. The instruments were found to be weak with significant variation and low correlation with the endogenous variable. Ultimately, the less-than-ideal instruments were not used as they undermined the precision of the estimator. A description of the IV process used in Chapter VI is discussed in this Section; however, the IV results are not included in the results of the third study.

3.5.8. Description of Parametric Models Used

This research uses multiple linear regression models. The empirical specification used in Chapter IV to investigate the relationship between public health accreditation and public health outcomes is shown below:

$$Y_{it} = \beta_0 + \beta_1(Treat_i * Post_t) + \beta_2 Treat_i + \beta_3 Post_t + \beta_4 X_{it} + u_{it}$$

where the variables in LHD = i at time = t are Y_{it} are the public health outcome measures (obesity prevalence, sexually transmitted infections, diabetes prevalence, and HIV prevalence); $Treat_i$ is an indicator variable = 0 if LHD is not accredited; = 1 if LHD is accredited; $Post_t$ is a time-indicator variable = 0 if before 2016; = 1 if after 2016; X_{it} is a vector of control variables; β are the parameters to be estimated; β_1 is the coefficient of the interaction term (DiD estimate of impact of accreditation on public health outcomes); and u_{it} is a random error term.

The empirical specification used in Chapter V to investigate the relationship between public health accreditation and the effectiveness of public health activities is as follows:

$$Y_{it} = \beta_0 + \beta_1(Treat_i * Post_t) + \beta_2 Treat_i + \beta_3 Post_t + \beta_4 X_{it} + u_{it}$$

where the variables in LHD = i at time = t are Y_{it} as the effectiveness of public health activities (Assessment Activities, Policy Development Activities, Assurance Activities, and Total Activities); $Treat_i$ is an indicator variable = 0 if LHD is not accredited; = 1 if LHD is accredited; $Post_t$ is a time-indicator variable = 0 if before 2016; = 1 if after 2016; X_{it} is a vector of control variables; β are the parameters to be estimated; β_1 is the coefficient of the interaction term (DiD estimate of impact of accreditation on public health outcomes); and u_{it} is a random error term.

The empirical specification used in Chapter VI to investigate the relationship between LHD expenditures and public health outcomes is shown below:

$$\mathrm{Y_{it}} = \beta_0 + \beta_1 \mathrm{X_{it}} + \beta_2 \mathrm{Z_{it}} + \alpha \mathrm{T_i} + \mathrm{u_{it}}$$

where the variables in LHD *i* at time t are - Y_{it} as public health outcome measures (obesity prevalence, sexually transmitted infections, diabetes prevalence, and HIV prevalence); X_{it} as LHD expenditures per capita; Z_{it} as a vector of control variables; β as parameters to be estimated; αT_i as the time trend; and u_{it} as a random error term.

3.5.9. Description of Descriptive Analytical Tools Used

Stata statistical software is used to analyze data (StataCorp LP, College Station, TX). Descriptive statistics, calculated for all variables, primarily provide context for the multivariate analysis, and include standard measures such as the mean, median, mode, minimum, maximum, variance, and standard deviation. All study variables are evaluated through a series of data quality assessments, range checks, and trend analyses to detect irregularities and outlier values.

3.5.10. Significance Tests

Statistical significance is assessed using p-values with a 2-sided $P \leq .05$ considered as statistically significant. An unbalanced panel is used to conduct the study and missing data in the sample is appropriately handles. In Chapter VI, a Little’s Missing Completely at Random (MCAR) test is run to test the assumption of expenditures missing completely at random (Li, 2013). If the p-value for Little’s MCAR test is not significant, the data may be assumed to be missing completely at random. The test provides evidence that the missing data in the variable of interest does not bias the study inferences. The studies account for the temporal correlation that exists among observations taken on the same communities over time, and control for the clustering of communities within states. Robust standard errors are employed to address the clustering of communities and to construct absolute values of t-statistics.

CHAPTER IV

THE EFFECT OF PUBLIC HEALTH ACCREDITATION ON PUBLIC HEALTH OUTCOMES

4.1. Abstract

The aim of public health accreditation is community health status advancement. Despite the growth of public health accreditation programs in the last decade, the literature on its impact on public health outcomes remains relatively limited. The objective of this study is to evaluate the impact of local health department (LHD) public health accreditation on public health outcomes in the United States. Using local level public health outcomes panel data and a difference-in-difference methodology, the difference in the change in public health outcomes across counties in Florida and control states is quantified, before and after obtaining public health accreditation. Linear probability multivariate regression models with state and time fixed effects are employed. It was hypothesized that there would be greater reductions in public health outcomes in Florida counties with accredited LHDs. Accreditation data from the Public Health Accreditation Board and public health measures from County Health Rankings Annual Reports are used. Analyses were performed at the LHD level using local data representing 2,194 LHDs, covering 50 U.S. states. Florida was considered the treatment state. Participants were accredited LHDs in Florida, non-accredited LHDs in Non-Florida states, non-accredited LHDs in ten similar states, accredited LHDs in ten similar states, and accredited LHDs in Non-Florida states. Four public health measures are examined: obesity prevalence, sexually transmitted infections, diabetes prevalence, and HIV prevalence. For communities with accredited LHDs in the state of Florida, public health

accreditation was associated with decreases in diabetes prevalence and HIV prevalence compared to communities with unaccredited LHDs outside the state of Florida. Based on local level data from 2013-2019, causal estimates of the impact of public health accreditation on public health outcomes are provided. Public health accreditation was significantly associated with improvements to local level public health outcomes. Public health accreditation can be a significant driver for health improvement and a catalyst to improve public health. The findings of this study can benefit LHD leadership considering the pursuit and adoption of accreditation as it is an effective method to improving public health.

4.2. Introduction

In 2011, the Public Health Accreditation Board (PHAB) launched the national, voluntary public health accreditation program as a strategy to advance the quality and performance of local health departments (LHDs) (PHAB, 2021b). PHAB notes that as of March 2022, over 90% of the U.S. population was covered by an accredited local or state health department (PHAB, 2021b). A growing body of literature reports the positive impact of public health accreditation on performance measurement and improvement (Kronstadt et al., 2016; Beitsch et al., 2018; Ingram et al., 2018; Allen, 2019; Scutchfield, 2009). However, little is known of the impact of public health accreditation on public health outcomes.

Despite the growth of public health accreditation programs in the last decade, the literature on its impact on public health outcomes remains relatively limited with available studies primarily employing observational designs (Joly et al., 2007). Some studies assess the impact of accreditation on health outcomes but focus on the accreditation of other organizations such as hospitals and social services organizations in the healthcare system (Mays, 2004; Emmett, 2018). The available literature suggests that public health accreditation may improve quality and accountability (Bender et al., 2010; Russo, 2007; Brewer et al., 2007), and may hold potential for promoting improvements in service delivery, operations, and outcomes in public health (Mays, 2004a), but the direct link to outcome improvement is unclear.

PHAB developed a research agenda in 2013 to expand the evidence base for accreditation. One key research question prioritized in the research agenda included: What impact, if any, does LHD accreditation have on health outcomes? (Lenaway et al., 2006; Joly et al., 2007; Riley et al., 2012; Kronstadt et al., 2015). This study attempts to answer that question. Studies assessing the impact of accreditation are prone to self-selection bias since public health accreditation is a voluntary process. The selection of treatment and comparison groups is done nonrandomly. Better performing LHDs are more likely to pursue accreditation and select treatment. The impact of public health accreditation is evaluated using an approach which reduces bias with the state of Florida serving as a natural experiment where it appears "as if" a treatment is randomly assigned. Florida's accreditation as an integrated local public health department system is examined as an intervention since it is a unique policy where all LHDs in Florida applied for accreditation as a local public health department system in 2016. All 67 Florida counties with their mix of lower and higher performing LHDs were expected to comply, thus minimizing the risk of selection bias. LHDs across the U.S. achieved accreditation at different times allowing for the opportunity to calculate the effect of the accreditation on public health outcomes by using several potential control groups. The findings of this study add to the Public Health Services and Systems Research field of inquiry by establishing that some public health outcomes are more readily influenced by public health accreditation.

4.3. Methods

The impact of LHD accreditation on four public health measures is assessed and it was hypothesized that accreditation results in positive changes to public health outcomes. A quasi-experimental approach is employed, and a panel data difference-in-difference estimator is provided. The difference-in-difference estimation is found by comparing the four public health outcomes in communities with accredited LHDs in Florida and unaccredited LHDs in control states before and after the year the intervention occurred.

The effect of the intervention is measured with the difference-in-differences approach where we have access to data for two groups. The treatment group was exposed to the intervention, while the control group was not. Other than the policy change, the two groups do not have different experiences. The control group is used as counterfactual which is what would have happened to the treatment group without the intervention. Both groups are observed for more than two time periods, before and after the intervention, and the average difference in outcomes in both groups before and after the intervention is considered. The approach compares two differences: the difference in the outcome before and after treatment, and the difference between those differences between the treated and control groups. The difference between both groups is the average effect of the intervention.

The study design does not require that treatment and control groups be the same in at baseline. The main assumption of this design is that the outcomes are parallel for the control and treatment groups prior to the intervention. Whether or not the parallel trends assumption is met is assessed by graphical and statistical inspection to ensure that the average treatment effect is unbiased. The study period was divided into three policy periods. Due to the availability of public health outcomes data, the pre-intervention period was defined as 2010-2015, the implementation period was 2016 (the year in which Florida's LHDs achieved accreditation), and the post-intervention period was 2017-2018. Section 3.3.4 provides more information about the data availability, and Section 3.5.6 provides more detail about the difference-in-difference approach.

Accreditation and re-accreditation status data is used as provided by the PHAB to create a panel dataset and generate a binary accreditation time variable capturing the year in which each LHD was accredited. Each LHD is identified into categories: *Always Accredited* - LHDs that were accredited in all periods or the accreditation time variable equaled to 1 from 2010 to 2018; *Never Accredited* - LHDs that were never accredited or the accreditation time variable equaled to 0 from 2010-2018; *Unaccredited Then Accredited* - LHDs that were unaccredited in 2010 with the accreditation time variable equal to 0 but changed to accredited during 2011-2018 with the accreditation time variable equal to 1; *Accredited Then Unaccredited* - LHDs that saw multiple changes in accreditation status between 2010-2018. LHDs were not categorized into multiple groups. It is problematic to use the *Always Accredited* group as a control group in analyses since using prior treated units will produce biased results (Baker, 2020; Callaway, 2020). We instead use the *Never Accredited* group as the control group with the *Unaccredited Then*

Accredited group as the intervention. Due to the inconsistent variation, the *Accredited Then Unaccredited* category is excluded from further grouping in the analysis.

LHDs were then segmented by their location: *LHDs from all Florida counties*; *LHDs from all states other than the state of Florida*; and *LHDs from ten states* which neighbor Florida or have similar demographics and population size: North Carolina, New York, Illinois, California, Connecticut, Pennsylvania, Texas, Georgia, Alabama, and Tennessee. The time accreditation variable and the state variable form the basis of identifying each LHD into one of the following groups: accredited LHDs in Florida; unaccredited LHDs in Non-Florida states; unaccredited LHDs in ten similar states; accredited LHDs in ten similar states; accredited LHDs in Non-Florida states; and unaccredited LHDs in Non-Florida states.

It is hypothesized that accreditation results in improved public health outcomes. To test this hypothesis using a difference-in-difference approach, a non-intervention control group is needed to compare to the intervention. The comparison group captures any potential secular trends unrelated to accreditation that might be affecting the study outcomes during this same period. Several potential comparison groups are used, representing the changes that would have occurred in treatment group had the intervention not taken place. The three specifications used to assess the changes between an intervention and the multiple comparison groups are shown in Table 6. In Specification (1), the differences between accredited LHDs in Florida are compared to unaccredited LHDs in Non-Florida states (Figure 1). In the figure, $\Delta 1$ signifies the difference between accredited LHDs in Florida and unaccredited LHDs in Non-Florida states. It is expected that after the intervention, the distance increases for the treatment group because the outcomes are getting better for those who received treatment.

An additional model is tested in Specification (1) by comparing unaccredited LHDs in ten similar states. A more accurate control for Florida among ten similar states that did not implement comparable policies over the same period was chosen. By using many potential control groups (ten similar states) to create a synthetic control group, evidence that is less subject to the self-selection bias observed in all Non-Florida states group in Specification (1) is presented. In Specification (2), the control group is adjusted to accredited LHDs in Non-Florida states (Figure 2). This specification suffers from bias as it includes controls that were previously treated (Bertrand et al., 2004; Wooldridge, 2012). This specification is included in the analysis to test our expectations that the difference or the gap between treated and untreated gets smaller suggesting less improvement in this group.

In Specification (3), the intervention group is adjusted to accredited LHDs in Non-Florida states, and the control group to unaccredited LHDs in Non-Florida states (Figure 3). Like Specification 2, this specification also suffers from selection bias since we use accredited LHDs in Non-Florida states as treatment. Unlike LHDs in Florida, this group does not have an intervention where all LHDs are required to undertake the accreditation process. Since higher quality LHDs are more likely to pursue accreditation, we expect a bias in result in the opposite direction. This specification is included in the analysis to test the expectation of a positive and larger improvement in this group.

Table 6. Intervention and Control Groups

		Intervention Group	Control Group
Specification 1	Model 1	Accredited LHDs in Florida	Unaccredited LHDs in non-Florida states
	Model 2	Accredited LHDs in Florida	Unaccredited LHDs in ten similar states
Specification 2		Accredited LHDs in Florida	Accredited LHDs in ten similar states
Specification 3		Accredited LHDs in non-Florida states	Unaccredited LHDs in non-Florida states

Table 6: This table shows the intervention and control groups used in the difference-in-difference analysis. Florida represents all Florida counties. Non-Florida states represent all states other than the state of Florida. The ten similar states represent states which neighbor Florida or have similar demographics and population size: North Carolina, New York, Illinois, California, Connecticut, Pennsylvania, Texas, Georgia, Alabama, and Tennessee.

Figure 1. Difference-in-Difference Specification 1

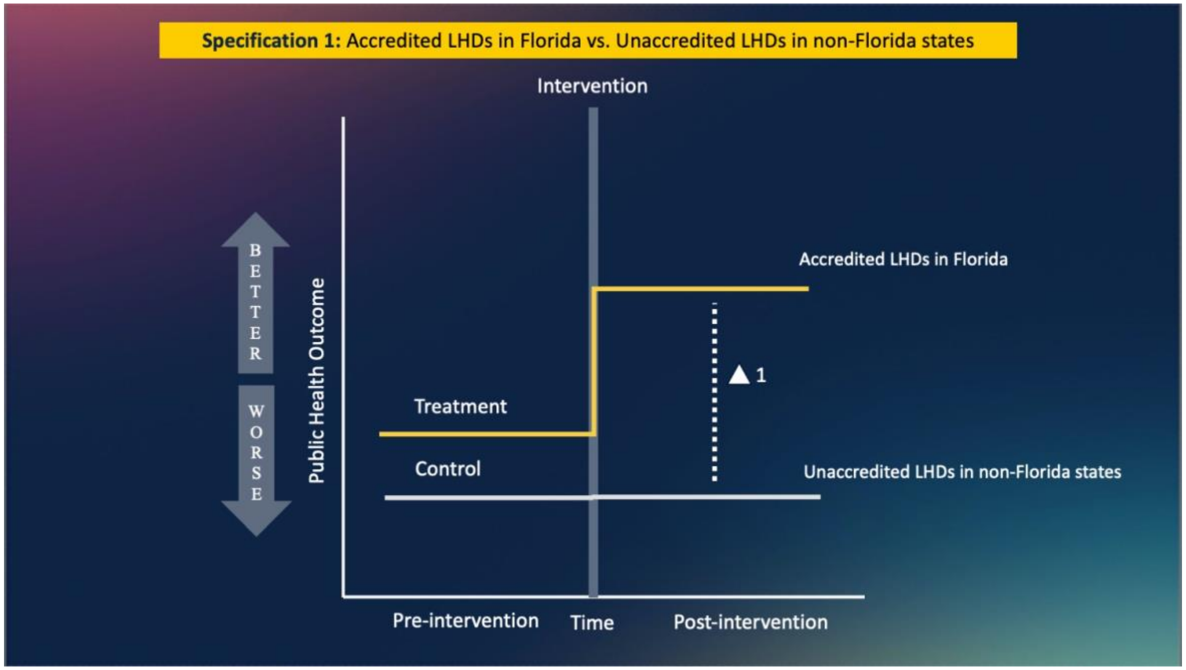

Figure 1: This figure shows Specification (1) tested in the difference-in-difference analysis. In this study, it is hypothesized that accreditation results in improved public health outcomes. Specification (1) tests that hypothesis by measuring the differences between accredited LHDs in Florida compared to unaccredited LHDs in Non-Florida states. In the figure, Δ1 signifies the difference between accredited LHDs in Florida and unaccredited LHDs in Non-Florida states. The expectation is that after the intervention, the gap increases for the treatment group because the outcomes are getting better for those who received treatment. An additional model is tested in Specification (1) by measuring the differences between unaccredited LHDs in ten similar states.

Figure 2. Difference-in-Difference Specification 1.2

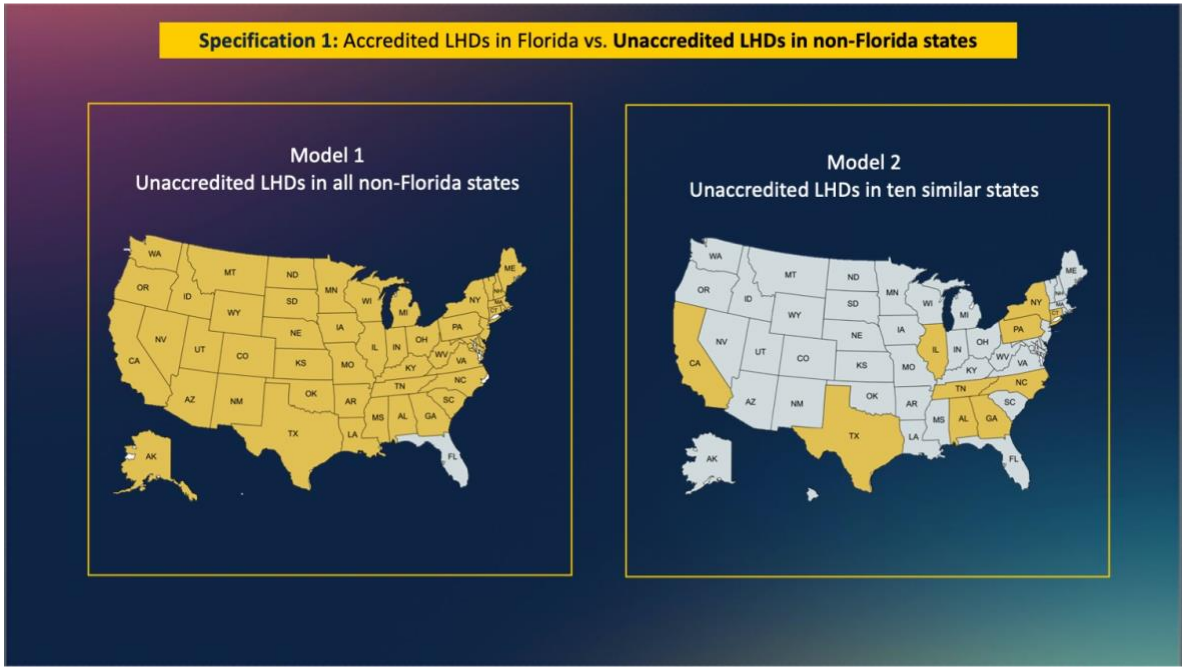

Figure 2: Specification (1) tests two models. Model 1 compares unaccredited LHDs in all Non-Florida states. An additional model is tested by comparing unaccredited LHDs in ten similar states. The ten similar states of North Carolina, New York, Illinois, California, Connecticut, Pennsylvania, Texas, Georgia, Alabama, and Tennessee, provide a more accurate control for Florida among similar states that did not implement similar policies over the same period. These states provide an apples-to-apples comparison. These states were chosen because they neighbor Florida or have similar demographics and population size, and in the literature, they are commonly referred to as suitable comparison states to Florida.

Figure 3. Difference-in-Difference Specification 2

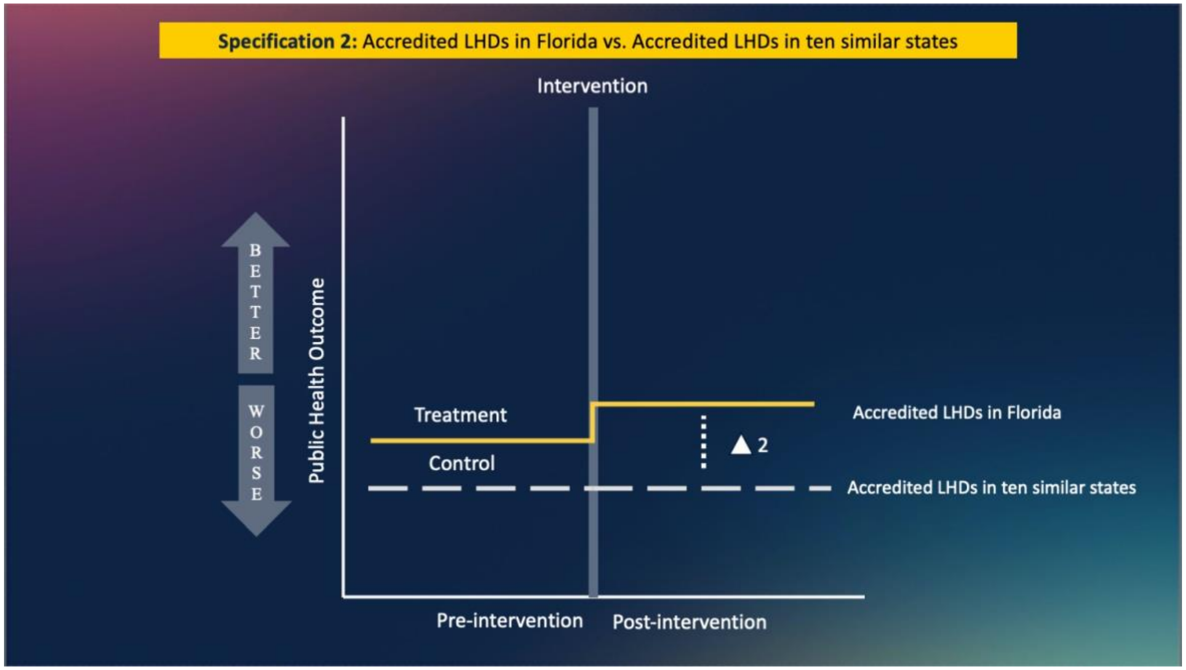

Figure 2: This figure shows Specification (2) tested in the difference-in-difference analysis. In this study, it is hypothesized that accreditation results in improved public health outcomes. Specification (2) tests that hypothesis by measuring the differences between accredited LHDs in Florida compared to accredited LHDs in Non-Florida states. In the figure, Δ2 signifies the difference between accredited LHDs in Florida and accredited LHDs in Non-Florida states. Since the comparison group "accredited LHDs in ten similar states" includes controls that were previously treated, it is expected that it can bias results. This specification is included in the analysis to test the expectation that the difference or the gap between treated and untreated gets smaller suggesting less improvement in this group.

Figure 4. Difference-in-Difference Specification 3

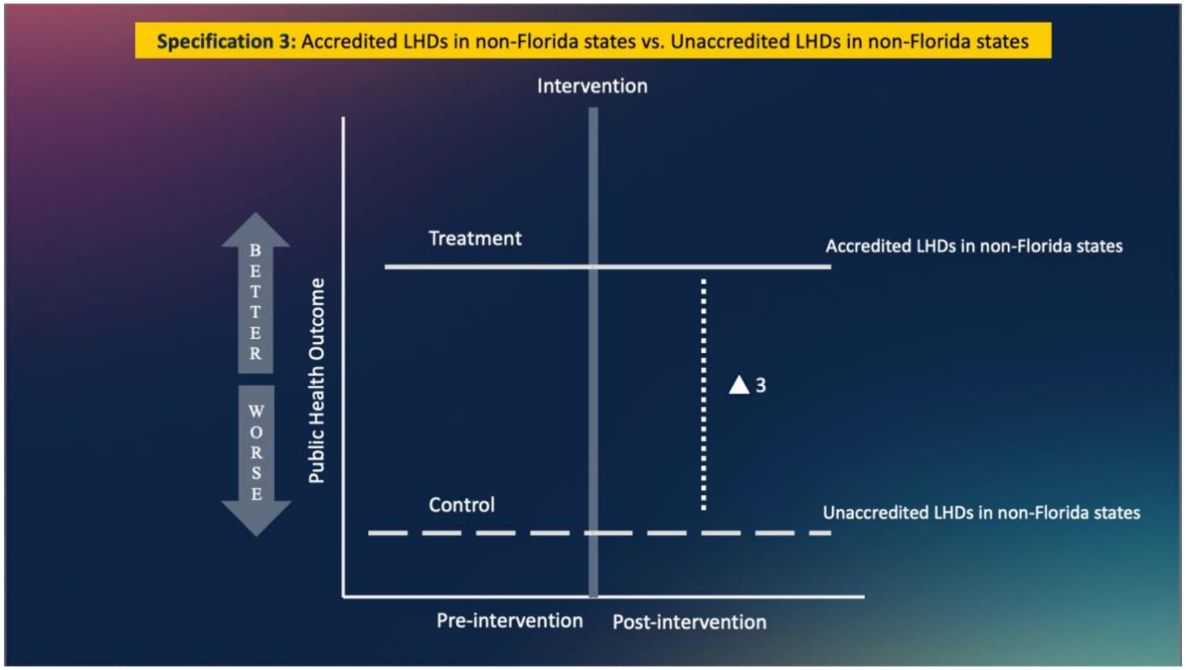

Figure 4: This figure shows Specification (3) tested in the difference-in-difference analysis. In this study, we hypothesize that accreditation results in improved public health outcomes. Specification (3) tests that hypothesis by measuring the differences between accredited LHDs in Non-Florida states compared to unaccredited LHDs in Non-Florida states. In the figure, Δ3 signifies the difference between accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states. This specification also suffers from selection bias since we use accredited LHDs in Non-Florida states as treatment. Unlike LHDs in Florida, this group does not have an intervention where all LHDs are required to undertake the accreditation process. Since higher quality LHDs are more likely to pursue accreditation, we expect a bias in result in the opposite direction. We included this specification in the analysis to test our expectations of a positive and larger improvement in this group.

The main outcome variables include a set of public health outcomes available in the County Health Rankings Annual Reports. **Obesity prevalence** is the percentage of the adult population (age 20 and older) that reports a body mass index (BMI) greater than or equal to 30 kg/m2 provided by the CDC Diabetes Interactive Atlas. **Sexually transmitted infections** measure the number of newly diagnosed chlamydia cases per 100,000 population provided by the National Center for Hepatitis, HIV, STD, and TB Prevention. **Diabetes prevalence** is the percentage of adults aged 20 and above with diagnosed diabetes from the CDC Diabetes Interactive Atlas. **HIV prevalence** is the number of people aged 13 years and older living with a diagnosis of human immunodeficiency virus (HIV) infection per 100,000 population from the National Center for Hepatitis, HIV, STD, and TB Prevention. The County Health Ranking Annual Reports for years 2014-2022 were used for the outcome variables since they best correspond with the study period. More information on the County Health Ranking Annual Reports is available in Section 3.3.4.

Covariates known to influence health at the local level are included in the analysis. **Primary care physicians** measure the ratio of population to primary care physicians from the Health Resources & Services Administration. **Preventable hospital stays** are the rate of hospital stays for ambulatory-care sensitive conditions per 100,000 Medicare enrollees from the Dartmouth Atlas of Health Care. **High school graduation** is the percentage of ninth-grade cohort that graduates in four years from the National Center for Education Statistics. **Unemployed** is the percentage of population ages 16 and older unemployed but seeking work from the Bureau of Labor Statistics. **Poverty** is the percentage of people under age 18 in poverty provided by the Small Area Income and

Poverty Estimates. **Uninsured adults** measures the percentage of population under age 65 without health insurance provided by the Small Area Health Insurance Estimates. **Median household income** is the income where half of households in a county earn more, and half of households earn less provided by the Small Area Income and Poverty Estimates. **Population** is the total population size of the jurisdiction. **Age** is the percentage of the population that is 65 years and older. **Race** is the percentage of the population that is Non-Hispanic African American. **Ethnicity** is the percentage of the population that is Hispanic. Population, age, race, and ethnicity measures are provided by the Census Population Estimates. The County Health Rankings Annual Reports for years 2012-2022 were used for the control variables. We matched the outcomes and covariate data with the PHAB accreditation data by their common Federal Information Processing Standard (FIPS) county codes. Average weights were generated based on the number of LHDs serviced in each FIPS code to account and better estimate when one FIPS code represented several LHDs or one LHD represented several FIPS codes. We chose to incorporate weights into the data to address LHDs serving multiple counties as well as counties served by multiple LHDs.

Study Population

The sample includes all U.S. public health agencies meeting the national definition of an LHD: "an administrative or service unit of local or state government that is concerned with health and carries out some responsibility for the health of a jurisdiction smaller than the state" (NACCHO, 2017a).

There are approximately 2,800 agencies or units that met this definition in the U.S. Data is analyzed for 2,194 LHDs, covering 50 U.S. states.

Statistical Analysis

A panel data difference-in-differences model is estimated to quantify the difference in the change in public health outcomes across counties in Florida and control states, before and after obtaining public health accreditation. It is hypothesized that there would be greater reductions in public health outcomes in Florida counties with accredited LHDs as indicated by negative difference-in-difference coefficients. Descriptive statistics, calculated for all variables, primarily provide context for the multivariate analysis. All study variables are evaluated through a series of data quality assessments, range checks, and trend analyses to detect irregularities and outlier values.

Outcomes for the same counties over time are observed which allows for the estimation of local-level panel data with fixed effects to control for unobserved heterogeneity. Linear probability multivariate regression models with state and time fixed effects are employed to control for unobservable time and group characteristics that confound the effect of the treatment on the outcome and give reliable estimates of average effects while having an intuitive interpretation (Stata, 2021; Angrist & Pischke, 2008). The linear probability models provide estimated percentage-point changes in the treatment relative to the control. These results can be interpreted as within-LHD changes based on changes in various explanatory variables. This study accounts for the temporal correlation that exists among observations taken on the same communities over time, and controls for the clustering of communities within states (Bertrand et al., 2004). Robust standard errors are employed and clustered at the state (intervention) level to account for within-state serial correlation. To determine between a random effect and a fixed effects model, a Hausman specification test was conducted. Results from the test revealed that the fixed effects model was the more efficient model.

The study design does not require that treatment and control states are comparable in their treatment status or health outcomes at baseline; rather, it assumes that trends in treatment status or public health outcomes were similar before 2016. Changes in the comparison states represented the changes that would have occurred in Florida had the intervention (integrated accreditation) not taken place. To assess the appropriateness of this assumption, the data was graphically and statistically inspected for differential temporal trends during the pre-intervention period. The visual inspection was completed with the use of line graphs to visualize outcomes over time (Figures 4-7). A Granger-type causality model was fitted where the model was augmented with dummies for each pretreatment–treatment period for the treated observations. A joint test of the coefficients on these dummies against zero is used as a test of the null hypothesis that no anticipatory effects have taken place. Since the internal validity of difference-in-difference models are ensured, the difference-in-difference estimation of the causal effect is unbiased and correct.

Figure 5. Graphical Representation of Parallel Trends for Specification 1

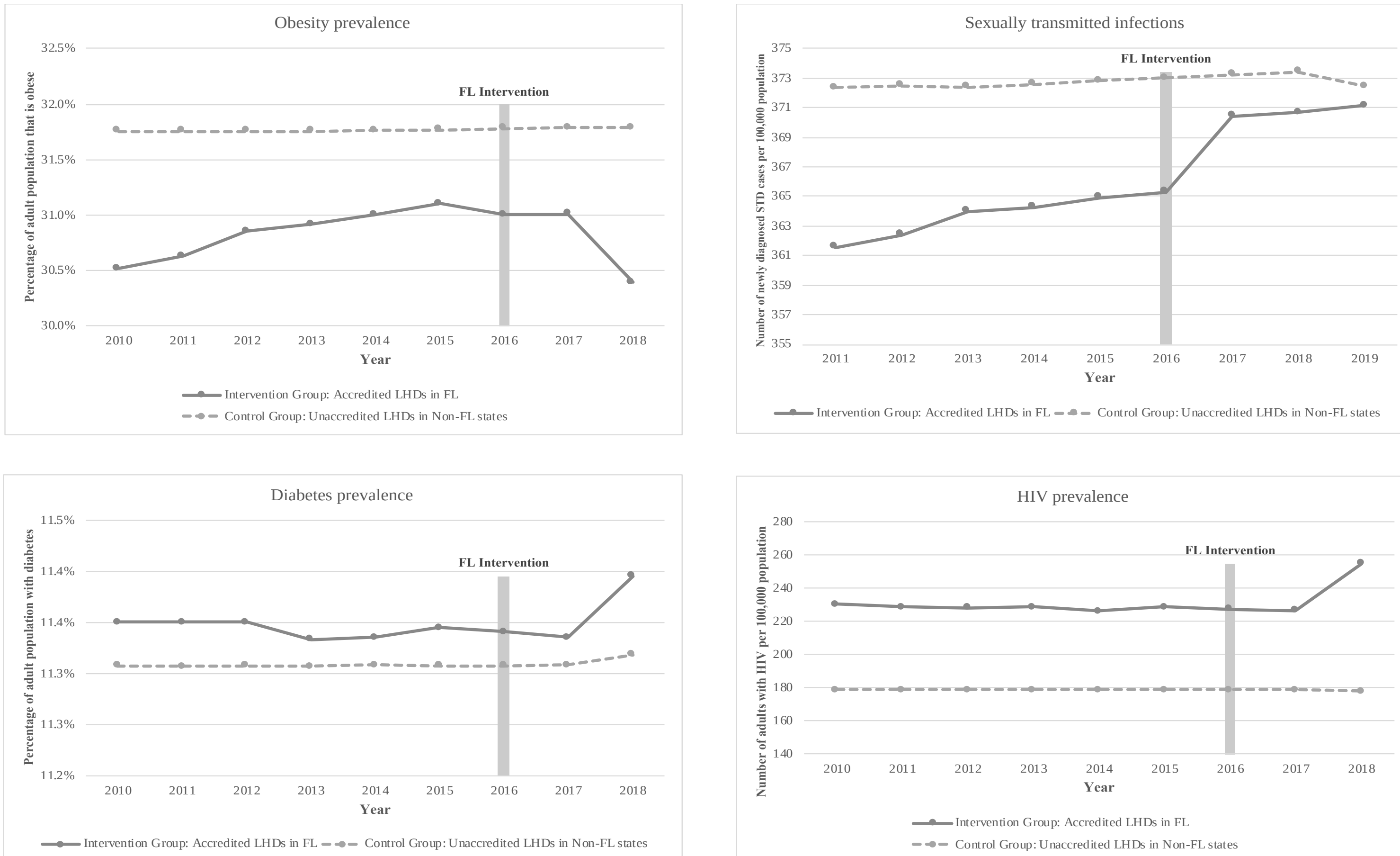

Figure 5. The figure shows the graphical representation of parallel trends for Specification (1) comparing accredited LHDs in Florida and unaccredited LHDs in Non-Florida states. The line graphs were used to visually inspect the data to determine if the parallel trends assumption was met.

Figure 6. Graphical Representation of Parallel Trends for Specification 1.2

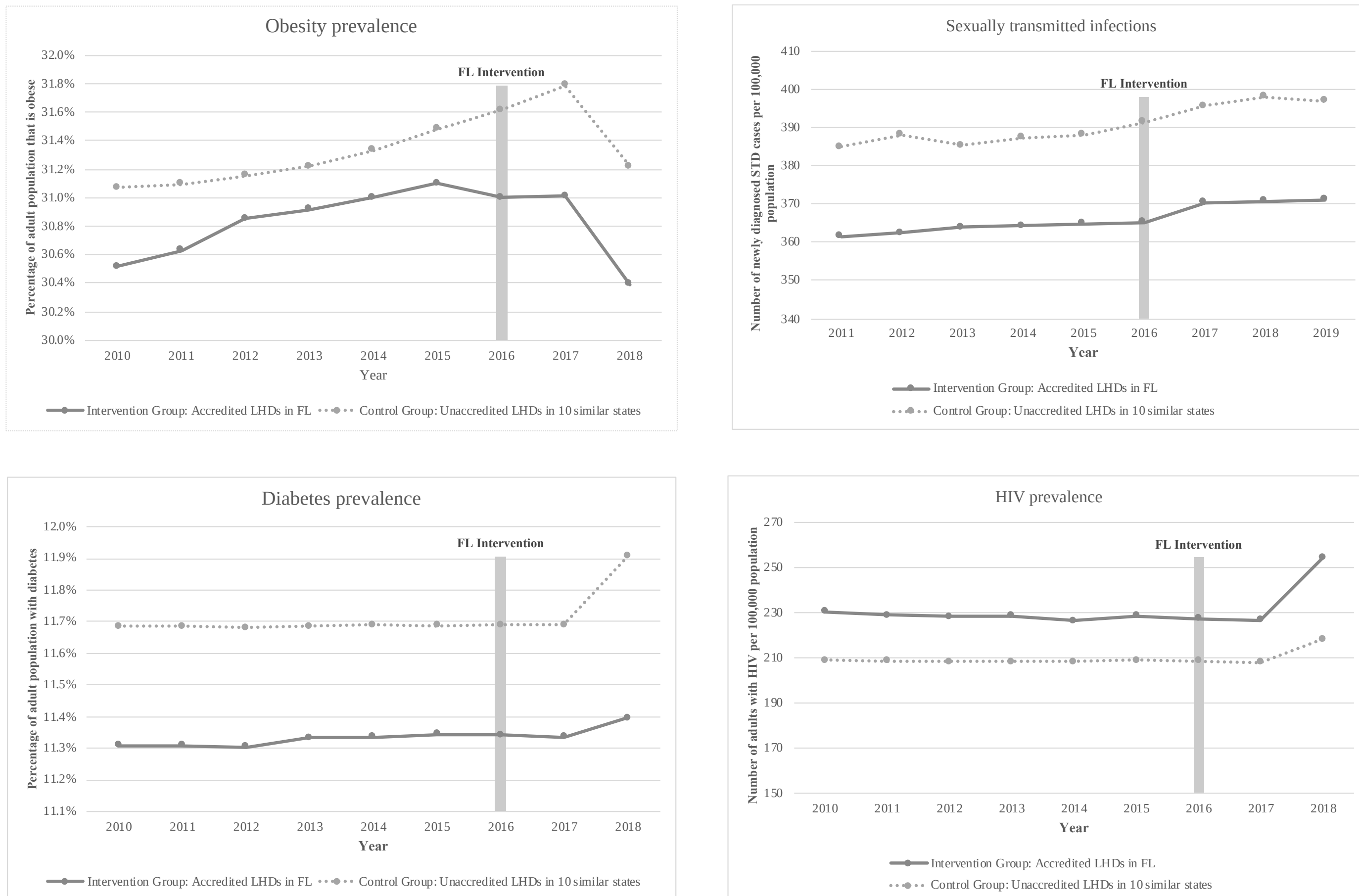

Figure 6. The figure shows the graphical representation of parallel trends for Model 2 of Specification (1) comparing accredited LHDs in Florida and unaccredited LHDs in ten similar states. The line graphs were used to visually inspect the data to determine if the parallel trends assumption was met.

Figure 7. Graphical Representation of Parallel Trends for Specification 2

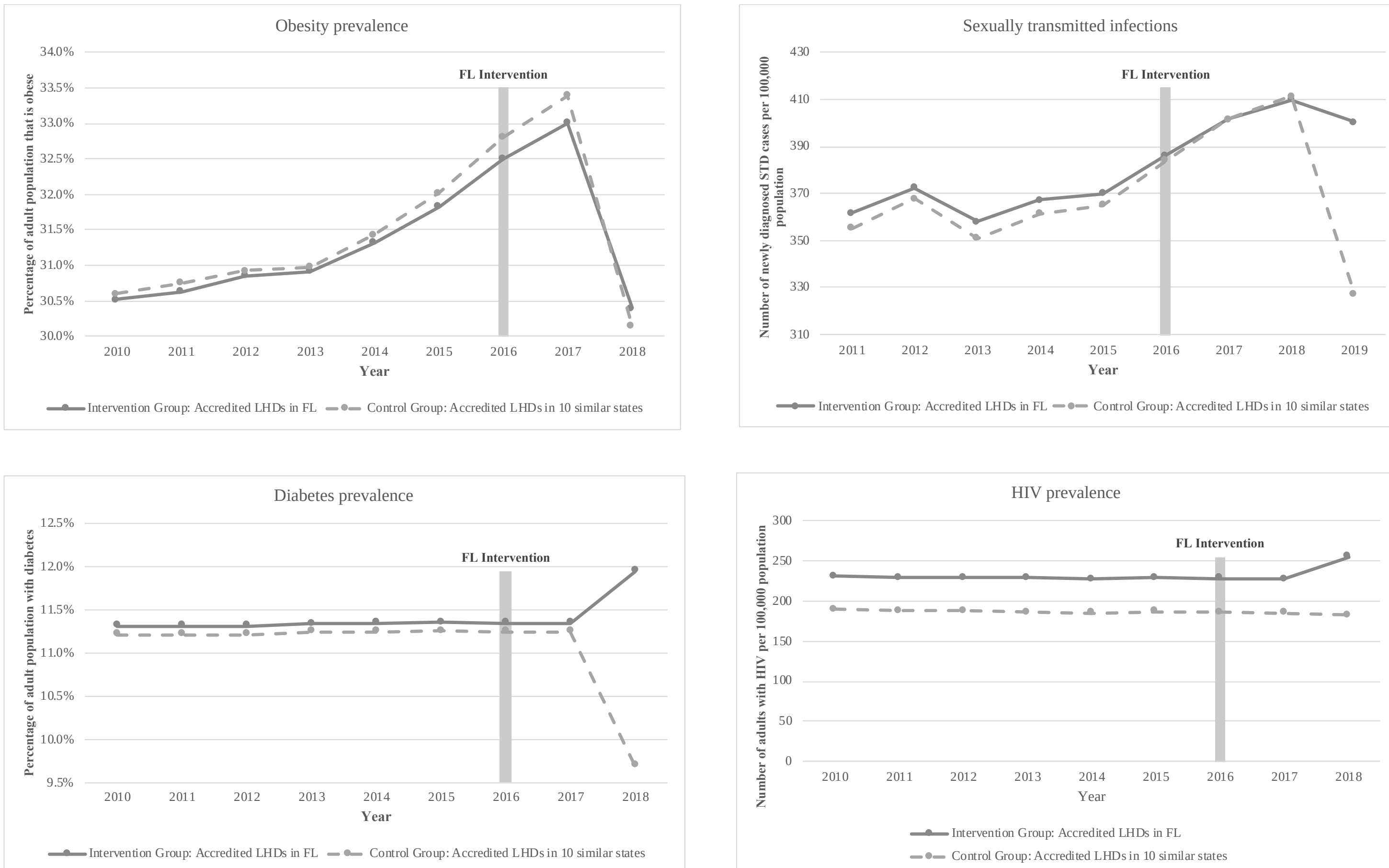

Figure 7. The figure shows the graphical representation of parallel trends for Specification (2) comparing accredited LHDs in Florida and accredited LHDs in ten similar states. The line graphs were used to visually inspect the data to determine if the parallel trends assumption was met.

Figure 8. Graphical Representation of Parallel Trends for Specification 3

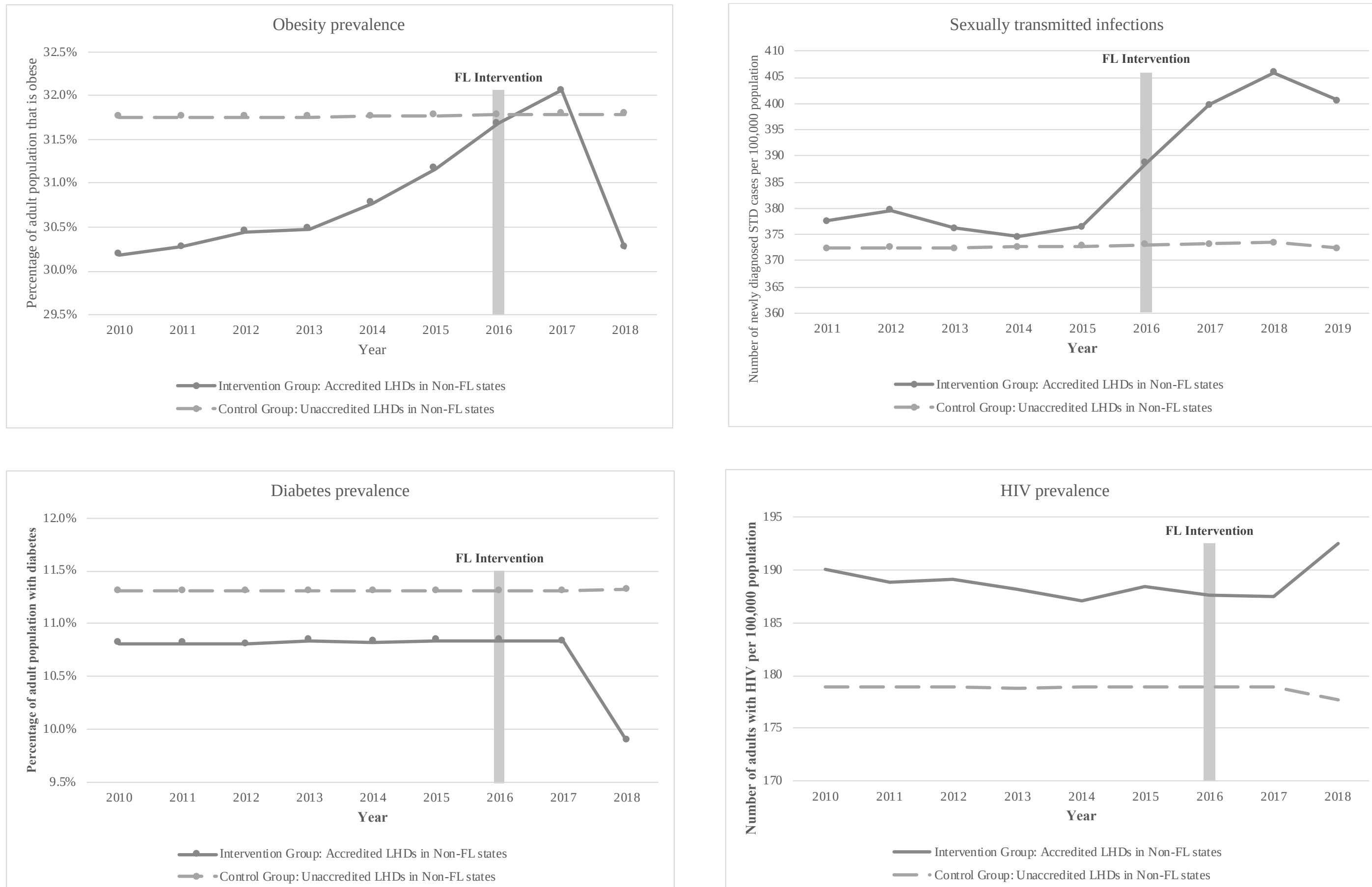

Figure 8. The figure shows the graphical representation of parallel trends for Specification (3) comparing accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states. The line graphs were used to visually inspect the data to determine if the parallel trends assumption was met

Ordinary least squares estimation with Stata statistical software is used to analyze the data (StataCorp LP, College Station, TX). The xtdidregress command available with Stata was also used to estimate the average treatment effect (ATET) on the treated by difference-in-differences. Since a small number of LHD groups (50 states) are used to make reliable inferences about the treatment effect, alternate methods were tested: bias-corrected standard errors with the Bell and McCaffrey (2002) degrees-of-freedom adjustment; aggregation method proposed by Donald and Lang (2007); and the wild-cluster bootstrap to obtain p-values and confidence intervals with a seed set at 1,000 replications to make results replicable (Bell & McCaffrey, 2002; Cameron, 2015). More information about these methods can be found in Section 3.5.6.

4.4. Results

Table 7 provides summary statistics of accredited LHDs in the state of Florida, unaccredited LHDs in Non-Florida states, unaccredited LHDs in ten similar states, accredited LHDs in ten similar states, and accredited LHDs in Non-Florida states, pre and post intervention. It reports averages and the standard deviation for the dependent and control variables. In communities with accredited LHDs in the state of Florida, average rates increased for the four public health outcomes – obesity prevalence (+6.1%), STDs (+12.4%), diabetes prevalence (+0.9%), and HIV prevalence (+20.0%) – when comparing pre and post averages. The average rates for the dependent variables were relatively unchanged in communities with unaccredited LHDs in Non-Florida states, excluding HIV prevalence which saw a decrease of 2.9%. In communities with unaccredited LHDs in ten similar states, average rates increased for the four public health outcomes – obesity prevalence (+1.8%), STDs (+7.2%), diabetes prevalence (+3.5%), and HIV prevalence (+9.7%).

Table 7. Summary Statistics of Intervention and Comparison Groups, Pre-Intervention and Post-Intervention

	Accredited LHDs in State of Florida			**Unaccredited LHDs in Non-Florida states**			**Unaccredited LHDs in Ten Similar States**		
Variables	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change
Obesity prevalence (%)	31.094 (4.478)	33.001 (5.962)	6.10%	31.612 (4.879)	31.785 (4.850)	0.50%	31.234 (4.641)	31.789 (4.943)	1.80%
Sexually transmitted infections (per 100,000)	361.088 (253.179)	406.001 (277.587)	12.40%	372.9 (264.531)	374.185 (267.61)	0.30%	370.125 (259.011)	396.807 (257.936)	7.20%
Diabetes prevalence (%)	11.2 (2.8)	11.3 (2.7)	0.90%	11.3 (2.8)	11.3 (2.8)	0.00%	11.3 (2.8)	11.7 (2.8)	3.50%
HIV prevalence (per 100,000)	188.915 (219.817)	226.645 (259.806)	20.00%	184.186 (210.01)	178.873 (202.153)	-2.90%	189.521 (214.892)	207.967 (226.395)	9.70%
Primary care physicians (per 100,000)	0.001 (0)	0.001 (0)	0.00%	0.001 (0)	0.001 (0)	0.00%	0.001 (0)	0.001 (0)	0.00%
Preventable hospitalizations (per 100,000)	1749.068 (2430.048)	1740.553 (2436.488)	-0.50%	1746.94 (2435.044)	1754.784 (2443.302)	0.40%	1764.213 (2438.269)	1780.386 (2457.682)	0.90%
High school graduation (%)	85.2 (9)	84.8 (9.2)	-0.50%	85.4 (8.9)	85.6 (8.8)	0.20%	85.5 (8.9)	85.8 (8.7)	0.40%
Unemployed (%)	6.3 (2.9)	6.3 (2.9)	0.00%	6.3 (2.9)	6.3 (2.9)	0.00%	6.4 (2.8)	6.5 (2.9)	1.60%
Poverty (%)	22.6 (9.1)	22.7 (9.2)	0.40%	22.7 (9.2)	22.7 (9.2)	0.00%	23.1 (9.1)	23.4 (9.2)	1.30%
Uninsured (%)	17.7 (7.4)	18 (7.5)	1.70%	17.7 (7.4)	17.7 (7.4)	0.00%	18 (7.6)	18.9 (7.8)	5.00%
Median household income ($)	49119.416 (13346.192)	49162.345 (13449.736)	0.10%	48930.975 (13304.615)	48877.592 (13284.371)	-0.10%	48821.217 (13263.486)	48707.945 (13266.878)	-0.20%
Population (total)	196000 (1160000)	197000 (1150000)	0.50%	187000 (1190000)	186000 (1200000)	-0.50%	212000 (1370000)	221000 (1450000)	4.20%
Age (%)	18 (4.8)	18 (4.8)	0.00%	18 (4.7)	18 (4.7)	0.00%	17.8 (4.7)	17.8 (4.6)	0.00%
Race (%)	9.1 (14.2)	9.1 (14.1)	0.00%	9 (14.4)	9 (14.4)	0.00%	9.8 (14.6)	10.1 (14.7)	3.10%
Ethnicity (%)	9.2 (13.5)	9.3 (13.5)	1.10%	9 (13.6)	9 (13.6)	0.00%	10.3 (15)	10.8 (15.6)	4.90%

Table 7. Summary Statistics of Intervention and Comparison Groups, Pre and Post Intervention, Cont'd

	Accredited LHDs in Ten Similar States			**Accredited LHDs in Non-Florida states**		
Variables	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change
Obesity prevalence (%)	31.093 (4.469)	33.391 (5.945)	7.4%	31.086 (4.488)	32.061 (5.961)	3.1%
Sexually transmitted infections (per 100,000)	360.293 (254.098)	406.689 (283.62)	12.9%	363.284 (253.144)	403.302 (271.575)	11.0%
Diabetes prevalence (%)	11.2 (2.8)	11.2 (2.7)	0.0%	11.2 (2.8)	10.8 (2.6)	-3.6%
HIV prevalence (per 100,000)	186.545 (215.738)	184.577 (208.445)	-1.05%	186.7 (216.342)	187.468 (219.307)	0.4%
Primary care physicians (per 100,000)	0.001 (0)	0.001 (0)	0.0%	0.001 (0)	0.001 (0)	0.0%
Preventable hospitalizations (per 100,000)	1747.217 (2428.551)	1724.769 (2418.015)	-1.3%	1741.447 (2416.477)	1681.47 (2356.141)	-3.4%
High school graduation (%)	85.4 (9)	85.4 (8.9)	0.0%	85.3 (8.9)	85.1 (8.9)	-0.2%
Unemployed (%)	6.3 (2.8)	6.3 (2.9)	0.00%	6.3 (2.8)	6.3 (2.8)	0.0%
Poverty (%)	22.5 (9.2)	22.5 (9.2)	0.0%	22.3 (9.1)	22.1 (9.1)	-0.9%
Uninsured (%)	17.6 (7.4)	17.7 (7.5)	0.6%	17.5 (7.4)	17.2 (7.4)	-1.7%
Median household income ($)	49184.611 (13401.693)	49265.316 (13544.376)	0.2%	49695.493 (13716.289)	50023.393 (13973.038)	0.7%
Population (total)	193000 (1170000)	194000 (1170000)	0.52%	202000 (1150000)	207000 (1130000)	2.5%
Age (%)	17.9 (4.7)	17.9 (4.7)	0.0%	17.8 (4.7)	17.7 (4.7)	-0.6%
Race (%)	9 (14.2)	9 (14.2)	0.0%	8.8 (14.1)	8.8 (13.9)	0.0%
Ethnicity (%)	9.2 (13.5)	9.1 (13.5)	-1.1%	9.2 (13.5)	9.3 (13.4)	1.1%

Table 7. The table shows the summary statistics of the intervention and control groups used in the study. Standard deviation (SD) in parenthesis. Pre-intervention period is 2013-2015, post-intervention period is 2017-2019. Data from the 2013-2019 County Health Rankings Annual Report is used

Communities with accredited LHDs in ten similar states saw increases to all public health outcomes, excluding HIV prevalence which saw a minor decrease of 1.05% over time. In communities with accredited LHDs in Non-Florida states, average rates increased for three of the four public health outcomes – obesity prevalence (+3.1%), STDs (+11.0%), and HIV prevalence (+0.4%) – excluding diabetes prevalence which saw a decrease of 3.6% over time.

Table 8 displays the difference-in-difference analysis results where accredited LHDs in Florida are used as the intervention and unaccredited LHDs outside the state of Florida are used as a comparison group. In the difference-in-differences analyses, there were significant changes in diabetes prevalence and HIV prevalence in the state of Florida relative to all Non-Florida states. For accredited LHDs in the state of Florida, the predicted diabetes prevalence rate would be 0.1 lower per 100,000 population than for unaccredited LHDs in all Non-Florida states. For accredited LHDs in the state of Florida, public health accreditation was associated with a significant 3.02 decline per 100,000 population in HIV prevalence compared with all other states. The xtdidregress Stata command was also used and saw similar results with changes to the standard errors.

Table 8. Difference-in-Difference Regression Results on the Impact of Public Health Accreditation Intervention on Public Health Outcomes

	Specification 1		**Specification 2**	**Specification 3**
Public health outcomes	Model 1 Beta coefficient (95% CI)	Model 2 Beta coefficient (95% CI)	Beta coefficient (95% CI)	Beta coefficient (95% CI)
Obesity prevalence (%)	0.000 (-0.002, 0.003)	0.003 (-0.001, 0.007)	-0.016 (-0.059, 0.028)	0.002 (-0.001, 0.004)
Sexually transmitted infections (per 100,000)	5.420 (-7.049, 17.897)	10.424 (-15.608, 36.457)	-24.349 (-76.159, 27.462)	6.120 (-3.873, 16.114)
Diabetes prevalence (%)	**-0.001* (-0.001, -0.000)**	-0.001 (-0.002, 0.000)	0.000 (-0.018, 0.017)	0.000 (-0.001, 0.000)
HIV prevalence (per 100,000)	**-3.019** (-4.349, -1.690)**	-2.312 (-5.599, 0.975)	-10.182 (-48.028, 27.664)	1.537 (-2.619, 5.692)

Table 8. The figure shows the difference-in-difference regression results on the impact of public health accreditation intervention on public health outcomes. The difference-in-difference model is estimated using panel data fixed effects. The model includes time specific fixed effects and controls for primary care, socioeconomic, and demographic characteristics at the local level. Data from the 2014-2022 County Health Rankings Annual Reports is used. The study compares multiple intervention and control groups to ensure robust results: Specification (1) provides results for two models. Model 1 reveals results for accredited LHDs in Florida and unaccredited LHDs in Non-Florida states. Model 2 reveals results for accredited LHDs in Florida and unaccredited LHDs in ten similar states. Specification (2) compares accredited LHDs in Florida and accredited LHDs in ten similar states. Specification (3) compares accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states. 95% confidence intervals in parenthesis. *Significant at 5%. **Significant at 1%.

Robustness Test

Results were robust to an alternative comparison group by assessing an additional model for Specification (1) with LHDs from ten control states that were like the state of Florida. Table 8 reports the difference-in-difference estimates with the alternative comparison groups. Findings suggests that for accredited LHDs in the state of Florida, public health accreditation was not associated with a significant impact on any of the four studied outcomes compared to unaccredited LHDs in the 10 control states. Two specifications were further tested which produced similar results to the second model under Specification (1). Results from Specification (2) reveal that for accredited LHDs in the state of Florida, public health accreditation was not associated with a significant impact on any of the four studied outcomes compared to unaccredited LHDs in the Non-Florida states. Results from Specification (3) suggest that for accredited LHDs in Non-Florida states, public health accreditation was not associated with a significant impact on any of the four studied outcomes compared to unaccredited LHDs in the Non-Florida states.

4.5. Discussion

Based on local level data, causal estimates of the impact of public health accreditation on public health outcomes are provided. Results suggest that public health accreditation was significantly associated with differences in diabetes prevalence and HIV prevalence. For accredited LHDs in the state of Florida, public health accreditation was associated with decreases in diabetes prevalence and HIV prevalence compared to unaccredited LHDs in Non-Florida states.

The magnitude of the effects suggests that public health accreditation was associated with a 0.1-percentage-point change in the percentage of adults with diabetes and a 3.02-percentage-point change in the number of adults with HIV. Currently in the U.S., 37.3 million adults have diabetes (CDC, 2022a). The effect of a 0.1 decrease per 100,000 population would be 37,300 fewer adults with diabetes. Estimates of cost expenditures reveal that people with diagnosed diabetes have average medical expenditures of $16,752 per year (ADA, 2018). Similarly, an estimated 1.2 million adults have HIV (CDC, 2022b). The effect of a 3.02 decline per 100,000 population would be 36,240 fewer adults with HIV. Estimates of cost expenditures reveal that people living with HIV have average direct expenditures of $31,147 (Ritchwood et al., 2017). The effect of the intervention may appear as a seemingly small change, but it matters in public health since LHDs are concerned with moving the needle of public health. From a public health perspective, these changes make a significant difference in that they represent thousands of people. From a governmental perspective, the cost avoidance would be sizeable.

Quasi-experimental evaluations of public health interventions often face a risk of selection bias threatening the internal validity of the study when the selection of treatment and comparison groups is done nonrandomly. Any observed intervention impacts may reflect the underlying difference between the intervention and control groups, rather than the true effect of the intervention. The intervention in the state of Florida provided an ideal landscape to assess the impact of public health accreditation on public health outcomes. In 2016, Florida received first-in-the-nation accreditation for the entire integrated local public health department system in the state. Seeking public health accreditation is a voluntary process. However, all Florida counties with their mix of lower and higher performing LHDs underwent the accreditation process and demonstrated conformity with PHAB standards and measures necessary to attain accreditation. With all LHDs across the state of Florida expected to comply, the risk of selection bias is minimized (Kronstadt et al., 2015; Kronstadt et al., 2016).

In this study, multiple intervention and control groups are compared to ensure robust results. Specification (1) produced results for accredited LHDs in Florida compared to unaccredited LHDs in Non-Florida states. This specification revealed statistically significant results at the 1% and 5% level. An additional model is run under this specification using LHDs in Florida compared to LHDs in ten similar states. Under the additional model, public health outcomes in the state of Florida pre-intervention were not statistically different or better than the control group. The robustness check suggests that the results of the additional model in Specification (1) are not driven by selection based on LHD observable characteristics or by changes to county-level characteristics. Additionally, the magnitudes of the effects on public health outcomes are too small to produce substantial selection bias in the base results, indicating that public health accreditation indeed impacted public health outcomes in counties that achieved accreditation. Results from Specification (2) comparing accredited LHDs in Florida with accredited LHDs in Non-Florida states suffered from bias as it includes controls that were previously treated. As expected, results from Specification (3) present larger and positive coefficients.

A plausible explanation as to why diabetes prevalence and HIV prevalence in Specification (1) presents a negative coefficient compared to the positive coefficient in Specification (4) may be explained by the practice of accreditation, and its focus on processes. When pursuing accreditation, LHDs assess themselves against PHAB Standards pertaining to the 10 Essential Public Health Services (Figure 1), and focus on the development and implementation of policies, systems, programs, and services (PHAB, 2022b). The process of accreditation may place greater emphasis on assessing in-place processes compared to the attainment of certain public health outcomes. Another reason may be that higher performing LHDs may be more likely to achieve accreditation than poorer performing LHDs. This may be an indication that higher performing LHDs have more processes, operations, and resources to achieve accreditation more easily, and may be more willing to pursue accreditation. In this regard, a willingness to pursue accreditation may be a signal of a higher performing LHD. Additionally, LHDs in communities with better public health outcomes may be more inclined to pursue and achieve accreditation. Within this context, accredited LHDs with better outcomes at baseline are more likely to have improved population-based health outcomes compared to unaccredited LHDs. It is also important to note that LHDs who would benefit the most from the structure of accreditation likely service communities with poor public health outcomes. The benefits of accreditation can be especially attractive to these LHDs who have a higher incentive to pursue accreditation. Achieving public health accreditation may hold the potential for increased opportunities for resources in the shape of increased access to funding. The increase in funding can support quality and performance improvement, address infrastructure gaps, provide opportunities to pilot new programs and processes, expand competitiveness and service value, and better ensure success with grant funding (PHAB, 2011; McCullough & Fenton, 2011). It may take more time for the benefits of accreditation to be reaped in these communities.

The public health outcomes were deliberately chosen for this analysis. First, most LHDs have services and programs to address obesity prevalence, STDs, diabetes prevalence, and HIV prevalence. Recent LHD data reveals that half of all surveyed LHDs provide screening for BMI; 59% of LHDs provide population-based primary prevention for physical activity and nutrition; 70% provide direct services for STD screening; over half (52%) provide treatment for STDs; 39% provide screening for diabetes; over 60% provide screening for HIV/AIDS, and almost half (46%) of LHDs provide treatment for HIV/AIDS (NACCHO, 2020). These outcomes are likely amendable to the contribution and services of LHDs. Additionally, data was available to conduct a robust difference-in-difference analysis for these outcomes. The County Health Rankings Annual Reports provided single-year data for the study period. Also, PHAB identified an organizing framework for their reporting requirements based on the Kindig (2003) model of public health in which mortality, health-related quality of life, preventive healthcare, individual behavior, social environment, physical environment, and genetics are identified as the seven broad areas for public health outcomes (Kindig, 2003). The four public health outcomes in this study are categorized under the health-related Quality of Life area of the model and provide relevant evidence in connection to PHAB's reporting requirements. The public health outcomes used in our analysis are valuable public health indicators with many potential factors able to influence them. The public health outcomes found to be significant in the analysis are long-term health outcomes with their effects not being seen for years after a policy or intervention is implemented. Since data was available, the study assessed accredited and unaccredited LHDs between 2-3 years post-intervention. More time may be needed to see the effects of accreditation on these public health outcomes. Future research requires more data on local level health measures to assess if accreditation exerts significant impacts on other public health outcomes.

There are some potential reasons why public health accreditation may exert significant impacts on the public health outcomes, specifically diabetes prevalence and HIV prevalence. First, LHDs track key outcomes to generate information that drives action (Groseclose & Buckeridge, 2017). As part of the accreditation process, LHDs commonly track public health outcomes data for diabetes, obesity, and sexually acquired infections (PHAB, 2021c). Significantly, 87.3% of LHDs report tracking diabetes prevalence, and 70.4% of LHDs report tracking HIV prevalence (PHAB, 2021d). By routinely tracking these outcomes, LHDs generate information that can be used to improve the quality of their decisions and the effectiveness of their actions (Groseclose & Buckeridge, 2017). Second, accreditation forces LHDs to self-critique and reinforces commitment to best practices. The underlying assumption is that achieving accreditation allows LHDs to increase quality improvement and performance which ultimately results in public health improvement. Prior research strengthens the premise that LHD performance is improved by public health accreditation. Some of the frequently cited benefits of accreditation include improvements in quality, outcomes, and service operations due to increases in infrastructure, quality improvement policies and procedures, and consistent and predictable service operations (McCullough & Fenton, 2011). Accredited LHDs also report immediate quality improvement and performance management benefits such as increased accountability, improved management processes, and improved awareness and focus on quality improvement efforts (Siegfried et al., 2018). Third, LHDs report that their agencies' work most commonly demonstrate conformity with the following accreditation measures: Cross Sector Collaboration (Measure 4.1 as shown in Table 2); Health Education and Promotion (Measure 3.1); Public Health Data (Measure 1.3); Community Health Improvement Plan (Measure 5.2); and Engagement of Target Population in Public Health Strategy (Measure 4.2) (PHAB, 2021a). These measures greatly correlate with the work LHDs perform to address diabetes prevalence and HIV prevalence. Fourth, with accreditation's emphasis on public health services, some LHDs decreased direct preventive clinical services over time to focus on population-based health activities (NACCHO, 2017a). LHDs provide these population-based health services and address more localized issues by engaging in multi-sectoral partnerships (NACCHO, 2017b). Services targeting diabetes prevalence and HIV prevalence commonly focus on preventive efforts and LHD partnerships. Fifth, federal funding provided to LHDs often dictates certain programs and activities to be performed. In 2020, LHDs were awarded $45 million to support programs to improve health outcomes for adults with diabetes, and $400 million to support HIV surveillance and prevention efforts (CDC, 2021b; CDC, 2021c). LHDs are expected to administer these funded programs in conjunction with the standards denoted in the accreditation process.

The purpose of public health accreditation is improved public health (PHAB, 2021d; Joly et al., 2007; Kronstadt et al., 2016; Allen et al., 2019), but little evidence exists that examines the impact of PHAB accreditation on public health improvement. This research provides a glimpse into whether accreditation is reaching its goal of public health improvement. Results indicate that public health accreditation can be a significant driver for public health improvement and a catalyst to improve public health. To the author's knowledge, this is one of the first studies to relate the accreditation process to public health outcome improvement using a quasi-experimental design. It is possible that some studies have not assessed the impact of accreditation on health outcomes based on the belief that there are many factors beyond the influence of governmental public health departments that influence health status, thus making it difficult to link public health interventions to improved health status (Exploring Accreditation Final Report, 2006). In this study, an empirical link between public health accreditation and outcomes is presented, suggesting that accreditation can be a method for LHDs to improve public health.

Strengthening the evidence base around public health accreditation is a key priority for public health practitioners and researchers. The findings of this study can benefit LHD leadership considering the pursuit and adoption of accreditation as it is an effective method in improving public health. Additionally, accredited LHDs can benefit from these findings by taking the next step of being accountable for public health outcomes, not solely accreditation processes, and taking greater ownership in how accreditation measures take shape in their local communities. The findings of this study also benefit PHAB and add to the literature in Public Health Services and Systems Research by providing greater clarity on effective public health practice (Kronstadt et al., 2015).

The study has several strengths. The difference-in-difference design employed is well-suited to study causal relationships by comparing outcomes of groups exposed to different interventions at different times (Wing et al., 2018). Several steps were taken to ensure that a well-designed quasi-experiment addressed various threats to validity. In the difference-in-difference specification, public health outcomes between accredited and unaccredited LHDs, before and after 2016 are compared. The research method compares change over time in outcomes for communities serviced by LHDs that received the intervention to change over time in outcomes for communities serviced by LHDs that did not receive the intervention. This quasi-experimental approach offers a stronger study design than simply tracking changes within the state of Florida over time. Comparison groups that are as similar as possible to the treatment group in terms of baseline characteristics were identified. The control group was appropriately chosen with LHDs from neighboring states used as a counterfactual, capturing any potential trends unrelated to accreditation that might be affecting the study outcomes during the same period. The data was graphically and statistically inspected to test the parallel trend assumption and ensure that there was not any biased estimation of the causal effect. Since research design's assumptions were met, a strong case for a causal effect of the intervention on the public health outcomes is presented.

Limitations

Results can be used to shed light on the casual impact of accreditation on health outcomes, but only after considering the following limitations. First, with the use of observational data, the possibility of selection and information bias is introduced. Second, some of the states in the study use older accreditation versions. Third, the use of County Health Rankings data may not provide all the necessary information to measure the effects of the policy. Fourth, the study focuses on one state as the treatment. Fifth, the study findings may not be generalizable to other settings, particularly since the integrated system is no longer an option for other states.

Implications for Policy and Practice

- Little evidence exists that examines the impact of PHAB accreditation on public health outcomes.
- Given the mission of PHAB accreditation is public health improvement, identifying the impact of accreditation on public health outcomes is essential to understanding the utility of accreditation.
- This research provides a glimpse into whether accreditation is reaching its goal of public health improvement. Results indicate that public health accreditation can be a significant driver for public health improvement and a catalyst to improve public health.
- The findings of this study can benefit LHD leadership considering the pursuit and adoption of accreditation as it is a method for LHDs to improve public health.

CHAPTER V

THE EFFECT OF PUBLIC HEALTH ACCREDITATION ON THE EFFECTIVENESS OF PUBLIC HEALTH ACTIVITIES

5.1. Abstract

A key goal of public health accreditation is the strengthening of local health departments' (LHD) capacity to deliver essential public health services. The objective of this study is to evaluate the impact of public health accreditation on the effectiveness of essential public health activities provided by LHDs. A quasi-experimental design with the use of a panel data difference-in-difference estimator is used to estimate the treatment effect between public health accreditation and public health activity effectiveness. Effectiveness measures in accredited LHDs in Florida to unaccredited LHDs in control states before and after 2016 when Florida achieved accreditation for the entire integrated local public health department system in the state are compared. Linear probability multivariate regression models with state and time fixed effects are employed. Accreditation data from the Public Health Accreditation Board and effectiveness measures from the National Longitudinal Survey of Public Health Systems are used. Analyses were performed at the LHD level using local data representing 2,194 LHDs, covering 50 U.S. states. Florida was considered the treatment state. Participants were accredited LHDs in Florida, unaccredited LHDs in Non-Florida control states, unaccredited LHDs in ten control states, accredited LHDs in ten control states, and accredited LHDs in Non-Florida control states. The effectiveness of 19 essential public health activities, as well as composite measures for Assessment, Policy Development,

and Assurance activities are assessed. The difference-in-difference estimations indicate that public health accreditation had no significant impact on 18 of the 19 public health activities. For accredited LHDs in the state of Florida, the predicted effectiveness average for Public Health Activity 12 (Identify and Allocate Resources Based on Community Health Plan) would be 26.3% lower than for unaccredited LHDs in all Non-Florida states. Public health accreditation did not translate to the improved effectiveness of public health activities for LHDs. Accreditation may prepare LHDs to engage in quality improvement and implement standards to improve processes. Accreditation should be viewed as one element that complements other performance improvement strategies to achieve a significant effect in the public health system.

5.2. Introduction

Serving as the backbone of the local public health system, local health departments (LHDs) are expected to provide the 10 Essential Services of Public Health (Table 1). The Essential Services describe the public health activities that all communities should undertake and organize around the three-core functions of public health: Assessment, Policy Development, and Assurance. LHDs pursuing accreditation are assessed against standards and measures pertaining to the 10 Essential Services of Public Health (Tables 2-3). Public health department accreditation standards address a range of core public health programs and activities including, for example, environmental public health, health education, health promotion, community health, chronic disease prevention and infectious disease, injury prevention, maternal and child health, public health emergency preparedness, access to clinical services, public health laboratory services, vital records and health statistics, management, and governance (NACCHO, 2020).

The national, voluntary public health accreditation program was launched in 2011 by the Public Health Accreditation Board (PHAB) to advance the quality and performance of local health departments (LHDs). As of March 2022, 91% of the U.S. population benefited from local health department accreditation through the PHAB (PHAB, 2021a). In 2016, the Florida Department of Health received first-in-the-nation national accreditation as an integrated department of health when all 67 county health departments met national standards for public health performance management and continuous quality improvement (PHAB, 2021a). A key goal of public health accreditation is the strengthening of local health departments' capacity to deliver essential public health services.

A growing body of literature reports the positive impact of public health accreditation on performance measurement and improvement (Kronstadt et al., 2016; Beitsch et al., 2018; Ingram et al., 2018; Allen, 2019). Accreditation may help stimulate LHD organizational supports for evidence-based decision making, and provide pathways to accountability, consistency, and better fit between community needs and public health services (Allen, 2019; Shah et al., 2015). Accreditation also serves as a key driver for the uptake of quality improvement and performance management (Beitsch et al., 2018). The process of accreditation may help public health systems develop the public health system capital necessary to protect and promote the public's health (Ingram et al., 2018). A literature review on other service industries hints of accreditation's potential in improving service delivery, operations, and outcomes in public health (Mays, 2004). The available literature focused on public health accreditation tends to be descriptive in nature and sheds light on the perceived pros and cons to achieving accreditation (Chapman, 2018; Kronstadt et al., 2016; Mays, 2004; McCullough & Fenton, 2011; Siegfried et al., 2018; Riley et al., 2012; Beatty et al., 2015; Beatty et al., 2018). The observational nature of most of the public health accreditation literature limits its value in providing convincing conclusions on its impact (Hussein et al., 2021). Despite the increase in accredited LHDs across the U.S., the evidence base concerning the impact of accreditation programs and the effectiveness of LHD activities remains sparse.

The Public Health Accreditation Board (PHAB) encourages the production of quality research to advance the science base of accreditation and systems change in public health and has routinely revised their research agenda to highlight priority areas to foster research related to accreditation (PHAB, 2021a). Evidence from this study helps the Public Health Services and Systems Research field better understand the impact of accreditation. The study answers the research question: What impact, if any, does LHD accreditation have on the effectiveness of essential public health activities?

Studies assessing the impact of accreditation are prone to self-selection bias since public health accreditation is a voluntary process. The impact of public health accreditation is evaluated by using an approach which eliminates bias with the state of Florida serving as a natural experiment. Florida's accreditation as an integrated local public health department system as an intervention is examined as a unique policy where all LHDs in Florida applied for accreditation as a local public health department system in 2016. LHDs across the U.S. achieved accreditation at different times allowing the opportunity to calculate the effect of the accreditation on the effectiveness of public health activities by using several potential control groups.

5.3. Methods

A quasi-experimental design with the use of a panel data difference-in-difference estimator is used to estimate the treatment effect between public health accreditation and public health activity performance. It is hypothesized that public health accreditation positively impacts the effectiveness of public health activities. Performance measures in LHDs in Florida and control states before and after 2016 when Florida achieved accreditation for the entire integrated local public health department system in the state are compared. The pre-intervention period was defined as 2013-2015, the intervention period was 2016, and the post-intervention period was 2017-2019.

A panel dataset was created based on date of accreditation or reaccreditation data as provided as a downloadable Excel spreadsheet by the PHAB. A binary accreditation time variable captured the year in which each LHD was accredited. For easy reference, each LHD was identified as belonging into one of the following four categories: Always Accredited (accreditation time variable equaled to 1 from 2013 to 2019), Never Accredited (accreditation time variable equaled to 0 from 2013-2019), Unaccredited then Accredited (accreditation time variable equal to 0 but changed to 1 during 2014-2019) and Accredited then Unaccredited (accreditation time variable saw multiple changes between 2013-2019. Since the Always Accredited group and the Accredited then Unaccredited group use prior treated units and have the potential of producing biased results (Baker, 2020; Callaway, 2020), the Never Accredited group is used as the control group.

LHDs were then grouped by their location: *LHDs from all Florida counties*; *LHDs from all states other than the state of Florida*; and *LHDs from ten states* which neighbor Florida or have similar demographics and population size: North Carolina, New York, Illinois, California, Connecticut, Pennsylvania, Texas, Georgia, Alabama, and Tennessee. LHDs were divided into groups according to accreditation status and state: accredited in Florida; unaccredited in Non-Florida states; unaccredited in in ten similar states; accredited LHDs in Non-Florida states; and unaccredited LHDs in Non-Florida states.

It is hypothesized that accreditation results in improved effectiveness of public health activities. To test this hypothesis using a difference-in-difference approach, a non-intervention control group is needed to compare to the intervention. The comparison group captures any potential secular trends unrelated to accreditation that might be affecting the study outcomes during this same period. Three specifications are used to assess changes between an intervention and multiple control groups (Table 6). In Specification (1), the differences between accredited LHDs in Florida are compared to unaccredited LHDs in Non-Florida states (Figure 1). An additional model is tested in Specification (1) by comparing unaccredited LHDs in ten similar states. A more accurate control for Florida among ten similar states that did not implement comparable policies over the same period is used. By using many potential control groups (ten similar states) to create a synthetic control group, evidence that is less subject to the self-selection bias observed in all Non-Florida states group in Specification (1) is presented. In Specification

(2), the control group is adjusted to accredited LHDs in Non-Florida states (Figure 2). This specification suffers from bias as it includes controls that were previously treated. We focus on the interpretation of the other specifications since they include non-biased groups (Bertrand et al., 2004; Wooldridge, 2012). In Specification (3), the intervention group is adjusted to accredited LHDs in Non-Florida states, and the control group to unaccredited LHDs in Non-Florida states (Figure 3). This specification also suffers from selection bias. It was expected that a bias in result in the opposite direction would occur since higher quality LHDs are more likely to pursue accreditation. This specification is included in the analysis to test the expectation of a positive and larger improvement in this group.

The main outcome variable is the effectiveness of public health activities. The National Longitudinal Survey of Public Health Systems (NALSYS), a validated survey of local public health officials, measures how effectively each public health activity is carried out in the community based on a 5-point Likert scale ranging from "meets no needs or 0%" to "fully meets needs or 100%." Response sets used in the survey instrument were designed with numeric anchor points to support approximations to an interval scale (Mays & Hogg, 2015; Norman, 2010). Activity-specific measures combining the average measures of effectiveness for each of the 3 public health functions are used: **Assessment** (activities 1 through 6 in Table 4), **Policy Development** (activities 7 through 15), and **Assurance** (activities 16 through 19) are included. All the performance measures based on these activities were self-reported by LHD officials and reflect the perceptions and perspectives of the respondents (Mays et al., 2004b). Data for these variables are obtained from five waves (2006, 2012, 2014, 2016, and 2018) of the NALSYS.

Covariates known to influence health at the local level are also included in the analysis. **Primary care physicians** measure the ratio of population to primary care physicians from the Health Resources & Services Administration. **Preventable hospital stays** are the rate of hospital stays for ambulatory-care sensitive conditions per 100,000 Medicare enrollees from the Dartmouth Atlas of Health Care. **High school graduation** is the percentage of ninth-grade cohort that graduates in four years from the National Center for Education Statistics. **Unemployed** is the percentage of population ages 16 and older unemployed, but seeking work, from the Bureau of Labor Statistics. **Poverty** is the percentage of people under age 18 in poverty provided by the Small Area Income and Poverty Estimates. **Uninsured adults** measure the percentage of population under age 65 without health insurance provided by the Small Area Health Insurance Estimates. **Median household income** is the income where half of households in a county earn more, and half of households earn less provided by the Small Area Income and Poverty Estimates. **Population** is the total population size of the jurisdiction. **Age** is the percentage of the population that is 65 years and older. **Race** is the percentage of the population that is Non-Hispanic African American. **Ethnicity** is the percentage of the population that is Hispanic. Population, age, race, and ethnicity measures are provided by the Census Population Estimates. Data for the outcome and covariate variables was available from 2013-2019. The outcomes and covariate data were matched with the PHAB accreditation data by their common Federal Information Processing Standard (FIPS) county codes.

Study Population

The study population includes all U.S. public health agencies meeting the national definition of an LHD: "an administrative or service unit of local or state government that is concerned with health and carries out some responsibility for the health of a jurisdiction smaller than the state" (NACCHO, 2017a). Data is analyzed for 2,156 LHDs, covering 50 U.S. states.

Statistical Analysis

A difference-in-difference fixed-effects model is used to estimate the effect of public health accreditation by comparing the performance measures of accredited LHDs (intervention group) to that of unaccredited LHDs (control group) before and after accreditation (intervention) between 2012 and 2019 (El-Shal, et al., 2021). It was postulated that there would be greater increases in performance in Florida counties with accredited LHDs as indicated by positive difference-in-difference coefficients. The difference-in-difference method controls for both observed and unobserved characteristics that are time invariant and eliminates any confounding that might be caused by LHD effects which are constant over time within each LHD. The study tested whether Florida counties with accredited LHDs saw improvement in performing public health activities. Different specifications were tested to compare an intervention and control group: (1.1) Accredited LHDs in Florida and unaccredited LHDs in Non-Florida states; (1.2) Accredited LHDs in Florida and unaccredited LHDs in ten similar states; (2)

Accredited LHDs in Florida and accredited LHDs in ten similar states; (3) Accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states (Table 6).

Table 6. Intervention and Control Groups

	Specification 1		Specification 2	Specification 3
	Model 1	**Model 2**		
Intervention group	Accredited LHDs in Florida	Accredited LHDs in Florida	Accredited LHDs in Florida	Accredited LHDs in Non-Florida states
Control group	Unaccredited LHDs in Non-Florida states	Unaccredited LHDs in ten similar states	Accredited LHDs in ten similar states	Unaccredited LHDs in Non-Florida states

Table 6: This table shows the intervention and control groups used in the difference-in-difference analysis. Florida represents all Florida counties. Non-Florida states represent all states other than the state of Florida. The ten control states represent states which neighbor Florida or have similar demographics and population size: North Carolina, New York, Illinois, California, Connecticut, Pennsylvania, Texas, Georgia, Alabama, and Tennessee.

Figure 8. Difference-in-Difference Specification 1

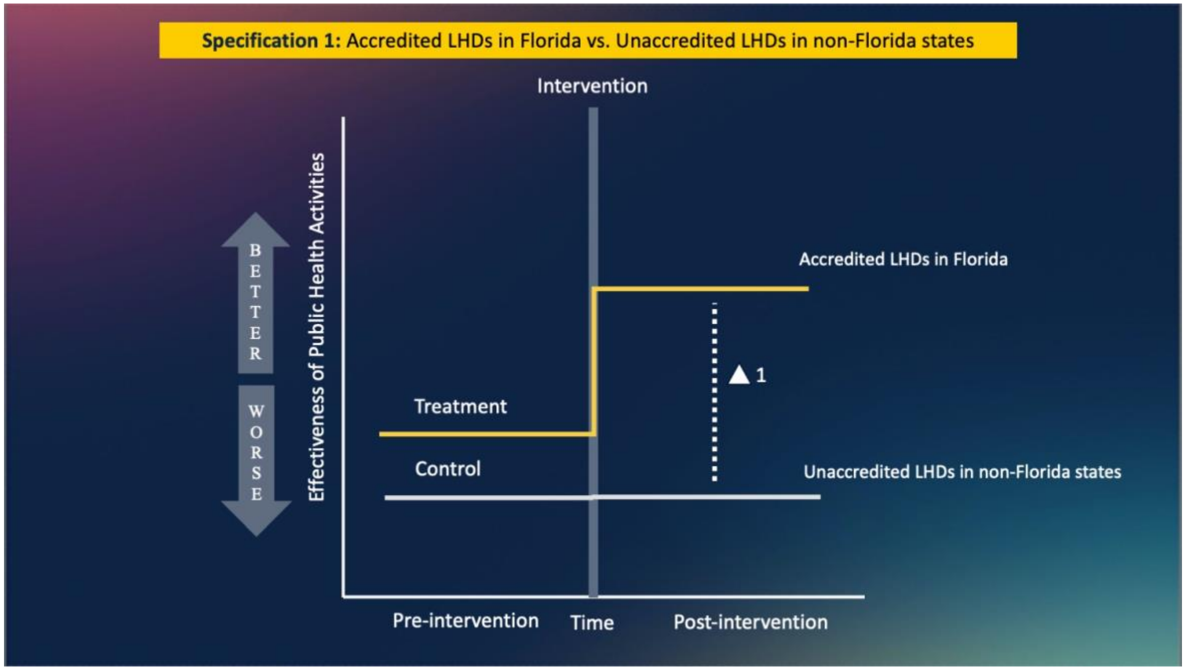

Figure 8: This figure shows Specification (1) tested in the difference-in-difference analysis. In this study, it is hypothesized that accreditation results in improved effectiveness of public health activities. Specification (1) tests that hypothesis by measuring the differences between accredited LHDs in Florida compared to unaccredited LHDs in Non-Florida states. In the figure, Δ1 signifies the difference between accredited LHDs in Florida and unaccredited LHDs in Non-Florida states. An additional model is tested in Specification (1) by measuring the differences between unaccredited LHDs in ten similar states.

Figure 9. Difference-in-Difference Specification 2

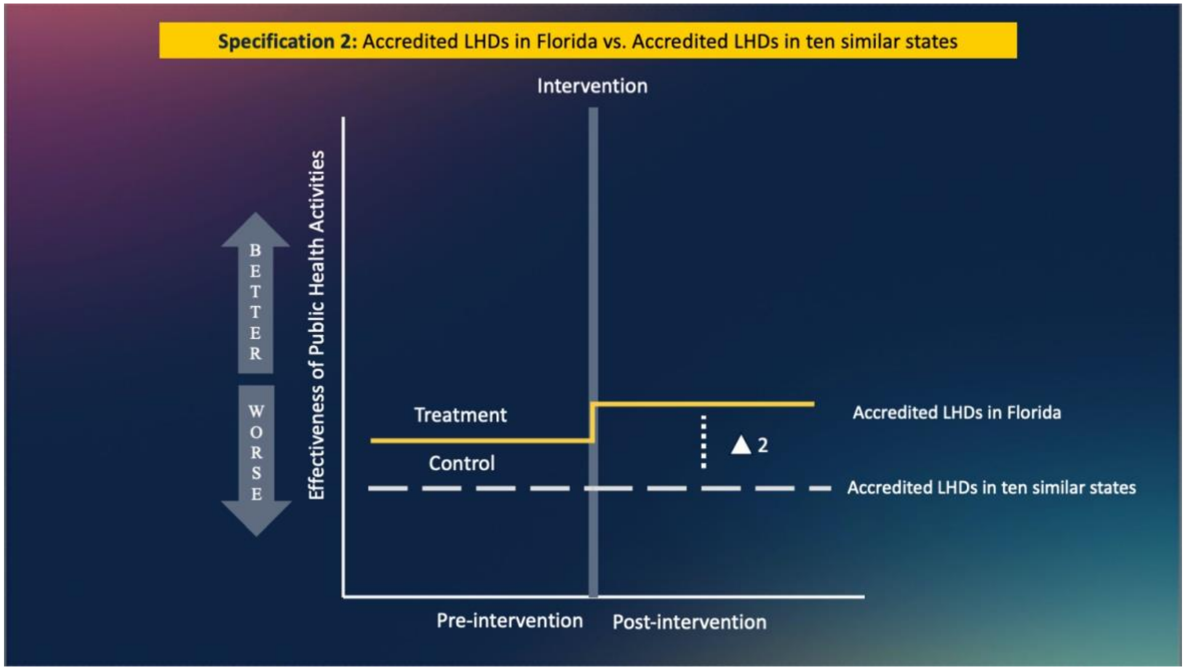

Figure 9: This figure shows Specification (2) tested in the difference-in-difference analysis. In this study, it is hypothesized that accreditation results in improved effectiveness of public health activities. Specification (2) tests that hypothesis by measuring the differences between accredited LHDs in Florida compared to accredited LHDs in Non-Florida states. In the figure, Δ2 signifies the difference between accredited LHDs in Florida and accredited LHDs in Non-Florida states.

Figure 10. Difference-in-Difference Specification 3

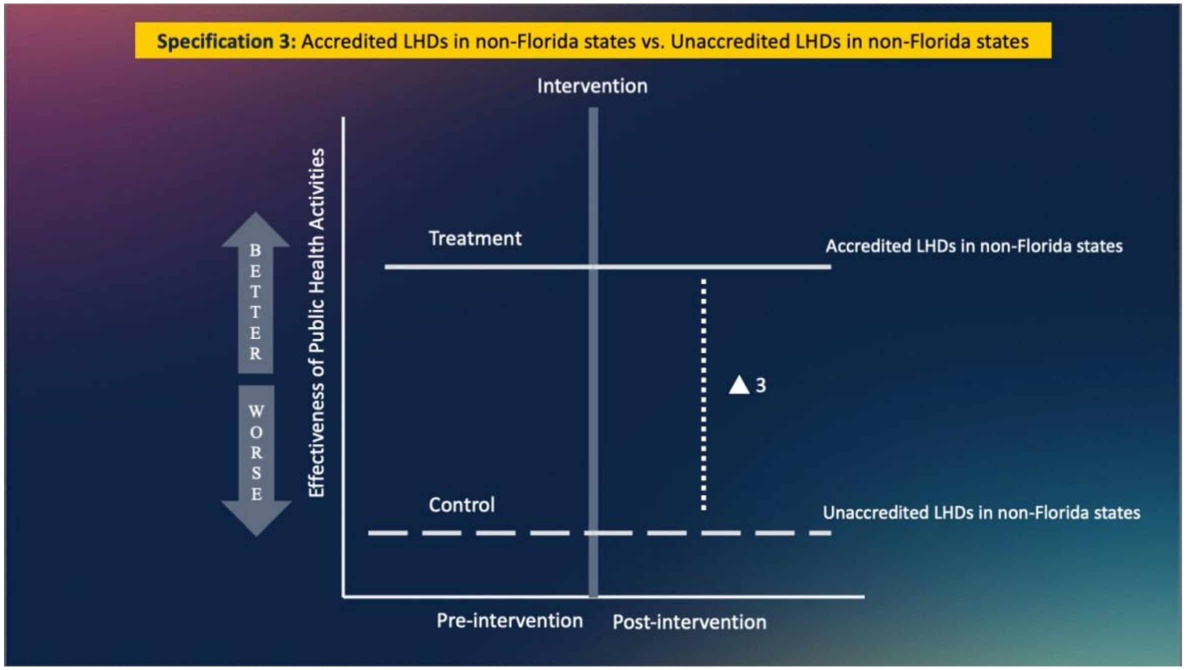

Figure 10: This figure shows Specification (3) tested in the difference-in-difference analysis. In this study, it is hypothesized that accreditation results in improved effectiveness of public health activities. Specification (3) tests that hypothesis by measuring the differences between accredited LHDs in Non-Florida states compared to unaccredited LHDs in Non-Florida states. In the figure, Δ3 signifies the difference between accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states.

The study design does not require that treatment and control groups are comparable in their treatment status or outcomes at baseline; rather, it assumes that trends in treatment status or health outcomes were similar in these states before 2016. Before performing the difference-in-differences analysis, the trends in performance before the intervention in 2016 are first assessed with the use of line graphs. Pre-intervention, the trends in performance were parallel between the accredited LHDs and unaccredited LHDs for most of the performance outcomes. Data is then statistically inspected by fitting a Granger-type causality model and augmenting the model with dummy variables for each pretreatment–treatment period for the treated observations. A joint test of the coefficients on the dummy variables against 0 was used as a test of the null hypothesis that no anticipatory effects had taken place. The graphical and statistical assessment of the trends suggested that the control groups were appropriately chosen as a counterfactual and captured any potential trends unrelated to accreditation that might be affecting the study outcomes during the same period.

Context is provided for the multivariate analysis by calculating descriptive statistics for all the variables. All variables were evaluated to detect irregularities and outlier values. Linear probability multivariate regression models with state and time fixed effects and standard errors clustered at the state (intervention) level are employed. Linear probability models are interpreted as percentage-point changes in the treatment compared to the control. Outcomes for the same counties are observed over time and unobserved heterogeneity is controlled for by estimating local level panel data with fixed effects. This approach allows for controlling of unobservable time and group characteristics that confound the effect of the treatment on the outcome (Stata, 2021).

5.4. Results

Table 9 provides summary statistics of accredited LHDs in the state of Florida, unaccredited LHDs in Non-Florida states, unaccredited LHDs in ten control states, accredited LHDs in 10 control states, and accredited LHDs in Non-Florida states, pre (2013-2015) and post (2017-2019) intervention. It reports averages and the standard deviation for the dependent variables. For accredited LHDs in Florida, average rates decreased for 17 of the 19 public health activities when comparing pre-intervention and post-intervention averages. The average rates for the composite activities of Assessment, Policy Development, Assurance, and Total Activities all saw decreases between 0.07% – 0.08%. The average rates for the dependent variables were relatively unchanged in the unaccredited LHDs in Non-Florida states comparison group post-intervention, except for slight decreases of -0.01% in Activity 2 and Activity 8. For unaccredited LHDs in ten similar states, average rates decreased for all the public health activities as well as the composite activities when comparing pre and post averages, except for Activity 13 which remained the same during the study period. For accredited LHDs in ten similar states and accredited LHDs in Non-Florida states, all the public health activities and the composite activities saw reductions, except Activity 12 and Activity 13 with increases ranging from 0.02% - 0.03%. For accredited LHDs in the state of Florida, unaccredited LHDs in Non-Florida states, unaccredited LHDs in ten control states, accredited LHDs in 10 control states, and accredited LHDs in Non-Florida states, LHD directors rated the effectiveness of Activity 3 in their jurisdictions at an average of 82.5% - 84.1% and the effectiveness of Activity 6 at an average of 17.25% - 19% based on the maximum rating that would be obtained if the activities were fully meeting community needs.

Table 9. Summary Statistics of Intervention and Comparison Groups, Pre-Intervention, During, Post-Intervention

Effectiveness of Public Health Activity	Accredited LHDs in Florida			Unaccredited LHDs in Non-Florida States			Unaccredited LHDs in Ten Similar States		
	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change
Activity 1	64.7 (33)	61.5 (36)	-0.05	59 (36)	59.7 (36)	0.01	63.7 (34.5)	62.5 (36)	-0.02
Activity 2	42.3 (36.5)	35.6 (35.6)	-0.16	35.2 (35.9)	34.9 (35.6)	-0.01	39.2 (36.6)	35.2 (35.6)	-0.10
Activity 3	85.4 (17.6)	82.1 (20.5)	-0.04	82.5 (20.1)	82.4 (20.3)	0.00	85.3 (17.2)	82.9 (20.1)	-0.03
Activity 4	74.7 (27)	74 (27.6)	-0.01	73.2 (27.9)	73.6 (27.7)	0.01	75.1 (26.6)	74.5 (27.6)	-0.01
Activity 5	45.9 (35.3)	40.4 (36.1)	-0.12	39.4 (36.1)	39.7 (36)	0.01	45.6 (36.1)	42.4 (36.3)	-0.07
Activity 6	19.7 (30.6)	17.8 (29.6)	-0.10	17.1 (29.3)	17.4 (29.5)	0.02	19.6 (30.8)	18.4 (30.1)	-0.06
Activity 7	55.1 (31.9)	51.6 (32.7)	-0.06	52.2 (32.3)	52.1 (32.4)	0.00	55.6 (31.5)	53 (32.6)	-0.05
Activity 8	48.2 (32.9)	45.9 (34.3)	-0.05	45.9 (33.8)	45.6 (33.7)	-0.01	49.2 (33.1)	46.5 (34.3)	-0.05
Activity 9	57.7 (34.5)	53 (36.8)	-0.08	50.8 (36.7)	51.3 (36.6)	0.01	56.6 (36)	54.5 (37.1)	-0.04
Activity 10	49 (31.3)	46.1 (33.4)	-0.06	43.9 (33.2)	44.2 (33.2)	0.01	48.4 (32.3)	46.8 (33.3)	-0.03
Activity 11	42.9 (36.3)	38.6 (35.8)	-0.10	35.4 (36.2)	35.7 (36.1)	0.01	41.5 (36.7)	39.2 (36.6)	-0.06
Activity 12	19.9 (28.8)	20.3 (29)	0.02	18.7 (28.5)	18.8 (28.3)	0.01	20.7 (29.2)	20.4 (29.2)	-0.01
Activity 13	27.2 (30.4)	27.7 (30.2)	0.02	25.8 (29.9)	26.1 (29.9)	0.01	27.8 (30.6)	27.7 (30.2)	0.00
Activity 14	35.8 (38.8)	31.8 (38)	-0.11	29.9 (37.6)	29.9 (37.5)	0.00	33 (38.5)	32 (38.2)	-0.03
Activity 15	27.1 (31.9)	25.8 (32.3)	-0.05	25.9 (32.1)	25.9 (32.2)	0.00	29.4 (33)	27.6 (33)	-0.06
Activity 16	20.2 (29.8)	19 (29.7)	-0.06	17.5 (29)	17.9 (29.3)	0.02	19.9 (30.4)	19 (30.1)	-0.05
Activity 17	24.7 (32.2)	22.4 (31.9)	-0.09	20.8 (30.8)	20.8 (30.8)	0.00	24.3 (32.3)	22.1 (31.8)	-0.09
Activity 18	48.8 (31.3)	46.1 (33.3)	-0.06	45.2 (32.9)	45.7 (32.9)	0.01	49.2 (31.3)	47.2 (33)	-0.04
Activity 19	57.1 (32.3)	52.1 (36.3)	-0.09	52.2 (35.1)	52.4 (35.1)	0.00	57 (33.6)	53.5 (35.9)	-0.06
Average Assessment Activities (1-6)	55.5 (19.5)	51.8 (20.9)	-0.07	51.1 (20.5)	51.3 (20.6)	0.00	54.8 (20)	52.6 (21.1)	-0.04
Average Policy Development Activities (7-14)	40.4 (21.4)	37.6 (22.4)	-0.07	36.4 (22)	36.5 (22)	0.00	40.1 (21.9)	38.2 (22.7)	-0.05
Average Assurance Activities (15-19)	37.6 (22.8)	34.8 (24.3)	-0.07	33.9 (23.9)	34.2 (23.9)	0.01	37.5 (23.7)	35.4 (24.5)	-0.06
Average Total Activities (1-19)	44.7 (18.5)	41.1 (19.9)	-0.08	40.5 (19.3)	40.6 (19.3)	0.00	44 (19.1)	41.8 (20.1)	-0.05

Table 9. Summary Statistics of Intervention and Comparison Groups, Pre-Intervention, During, Post-Intervention, Cont'd

	Accredited LHDs in Ten Similar States			Accredited LHDs in Non-Florida states		
Effectiveness of Public Health Activity	Pre-intervention	Post-intervention	% Change	Pre-intervention	Post-intervention	% Change
Activity 1	63.4 (33.9)	60.8 (36.6)	-0.04	63.8 (34)	61.1 (36.7)	-0.04
Activity 2	41.6 (37)	34.4 (35.5)	-0.17	42.2 (36.9)	35 (35.7)	-0.17
Activity 3	85.1 (17.6)	81.8 (20.8)	-0.04	85.3 (17.6)	81.9 (20.8)	-0.04
Activity 4	73.9 (27.4)	73.7 (27.9)	0.00	74.3 (27.2)	73.9 (27.7)	-0.01
Activity 5	45.3 (36)	39.8 (36.3)	-0.12	45.9 (35.9)	40.2 (36.3)	-0.12
Activity 6	19.6 (30.6)	17.3 (29.4)	-0.12	19.5 (30.5)	17.4 (29.4)	-0.11
Activity 7	55.2 (31.9)	51.1 (32.7)	-0.07	55.7 (31.9)	51.5 (32.7)	-0.08
Activity 8	48.2 (33.2)	45.9 (34.5)	-0.05	48.7 (33.1)	46.5 (34.5)	-0.05
Activity 9	56.7 (35.3)	52.3 (37.2)	-0.08	57.4 (35.3)	52.7 (37.3)	-0.08
Activity 10	47.5 (31.8)	45.2 (33.7)	-0.05	47.9 (31.7)	45.6 (33.6)	-0.05
Activity 11	41.6 (36.7)	37.7 (36)	-0.09	42.2 (36.7)	38.3 (36.2)	-0.09
Activity 12	19.7 (28.9)	20 (29)	0.02	20 (29.2)	20.5 (29.5)	0.03
Activity 13	26.6 (30.5)	27.4 (30.3)	0.03	27 (30.5)	27.9 (30.4)	0.03
Activity 14	34.1 (38.8)	31.2 (37.9)	-0.09	34.6 (39)	31.9 (38.1)	-0.08
Activity 15	27.5 (32)	25.8 (32.5)	-0.06	27.3 (32)	26.1 (32.6)	-0.04
Activity 16	19.3 (29.7)	18.4 (29.6)	-0.05	19.8 (29.7)	18.9 (29.7)	-0.05
Activity 17	23.7 (31.8)	21.6 (31.8)	-0.09	24.2 (31.9)	22.2 (32.1)	-0.08
Activity 18	48 (31.8)	45.3 (33.5)	-0.06	48.3 (31.8)	45.7 (33.4)	-0.05
Activity 19	56.6 (32.7)	51.5 (36.5)	-0.09	57 (32.7)	51.9 (36.4)	-0.09
Average Assessment Activities (1-6)	54.9 (19.9)	51.2 (21.1)	-0.07	55.3 (19.9)	51.5 (21.1)	-0.07
Average Policy Development Activities (7-14)	39.8 (21.8)	37.1 (22.7)	-0.07	40.3 (21.8)	37.7 (22.8)	-0.06
Average Assurance Activities (15-19)	36.8 (23.3)	34.1 (24.4)	-0.07	37.3 (23.3)	34.6 (24.5)	-0.07
Average Total Activities (1-19)	44.2 (19)	40.6 (20.1)	-0.08	44.6 (18.9)	41.1 (20.2)	-0.08

Table 9. The table shows the summary statistics of intervention and control groups used in the study. Pre-intervention period is 2013-2015, post-intervention period is 2017-2019. Standard deviation (SD) in parenthesis. Percentages indicate the average rate in which the activity is effectively implemented. Data from the 2012-2018 National Longitudinal Survey of Public Health Systems is used.

Table 10 displays the difference-in-difference analysis results where accredited LHDs in Florida are used as the intervention and unaccredited LHDs outside the state of Florida are used as a comparison group. The difference-in-difference estimation reveals that only one Public Health Activity was significantly impacted by public health accreditation. For accredited LHDs in the state of Florida, the predicted effectiveness rating for Public Health Activity 12 (Identify and Allocate Resources Based on Community Health Plan) would be 26.3% lower than for unaccredited LHDs in Non-Florida states. These results were statistically significant at the 1%.

Robustness Test

Our study results were robust to an alternative comparison group by assessing ten states that were like the state of Florida. Table 11 reports the difference-in-difference estimates with this alternative comparison group. Results suggest that for accredited LHDs in the state of Florida, the predicted effectiveness average for Public Health Activity 12 (Identify and Allocate Resources Based on Community Health Plan) would be 24.0% lower compared to unaccredited LHDs in the 10 control states. These results were statistically significant at the 5% level. For accredited LHDs outside of Florida, the predicted effectiveness average for Public Health Activity 3 (Investigate Adverse Health Events, Outbreaks, and Hazards) would be 5.3% lower compared to unaccredited LHDs in Non-Florida control states.

Table 10. Difference-in-Difference Regression Results on the Impact of Public Health Accreditation on the Effectiveness of Public Health Activities

	Specification 1		Specification 2	Specification 3
Effectiveness	Model 1 Beta coefficient (95% CI)	Model 2 Beta coefficient (95% CI)	Beta coefficient (95% CI)	Beta coefficient (95% CI)
Activity 1	0.002 (-0.185, 0.189)	-0.063 (-0.251, 0.125)	0.123 (-0.253, 0.499)	0.001 (-0.091, 0.093)
Activity 2	-0.186 (-0.393, 0.022)	-0.157 (-0.404, 0.09)	0.532 (-0.212, 1.276)	-0.001 (-0.118, 0.116)
Activity 3	0.05 (-0.059, 0.16)	0.031 (-0.088, 0.150)	0.296 (-0.178, 0.769)	**-0.053 (-0.104, -0.002) ***
Activity 4	0.137 (-0.025, 0.299)	0.127 (-0.056, 0.309)	-0.385 (-0.867, 0.098)	0.001 (-0.081, 0.082)
Activity 5	0.06 (-0.154, 0.275)	0.142 (-0.106, 0.391)	0.657 (-0.131, 1.445)	-0.063 (-0.171, 0.045)
Activity 6	0.18 (-0.16, 0.197)	0.023 (-0.196, 0.243)	-0.606 (-1.319, 0.107)	0.016 (-0.088, 0.121)
Activity 7	-0.101 (-0.309, 0.106)	-0.020 (-0.265, 0.224)	0.216 (-0.596, 1.028)	-0.003 (-0.107, 0.100)
Activity 8	-0.017 (-0.228, 0.193)	-0.052 (-0.301, 0.197)	-0.145 (-0.799, 0.509)	-0.030 (-0.134, 0.075)
Activity 9	-0.018 (-0.213, 0.177)	-0.011 (-0.222, 0.200)	-0.111 (-0.651, 0.430)	-0.012 (-0.108, 0.084)
Activity 10	-0.039 (-0.199, 0.121)	-0.029 (-0.189, 0.132)	-0.108 (-0.534, 0.318)	-0.057 (-0.134, 0.02)
Activity 11	0.06 (-0.149, 0.268)	0.016 (-0.236, 0.267)	0.523 (-0.260, 1.306)	0.01 (-0.106, 0.126)
Activity 12	**-0.263 (-0.448, -0.078) ****	**-0.240 (-0.472, -0.009) ***	-0.246 (-1.086, 0.594)	0.029 (-0.078, 0.135)
Activity 13	-0.035 (-0.212, 0.142)	-0.012 (-0.220, 0.195)	-0.311 (-0.992, 0.370)	-0.045 (-0.140, 0.051)
Activity 14	0.171 (-0.062, 0.404)	0.181 (-0.098, 0.460)	0.483 (-0.292, 1.258)	-0.070 (-0.206, 0.066)
Activity 15	-0.034 (-0.231, 0.162)	0.034 (-0.201, 0.270)	0.316 (-0.381, 1.012)	0.082 (-0.028, 0.193)
Activity 16	-0.023 (-0.2, 0.155)	0.053 (-0.172, 0.277)	0.078 (-0.689, 0.845)	-0.074 (-0.178, 0.031)
Activity 17	-0.097 (-0.291, 0.098)	-0.105 (-0.359, 0.149)	0.356 (-0.456, 1.168)	0.058 (-0.060, 0.176)
Activity 18	-0.133 (-0.334, 0.068)	-0.138 (-0.365, 0.089)	-0.336 (-1.06, 0.388)	0.045 (-0.055, 0.146)
Activity 19	-0.162 (-0.375, 0.052)	-0.212 (-0.463, 0.039)	-0.168 (-1.009, 0.674)	0.007 (-0.098, 0.112)
Average Assessment Activities (1-6)	0.000 (-0.107, 0.107)	-0.019 (-0.140, 0.103)	0.091 (-0.209, 0.392)	-0.016 (-0.072, 0.040)
Average Policy Development Activities (7-14)	-0.057 (-0.177, 0.063)	-0.032 (-0.173, 0.110)	0.064 (-0.271, 0.398)	0.002 (-0.064, 0.068)
Average Assurance Activities (15-19)	-0.113 (-0.255, 0.028)	-0.112 (-0.281, 0.058)	-0.019 (-0.587, 0.549)	0.022 (-0.053, 0.096)
Average Total Activities (1-19)	-0.054 (-0.156, 0.049)	-0.061 (-0.176, 0.053)	0.023 (-0.294, 0.339)	0.004 (-0.053, 0.061)

Table 10. The table depicts the difference-in-difference regression results on the impact of public health accreditation intervention on the effectiveness of public health services. Difference-in-difference model is estimated using panel data fixed effects. The model includes time specific fixed effects and controls for primary care, socioeconomic, and demographic characteristics at the local level. Treatment and control group: Specification (1.1) Accredited LHDs in Florida and unaccredited LHDs in Non-Florida states; Specification (1.2) Accredited LHDs in Florida and unaccredited LHDs in ten similar states; Specification (2) Accredited LHDs in Florida and accredited LHDs in ten similar states; Specification (3) Accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states. 95% confidence intervals in parenthesis. *Significant at 5%. **Significant at 1%.

Table 11. Robustness Check. Difference-in-Difference Regression Results on the Impact of Public Health Accreditation on Public Health Outcomes

	Specification 1		Specification 2	Specification 3
Effectiveness	Model 1 Beta coefficient (95% CI)	Model 2 Beta coefficient (95% CI)	Beta coefficient (95% CI)	Beta coefficient (95% CI)
Activity 1	0.002 (-0.185, 0.189)	-0.063 (-0.251, 0.125)	0.123 (-0.253, 0.499)	0.001 (-0.091, 0.093)
Activity 2	-0.186 (-0.393, 0.022)	-0.157 (-0.404, 0.09)	0.532 (-0.212, 1.276)	-0.001 (-0.118, 0.116)
Activity 3	0.05 (-0.059, 0.16)	0.031 (-0.088, 0.150)	0.296 (-0.178, 0.769)	**-0.053 (-0.104, -0.002) ***
Activity 4	0.137 (-0.025, 0.299)	0.127 (-0.056, 0.309)	-0.385 (-0.867, 0.098)	0.001 (-0.081, 0.082)
Activity 5	0.06 (-0.154, 0.275)	0.142 (-0.106, 0.391)	0.657 (-0.131, 1.445)	-0.063 (-0.171, 0.045)
Activity 6	0.18 (-0.16, 0.197)	0.023 (-0.196, 0.243)	-0.606 (-1.319, 0.107)	0.016 (-0.088, 0.121)
Activity 7	-0.101 (-0.309, 0.106)	-0.020 (-0.265, 0.224)	0.216 (-0.596, 1.028)	-0.003 (-0.107, 0.100)
Activity 8	-0.017 (-0.228, 0.193)	-0.052 (-0.301, 0.197)	-0.145 (-0.799, 0.509)	-0.030 (-0.134, 0.075)
Activity 9	-0.018 (-0.213, 0.177)	-0.011 (-0.222, 0.200)	-0.111 (-0.651, 0.430)	-0.012 (-0.108, 0.084)
Activity 10	-0.039 (-0.199, 0.121)	-0.029 (-0.189, 0.132)	-0.108 (-0.534, 0.318)	-0.057 (-0.134, 0.02)
Activity 11	0.06 (-0.149, 0.268)	0.016 (-0.236, 0.267)	0.523 (-0.260, 1.306)	0.01 (-0.106, 0.126)
Activity 12	**-0.263 (-0.448, -0.078) ****	**-0.240 (-0.472, -0.009) ***	-0.246 (-1.086, 0.594)	0.029 (-0.078, 0.135)
Activity 13	-0.035 (-0.212, 0.142)	-0.012 (-0.220, 0.195)	-0.311 (-0.992, 0.370)	-0.045 (-0.140, 0.051)
Activity 14	0.171 (-0.062, 0.404)	0.181 (-0.098, 0.460)	0.483 (-0.292, 1.258)	-0.070 (-0.206, 0.066)
Activity 15	-0.034 (-0.231, 0.162)	0.034 (-0.201, 0.270)	0.316 (-0.381, 1.012)	0.082 (-0.028, 0.193)
Activity 16	-0.023 (-0.2, 0.155)	0.053 (-0.172, 0.277)	0.078 (-0.689, 0.845)	-0.074 (-0.178, 0.031)
Activity 17	-0.097 (-0.291, 0.098)	-0.105 (-0.359, 0.149)	0.356 (-0.456, 1.168)	0.058 (-0.060, 0.176)
Activity 18	-0.133 (-0.334, 0.068)	-0.138 (-0.365, 0.089)	-0.336 (-1.06, 0.388)	0.045 (-0.055, 0.146)
Activity 19	-0.162 (-0.375, 0.052)	-0.212 (-0.463, 0.039)	-0.168 (-1.009, 0.674)	0.007 (-0.098, 0.112)
Average Assessment Activities (1-6)	0.000 (-0.107, 0.107)	-0.019 (-0.140, 0.103)	0.091 (-0.209, 0.392)	-0.016 (-0.072, 0.040)
Average Policy Development Activities (7-14)	-0.057 (-0.177, 0.063)	-0.032 (-0.173, 0.110)	0.064 (-0.271, 0.398)	0.002 (-0.064, 0.068)
Average Assurance Activities (15-19)	-0.113 (-0.255, 0.028)	-0.112 (-0.281, 0.058)	-0.019 (-0.587, 0.549)	0.022 (-0.053, 0.096)
Average Total Activities (1-19)	-0.054 (-0.156, 0.049)	-0.061 (-0.176, 0.053)	0.023 (-0.294, 0.339)	0.004 (-0.053, 0.061)

Table 11. The table provides the robustness check results of the difference-in-difference regression analysis on the impact of public health accreditation intervention on the effectiveness of public health services. Difference-in-difference model is estimated using panel data fixed effects. The model includes time specific fixed effects and controls for primary care, socioeconomic, and demographic characteristics at the local level. Treatment and control group: Specification (1.1) Accredited LHDs in Florida and unaccredited LHDs in Non-Florida states; Specification (1.2) Accredited LHDs in Florida and unaccredited LHDs in ten similar states; Specification (2) Accredited LHDs in Florida and accredited LHDs in ten similar states; Specification (3) Accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states. 95% confidence intervals in parenthesis. *Significant at 5%. **Significant at 1%.

5.5. Discussion

This study evaluates the impact of public health accreditation on the effectiveness of LHDs to deliver essential public health activities. The effect of accreditation is analyzed through study of the difference-in-difference of pre-intervention and post-intervention effectiveness ratings in the accredited and unaccredited control groups of LHDs in 2012-2019. The descriptive analysis revealed reductions to the effectiveness averages of each public health activity when comparing pre-intervention and post-intervention averages for accredited LHDs in Florida, unaccredited LHDs in ten similar states, accredited LHDs in ten similar states, and accredited LHDs in Non-Florida states, and increases to the effectiveness averages of each public health activity when comparing pre-intervention and post-intervention for unaccredited LHDs in Non-Florida states. The difference-in-difference estimations indicate that public health accreditation had no significant impact on 18 out of the 19 public health activities. Evidence demonstrates that public health accreditation was associated with a statistically significant decline in Activity 12.

Robust results are ensured by comparing multiple intervention and control groups. In the base Specification (1.1), accredited LHDs in Florida are compared to unaccredited LHDs in Non-Florida states. Specification (1.2) provides a robustness check by comparing accredited LHDs in Florida with unaccredited LHDs in 10 states that are like the state of Florida. This control group is less subject to selection bias and captures any potential secular trends unrelated to accreditation that might be affecting effectiveness during this same period. The magnitudes of the effects on effectiveness measures are too small to produce substantial selection bias in the main results, suggesting that public health accreditation indeed affected delivery effectiveness in counties that achieved accreditation. Specification (2) comparing accredited LHDs in Florida and accredited LHDs in ten control states suffered from bias with the inclusion of a previously treated control. Specification (3) comparing accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida control states also suffered from selection bias; however, this group reveals the differences in a voluntary vs. mandatory process. LHDs in Florida were required to participate in a voluntary accreditation program. To achieve accreditation, LHDs focus on standards and measures, not necessarily the effective delivery of public health services. Specification (1.1) and (1.2) reflect the LHDs focus on the completion of a process compared to the commitment to improvement. It is likely that higher quality LHDs are more likely to pursue accreditation. The results from Specification (4) confirm these assumptions in that the coefficients for these group are larger and positive.

A robust econometric technique, the difference-in-differences approach, is used where LHDs are compared using control groups of nonaccredited LHDs and accredited LHDs in Florida before and after 2016 and any time invariant differences between the groups of LHDs and between the study period are adjusted. Accreditation status in the state of Florida is used as the intervention since all Florida LHDs were expected to achieve accreditation as an integrated public health system. The decision for Florida LHDs to obtain accreditation is exogenous, and thus, treatment self-selection is reduced. The research design is well-suited to study causal relationships and offers a stronger study design than simply tracking changes within LHDs in the state of Florida over time (Wing et al., 2018). The difference-in-difference approach prevents any temporal changes that affected the effectiveness in all LHDs over the same period to be attributed to an intervention impact.

Results show that public health accreditation was associated with a significant decline in the effectiveness of Activity 12. LHDs post-accreditation may be less effective in developing a community health action plan since public health accreditation is a voluntary program where LHDs must satisfy PHAB prerequisites by completing a community health assessment (CHA), a community health improvement plan (CHIP), and an agency strategic plan (Carman & Timsina, 2015; Singh & Carlton, 2017). The CHA, addressed in PHAB Domain 1, is a systematic, collaborative method to assess the health needs of a community, and the CHIP and strategic plan are action plans to address the health needs of the community. LHDs may treat these activities as a "one-time deal".

There are some reasons why accreditation was not a significant predictor of LHD effectiveness. In achieving accreditation, LHDs focus on completing standards and documentation, not necessarily the effective delivery of public health services. The focus is on the completion of a process instead of the commitment to improvement. The implementation of public health standards is no guarantee for continuous improvement. It is possible that LHDs view accreditation as a snapshot review rather than a continual assessment. Other continuous quality improvement methods are necessary to sustain a positive impact of accreditation (Devkaran & O'Farrell, 2015). Next, LHDs with fewer employees and resources conduct community health assessments and planning but find it difficult to address all the accreditation standards (Allen, 2019). With limited resources, LHD officials may choose which accreditation standards receive more attention. Additionally, the benefits of accreditation may be more linked with improved workforce development, increased communication, or strengthened community relationships (PHAB, 2021d), and less with improved effectiveness of service delivery. Last, the PHAB accreditation process was only launched in 2013, and the effect of PHAB accreditation may still not be apparent. Perhaps more time is needed to see the actual benefits for LHDs (Albashir, 2018).

It is not uncommon to see stark differences in the descriptive statistics compared to the inferential statistics. In this case, the descriptive statistics revealed that the effectiveness rating of Activity 12 (Identify and Allocate Resources Based on Community Health Plan) increased when comparing pre-intervention and post-intervention averages for all the intervention and control groups, excluding the unaccredited LHDs in ten similar states group, and the effectiveness rating of Activity 13 (Deploy Resources to Address Priority Health Needs) increased when comparing pre-intervention and post-intervention averages for all the intervention and control groups, while the inferential statistics suggested that accreditation was associated with a significant decline in the effectiveness rating of Activity 12. It is important to distinguish that the descriptive statistics summarize the key features of the data, and the inferential statistics provided by the difference-in-difference estimation examine the relationships between the variables and produce generalizations about the population based on a representative sample.

PHAB has developed priority research questions and requested more robust research to help strengthen the evidence base around accreditation. This study reveals that public health accreditation did not translate to the improved effectiveness of public health activities for LHDs. Accreditation may prepare LHDs to engage in quality improvement and implement standards to improve processes. Accreditation should be viewed as one element that complements other performance improvement strategies to achieve a significant effect in the public health system (Hussein et al., 2021). Additional studies can explore the utility of public health accreditation as a performance improvement method for public health improvement. Future research requires annual data on the effectiveness of public health activities to be collected.

The study is unique and has several strengths in that a longitudinal design is utilized, exogenous confounders are controlled, and difference-in-difference estimations are used to help detect causal conclusions of accreditation effects (Hussein et al., 2021). To the author's knowledge, this is one of the first studies to answer the research question focused on the impact of accreditation on effectiveness of public health activities and offer insight into another dimension of performance. This study is the first to use the state of Florida as an intervention, and appropriately chose multiple control groups that capture any potential trends unrelated to accreditation that might be affecting the study outcomes during the same period. Data was graphically and statistically inspected to test the parallel trend assumption and ensure that there was not any biased estimation of the causal effect. Results from this study help grow the evidence base surrounding accreditation and public health practice.

Limitations

The study has limits. First, the quasi-experimental nature of the analysis attempts to establish causality with observational data. Second, self-reported LHD data is used. Social desirability bias could result in respondents overreporting the effectiveness of their public health activities. Third, with the use of observational data, the possibility of selection and information bias is introduced. Fourth, the study focuses on one state as the treatment. Fifth, some of the states in the study use older accreditation versions. Sixth, the study findings may not be generalizable to other settings.

Implications for Policy and Practice

- A key goal of public health accreditation is the strengthening of local health departments' (LHD) capacity to deliver essential public health services.
- Evidence from this study helps the Public Health Services and Systems Research field better understand the impact of accreditation.
- This study reveals that public health accreditation did not translate to the improved effectiveness of public health activities for LHDs.
- Accreditation should be viewed as one element that complements other performance improvement strategies to achieve a significant effect in the public health system.

CHAPTER VI

THE EFFECT OF PUBLIC HEALTH FUNDING ON PUBLIC HEALTH OUTCOMES

6.1. Abstract

Existing evidence on the impact of local health department (LHD) funding on public health outcomes is mixed with the variation in results largely explained by the selected unit of analysis and the research design employed. The objective of this study is to assess the impact of LHD expenditures on public health measures using counties as the unit of analysis. Linear probability multivariate regression models with the use of local level cross-sectional and panel data are employed to examine whether increased LHD funding translates to public health benefits. A one-year and a two-year lag structure are also used to quantify the longer-term public health effects of changes in LHD expenditures. Expenditure data from the National Association of County and City Health Officials Profile Surveys and public health measures from County Health Rankings Annual Reports are used. Analyses were performed at the LHD level using local data representing 2,420 LHDs, covering 48 U.S. states. Participants were LHDs reporting expenditure data in 2010, 2013, 2016, and 2019. Four public health measures are examined – obesity prevalence, sexually transmitted infections, diabetes prevalence, and HIV prevalence. Results from cross-sectional, pooled ordinary least squares (OLS), and panel data with fixed effects reveal that increased LHD expenditures per capita was not associated with any of the public health outcomes studied. In the cross-sectional and pooled ordinary least squares models, the direction of the coefficients for all the outcomes were negative, and in the panel data with fixed effects, the direction of the

coefficients was positive. The fixed effects estimation suggests important unobserved variables may drive public health outcomes. Research designs that do not control for omitted variable bias may lead one to conclude that large expenditures explain better health outcomes. A research design that addresses reverse causation bias must be employed to properly answer whether increased LHD funding translates to improved public health.

6.2. Introduction

Local health departments (LHDs), the backbone of the nation's public health system, receive funding from a complex mix of streams and are expected to mesh various funding sources to finance services (NACCHO, 2020; McCullough, 2018; Mays & Smith, 2011). The National Association of County and City Health Officials (NACCHO) reported that average LHD expenditures per capita decreased 30% from 2008 to 2019 (NACCHO, 2020). Since the start of the Great Recession, LHDs eliminated a cumulative total of approximately 55,000 jobs due to hiring freezes and budget cuts (NACCHO, 2017b). Funding fluctuations often result in budgetary restrictions, workforce reductions, and greater inefficiency which can jeopardize the basic services that LHDs provide to address various health needs and improve public health (NACCHO, 2017b; Bekemeier et al., 2012). Most LHDs made changes to their services after the implementation of the Patient Protection and Affordable Care Act, shifting toward the provision of more population-focused activities such as community assessment, epidemiology, and surveillance (Bekemeier et al., 2012; NACCHO, 2017b; NACCHO, 2014). Amid a changing public health landscape influenced by economic shocks and wide sweeping legislation, LHD officials require evidence on the impact of LHD funding on public health outcomes to effectively allocate scarce resources for the best health returns.

Although a growing body of research has attempted to investigate the impact of public health funding on health outcomes, the findings vary widely. The reason substantial variations in results are seen across studies is complex. Some of the variation in results can be explained by the methodological research design employed (cross-sectional vs. panel) and the selected unit of analysis employed (national, regional, state, local) (Singh, 2014). Cross-national and regional-level cross-sectional literature reveal that health resources have little or no effect on mortality rates (Filmer & Pritchett, 1999; Rivera, 2001). National and state-level cross-sectional evidence observes risky behaviors and HIV prevalence decline as HIV prevention spending increases (Linas et al., 2006; Holtgrave & Kates, 2007). Evidence from state-level panel designs suggest reductions to sexually transmitted infection incidence rates and infectious disease morbidity are associated with increased prevention and local health funding (Chesson et al., 2005; Erwin et al., 2011). A more recent state-level panel design study suggests that states with higher one-year lagged ratios of social-to-health spending had significantly better health outcomes for adult obesity, asthma, mentally unhealthy days, days with activity limitations, and mortality rates for lung cancer, acute myocardial infarction, and type 2 diabetes (Bradley et al., 2016). Local-level cross-sectional evidence shows increased LHD funding has no effect in improving mortality outcomes (Schenck et al., 2015). Using a similar design, studies examining expenditures for programs targeting tobacco control found smoking prevalence declines as funding increased (Tauras et al., 2005; Farrelly et al., 2008), and better performance on health rankings were observed in counties that spent relatively more of their total expenditures on community health care and public health (McCullough & Leider, 2017). State-specific studies using local-level panel designs suggest that increased targeted expenditures lead to decreases in all-cause mortality and infant mortality, and improvements in health rankings (Brown, 2014; Bernet et al., 2018; McCullough & Leider, 2017). Similarly, a local-level panel design study using approaches with less-than-ideal instruments reveals that increased public health funding is associated with reductions in infant mortality and deaths from cancer, heart disease, and diabetes (Mays & Smith, 2011). It is worth noting that both the definition of public health spending (e.g., LHD only vs. local government) and the source of the spending data (e.g., NACCHO vs. U.S. Census) vary across studies, which likely contributes to the inconsistency in findings.

Robust quantitative approaches with the use of local-level cross-sectional and panel data are employed to demonstrate whether public health benefits are associated with higher levels of public health funding. The study is guided and informed by the research question: What is the impact of LHD expenditures on local-level public health outcomes? The study investigated the central hypothesis: Increased LHD expenditures improve local-level public health outcomes. Our study contributes to the literature by demonstrating that the mixed results from other studies could be explained by the different methodological approaches used, and how various approaches can be used to reduce potential biases.

6.3. Methods

An observational study was conducted with the use of multivariate linear regression models to examine the association between LHD expenditures and eight public health measures over a nine-year period. The primary exposure variable of interest in this study is **local health department (LHD) expenditures** measured as per capita LHD expenditures - expended public health dollars divided by the population of LHDs' jurisdiction. Data for the exposure variable is obtained from the NACCHO Profile Surveys, the only longitudinal study of its kind providing information on LHD infrastructure and practice (NACCHO, 2020). Four waves of NACCHO profile data - 2010, 2013, 2016, and 2019 - are used. Expenditures per capita are adjusted to represent 2021 constant dollars by employing a model proposed by NACCHO where the weighted average of the general Consumer Price Index (CPI) is used. The value for per capita LHD expenditures is transformed via the natural logarithm to reduce skewness and outliers in the LHD expenditure measure, create a more normal distribution to improve model fit, and for ease in interpretation of results.

The main outcome variables include public health and mortality outcome measures available in the County Health Rankings and provide a comprehensive representation of the health of a local community. **Obesity prevalence** is the percentage of the adult population (age 20 and older) that reports a body mass index (BMI) greater than or equal to 30 kg/m2 from the CDC Diabetes Interactive Atlas. **Sexually transmitted infections** measure the number of newly diagnosed chlamydia cases per 100,000 population provided by National Center for Hepatitis, HIV, STD, and TB Prevention. **Diabetes prevalence** is the percentage of adults aged 20 and above with diagnosed diabetes from the CDC Diabetes Interactive Atlas. **HIV prevalence** is the number of people aged 13 years and older living with a diagnosis of human immunodeficiency virus (HIV) infection per 100,000 population from the National Center for Hepatitis, HIV, STD, and TB Prevention. County Health Ranking Annual Reports that best correspond with the study period are used. The annual reports for years 2014, 2017, and 2020 were used for the outcome variables: obesity prevalence and diabetes prevalence. The annual reports for years 2013, 2016, 2019, and 2022 were used for the outcome variable: STD. The annual reports for years 2014, 2017, 2020, and 2022 were used for the outcome variable: HIV prevalence. More information about the County Health Rankings Annual Reports can be found in Section 3.3.4.

Factors known to influence health at the local level, including demographic and socio-economic composition, total population characteristics, healthcare resources, and LHD characteristics are included in the model as control variables as provided by the Robert Wood Johnson Foundation's County Health Rankings. **Uninsured adults** measure the percentage of population under age 65 without health insurance provided by the Small Area Health Insurance Estimates. **Primary care physicians** measures the ratio of population to primary care physicians from the Health Resources & Services Administration. **Preventable hospital stays** are the rate of hospital stays for ambulatory-care sensitive conditions per 100,000 Medicare enrollees from the Dartmouth Atlas of Health Care. **High school graduation** is the percentage of ninth-grade cohort that graduates in four years from the National Center for Education Statistics. **Unemployment** is the percentage of population ages 16 and older unemployed but seeking work from the Bureau of Labor Statistics. **Children in poverty** is the percentage of people under age 18 in poverty provided by the Small Area Income and Poverty Estimates. **Population** is the total population size of the jurisdiction. **Age** is the percentage of the population that is 65 years and older. **Race** is the percentage of the population that is Non-Hispanic African American. **Ethnicity** is the percentage of the population that is Hispanic. Population, age, race, and ethnicity measures are provided by the Census Population Estimates. **Median household income** is the income where half of households in a county earn more, and half of households earn less provided by the Small Area Income and Poverty Estimates. Like the outcome variables, data for the control variables also best correspond with the study period.

Study Population

The NACCHO Profile Survey was completed by LHD representatives reporting expenditure data in 2010, 2013, 2016 and 2019. Analyses were performed at the county-level using local data representing 2,420 LHDs, covering 48 U.S. states (excluding Rhode Island and Hawaii since their state health departments operate on behalf of local public health and have no sub-state units) (NACCHO, 2017a). The public health outcome data from the County Health Rankings are also based on counties. The expenditure data and the public health outcome data are matched by their common Federal Information Processing Standard (FIPS) county codes. Average weights were generated based on the number of LHDs serviced in each FIPS code to account and better estimate when one FIPS code represented several LHDs or one LHD represented several FIPS code. Weights are incorporated into the data to address LHDs serving multiple counties as well as counties served by multiple LHDs.

Statistical Analysis

Descriptive statistics including mean, standard deviation, and median were computed for all variables to characterize the sample. Linear probability multivariate regression models were used to estimate the effect of LHD expenditures on the public health outcome measures while controlling for the effects of community demographic, socioeconomic, health resources, and total population characteristics. A cross-sectional design with ordinary least squares (OLS) regression by each survey year - 2010, 2013, 2016 and 2019 - is first tested. A pooled OLS regression as well as a panel design with random-effects and fixed-effects are then tested. Results for these models include clustered standard errors. Next, the Hausman specification test is employed to differentiate between a fixed effects model and a random effects model in the panel analysis. According to the results of the Hausman test, the panel data model with fixed effects was more efficient, and subsequently used for model estimation. More information about the Methods can be found in Section 3.5.4 and Section 3.5.5.

The empirical specification used is shown below where Y_{it} is the dependent variable where i=entity and t=time, X_{it} represents the independent variable, Z_{it} represents a vector of control variables, β are the parameters to be estimated, a_{Ti} represents the time trend, and u_{it} is the error term. Given that multiple time points are included in the sample, a time trend variable is included in the model to control for systematic differences across time. The base model (1) uses the same years available for the primary exposure variable of interest - 2010, 2013, 2016, and 2019.

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \alpha T_i + u_{it}} \qquad (1)$$

Based on the understanding that there are time lags between when financial resources are invested and when improved public health outcomes are seen, a lag structure is used to quantify the longer-term public health effects of changes in LHD expenditures. Empirical evidence for the appropriate length of time lags and its variation across outcomes is currently limited.8 As part of a robust estimation strategy, empirical specification (2) and (3) are tested with varying lag structures between LHD expenditures and public health outcomes. Model (2) uses a one-year lag, allowing for the use of all four waves of observations on LHD expenditures during 2010-2019, linked with health outcomes one year later - 2011, 2014, 2017, and 2020.

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Z_{it-1} + \alpha T_i + u_{it}} \qquad (2)$$

Model (3) tests a two-year lag structure - 2012, 2015, and 2018, which reduces the total available sample size by excluding data points on LHD expenditure in 2019 since they cannot be linked to health outcomes data that is not yet available for 2021.

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 X_{it-2} + \beta_2 Z_{it-2} + \alpha T_i + u_{it}} \qquad (3)$$

An unbalanced panel is used to conduct our study and missing data in the sample appropriately handled. As a first measure, expenditure data in 2005 was not used due to data inconsistencies. Data is assessed to determine the percent of LHDs reporting expenditure data in each wave of the survey - 81% of surveyed LHDs reported expenditures in 2010, 76% of LHDs in 2013, 67% of LHDs in 2016, and 48% of LHDs in 2019. From 2010-2019, an average of 68% of surveyed LHDs provided expenditure data that was used for the study. A Little's Missing Completely at Random (MCAR) test is run to test the assumption of expenditures missing completely at random (Li, 2013). Since the p-value (p=0.9545) for Little's MCAR test is not significant, the data may be assumed to be missing completely at random. The test provides evidence that the missing data in the variable of interest does not bias the study inferences.

Stata statistical software is used to analyze data (StataCorp LP, College Station, TX). The Institutional Review Board of Florida International University determined that this study was exempt.

6.4. Results

Changes in Independent Variables

Descriptive statistics are presented in Table 12. Average LHD expenditures per capita decreased from $57.43 in 2010 to $52.68 in 2016 and began to slightly increase to $54.50 in 2019 (Table 1). During the study period, the average LHD expenditures per capita was $55.27.

Table 12. Overall Local Health Department Expenditures per Capita and Changes in Public Health Outcomes and Control Variables between 2010 and 2019

	Mean	(S.D.) *
Expenditures per capita†		
Year 2010, $	57.43	(67.39)
Year 2013, $	55.47	(101.13)
Year 2016, $	52.68	(89.31)
Year 2019, $	54.5	(63.14)
Overall, $	55.27	(83.51)
Public health outcomes‡		
Obesity prevalence, %		
Year 2010	0.31	(0.05)
Year 2013	0.33	(0.05)
Year 2016	0.32	(0.05)
Year 2019	0.31	(0.05)
Overall	0.33	(0.05)
STD* per 100,000		
Year 2010	317.35	(231.55)
Year 2013	314.82	(212.62)
Year 2016	318.65	(224.02)
Year 2019	319.85	(224.56)
Overall	317.66	(223.25)
Diabetes prevalence, %		
Year 2010	0.10	(0.03)
Year 2013	0.11	(0.03)
Year 2016	0.12	(0.03)
Year 2019	0.13	(0.03)
Overall	0.11	(0.03)
HIV prevalence per 100,000 population		
Year 2010	160.49	(186.87)
Year 2013	161.31	(190.03)
Year 2016	162.07	(183.14)
Year 2019	160.27	(184.16)
Overall	161.03	(186.01)

Table 12. Overall Local Health Department Expenditures per Capita and Changes in Public Health Outcomes and Control Variables between 2010 and 2019, Cont'd

	Mean	**(S.D.) ***
Control variables‡		
Uninsured adults, %	0.16	(0.07)
Primary care physicians per 100 000 residents	18.36	(38.82)
Preventable hospital stays per 100 000 population	2165.73	(2248.58)
High school graduation, %	0.86	(0.08)
Unemployment, %	0.06	(0.03)
Children in poverty, %	0.21	(0.09)
Population size, total	194,137.30	(1,268,236)
Age, %	0.18	(0.04)
Race, %	0.07	(0.12)
Ethnicity, %	0.07	(0.10)
Median household income, $	50,291.61	(14,892.75)

Table 12. The table provides the summary statistics for the independent variable, dependent variables, and control variables. *S.D. is standard deviation. STD is sexually transmitted infections. † Data for expenditures per capita were obtained from the NACCHO National Profile surveys in 2010, 2013, 2016, and 2019. All amounts expressed in 2020 constant dollars. The four waves of observations of local health department expenditures during 2010-2019 revealed significant variability in funding across time.

Changes in Dependent Variables

Rates for obesity prevalence, diabetes prevalence, and HIV prevalence remained relatively unchanged between 2010 and 2019 (Table 12). During the span of nine years, STD was the only public health measure to increase by 0.78%. Between 2010 and 2019, the number of newly diagnosed STD cases averaged 317.66 per 100,000 population, and the number of people aged 13 years and older living with a diagnosis of HIV infection averaged 161.03 per 100,000 population. In the overall population, 31% of the adult population reported a body mass index greater than or equal to 30 kg/m2, and 11% of adults aged 20 and above were diagnosed with diabetes.

Multiple Linear Regression

Model 1: The Base Model

Table 13 depicts the cross-sectional OLS and panel data with fixed-effects regression results for changes in LHD expenditures per capita and public health measures. The cross-sectional OLS model for year 2013 reveals that holding other factors constant, increased LHD expenditures per capita was not associated with any of the public health outcomes studied. The direction of the coefficients was negative for obesity prevalence, STDs, and HIV prevalence.

The cross-sectional OLS model for year 2016 and year 2019 also suggests that increased LHD expenditures per capita was not associated with any of the public health outcomes studied. In the cross-sectional OLS model for year 2016, the direction of the coefficients was negative for obesity prevalence, STDs, and HIV prevalence. In the cross-sectional OLS model for year 2019, the direction of the coefficients was negative for obesity prevalence, STDs, and diabetes prevalence.

The pooled OLS estimation suggests that a 10-percent increase in LHD funding was not significantly associated with any reductions in the public health outcomes, holding constant all other variables in the model. The direction of the coefficients was negative for obesity prevalence and STDs.

In the panel data with fixed effects, none of the public health outcomes were significantly impacted by increased LHD expenditures per capita. The direction of the coefficients was positive for obesity prevalence, STDs, and diabetes prevalence.

Table 13. Multiple Linear Regression Results for Local Health Department Expenditures and Public Health Outcomes

Public health outcomes	OLS Year 2013 Beta coefficient (95% CI)	OLS Year 2016 Beta coefficient (95% CI)	OLS Year 2019 Beta coefficient (95% CI)	Pooled OLS Beta coefficient (95% CI)	Fixed Effects Beta coefficient (95% CI)
Obesity prevalence	-0.001 (-0.007, 0.006)	-0.002 (-0.009, 0.006)	-0.004 (-0.01, 0.002)	-0.002 (-0.007, 0.003)	0.002 (-0.003, 0.006)
Sexually transmitted infections	-2.852 (-26.171, 20.466)	-2.503 (-24.09, 19.083)	-16.697 (-37.735, 4.34)	-4.738 (-16.955, 7.479)	1.828 (-13.186, 16.841)
Diabetes prevalence	0.003 (-0.003, 0.008)	0.003 (-0.003, 0.008)	-0.002 (-0.004, 0.001)	0.001 (-0.002, 0.003)	0 (-0.002, 0.003)
HIV prevalence	-6.576 (-36.041, 22.889)	-5.948 (-34.176, 22.28)	18.398 (-13.561, 50.357)	5.549 (-13.463, 24.561)	-6.077 (-14.879, 2.724)

Table 13. The table shows the multiple linear regression results for LHD expenditures and public health outcomes. OLS refers to the ordinary least squares model. Fixed Effects refers to panel data model with fixed effects. Data for expenditures per capita were obtained from the NACCHO National Profile surveys in 2010, 2013, 2016, and 2019. All amounts expressed in 2021 constant dollars. Public health outcome data were obtained from County Health Rankings Annual Reports. * p<0.1; ** p<0.05; *** p<0.01.

Model 2: The One-Year Lag Model & Model 3: The Two-Year Lag Model

The analysis was repeated with a one-year lag structure, allowing for the use of all four waves of observations on LHD expenditures during 2010-2019, linked with public health outcomes one-year later - 2011, 2014, 2017, and 2020; and a two-year lag structure - 2012, 2015, and 2018 - which reduced the total available sample size by excluding data points on LHD expenditures in 2019 since they cannot be linked to future public health outcomes data in 2021 (as they are not yet available in the County Health Rankings data). The multivariate linear regression results for changes in expenditures per capita and health measures using the one-year and two-year lag are presented in Table 14. In the pooled OLS model with the one-year lag structure, increased LHD expenditures per capita was not associated with any of the public health outcomes studied. The direction of the coefficients was negative for obesity prevalence, STDs, and diabetes prevalence. No significant results were found in the panel data model with fixed-effects with the one-year lag structure. The direction of the coefficients was negative for obesity prevalence and STDs. The cross-sectional OLS model for year 2013 and year 2019 with the two-year lag structure reveals that holding other factors constant, increased LHD expenditures per capita was significantly associated with reduction in obesity prevalence. The magnitude of the estimates suggests a 10-percent increase in LHD funding was associated with a 0.6% decrease in obesity prevalence. These results were significant at the 10% significance level. In the pooled OLS model with the two-year lag structure, no significant results were found between LHD expenditures and the public health outcomes, and the direction of the coefficients was negative for obesity prevalence and STDs.

Table 14. Lag Structure Multiple Linear Regression Results for Local Health Department Expenditures and Public Health Outcomes

Public health outcomes	**OLS** **Year 2013** Beta coefficient (95% CI)	 **Year 2016** Beta coefficient (95% CI)	 **Year 2019** Beta coefficient (95% CI)	**Pooled OLS** Beta coefficient (95% CI)	**Fixed Effects** Beta coefficient (95% CI)
Model 2: **One-year lag§**					
Obesity prevalence	-0.004 (-0.011, 0.003)	0.002 (-0.006, 0.009)	-0.004 (-0.011, 0.002)	-0.003 (-0.008, 0.003)	-0.001 (-0.005, 0.003)
Sexually transmitted infections	-13.393 (-33.567, 6.78)	-4.961 (-28.15, 18.228)	-17.621 (-44.419, 9.177)	-10.793 (-22.239, 0.653)	-4.549 (-16.21, 7.112)
Diabetes prevalence	-0.002 (-0.007, 0.003)	0.001 (-0.003, 0.004)	0 (-0.003, 0.003)	-0.001 (-0.003, 0.001)	0 (-0.002, 0.003)
HIV prevalence	-4.817 (-30.55, 20.916)	-11.305 (-40.466, 17.857)	12.234 (-5.427, 29.896)	3.614 (-10.508, 17.737)	7.268 (-0.556, 15.093)
Model 3: **Two-year lag¶**					
Obesity prevalence	**-0.006 (-0.013, 0) ***	0 (-0.007, 0.008)	**-0.004 (-0.008, 0) ***	-0.004 (-0.008, 0.001)	-0.003 (-0.006, 0.001)
Sexually transmitted infections	-16.135 (-37.097, 4.827)	-5.99 (-28.454, 16.473)	-14.972 (-37.701, 7.756)	-7.845 (-18.91, 3.22)	-1.403 (-14.029, 11.224)
Diabetes prevalence	-0.001 (-0.003, 0.002)	0 (-0.002, 0.003)	0 (-0.002, 0.002)	0 (-0.001, 0.002)	0 (-0.001, 0.002)
HIV prevalence	-6.972 (-42.226, 28.283)	-16.381 (-40.476, 7.714)	17.533 (-10.523, 45.588)	3.507 (-13.666, 20.679)	2.692 (-5.806, 11.189)

Table 14. The table depicts the multiple linear regression results for Model 2 and Model 3 of changes in expenditures per capita and public health outcomes. Model 2 uses a one-year lag, and Model 3 uses a two-year lag between expenditures and public health outcomes. OLS refers to ordinary least squares model. Fixed Effects refers to panel data model with fixed effects. Data for expenditures per capita were obtained from the NACCHO National Profile surveys in 2010, 2013, 2016, and 2019. All amounts expressed in 2021 constant dollars. Public health outcome data were obtained from County Health Rankings Annual Reports. § A one-year lag structure was used linking public health outcomes to expenditures per capita one year later in 2011, 2014, 2017, 2019. ¶ A two-year lag structure was used linking public health outcomes to expenditures per capita two years later in 2012, 2015, and 2018. * $p<0.1$; ** $p<0.05$

In the panel data model with fixed effects with the two-year lag structure, no significant results were found between LHD expenditures and the public health outcomes, and the direction of the coefficients was negative for obesity prevalence and STDs.

6.4. Discussion

This study assesses the impact of LHD expenditures on public health outcomes based on recent local expenditure data across the U.S. A set of public health measures are studied, and counties are used as the unit of analysis to expound on the important role of LHDs in the public health system. It is hypothesized that increased LHD expenditures improves public health outcomes as shown by decreases to the regression coefficients. In this study, robust quantitative approaches with the use of local-level cross-sectional and panel data are employed to demonstrate how the mixed results on the impact of public health funding on public health outcomes may be explained by the methodological approach used.

In the cross-sectional models for years 2013, 2016, and 2019, results reveal that an increase in LHD expenditures is not significantly associated with any of the public health outcomes studied. The pooled OLS model reflects similar findings with none of the outcomes being statistically significant. In the panel data model with fixed effects, there is not a significant association between LHD expenditures and the public health outcomes, but the direction of the coefficients shifted to positive for obesity prevalence, STDs, and diabetes prevalence.

With the use of each methodological approach, potential biases are addressed. First, aggregation bias can result when a relationship existing at one level of analysis (i.e., state-level) is assumed to demonstrate the same strength at another level of analysis (i.e., local level). Results suffering from this bias will overestimate or underestimate the strength of the relationship. This bias is addressed by performing analyses at the local LHD level using local data. Second, omitted variable bias can result when a relevant variable is excluded, and results are biased with inconsistent estimates. This bias can be seen in the way public health funding affects health without the inclusion of other relevant variables that may explain the relationship. This bias is addressed by employing a panel design with fixed effects. Lastly, reverse causation bias can result when it is wrongly assumed that one variable is the cause while the other is the effect. This bias can be seen in the way LHD funding can affect the health of a local community, and conversely, in the way that the health of a local community can affect the funding that a LHD receives. To control for the potential endogeneity of public health funding, a natural experimental design was first tested by relying on instrumental variables methods to study the relationship between LHD funding and the public health outcome measures. Measures of public health governance and decision-making structures were exploited as instrumental variable but were found to be weak instruments with significant variation and low correlation with the endogenous variable (Mays et al., 2016). More information about instrumental variables is available in Section 3.5.7. For this reason, the effect of LHD expenditures on the public health outcome measures are estimated using linear probability multivariate regression models.

Negative coefficients in the regression results were expected, indicating that increased funding translates to a reduction in poor health outcomes. In the cross-sectional and the pooled OLS models, the results returned negative coefficients. These results show a biased estimate of the degree to which expenditures affect health outcomes because it suffers from omitted variable bias, thus reducing the coefficients, and making them more negative. With the fixed-effects estimation, the direction of the effect changed, and the coefficients became more positive suggesting that an increase in expenditures is associated with an increase in these outcomes. As an example, the pooled OLS model suggested that a 10% increase in LHD expenditures *reduced* STDs by 4.738 per 100,000 population, whereas the panel data with fixed-effect model revealed that a 10% increase in LHD expenditures *increased* premature deaths by 1.828 per 100,000 population. When unobserved variables influencing both expenditures and the outcome variable (such as community characteristics like local area medical spending, and LHD characteristics like scope of health services performed) are omitted, the regression incorrectly attributes improved outcomes to higher levels of expenditures, when at least part of this should be attributed to another variable (Mays & Smith, 2009). The use of pooled and cross-sectional OLS models may lead one to conclude that large expenditures explain better outcomes or a significant negative relationship between public health funding and health outcomes could exist where it in fact does not. Model 2 and Model 3 lag structure results reveal the effects are less pronounced over time, confirming that bias exists. The panel data model with fixed-effects removes the omitted variable bias by measuring changes within groups across time.

Although the results of the base model were not significant, the coefficients of the estimates went in opposing directions based on the model. In the cross-sectional OLS model, increased LHD expenditures had negative coefficients compared to the fixed effects model where increased LHD expenditures had positive coefficients, suggesting it worsened public health outcomes. There are some potential reasons that may explain the upward and downward bias of the results. First, the efficiency of the LHD may be the main driver transforming increased LHD expenditures into improved public health outcomes as efficient LHDs may have more political power, can request more money, and can allocate it more effectively. It is possible that an increase in LHD expenditures to inefficient LHDs will not translate into improved outcomes, and in this sense, efficiency, not increased expenditures, may be the true driver to improved outcomes. Due to the heterogeneity between LHDs, the defining factor or measure of efficiency is not able to be identified as it is an unobserved characteristic. If omitted from the model, this variable could upward bias the effect of expenditures. Second, it is possible that increased expenditures may be provided to LHDs in communities with the worst health outcomes or in greater need. For example, states may address the high incidence of sexually transmitted infections by increasing funding to LHDs in counties with the highest rates. An increase in expenditures often results in LHD funneling money to specific programs, likely allocating to those areas with biggest need (in this case, STD screening and treatment). However, it is possible that LHDs may decide to allocate more funding to areas with less need, and thus, the outcome (STD incidence) may get worse.

In the pooled OLS model, the results are biased due to omitted variable bias and reverse causation bias. In the panel data model with fixed effects, omitted variable bias is controlled, but reverse causation bias is still in place. The panel data model with fixed effects can eliminate the omitted variable bias by controlling for unobserved variables that do not rapidly change overtime. This may explain why the apparent effect of increased expenditures improves health outcomes vanishes with the panel design and fixed-effects model, indicating that unobserved variables, not increased funding, may be a potential key driver to improved public health outcomes. The study highlights the need to control for omitted variable bias as other public health system components, such as LHD efficiency, resource allocation, political power, and organizational efficiency, may influence the results. To control for both omitted variable bias and reverse causation bias, an instrumental variables approach is needed. Unfortunately, potential instruments are weak with current data limitations posing additional challenges. Future research can address the endogeneity issue between LHD expenditures and public health outcomes.

The analysis was also conducted with a one-year and a two-year lag structure. The cross-sectional OLS model with the two-year lag structure suggested that obesity prevalence was significantly associated with increased LHD expenditures per capita. The magnitude of the effects suggests a 10-percent increase in LHD funding was associated with a -0.6-percentage-point change in the percentage of adults with obesity. The U.S. obesity prevalence was 42.4% in 2017-2018 which is roughly 138 million obese adults (CDC, 2021d). The effect of such a change would be 831,815 fewer adults with obesity. These results are consistent with the results of a previous state-level study (Bradley, 2016). It is worth noting that these results were significant at the 10% significance level. A 5% significance level is commonly used as the standard when measuring the probability of rejecting the null hypothesis when it is true. The two-year lag model has a

10% chance of producing a significant result when the null hypothesis is correct and has an increased chance of a false positive.

In assessing year-to-tear changes, this study may not detect meaningful associations in some public health measures as it may be difficult to influence certain public health outcomes within a nine-year period. Similarly, variations in how LHDs spend their funds might account for differences in trends across outcomes. It is important to note that significant variability in LHD funding was shown within the study period. National trends and events occurring during the study period could influence public health funding. At the start of this period, LHDs suffered significant cuts with reductions in federal funding in the wake of the Great Recession. Toward the latter part of the study period, there were shifts in funding with the enactment of the Affordable Care Act. It may be possible that consistent long-term investment may have more considerable impact on the examined public health outcomes which may not be susceptible to immediate change.

Each NACCHO Profile Study provides total expenditures and revenue figures for the most recently completed fiscal year and the key variable in this study derives from the total expenditure figures. It was not within the scope of this paper to segment the revenue sources. Due to current data limitations, it is unclear how funding is invested in specific programs, services, and activities by each LHD. There is a need for more detailed and consistent LHD financial data to be collected nationally and over time to support analyses on optimal levels of public health resources to meaningfully impact public health measures. Future research requires better data and better research methods to disentangle the effect and provide more clarity on this important research question.

A key takeaway of this research is that more detailed data and robust research approaches are needed to effectively answer if increased LHD funding translates to improved public health. There is a need for more detailed and consistent LHD financial data to be collected nationally and over time to support analyses on optimal levels of public health resources to meaningfully impact public health measures. Single year data needs to be collected for a variety of public health outcomes. Likewise, research methods fully addressing the reverse causation bias are needed.

Results from the more robust approach of this study revealed that funding was not significantly predictive of better public health outcomes. Wider infrastructure change and improvements in public health practices may be needed (Erwin et al., 2011). Local health systems may see a greater impact in increasing funding to more efficient LHDs compared to those with higher rates. Increased LHD expenditures may allow public health agencies to provide more services or activities directed to public health improvement but increasing funding to deliver more services may not be an effective approach for LHD officials. Perhaps there is a case to be made for LHDs to use their central role in the system to marshal health partners toward common public health goals. Future research can assess how LHD expenditures drive the local public health system and identify the specific services where public health resources can be most effectively allocated to improve public health outcomes.

This study is timely given the continued funding challenges for public health infrastructure and services. This study also adds to the existing literature by employing robust quantitative approaches with the use of local-level cross-sectional and panel data and examining the variation in Public Health Services and Systems literature to determine if more public health funding translates to improved public health outcomes. Notably, the research methods have several strengths. First, the impact of LHD expenditures on public health measures are assessed using counties as the unit of analysis to focus on the important role of LHDs in the public health system. Second, multiple years of public health funding data are used rather than a pre-post comparison. Third, a set of public health measures at the local level are used and a broader range of potentially significant confounding variables are controlled. Fourth, robust regression models with varying lag structures are tested and differences in LHD funding and public health measures over time are observed. Fifth, the study establishes temporal ordering and ensures a higher degree of internal validity due to stronger causal inferences.

Limitations

Although this study offers valuable insight into the associations between public health funding and public health outcomes, the study had limitations. First, even within the longitudinal design, a clear link between public health funding and public health outcomes is not proven. Any association found between changes in LHD expenditures and changes in public health measures does not establish causality, and there is a potential for endogeneity. Second, the use of secondary data may not include all the relevant information for analysis. Third, selection bias is possibly introduced in the study with the differential loss to follow-up for LHDs not completing the NACCHO surveys during the study period. NACCHO data is self-reported and not independently verified, and the study population and the respondents are different for each wave of data

(NACCHO, 2020). Fourth, the use of clear and strict inclusion criteria can limit generalizability of results to other segments of the population.

Implications for Policy and Practice

- The study demonstrates that the mixed results from existing evidence can be explained by the different methodological approaches used and assesses how those approaches are able to reduce potential biases.
- The study highlights the need to control for omitted variable bias and reverse causation bias as other public health system components may influence the results, thus leading one to conclude that large expenditures explain better health outcomes.
- Important unobserved variables such as the efficiency of a local health department may drive public health outcomes and may be the main driver transforming increased expenditures into improved health outcomes.
- A key takeaway of this research is that more detailed data and robust research approaches are needed to effectively answer if increased LHD funding translates to improved public health.

CHAPTER VII

CONCLUSION

7.1. Conclusion

LHDs across the U.S. are extremely diverse in a variety of ways. As the front-line force responsible for providing essential public health services, LHDs have long played a central role in the local public health system. In recent times, more LHDs have become accredited and public health funding has become increasingly scarce. Public health accreditation and public health funding have the potential to transform the way LHDs deliver public health, but it is unclear if they are having their intended impact of public health improvement. It is vital to know what impact these public health practice decisions are having on the public health system. It is within that knowledge gap that this research assesses the impact of public health accreditation and public health funding from a local health system perspective. It is beneficial for LHDs to understand the impact of their efforts to better influence future decision-making. To better understand the impact that these public health practice decisions are having on the public health system, this dissertation employed a quantitative study design based on LHD and local level public health data. By investigating how LHD accreditation and funding impact outcomes, this dissertation could guide policymakers and others in decisions about LHD capacity being effectively aimed to protect and improve health outcomes. Data from the National Association of County and City Health Officials Profile Surveys, Public Health Accreditation Board, County Health Rankings Annual Reports, and the National Longitudinal Survey of Public Health Systems were used to conduct three studies:

1. The Impact of Public Health Accreditation on Public Health Outcomes
2. The Impact of Public Health Accreditation on the Effectiveness of Public Health Activities
3. The Impact of Public Health Funding on Public Health Outcomes, 2010-2019

Chapter IV examines the impact of public health accreditation on public health outcomes in the U.S. This chapter uses local level health outcomes panel data and a difference-in-difference methodology to quantify the difference in the change in public health outcomes across counties in Florida and control states, before and after obtaining public health accreditation. For communities with accredited LHDs in the state of Florida, public health accreditation was associated with decreases in diabetes prevalence and HIV prevalence compared to communities with unaccredited LHDs outside the state of Florida. This research provides a glimpse into whether accreditation is reaching its goal of public health improvement. This study suggests that public health accreditation can be a driver for health improvement and a catalyst to advance public health. The findings of this study can benefit LHD leadership considering the pursuit and adoption of accreditation as it is an effective method in improving public health.

Chapter V examines the impact of LHD public health accreditation on the effectiveness of essential public health activities provided by LHDs. This is the first study to use a quasi-experimental design with the use of a panel data difference-in-difference estimator to estimate the treatment effect between public health accreditation and the effectiveness of public health activities. The findings emphasize that public health accreditation does not lead to the improved effectiveness of public health activities. From the policy perspective, this study highlights that public health accreditation can be viewed as a starting point or one element that complements other performance improvement strategies to achieve a significant effect in the health system.

Chapter VI provides evidence on the impact of LHD expenditures on public health measures using counties as the unit of analysis. The primary objective of this chapter is to employ multivariate linear regression models with the use of local-level cross-sectional and panel data to examine whether increased LHD funding translates to public health benefits. Results from cross-sectional and pooled ordinary least squares models suggest that increased LHD expenditures was not associated with any of the public health outcomes studied. This chapter provides information on research designs that do not control for omitted variable bias or reverse causation bias which may lead one to conclude that large expenditures explain better health outcomes.

The contribution of LHDs in the health system will continue to play an increasing role in the future. Since performance expectations are high and public health funding is scarce, LHD leadership will continually be interested in finding the most effective ways of improving public health. This research can provide compelling and useful evidence for public health policy makers and management to conduct their work for the most public health impact. The implications of these findings suggest that public health accreditation and public health funding can be successful tools for public health practice if they are used as starting points and not as the sole solution to address public health problems. A similar conclusion is reached by Carman and Timsina (2015) when they contend that public health accreditation may be the vehicle LHDs use to improve operating environments and better manage resources (Carmen & Timsina, 2015). Public health accreditation and public health funding can be catalysts for public health improvement when used wisely. In and of themselves, they do not produce substantial improvements to the final outcomes. However, public health accreditation and public health funding can serve to impact other mechanisms, which ultimately impact the final outcomes.

7.2. Strengths

This research has several strengths. Robust quantitative research is used to help strengthen the evidence base around public health accreditation and public health funding. In this research, quasi-experimental designs are used for causal inference. The state of Florida's accreditation achievement as an integrated system is used as an intervention. Multiple intervention and control groups are assessed. Assumptions were rigorously tested to ensure that there was not any biased estimation of the causal effect. The study ensures a higher degree of internal validity due to stronger causal inferences. Longitudinal designs and cross-sectional designs are used to estimate relationships between variables of interest. The use of these approaches allows us to expound on the variation in results of existing literature on the topic. More granular research approaches are used to focus on the important role of LHDs in the local health system. Multiple years of the best available local level LHD data are used. A set of relevant public health measures are assessed at the local level. A broader range of potentially significant confounding variables are controlled in each study.

7.3. Limitations

Although this study uses the best available local level public health and LHD data, the data has limitations. The NACCHO data has several data restrictions, including gaps in years and the lack of segmented data on expenditures. LHD expenditures are earmarked for certain activities. It is difficult to assess the impact when the data does not provide information on specific activities. Not all local or state health departments take part in the surveys, and the study population and the respondents are different for each wave of data. Smaller LHDs with more limited capacity are less likely to participate in the surveys than those with greater capacity. Exclusion of LHDs with less capacity may result in an overestimation of capacity, resources, and performance in studies that use these datasets. Research findings can be restricted by the lack of a uniform chart of accounts to standardize expenditure information. Due to its self-reported nature, attrition and social desirability bias can occur. The use of County Health Rankings data may not provide all the necessary information to measure the effects of the intervention. Likewise, County Health Rankings data provide few public health outcomes with single year data. For the accreditation data, some of the states in the study use older accreditation versions. The 20 public health activities included in the NALSYS surveys do not represent a comprehensive and exhaustive set of activities required for effective local public health systems. The findings cannot be generalized beyond the 20 public health activities studied, and some of the evidence may overemphasize or underemphasize selected types of public health activities. The public health performance measures included in the survey do not capture possible variations in public health performance levels within local jurisdictions.

Research results should also be interpreted with the knowledge of the following limitations. Our control variables focused on the world of public health with political and administrative variables absent in the analysis. Associations found in the analysis may be influenced by ideology factors or fragmentation at the county level. The study findings may not be generalizable to other settings. The quasi-experimental nature of the analysis attempts to establish causality with observational data. With the use of observational data, the possibility of selection and information bias is introduced. With this design, random assignment is not able to be done. For the study that employs a longitudinal design, any associations found do not establish causality, and there is a potential for endogeneity. The use of secondary data may not include all the relevant information for analysis.

7.4. Further Research

This dissertation can pave the way for other research interested in further assessing the impact of public health accreditation and public health funding. Building on the study in Chapter VI, future research can assess other public health outcomes at the local level. The study in Chapter V can facilitate further research exploring the utility of public health accreditation as a performance improvement method for public health improvement. Building on the study in Chapter VI, future research can also assess how LHD expenditures drive the local public health system and identify the specific services where public health resources can be most effectively allocated to improve public health outcomes. Future studies would benefit from controlling for non-public health variables such as local political or administrative driver variables.

Better data is needed to conduct robust analyses. For example, single year data needs to be collected for a variety of public health outcomes. There is a need for more detailed and consistent LHD financial data to be collected nationally and over time to support analyses on optimal levels of public health resources to meaningfully impact public health measures. Likewise, future research requires better research methods, such as the use of quasi-experimental designs, to be able to disentangle the complex impact of accreditation and funding.

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APPENDICES

Results for Study 1: The Effect of Public Health Accreditation on Public Health Outcomes
Specification (1) Accredited LHDs in Florida and unaccredited LHDs in Non-Florida states

Regression results

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	0	.001	0.37	.716	-.002	.003	
Primary care physicians	3.619	2.211	1.64	.108	-.824	8.061	
Preventable hospitalizations	0	0	-0.68	.498	0	0	
High school	.001	.004	0.21	.837	-.007	.008	
Unemployed	.011	.013	0.87	.388	-.014	.037	
Poverty	.006	.008	0.72	.477	-.01	.022	
Uninsured	-.009	.006	-1.45	.153	-.022	.003	
Median income	0	0	-0.29	.77	0	0	
Population	0	0	0.25	.802	0	0	
Age	.002	.012	0.16	.871	-.022	.026	
Race	-.008	.025	-0.32	.749	-.059	.042	
Hispanic	.012	.027	0.46	.651	-.041	.066	
Year 2014	0	.	.	.	.	.	
Year 2015	.002	0	3.52	.001	.001	.003	***
Year 2016	.004	.001	5.30	0	.003	.006	***
Year 2017	.006	.002	3.16	.003	.002	.009	***
Year 2018	.01	.002	6.06	0	.007	.013	***
Year 2019	.016	.002	9.58	0	.013	.02	***
Year 2020	.025	.001	16.87	0	.022	.028	***
Year 2021	.032	.002	18.59	0	.029	.036	***
Constant	.305	.007	41.43	0	.29	.319	***

Mean dependent var	0.319	SD dependent var	0.048
R-squared	0.209	Number of obs	20125.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-98566.870	Bayesian crit. (BIC)	-98424.495

**** p<.01, ** p<.05, * p<.1*

Regression results

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	5.424	6.207	0.87	.386	-7.049	17.897	
Primary care physicians	20283.464	9641.606	2.10	.041	907.931	39658.997	**
Preventable hospitalizations	0	0	-0.42	.673	-.001	.001	
High school	-9.686	15.331	-0.63	.53	-40.495	21.122	
Unemployed	2.681	39.26	0.07	.946	-76.216	81.577	
Poverty	20.565	42.88	0.48	.634	-65.606	106.737	
Uninsured	-41.701	30.877	-1.35	.183	-103.75	20.349	
Median income	0	0	1.15	.257	0	.001	
Population	0	0	0.19	.851	0	0	
Age	-86.116	53.375	-1.61	.113	-193.378	21.146	
Race	57.74	100.08	0.58	.567	-143.378	258.858	
Hispanic	-46.763	79.004	-0.59	.557	-205.528	112.003	
Year 2014	0	.	.	.	.	.	
Year 2015	14.401	3.925	3.67	.001	6.514	22.288	***
Year 2016	-4.979	9.876	-0.50	.616	-24.825	14.867	
Year 2017	8.861	7.011	1.26	.212	-5.229	22.95	
Year 2018	11.647	10.842	1.07	.288	-10.141	33.434	
Year 2019	30.859	7.338	4.21	0	16.112	45.606	***
Year 2020	50.325	5.894	8.54	0	38.48	62.169	***
Year 2021	60.578	6.902	8.78	0	46.707	74.449	***
Constant	359.792	25.121	14.32	0	309.31	410.274	***

Mean dependent var	377.668	SD dependent var	247.805
R-squared	0.083	Number of obs	19882.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	226674.898	Bayesian crit. (BIC)	226817.054

*** *p<.01, ** p<.05, * p<.1*

Regression results

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	**-.001**	**0**	**-2.39**	**.021**	**-.001**	**0**	**
Primary care physicians	-1.815	1.754	-1.04	.306	-5.339	1.709	
Preventable hospitalizations	0	0	-2.96	.005	0	0	***
High school	.016	.004	3.89	0	.008	.024	***
Unemployed	-.08	.02	-4.03	0	-.12	-.04	***
Poverty	.029	.014	2.13	.038	.002	.057	**
Uninsured	-.096	.018	-5.34	0	-.132	-.06	***
Median income	0	0	-5.26	0	0	0	***
Population	0	0	2.73	.009	0	0	***
Age	-.081	.029	-2.84	.007	-.139	-.024	***
Race	.101	.031	3.20	.002	.037	.164	***
Hispanic	.296	.056	5.27	0	.183	.408	***
Year 2014	0	.	.	.	.	.	
Year 2015	0	0	-0.89	.376	-.001	0	
Year 2016	-.001	0	-1.38	.173	-.001	0	
Year 2017	0	0	0.17	.868	-.001	.001	
Year 2018	0	0	-0.43	.669	-.001	.001	
Year 2019	0	0	0.03	.974	-.001	.001	
Year 2020	0	0	0.71	.484	-.001	.001	
Year 2021	0	0	0.59	.559	-.001	.001	
Constant	.119	.011	11.22	0	.098	.14	***

Mean dependent var	0.114	SD dependent var	0.028
R-squared	0.067	Number of obs	20126.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-111277.457	Bayesian crit. (BIC)	-111135.082

**** p<.01, ** p<.05, * p<.1*

Regression results

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	**-3.02**	**.662**	**-4.56**	**0**	**-4.349**	**-1.69**	***
Primary care physicians	7445.062	4708.132	1.58	.12	-2016.283	16906.406	
Preventable hospitalizations	.001	0	2.46	.017	0	.002	**
High school	55.822	19.667	2.84	.007	16.3	95.344	***
Unemployed	-150.529	76.183	-1.98	.054	-303.626	2.567	*
Poverty	-44.686	40.387	-1.11	.274	-125.847	36.475	
Uninsured	10.038	50.929	0.20	.845	-92.308	112.385	
Median income	0	0	-1.57	.123	-.001	0	
Population	0	0	2.59	.012	0	0	**
Age	287.233	142.686	2.01	.05	.494	573.972	**
Race	826.857	259.117	3.19	.002	306.141	1347.573	***
Hispanic	646.455	209.421	3.09	.003	225.608	1067.303	***
Year 2014	0	.	.	.	.	.	
Year 2015	-1.939	1.251	-1.55	.127	-4.452	.574	
Year 2016	1.506	.973	1.55	.128	-.449	3.461	
Year 2017	-4.061	1.744	-2.33	.024	-7.565	-.556	**
Year 2018	-3.364	1.386	-2.43	.019	-6.149	-.578	**
Year 2019	-2.157	1.529	-1.41	.165	-5.23	.915	
Year 2020	-1.941	1.483	-1.31	.197	-4.922	1.039	
Year 2021	-2.493	1.434	-1.74	.089	-5.375	.39	*
Constant	-29.632	58.121	-0.51	.612	-146.431	87.168	

Mean dependent var	186.997	SD dependent var	208.559
R-squared	0.059	Number of obs	17077.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	184004.423	Bayesian crit. (BIC)	184143.842

*** *p<.01*, ** *p<.05*, * *p<.1*

Specification 1.2: Accredited LHDs in Florida and unaccredited LHDs in ten similar states

Regression results

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.003	.002	1.88	.09	-.001	.007	*
Primary care physicians	2.613	5.071	0.52	.618	-8.686	13.911	
Preventable hospitalizations	0	0	0.55	.596	0	0	
High school	-.006	.005	-1.36	.205	-.016	.004	
Unemployed	.003	.02	0.17	.869	-.041	.048	
Poverty	0	.012	0.00	.999	-.028	.028	
Uninsured	-.012	.017	-0.71	.496	-.05	.026	
Median income	0	0	-0.70	.498	0	0	
Population	0	0	-0.04	.97	0	0	
Age	-.017	.013	-1.25	.24	-.047	.013	
Race	-.027	.034	-0.79	.448	-.103	.049	
Hispanic	.009	.04	0.22	.828	-.08	.098	
Year 2014	0	.	.	.	.	.	
Year 2015	.002	.001	2.06	.067	0	.005	*
Year 2016	.004	.001	3.55	.005	.002	.007	***
Year 2017	.002	.003	0.49	.635	-.006	.009	
Year 2018	.005	.003	2.01	.072	-.001	.011	*
Year 2019	.011	.003	3.86	.003	.005	.017	***
Year 2020	.024	.003	7.54	0	.017	.032	***
Year 2021	.03	.004	8.34	0	.022	.038	***
Constant	.316	.015	20.52	0	.282	.35	***

Mean dependent var	0.313	SD dependent var	0.046
R-squared	0.172	Number of obs	7152.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-33754.769	Bayesian crit. (BIC)	-33686.017

**** p<.01, ** p<.05, * p<.1*

Regression results

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	10.424	11.683	0.89	.393	-15.608	36.457	
Primary care physicians	-4482.091	19278.524	-0.23	.821	-47437.319	38473.137	
Preventable hospitalizations	0	.001	-0.07	.949	-.002	.002	
High school	14.195	13.02	1.09	.301	-14.816	43.205	
Unemployed	-50.181	63.774	-0.79	.45	-192.279	91.916	
Poverty	-11.361	80.515	-0.14	.891	-190.76	168.037	
Uninsured	44.234	44.454	1.00	.343	-54.815	143.283	
Median income	.001	0	2.24	.049	0	.001	**
Population	0	0	0.03	.98	0	0	
Age	-193.392	86.128	-2.25	.049	-385.298	-1.487	**
Race	-36.101	111.372	-0.32	.753	-284.253	212.051	
Hispanic	-136.873	53.391	-2.56	.028	-255.834	-17.911	**
Year 2014	0	.	.	.	.	.	
Year 2015	10.15	5.429	1.87	.091	-1.947	22.247	*
Year 2016	-17.721	19.213	-0.92	.378	-60.531	25.088	
Year 2017	-3.77	10.058	-0.37	.716	-26.18	18.64	
Year 2018	2.584	21.573	0.12	.907	-45.484	50.653	
Year 2019	23.516	11.437	2.06	.067	-1.968	49	*
Year 2020	40.21	8.649	4.65	.001	20.938	59.481	***
Year 2021	51.633	11.784	4.38	.001	25.376	77.89	***
Constant	396.705	30.212	13.13	0	329.388	464.022	***

Mean dependent var	398.600	SD dependent var	219.653
R-squared	0.076	Number of obs	7123.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	81896.093	Bayesian crit. (BIC)	81964.804

**** p<.01, ** p<.05, * p<.1*

Regression results

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.001	0	-1.43	.182	-.002	0	
Primary care physicians	-5.839	4.429	-1.32	.217	-15.708	4.03	
Preventable hospitalizations	0	0	-0.64	.538	0	0	
High school	.018	.008	2.27	.047	0	.036	**
Unemployed	-.042	.04	-1.05	.32	-.13	.047	
Poverty	.019	.02	0.94	.367	-.026	.064	
Uninsured	-.135	.039	-3.50	.006	-.221	-.049	***
Median income	0	0	-2.73	.021	0	0	**
Population	0	0	1.33	.212	0	0	
Age	-.107	.05	-2.13	.059	-.219	.005	*
Race	.07	.045	1.55	.152	-.031	.171	
Hispanic	.287	.058	4.95	.001	.158	.416	***
Year 2014	0	.	.	.	.	.	
Year 2015	-.001	0	-1.82	.099	-.002	0	*
Year 2016	-.001	.001	-1.06	.313	-.002	.001	
Year 2017	.001	.001	1.41	.19	0	.002	
Year 2018	-.001	0	-1.82	.098	-.001	0	*
Year 2019	0	.001	0.53	.608	-.001	.002	
Year 2020	.001	0	2.26	.047	0	.002	**
Year 2021	0	.001	0.21	.837	-.001	.002	
Constant	.131	.02	6.71	0	.088	.175	***

Mean dependent var	0.119	SD dependent var	0.028
R-squared	0.068	Number of obs	7152.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-37605.182	Bayesian crit. (BIC)	-37536.431

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-2.312	1.475	-1.57	.148	-5.599	.975	
Primary care physicians	6447.411	13560.915	0.48	.645	-23768.19	36663.012	
Preventable hospitalizations	0	.001	0.54	.602	-.001	.002	
High school	45.39	28.508	1.59	.142	-18.13	108.91	
Unemployed	-384.689	97.572	-3.94	.003	-602.093	-167.284	***
Poverty	-105.101	65.476	-1.61	.14	-250.991	40.788	
Uninsured	188.814	90.715	2.08	.064	-13.313	390.941	*
Median income	0	.001	0.04	.967	-.001	.001	
Population	0	0	1.74	.113	0	0	
Age	74.274	259.518	0.29	.781	-503.968	652.516	
Race	1114.679	406.479	2.74	.021	208.988	2020.371	**
Hispanic	1122.188	193.551	5.80	0	690.931	1553.446	***
Year 2014	0	.	.	.	.	.	
Year 2015	-2.739	3.225	-0.85	.415	-9.924	4.445	
Year 2016	3.873	1.836	2.11	.061	-.217	7.964	*
Year 2017	-6.336	3.355	-1.89	.088	-13.811	1.138	*
Year 2018	-6.331	2.597	-2.44	.035	-12.117	-.544	**
Year 2019	-5.4	3.303	-1.64	.133	-12.759	1.959	
Year 2020	-4.643	2.963	-1.57	.148	-11.244	1.958	
Year 2021	-.945	2.531	-0.37	.717	-6.585	4.696	
Constant	-105.264	115.806	-0.91	.385	-363.295	152.768	

Mean dependent var	233.412	SD dependent var	242.810
R-squared	0.057	Number of obs	6616.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	75231.805	Bayesian crit. (BIC)	75299.777

**** p<.01, ** p<.05, * p<.1*

Specification 3: Accredited LHDs in Florida and accredited LHDs in ten similar states

Regression results

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.016	.014	-1.13	.34	-.059	.028	
Primary care physicians	1.738	6.2	0.28	.797	-17.993	21.47	
Preventable hospitalizations	0	0	0.23	.833	0	0	
High school	-.012	.001	-10.96	.002	-.016	-.009	***
Unemployed	.003	.013	0.24	.826	-.039	.046	
Poverty	.003	.002	1.43	.249	-.003	.009	
Uninsured	-.021	.017	-1.23	.306	-.077	.034	
Median income	0	0	-2.51	.087	0	0	*
Population	0	0	-12.07	.001	0	0	***
Age	.005	0	26.46	0	.004	.006	***
Race	.069	.06	1.14	.336	-.123	.261	
Hispanic	.057	.02	2.81	.067	-.007	.122	*
Year 2014	0	.	.	.	.	.	
Year 2015	.001	.001	1.53	.223	-.001	.004	
Year 2016	.016	.013	1.20	.317	-.027	.059	
Year 2017	.015	.014	1.14	.339	-.028	.058	
Year 2018	.016	.013	1.16	.33	-.027	.058	
Year 2019	.025	.014	1.83	.165	-.018	.068	
Year 2020	.014	.001	15.13	.001	.011	.017	***
Year 2021	.019	0	54.35	0	.018	.02	***
Constant	.305	.006	50.22	0	.286	.324	***

Mean dependent var	0.302	SD dependent var	0.052
R-squared	0.225	Number of obs	535.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-3069.759	Bayesian crit. (BIC)	-3056.912

**** p<.01, ** p<.05, * p<.1*

Regression results

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-24.349	16.28	-1.50	.232	-76.159	27.462	
Primary care physicians	-59553.568	1334.211	-44.64	0	-63799.621	-55307.514	***
Preventable hospitalizations	0	0	1.41	.254	-.001	.001	
High school	25.633	8.435	3.04	.056	-1.212	52.477	*
Unemployed	10.651	4.572	2.33	.102	-3.898	25.201	
Poverty	-151.53	19.283	-7.86	.004	-212.896	-90.164	***
Uninsured	69.058	15.664	4.41	.022	19.208	118.908	**
Median income	0	0	0.36	.742	-.001	.001	
Population	0	0	1.92	.151	0	0	
Age	-265.638	12.696	-20.92	0	-306.041	-225.235	***
Race	-843.698	49.237	-17.14	0	-1000.391	-687.005	***
Hispanic	-174.091	25.723	-6.77	.007	-255.952	-92.23	***
Year 2014	0	.	.	.	.	.	
Year 2015	-.919	.71	-1.29	.286	-3.178	1.34	
Year 2016	8.125	15.501	0.52	.636	-41.206	57.456	
Year 2017	15.277	15.858	0.96	.406	-35.192	65.745	
Year 2018	40.252	16.685	2.41	.095	-12.847	93.35	*
Year 2019	48.493	16.588	2.92	.061	-4.297	101.284	*
Year 2020	31.048	.345	89.97	0	29.95	32.147	***
Year 2021	43.142	2.594	16.63	0	34.888	51.397	***
Constant	603.76	16.175	37.33	0	552.284	655.235	***

Mean dependent var	397.888	SD dependent var	151.467
R-squared	0.151	Number of obs	535.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	5706.581	Bayesian crit. (BIC)	5719.427

*** $p<.01$, ** $p<.05$, * $p<.1$

Regression results

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	0	.005	-0.07	.946	-.018	.017	
Primary care physicians	1.859	.811	2.29	.106	-.722	4.439	
Preventable hospitalizations	0	0	-15.39	.001	0	0	***
High school	-.001	.005	-0.31	.774	-.016	.013	
Unemployed	-.032	.002	-13.26	.001	-.04	-.025	***
Poverty	.042	.005	9.27	.003	.027	.056	***
Uninsured	-.15	.014	-11.03	.002	-.193	-.107	***
Median income	0	0	-7.82	.004	0	0	***
Population	0	0	-5.94	.01	0	0	***
Age	-.067	.002	-32.09	0	-.074	-.061	***
Race	.089	.073	1.22	.311	-.143	.321	
Hispanic	.174	.029	6.11	.009	.084	.265	***
Year 2014	0	.	.	.	.	.	
Year 2015	-.002	.001	-3.43	.042	-.004	0	**
Year 2016	-.001	.006	-0.26	.811	-.019	.016	
Year 2017	.002	.006	0.31	.777	-.017	.021	
Year 2018	-.004	.005	-0.65	.564	-.021	.014	
Year 2019	-.001	.005	-0.23	.832	-.019	.016	
Year 2020	-.001	0	-2.81	.067	-.002	0	*
Year 2021	.001	0	2.83	.066	0	.003	*
Constant	.163	.006	27.49	0	.144	.182	***

Mean dependent var	0.118	SD dependent var	0.021
R-squared	0.150	Number of obs	535.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-3268.364	Bayesian crit. (BIC)	-3255.517

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-10.182	11.892	-0.86	.455	-48.028	27.664	
Primary care physicians	-15417.728	7521.416	-2.05	.133	-39354.229	8518.774	
Preventable hospitalizations	-.003	0	-9.01	.003	-.004	-.002	***
High school	82.173	1.25	65.74	0	78.195	86.151	***
Unemployed	-719.562	58.926	-12.21	.001	-907.092	-532.032	***
Poverty	145.554	35.962	4.05	.027	31.108	260.001	**
Uninsured	533.373	14.54	36.68	0	487.101	579.645	***
Median income	-.001	0	-4.99	.015	-.002	0	**
Population	0	0	0.94	.418	0	0	
Age	477.403	44.768	10.66	.002	334.932	619.875	***
Race	2078.53	85.068	24.43	0	1807.805	2349.255	***
Hispanic	1115.192	27.693	40.27	0	1027.062	1203.323	***
Year 2014	0	.	.	.	.	.	
Year 2015	.159	2.523	0.06	.954	-7.869	8.187	
Year 2016	21.81	9.257	2.36	.1	-7.65	51.27	*
Year 2017	-19.687	11.662	-1.69	.19	-56.801	17.428	
Year 2018	7.985	11.285	0.71	.53	-27.93	43.9	
Year 2019	12.595	11.505	1.09	.354	-24.02	49.209	
Year 2020	-2.373	2.626	-0.90	.433	-10.731	5.985	
Year 2021	9.11	.647	14.08	.001	7.051	11.17	***
Constant	-216.338	21.654	-9.99	.002	-285.252	-147.424	***

Mean dependent var	441.785	SD dependent var	379.409
R-squared	0.071	Number of obs	534.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	6344.352	Bayesian crit. (BIC)	6357.193

**** p<.01, ** p<.05, * p<.1*

Specification 4: Accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states.

Regression results

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.002	.001	1.47	.149	-.001	.004	
Primary care physicians	4.62	2.199	2.10	.041	.201	9.038	**
Preventable hospitalizations	0	0	-0.55	.586	0	0	
High school	.004	.004	1.04	.302	-.004	.012	
Unemployed	.014	.013	1.06	.292	-.012	.039	
Poverty	.005	.008	0.60	.555	-.011	.02	
Uninsured	-.006	.006	-1.10	.279	-.018	.005	
Median income	0	0	-0.40	.694	0	0	
Population	0	0	0.47	.643	0	0	
Age	.005	.014	0.35	.729	-.023	.033	
Race	-.005	.024	-0.22	.826	-.054	.043	
Hispanic	.006	.027	0.22	.825	-.048	.06	
Year 2014	0	.	.	.	.	.	
Year 2015	.002	.001	3.14	.003	.001	.003	***
Year 2016	.004	.001	4.94	0	.002	.006	***
Year 2017	.006	.002	3.21	.002	.002	.009	***
Year 2018	.01	.002	6.19	0	.007	.013	***
Year 2019	.016	.002	9.46	0	.013	.02	***
Year 2020	.025	.001	17.85	0	.022	.028	***
Year 2021	.032	.002	18.74	0	.029	.036	***
Constant	.299	.007	42.38	0	.285	.313	***

Mean dependent var	0.318	SD dependent var	0.049
R-squared	0.213	Number of obs	21171.000
F-test	59.065	Prob > F	0.000
Akaike crit. (AIC)	-103867.237	Bayesian crit. (BIC)	-103715.990

**** p<.01, ** p<.05, * p<.1*

Regression results

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	6.12	4.973	1.23	.224	-3.873	16.114	
Primary care physicians	20349.694	9281.903	2.19	.033	1697.012	39002.376	**
Preventable hospitalizations	0	0	-0.62	.537	-.001	.001	
High school	-13.383	14.498	-0.92	.36	-42.518	15.752	
Unemployed	-8.378	37.988	-0.22	.826	-84.718	67.962	
Poverty	29.935	41.014	0.73	.469	-52.485	112.355	
Uninsured	-46.085	29.597	-1.56	.126	-105.561	13.392	
Median income	0	0	1.79	.08	0	.001	*
Population	0	0	-0.05	.957	0	0	
Age	-97.998	51.558	-1.90	.063	-201.608	5.613	*
Race	89.578	95.207	0.94	.351	-101.748	280.903	
Hispanic	-40.001	79.426	-0.50	.617	-199.615	119.612	
Year 2014	0	.	.	.	.	.	
Year 2015	14.634	3.783	3.87	0	7.032	22.237	***
Year 2016	-3.475	9.783	-0.36	.724	-23.135	16.185	
Year 2017	10.704	6.926	1.55	.129	-3.213	24.622	
Year 2018	13.741	10.741	1.28	.207	-7.844	35.326	
Year 2019	33.135	7.254	4.57	0	18.558	47.712	***
Year 2020	53.601	5.939	9.03	0	41.666	65.536	***
Year 2021	63.915	7.052	9.06	0	49.743	78.087	***
Constant	356.011	23.368	15.23	0	309.051	402.971	***

Mean dependent var	379.042	SD dependent var	246.784
R-squared	0.092	Number of obs	20926.000
F-test	28.364	Prob > F	0.000
Akaike crit. (AIC)	238080.320	Bayesian crit. (BIC)	238231.346

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	0	.001	-0.56	.579	-.001	.001	
Primary care physicians	-1.771	1.617	-1.10	.279	-5.02	1.478	
Preventable hospitalizations	0	0	-2.96	.005	0	0	***
High school	.017	.004	4.49	0	.01	.025	***
Unemployed	-.08	.019	-4.16	0	-.119	-.041	***
Poverty	.031	.014	2.22	.031	.003	.06	**
Uninsured	-.093	.018	-5.28	0	-.129	-.058	***
Median income	0	0	-4.04	0	0	0	***
Population	0	0	3.32	.002	0	0	***
Age	-.091	.032	-2.86	.006	-.154	-.027	***
Race	.106	.032	3.29	.002	.041	.171	***
Hispanic	.299	.055	5.49	0	.19	.409	***
Year 2014	0	.	.	.	.	.	
Year 2015	0	0	-0.84	.403	-.001	0	
Year 2016	-.001	0	-1.35	.182	-.001	0	
Year 2017	0	0	-0.05	.957	-.001	.001	
Year 2018	0	0	0.00	.997	-.001	.001	
Year 2019	0	0	0.15	.882	-.001	.001	
Year 2020	0	0	0.64	.527	-.001	.001	
Year 2021	0	0	0.52	.603	-.001	.001	
Constant	.113	.01	11.13	0	.092	.133	***

Mean dependent var	0.113	SD dependent var	0.028
R-squared	0.068	Number of obs	21172.000
F-test	28.179	Prob > F	0.000
Akaike crit. (AIC)	-117695.932	Bayesian crit. (BIC)	-117544.684

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	1.537	2.068	0.74	.461	-2.619	5.692	
Primary care physicians	5257.066	4547.04	1.16	.253	-3880.553	14394.685	
Preventable hospitalizations	.001	0	3.38	.001	0	.002	***
High school	60.795	18.644	3.26	.002	23.329	98.261	***
Unemployed	-118.828	80.638	-1.47	.147	-280.876	43.221	
Poverty	-65.613	40.371	-1.63	.111	-146.742	15.517	
Uninsured	-2.265	44.372	-0.05	.959	-91.434	86.904	
Median income	-.001	0	-2.08	.042	-.001	0	**
Population	0	0	3.21	.002	0	0	***
Age	347.192	157.126	2.21	.032	31.434	662.949	**
Race	820.19	267.612	3.06	.004	282.404	1357.976	***
Hispanic	660.888	201.988	3.27	.002	254.978	1066.797	***
Year 2014	0	.	.	.	.	.	
Year 2015	-2.053	1.123	-1.83	.074	-4.31	.203	*
Year 2016	.346	.819	0.42	.674	-1.299	1.991	
Year 2017	-3.657	1.651	-2.22	.031	-6.975	-.34	**
Year 2018	-3.249	1.225	-2.65	.011	-5.711	-.786	**
Year 2019	-2.443	1.395	-1.75	.086	-5.246	.36	*
Year 2020	-1.91	1.399	-1.37	.178	-4.721	.901	
Year 2021	-2.846	1.333	-2.14	.038	-5.524	-.168	**
Constant	-29.079	57.421	-0.51	.615	-144.472	86.314	

Mean dependent var	179.995	SD dependent var	198.943
R-squared	0.069	Number of obs	18060.000
F-test	18.629	Prob > F	0.000
Akaike crit. (AIC)	192441.034	Bayesian crit. (BIC)	192589.261

*** *p<.01*, ** *p<.05*, * *p<.1*

Results for Study 2: The Effect of Public Health Accreditation on the Effectiveness of Public Health Activities
Specification 1: Accredited LHDs in Florida and unaccredited LHDs in Non-Florida states

Regression results

Effectiveness of Assessment Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	0	.033	-0.00	.998	-.067	.067	
Primary care physicians	-10.086	117.72	-0.09	.932	-246.778	226.606	
Prevent hospitalizations	0	.001	-0.24	.813	-.002	.002	
High school	-.106	.247	-0.43	.671	-.602	.391	
Unemployed	-.016	.997	-0.02	.987	-2.02	1.987	
Poverty	.513	.308	1.66	.103	-.107	1.132	
Uninsured	.124	.36	0.35	.731	-.599	.847	
Median income	0	0	1.82	.076	0	0	*
Population	0	0	-0.79	.433	0	0	
Age	-.072	1.426	-0.05	.96	-2.938	2.795	
Race	-1.881	1.991	-0.94	.35	-5.885	2.122	
Hispanic	-2.111	1.908	-1.11	.274	-5.946	1.725	
Year 2014	0	.	.	.	.	.	
Year 2016	.005	.031	0.15	.884	-.059	.068	
Year 2018	-.007	.058	-0.12	.906	-.123	.11	
Constant	.615	.436	1.41	.165	-.261	1.491	

Mean dependent var	0.519	SD dependent var	0.202
R-squared	0.021	Number of obs	1166.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-2211.586	Bayesian crit. (BIC)	-2145.789

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Policy Development Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.057	.038	-1.50	.141	-.133	.019	
Primary care physicians	26.352	78.425	0.34	.738	-131.42	184.123	
Prevent hospitalizations	0	.001	-0.48	.634	-.002	.001	
High school	-.048	.263	-0.18	.855	-.577	.481	
Unemployed	1.615	.771	2.09	.042	.063	3.167	**
Poverty	-.136	.298	-0.46	.651	-.735	.464	
Uninsured	-.662	.477	-1.39	.171	-1.62	.297	
Median income	0	0	2.49	.016	0	0	**
Population	0	0	0.88	.385	0	0	
Age	-.276	2.083	-0.13	.895	-4.466	3.913	
Race	-3.011	2.569	-1.17	.247	-8.178	2.157	
Hispanic	.506	2.281	0.22	.825	-4.084	5.095	
Year 2014	0	.	.	.	.	.	
Year 2016	.022	.039	0.57	.574	-.056	.099	
Year 2018	-.058	.079	-0.73	.468	-.218	.101	
Constant	.037	.651	0.06	.954	-1.272	1.347	

Mean dependent var	0.373	SD dependent var	0.215
R-squared	0.050	Number of obs	1121.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-2009.481	Bayesian crit. (BIC)	-1944.195

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

Effectiveness of Assurance Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	**-.113**	**.022**	**-5.08**	**0**	**-.158**	**-.069**	*****
Primary care physicians	-39.461	119.428	-0.33	.743	-279.586	200.664	
Prevent hospitalizations	.002	.001	1.89	.064	0	.003	*
High school	.102	.272	0.38	.708	-.444	.649	
Unemployed	.233	1.032	0.23	.822	-1.841	2.307	
Poverty	.64	.531	1.21	.234	-.427	1.707	
Uninsured	-.706	.495	-1.43	.16	-1.702	.29	
Median income	0	0	0.87	.386	0	0	
Population	0	0	-0.12	.905	0	0	
Age	1.099	2.733	0.40	.689	-4.395	6.593	
Race	-4.69	2.239	-2.09	.041	-9.191	-.189	**
Hispanic	-.894	1.931	-0.46	.645	-4.776	2.988	
Year 2014	0	.	.	.	.	.	
Year 2016	.029	.038	0.75	.456	-.048	.106	
Year 2018	-.014	.079	-0.18	.861	-.173	.146	
Constant	.257	.635	0.40	.688	-1.021	1.534	

Mean dependent var	0.356	SD dependent var	0.236
R-squared	0.026	Number of obs	1152.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-1550.040	Bayesian crit. (BIC)	-1484.400

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Total Public Health Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.054	.031	-1.73	.091	-.116	.009	*
Primary care physicians	-5.716	77.7	-0.07	.942	-162.027	150.596	
Prevent hospitalizations	0	.001	0.11	.913	-.001	.002	
High school	-.008	.228	-0.03	.973	-.466	.451	
Unemployed	.568	.737	0.77	.445	-.914	2.049	
Poverty	.063	.283	0.22	.823	-.505	.632	
Uninsured	-.26	.408	-0.64	.528	-1.081	.561	
Median income	0	0	2.26	.028	0	0	**
Population	0	0	0.83	.411	0	0	
Age	.981	1.716	0.57	.57	-2.47	4.433	
Race	-2.5	1.944	-1.29	.205	-6.411	1.41	
Hispanic	.561	1.756	0.32	.751	-2.971	4.094	
Year 2014	0	.	.	.	.	.	
Year 2016	-.009	.032	-0.29	.774	-.074	.056	
Year 2018	-.073	.066	-1.10	.275	-.206	.06	
Constant	-.078	.491	-0.16	.875	-1.065	.909	

Mean dependent var	0.413	SD dependent var	0.188
R-squared	0.035	Number of obs	1047.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-2303.516	Bayesian crit. (BIC)	-2239.118

**** p<.01, ** p<.05, * p<.1*

Specification 1.2: Accredited LHDs in Florida and unaccredited LHDs in ten similar states

Regression results

Effectiveness of Assessment Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.019	.055	-0.34	.744	-.142	.105	
Primary care physicians	-72.22	206.31	-0.35	.734	-531.908	387.467	
Prevent hospitalizations	-.002	.003	-0.59	.566	-.007	.004	
High school	.354	.361	0.98	.35	-.45	1.158	
Unemployed	.277	2.088	0.13	.897	-4.375	4.929	
Poverty	.742	.535	1.39	.195	-.449	1.933	
Uninsured	-.776	.678	-1.14	.279	-2.286	.735	
Median income	0	0	1.84	.096	0	0	*
Population	0	0	-0.98	.352	0	0	
Age	.712	2.472	0.29	.779	-4.795	6.22	
Race	-1.475	3.626	-0.41	.693	-9.554	6.603	
Hispanic	-.627	2.608	-0.24	.815	-6.437	5.183	
Year 2014	0	.	.	.	.	.	
Year 2016	-.035	.063	-0.56	.59	-.175	.105	
Year 2018	-.146	.088	-1.66	.128	-.342	.05	
Constant	.284	.709	0.40	.697	-1.296	1.864	

Mean dependent var	0.568	SD dependent var	0.201
R-squared	0.057	Number of obs	406.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-774.937	Bayesian crit. (BIC)	-734.873

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Policy Development Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.032	.04	-0.79	.449	-.121	.058	
Primary care physicians	-.042	172.623	-0.00	1	-384.67	384.586	
Prevent hospitalizations	-.002	.002	-1.19	.262	-.006	.002	
High school	-.151	.692	-0.22	.832	-1.694	1.392	
Unemployed	1.678	1.982	0.85	.417	-2.737	6.094	
Poverty	.489	.638	0.77	.461	-.932	1.91	
Uninsured	-2.058	.879	-2.34	.041	-4.016	-.1	**
Median income	0	0	2.52	.03	0	0	**
Population	0	0	-0.28	.788	0	0	
Age	-1.535	5.446	-0.28	.784	-13.669	10.599	
Race	-6.547	3.739	-1.75	.111	-14.879	1.784	
Hispanic	-.633	2.673	-0.24	.817	-6.588	5.322	
Year 2014	0	.	.	.	.	.	
Year 2016	.043	.068	0.63	.541	-.108	.195	
Year 2018	-.164	.123	-1.33	.212	-.439	.111	
Constant	1.016	.829	1.22	.249	-.832	2.863	

Mean dependent var	0.426	SD dependent var	0.222
R-squared	0.153	Number of obs	389.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-670.103	Bayesian crit. (BIC)	-630.467

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

Effectiveness of Assurance Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	**-.112**	**.019**	**-5.98**	**0**	**-.153**	**-.07**	*******
Primary care physicians	-12.389	147.238	-0.08	.935	-340.457	315.678	
Prevent hospitalizations	.001	.001	1.27	.232	-.001	.004	
High school	.496	.8	0.62	.549	-1.288	2.28	
Unemployed	-.049	1.893	-0.03	.98	-4.267	4.169	
Poverty	1.366	.968	1.41	.188	-.79	3.523	
Uninsured	-1.032	.899	-1.15	.277	-3.035	.97	
Median income	0	0	1.04	.323	0	0	
Population	0	0	-1.58	.146	0	0	
Age	-2.912	7.368	-0.40	.701	-19.329	13.504	
Race	-8.686	3.935	-2.21	.052	-17.454	.082	*
Hispanic	-.074	2.064	-0.04	.972	-4.673	4.525	
Year 2014	0	.	.	.	.	.	
Year 2016	.05	.043	1.17	.27	-.046	.146	
Year 2018	.014	.1	0.14	.892	-.209	.237	
Constant	1.175	.986	1.19	.261	-1.021	3.371	

Mean dependent var	0.412	SD dependent var	0.239
R-squared	0.066	Number of obs	404.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-496.206	Bayesian crit. (BIC)	-456.191

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Total Public Health Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.061	.039	-1.55	.152	-.149	.027	
Primary care physicians	-3.567	128.882	-0.03	.978	-290.734	283.599	
Prevent hospitalizations	0	.002	-0.22	.832	-.004	.004	
High school	.355	.548	0.65	.532	-.866	1.576	
Unemployed	.272	1.51	0.18	.861	-3.092	3.635	
Poverty	.857	.705	1.22	.252	-.713	2.428	
Uninsured	-1.251	.552	-2.26	.047	-2.481	-.02	**
Median income	0	0	3.35	.007	0	0	***
Population	0	0	-0.37	.716	0	0	
Age	-.492	4.844	-0.10	.921	-11.285	10.301	
Race	-4.765	3.456	-1.38	.198	-12.465	2.936	
Hispanic	1.33	2.154	0.62	.551	-3.468	6.129	
Year 2014	0	.	.	.	.	.	
Year 2016	-.012	.054	-0.23	.823	-.133	.108	
Year 2018	-.181	.097	-1.87	.091	-.397	.035	*
Constant	-.084	.774	-0.11	.915	-1.808	1.64	

Mean dependent var	0.460	SD dependent var	0.193
R-squared	0.147	Number of obs	360.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-815.489	Bayesian crit. (BIC)	-776.628

*** *p<.01*, ** *p<.05*, * *p<.1*

Specification 2: Accredited LHDs in Florida and accredited LHDs in ten similar states

Regression results

Effectiveness of Assessment Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.091	.174	0.52	.637	-.462	.644	
Primary care physicians	-574.148	208.621	-2.75	.071	-1238.074	89.778	*
Prevent hospitalizations	.02	.002	8.15	.004	.012	.028	***
High school	.672	.656	1.02	.381	-1.417	2.761	
Unemployed	19.207	.224	85.78	0	18.494	19.919	***
Poverty	-1.423	.121	-11.73	.001	-1.809	-1.037	***
Uninsured	-.456	.513	-0.89	.44	-2.09	1.178	
Median income	0	0	-0.06	.959	0	0	
Population	0	0	10.50	.002	0	0	***
Age	3.36	1.622	2.07	.13	-1.802	8.521	
Race	.776	1.987	0.39	.722	-5.549	7.101	
Hispanic	-7.376	1.045	-7.06	.006	-10.703	-4.049	***
Year 2014	0	.	.	.	.	.	
Year 2016	.452	.168	2.68	.075	-.084	.987	*
Year 2018	.557	.135	4.14	.026	.128	.986	**
Constant	-3.175	.602	-5.27	.013	-5.093	-1.258	**

Mean dependent var	0.644	SD dependent var	0.137
R-squared	0.491	Number of obs	73.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-199.422	Bayesian crit. (BIC)	-194.842

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Policy Development Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.064	.079	0.81	.477	-.186	.314	
Primary care physicians	1126.311	165.106	6.82	.006	600.871	1651.75	***
Prevent hospitalizations	-.005	.001	-3.51	.039	-.009	0	**
High school	-1.016	.248	-4.09	.026	-1.807	-.226	**
Unemployed	3.878	.049	79.11	0	3.722	4.034	***
Poverty	-1.534	.007	-206.57	0	-1.558	-1.511	***
Uninsured	-2.171	.107	-20.38	0	-2.51	-1.832	***
Median income	0	0	-1.26	.295	0	0	
Population	0	0	0.83	.469	0	0	
Age	-16.766	.48	-34.90	0	-18.295	-15.238	***
Race	-1.402	.248	-5.66	.011	-2.19	-.614	**
Hispanic	-15.376	.555	-27.70	0	-17.143	-13.609	***
Year 2014	0	.	.	.	.	.	
Year 2016	.378	.079	4.81	.017	.128	.628	**
Year 2018	.427	.076	5.60	.011	.185	.67	**
Constant	7.433	.201	37.05	0	6.794	8.071	***

Mean dependent var	0.490	SD dependent var	0.173
R-squared	0.385	Number of obs	71.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-186.463	Bayesian crit. (BIC)	-181.937

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Assurance Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.019	.043	-0.44	.69	-.156	.118	
Primary care physicians	154.304	127.171	1.21	.312	-250.41	559.018	
Prevent hospitalizations	-.001	.001	-1.11	.346	-.004	.002	
High school	1.292	.113	11.47	.001	.933	1.65	***
Unemployed	9.495	1.115	8.52	.003	5.948	13.043	***
Poverty	-1.738	.172	-10.08	.002	-2.286	-1.189	***
Uninsured	-.55	1.205	-0.46	.679	-4.386	3.286	
Median income	0	0	-10.76	.002	0	0	***
Population	0	0	0.45	.681	0	0	
Age	6.338	.902	7.03	.006	3.468	9.207	***
Race	-8.952	1.389	-6.45	.008	-13.372	-4.532	***
Hispanic	-.92	1.498	-0.61	.582	-5.687	3.847	
Year 2014	0	.	.	.	.	.	
Year 2016	.119	.052	2.30	.105	-.046	.285	
Year 2018	.12	.144	0.83	.465	-.337	.577	
Constant	.482	.71	0.68	.546	-1.777	2.74	

Mean dependent var	0.487	SD dependent var	0.204
R-squared	0.200	Number of obs	75.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-102.487	Bayesian crit. (BIC)	-97.852

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Total Public Health Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.023	.084	0.27	.805	-.245	.291	
Primary care physicians	1365.896	132.29	10.33	.002	944.89	1786.901	***
Prevent hospitalizations	.005	.002	2.73	.072	-.001	.01	*
High school	.139	.266	0.52	.638	-.708	.986	
Unemployed	12.671	.651	19.46	0	10.599	14.743	***
Poverty	-1.56	.023	-68.68	0	-1.632	-1.487	***
Uninsured	-.78	.319	-2.45	.092	-1.795	.234	*
Median income	0	0	-1.80	.17	0	0	
Population	0	0	10.87	.002	0	0	***
Age	-5.545	.82	-6.76	.007	-8.155	-2.935	***
Race	-.039	.779	-0.05	.964	-2.518	2.441	
Hispanic	-7.584	.219	-34.56	0	-8.282	-6.885	***
Year 2014	0	.	.	.	.	.	
Year 2016	.434	.088	4.91	.016	.153	.715	**
Year 2018	.54	.073	7.43	.005	.309	.772	***
Constant	.79	.203	3.89	.03	.143	1.437	**

Mean dependent var	0.531	SD dependent var	0.140
R-squared	0.357	Number of obs	67.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-190.003	Bayesian crit. (BIC)	-185.594

**** p<.01, ** p<.05, * p<.1*

Specification 3: Accredited LHDs in Non-Florida states and unaccredited LHDs in Non-Florida states.

Regression results

Effectiveness of Assessment Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.007	.03	-0.24	.814	-.067	.053	
Primary care physicians	-42.819	122.214	-0.35	.728	-288.546	202.908	
Prevent hospitalizations	-.001	.001	-0.60	.549	-.003	.002	
High school	-.059	.222	-0.27	.79	-.506	.387	
Unemployed	.237	.884	0.27	.789	-1.539	2.014	
Poverty	.184	.308	0.60	.554	-.436	.804	
Uninsured	.211	.297	0.71	.48	-.386	.809	
Median income	0	0	1.28	.206	0	0	
Population	0	0	0.46	.646	0	0	
Age	-.23	1.472	-0.16	.876	-3.19	2.729	
Race	-1.936	1.707	-1.13	.262	-5.368	1.497	
Hispanic	-1.728	1.703	-1.01	.316	-5.152	1.697	
Year 2014	0	.	.	.	.	.	
Year 2016	.014	.027	0.50	.622	-.042	.069	
Year 2018	.008	.048	0.17	.865	-.089	.105	
Constant	.642	.403	1.59	.118	-.169	1.453	

Mean dependent var	0.538	SD dependent var	0.202
R-squared	0.013	Number of obs	1384.000
F-test	2.270	Prob > F	0.020
Akaike crit. (AIC)	-2514.269	Bayesian crit. (BIC)	-2441.011

**** p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Policy Development Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	-.003	.031	-0.08	.933	-.066	.06	
Primary care physicians	13.404	91.852	0.15	.885	-171.378	198.186	
Prevent hospitalizations	-.001	.001	-0.65	.518	-.002	.001	
High school	.159	.237	0.67	.504	-.317	.636	
Unemployed	1.28	.649	1.97	.054	-.025	2.585	*
Poverty	-.033	.283	-0.12	.908	-.602	.536	
Uninsured	-.434	.34	-1.28	.208	-1.117	.25	
Median income	0	0	2.76	.008	0	0	***
Population	0	0	0.55	.584	0	0	
Age	-.271	1.851	-0.15	.884	-3.994	3.452	
Race	-2.813	2.331	-1.21	.234	-7.503	1.877	
Hispanic	.368	2.039	0.18	.857	-3.733	4.47	
Year 2014	0	.	.	.	.	.	
Year 2016	.016	.033	0.49	.627	-.05	.082	
Year 2018	-.051	.062	-0.83	.413	-.176	.074	
Constant	-.06	.582	-0.10	.918	-1.231	1.11	

Mean dependent var	0.396	SD dependent var	0.217
R-squared	0.037	Number of obs	1317.000
F-test	2.355	Prob > F	0.016
Akaike crit. (AIC)	-2281.754	Bayesian crit. (BIC)	-2209.191

*** *p<.01, *** *p<.05, * *p<.1*

Regression results

Effectiveness of Assurance Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.039	.035	1.12	.269	-.031	.11	
Primary care physicians	-79.298	122.243	-0.65	.52	-325.085	166.489	
Prevent hospitalizations	.001	.001	1.84	.072	0	.003	*
High school	.185	.201	0.92	.362	-.219	.589	
Unemployed	.249	.973	0.26	.799	-1.708	2.206	
Poverty	.653	.523	1.25	.218	-.398	1.704	
Uninsured	-.371	.356	-1.04	.303	-1.086	.345	
Median income	0	0	0.99	.328	0	0	
Population	0	0	-0.76	.449	0	0	
Age	1.156	2.324	0.50	.621	-3.518	5.829	
Race	-4.054	1.959	-2.07	.044	-7.993	-.115	**
Hispanic	-2.106	2.066	-1.02	.313	-6.26	2.048	
Year 2014	0	.	.	.	.	.	
Year 2016	.043	.033	1.33	.191	-.022	.109	
Year 2018	.017	.07	0.25	.803	-.122	.157	
Constant	.293	.601	0.49	.628	-.915	1.502	

Mean dependent var	0.371	SD dependent var	0.235
R-squared	0.026	Number of obs	1359.000
F-test	1.603	Prob > F	0.118
Akaike crit. (AIC)	-1844.831	Bayesian crit. (BIC)	-1771.828

*** *p<.01, ** p<.05, * p<.1*

Regression results

Effectiveness of Total Public Health Activities	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Accreditation	.01	.027	0.36	.723	-.045	.064	
Primary care physicians	-13.649	89.625	-0.15	.88	-193.951	166.653	
Prevent hospitalizations	0	.001	-0.01	.993	-.002	.002	
High school	.156	.21	0.75	.46	-.265	.578	
Unemployed	.641	.643	1.00	.324	-.654	1.935	
Poverty	.157	.312	0.50	.617	-.471	.786	
Uninsured	-.018	.307	-0.06	.954	-.635	.6	
Median income	0	0	2.24	.03	0	0	**
Population	0	0	0.72	.473	0	0	
Age	.683	1.622	0.42	.676	-2.581	3.946	
Race	-2.413	1.761	-1.37	.177	-5.955	1.129	
Hispanic	-.034	1.537	-0.02	.982	-3.126	3.058	
Year 2014	0	.	.	.	.	.	
Year 2016	.003	.027	0.12	.909	-.052	.058	
Year 2018	-.038	.053	-0.72	.474	-.145	.069	
Constant	-.116	.455	-0.26	.799	-1.031	.798	

Mean dependent var	0.434	SD dependent var	0.190
R-squared	0.028	Number of obs	1233.000
F-test	2.480	Prob > F	0.012
Akaike crit. (AIC)	-2633.002	Bayesian crit. (BIC)	-2561.361

**** p<.01, ** p<.05, * p<.1*

Results for Study 3: The Effect of Public Health Funding on Public Health Outcomes
OLS Year 2013

Linear regression

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-.001	.003	-0.26	.799	-.007	.006	
Uninsured	-.001	.059	-0.01	.99	-.121	.12	
Primary care physicians	-46.531	7.482	-6.22	0	-61.884	-31.179	***
Preventable hospitalizations	0	0	1.88	.071	0	0	*
High school	.076	.033	2.27	.032	.007	.144	**
Unemployed	-.189	.119	-1.59	.124	-.434	.055	
Poverty	.045	.045	1.02	.318	-.046	.137	
Median income	0	0	-3.01	.006	0	0	***
Population	0	0	-1.34	.192	0	0	
Age	-.201	.041	-4.85	0	-.286	-.116	***
Race	.089	.022	4.00	0	.043	.135	***
Hispanic	-.124	.02	-6.14	0	-.166	-.083	***
Full-time equivalents	0	.004	-0.05	.958	-.008	.008	
City	.007	.014	0.52	.61	-.021	.036	
City County	0	.	.	.	.	.	
County	.012	.016	0.73	.47	-.021	.044	
Multi-county	.006	.017	0.34	.74	-.028	.039	
Constant	.357	.064	5.59	0	.226	.488	***

Mean dependent var	0.310	SD dependent var	0.048
R-squared	0.468	Number of obs	809.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-3080.021	Bayesian crit. (BIC)	-3004.888

*** *p<.01*, ** *p<.05*, * *p<.1*

Linear regression

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-2.852	11.365	-0.25	.804	-26.171	20.466	
Uninsured	-96.407	226.053	-0.43	.673	-560.231	367.416	
Primary care physicians	99407.411	29084.899	3.42	.002	39730.128	159084.69	***
Preventable hospitalizations	.004	.005	0.78	.442	-.007	.015	
High school	-407.076	151.239	-2.69	.012	-717.394	-96.759	**
Unemployed	-494.53	344.546	-1.44	.163	-1201.481	212.421	
Poverty	264.686	172.614	1.53	.137	-89.488	618.86	
Median income	-.001	.001	-1.00	.324	-.003	.001	
Population	0	0	3.47	.002	0	0	***
Age	-887.911	172.587	-5.14	0	-1242.029	-533.792	***
Race	983.736	103.133	9.54	0	772.124	1195.347	***
Hispanic	135.36	99.943	1.35	.187	-69.707	340.427	
Full-time equivalents	-6.46	11.107	-0.58	.566	-29.249	16.329	
City	30.936	21.408	1.45	.16	-12.989	74.86	
City County	0	.	.	.	.	.	
County	86.383	23.74	3.64	.001	37.673	135.093	***
Multi-county	45.805	24.719	1.85	.075	-4.913	96.524	*
Constant	605.456	169.822	3.57	.001	257.01	953.902	***

Mean dependent var	327.559	SD dependent var	211.165
R-squared	0.621	Number of obs	805.000
F-test	174.526	Prob > F	0.000
Akaike crit. (AIC)	10154.400	Bayesian crit. (BIC)	10234.144

**** p<.01, ** p<.05, * p<.1*

Linear regression

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	.003	.003	0.97	.342	-.003	.008	
Uninsured	.051	.028	1.86	.074	-.005	.108	*
Primary care physicians	-14.003	4.136	-3.39	.002	-22.489	-5.517	***
Preventable hospitalizations	0	0	6.86	0	0	0	***
High school	.039	.02	1.97	.06	-.002	.08	*
Unemployed	.083	.051	1.62	.116	-.022	.188	
Poverty	.095	.035	2.73	.011	.024	.167	**
Median income	0	0	-0.68	.5	0	0	
Population	0	0	-0.49	.63	0	0	
Age	.089	.022	3.96	0	.043	.135	***
Race	.059	.013	4.52	0	.032	.086	***
Hispanic	-.066	.015	-4.41	0	-.097	-.035	***
Full-time equivalents	-.002	.003	-0.69	.494	-.007	.004	
City	.014	.005	2.61	.014	.003	.025	**
City County	0	.	.	.	.	.	
County	.018	.005	3.74	.001	.008	.027	***
Multi-county	.013	.005	2.80	.009	.003	.022	***
Constant	-.007	.028	-0.26	.799	-.065	.05	

Mean dependent var	0.111	SD dependent var	0.032
R-squared	0.509	Number of obs	809.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-3829.339	Bayesian crit. (BIC)	-3754.206

**** p<.01, ** p<.05, * p<.1*

Linear regression

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-6.576	14.36	-0.46	.651	-36.041	22.889	
Uninsured	-47.49	225.938	-0.21	.835	-511.076	416.096	
Primary care physicians	89426.187	50004.565	1.79	.085	-13174.706	192027.08	*
Preventable hospitalizations	.002	.004	0.64	.526	-.005	.01	
High school	-609.189	340.672	-1.79	.085	-1308.189	89.811	*
Unemployed	24.536	359.435	0.07	.946	-712.964	762.035	
Poverty	-34.059	170.084	-0.20	.843	-383.042	314.924	
Median income	.002	.001	1.30	.206	-.001	.004	
Population	0	0	2.12	.043	0	0	**
Age	164.153	217.604	0.75	.457	-282.334	610.64	
Race	887.942	287.185	3.09	.005	298.686	1477.198	***
Hispanic	386.171	184.868	2.09	.046	6.854	765.488	**
Full-time equivalents	25.762	21.039	1.22	.231	-17.408	68.931	
City	102.07	40.078	2.55	.017	19.836	184.303	**
City County	0	.	.	.	.	.	
County	97.417	50.818	1.92	.066	-6.852	201.686	*
Multi-county	95.202	36.423	2.61	.014	20.467	169.937	**
Constant	549.338	365.906	1.50	.145	-201.439	1300.116	

Mean dependent var	178.500	SD dependent var	217.101
R-squared	0.457	Number of obs	671.000
F-test	33.101	Prob > F	0.000
Akaike crit. (AIC)	8748.197	Bayesian crit. (BIC)	8824.846

**** p<.01, ** p<.05, * p<.1*

OLS Year 2016

Linear regression

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-.002	.004	-0.42	.68	-.009	.006	
Uninsured	-.085	.03	-2.87	.008	-.146	-.024	***
Primary care physicians	-43.402	7.371	-5.89	0	-58.526	-28.279	***
Preventable hospitalizations	0	0	0.37	.713	0	0	
High school	.111	.038	2.94	.007	.034	.189	***
Unemployed	-.062	.124	-0.50	.621	-.318	.193	
Poverty	.088	.04	2.23	.035	.007	.169	**
Median income	0	0	-4.43	0	0	0	***
Population	0	0	-2.36	.026	0	0	**
Age	-.109	.058	-1.89	.07	-.228	.009	*
Race	.104	.024	4.38	0	.055	.153	***
Hispanic	-.099	.016	-6.35	0	-.131	-.067	***
Full-time equivalents	.003	.003	0.91	.371	-.004	.01	
City	.014	.014	0.96	.344	-.015	.043	
City County	0	.	.	.	.	.	
County	.012	.018	0.64	.53	-.026	.049	
Multi-county	.011	.018	0.58	.565	-.027	.048	
Constant	.323	.061	5.24	0	.196	.449	***

Mean dependent var	0.308	SD dependent var	0.050
R-squared	0.489	Number of obs	650.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-2458.028	Bayesian crit. (BIC)	-2386.396

**** p<.01, ** p<.05, * p<.1*

Linear regression

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-2.503	10.521	-0.24	.814	-24.09	19.083	
Uninsured	-264.015	187.199	-1.41	.17	-648.115	120.085	
Primary care physicians	101408.46	20752.775	4.89	0	58827.284	143989.64	***
Preventable hospitalizations	-.004	.004	-1.06	.299	-.012	.004	
High school	-271.813	102.387	-2.65	.013	-481.893	-61.733	**
Unemployed	-1008.976	235.466	-4.29	0	-1492.112	-525.839	***
Poverty	419.354	218.118	1.92	.065	-28.187	866.895	*
Median income	-.001	.001	-0.67	.51	-.003	.001	
Population	0	0	1.03	.313	0	0	
Age	-984.558	169.919	-5.79	0	-1333.203	-635.912	***
Race	1103.814	105.74	10.44	0	886.854	1320.775	***
Hispanic	122.354	56.244	2.18	.039	6.951	237.757	**
Full-time equivalents	1.541	11.608	0.13	.895	-22.277	25.359	
City	14.215	25.608	0.56	.583	-38.329	66.758	
City County	0	.	.	.	.	.	
County	73.633	16.68	4.41	0	39.408	107.859	***
Multi-county	51.38	23.805	2.16	.04	2.535	100.224	**
Constant	599.077	195.239	3.07	.005	198.479	999.675	***

Mean dependent var	335.352	SD dependent var	224.018
R-squared	0.692	Number of obs	644.000
F-test	565.593	Prob > F	0.000
Akaike crit. (AIC)	8071.730	Bayesian crit. (BIC)	8147.681

**** p<.01, ** p<.05, * p<.1*

Linear regression

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	.003	.003	1.02	.316	-.003	.008	
Uninsured	.065	.025	2.56	.016	.013	.117	**
Primary care physicians	-20.955	4.922	-4.26	0	-31.054	-10.857	***
Preventable hospitalizations	0	0	4.23	0	0	0	***
High school	.047	.018	2.66	.013	.011	.083	**
Unemployed	.004	.057	0.07	.946	-.113	.121	
Poverty	.092	.031	2.99	.006	.029	.155	***
Median income	0	0	-1.71	.099	0	0	*
Population	0	0	-0.68	.5	0	0	
Age	.096	.029	3.31	.003	.037	.155	***
Race	.054	.013	4.16	0	.028	.081	***
Hispanic	-.057	.01	-5.47	0	-.078	-.036	***
Full-time equivalents	-.001	.002	-0.65	.522	-.006	.003	
City	.021	.003	7.89	0	.015	.026	***
City County	0	.	.	.	.	.	
County	.02	.004	4.88	0	.012	.028	***
Multi-county	.015	.004	3.51	.002	.006	.023	***
Constant	-.003	.034	-0.08	.935	-.072	.067	

Mean dependent var	0.112	SD dependent var	0.033
R-squared	0.521	Number of obs	650.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-3041.878	Bayesian crit. (BIC)	-2970.246

**** p<.01, ** p<.05, * p<.1*

Linear regression

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-5.948	13.733	-0.43	.668	-34.176	22.28	
Uninsured	-89.098	224.543	-0.40	.695	-550.654	372.458	
Primary care physicians	99021.91	49979.973	1.98	.058	-3713.396	201757.21	*
Preventable hospitalizations	.01	.005	2.04	.052	0	.019	*
High school	-681.251	368.817	-1.85	.076	-1439.365	76.864	*
Unemployed	-361.251	272.424	-1.33	.196	-921.228	198.725	
Poverty	467.222	251.708	1.86	.075	-50.172	984.616	*
Median income	.004	.002	2.04	.052	0	.007	*
Population	0	0	3.85	.001	0	0	***
Age	-125.801	129.291	-0.97	.34	-391.562	139.96	
Race	714.917	199.484	3.58	.001	304.872	1124.962	***
Hispanic	233.59	151.047	1.55	.134	-76.891	544.071	
Full-time equivalents	17.809	13.922	1.28	.212	-10.808	46.426	
City	52.5	39.52	1.33	.196	-28.734	133.734	
City County	0	.	.	.	.	.	
County	77.561	47.066	1.65	.111	-19.183	174.306	
Multi-county	78.468	31.672	2.48	.02	13.365	143.572	**
Constant	445.457	333.682	1.33	.193	-240.436	1131.351	

Mean dependent var	187.448	SD dependent var	232.987
R-squared	0.465	Number of obs	539.000
F-test	29.770	Prob > F	0.000
Akaike crit. (AIC)	7101.448	Bayesian crit. (BIC)	7174.373

*** *p<.01*, ** *p<.05*, * *p<.1*

OLS Year 2019

Linear regression

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-.004	.003	-1.34	.19	-.01	.002	
Uninsured	-.126	.053	-2.38	.025	-.234	-.017	**
Primary care physicians	-51.438	8.697	-5.91	0	-69.282	-33.594	***
Preventable hospitalizations	0	0	0.59	.563	0	0	
High school	.03	.035	0.86	.398	-.042	.101	
Unemployed	-.179	.09	-1.99	.057	-.364	.006	*
Poverty	.048	.051	0.94	.356	-.057	.154	
Median income	0	0	-3.82	.001	0	0	***
Population	0	0	-1.90	.068	0	0	*
Age	-.216	.052	-4.15	0	-.323	-.109	***
Race	.077	.017	4.47	0	.042	.112	***
Hispanic	-.046	.022	-2.12	.043	-.091	-.002	**
Full-time equivalents	.002	.004	0.44	.666	-.006	.009	
City	.049	.025	1.96	.06	-.002	.099	*
City County	0	.	.	.	.	.	
County	.053	.027	1.93	.064	-.003	.108	*
Multi-county	.05	.028	1.82	.081	-.007	.107	*
Constant	.431	.069	6.21	0	.289	.574	***

Mean dependent var	0.313	SD dependent var	0.051
R-squared	0.531	Number of obs	398.000
F-test	110.076	Prob > F	0.000
Akaike crit. (AIC)	-1512.666	Bayesian crit. (BIC)	-1444.896

******* *p<.01, ** p<.05, * p<.1*

Linear regression

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-16.697	10.253	-1.63	.115	-37.735	4.34	
Uninsured	-18.717	359.556	-0.05	.959	-756.465	719.03	
Primary care physicians	90881.145	28663.998	3.17	.004	32067.48	149694.81	***
Preventable hospitalizations	.001	.007	0.20	.845	-.012	.015	
High school	-226.39	176.236	-1.28	.21	-587.997	135.217	
Unemployed	-726.274	385.664	-1.88	.07	-1517.591	65.044	*
Poverty	231.334	244.106	0.95	.352	-269.531	732.199	
Median income	-.002	.002	-1.07	.292	-.005	.002	
Population	0	0	1.47	.153	0	0	
Age	-1296.602	195.094	-6.65	0	-1696.902	-896.302	***
Race	1064.025	109.31	9.73	0	839.739	1288.312	***
Hispanic	217.382	145.036	1.50	.146	-80.207	514.97	
Full-time equivalents	.788	13.354	0.06	.953	-26.612	28.189	
City	33.694	26.233	1.28	.21	-20.131	87.519	
City County	0	.	.	.	.	.	
County	102.094	23.795	4.29	0	53.272	150.917	***
Multi-county	57.794	23.276	2.48	.02	10.037	105.552	**
Constant	663.252	187.736	3.53	.002	278.05	1048.453	***

Mean dependent var	351.908	SD dependent var	230.938
R-squared	0.685	Number of obs	396.000
F-test	335.913	Prob > F	0.000
Akaike crit. (AIC)	5009.710	Bayesian crit. (BIC)	5077.394

*** *p<.01*, ** *p<.05*, * *p<.1*

Linear regression

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-.002	.001	-1.34	.19	-.004	.001	
Uninsured	-.025	.033	-0.76	.451	-.093	.042	
Primary care physicians	-23.227	5.258	-4.42	0	-34.016	-12.438	***
Preventable hospitalizations	0	0	2.26	.032	0	0	**
High school	.024	.026	0.95	.352	-.028	.077	
Unemployed	-.039	.061	-0.64	.531	-.163	.086	
Poverty	.128	.047	2.72	.011	.032	.224	**
Median income	0	0	-0.88	.387	0	0	
Population	0	0	1.38	.18	0	0	
Age	.08	.026	3.06	.005	.027	.134	***
Race	.029	.015	1.98	.058	-.001	.059	*
Hispanic	-.059	.011	-5.37	0	-.081	-.036	***
Full-time equivalents	.002	.002	0.89	.383	-.002	.006	
City	.018	.004	4.51	0	.01	.026	***
City County	0	.	.	.	.	.	
County	.027	.003	7.94	0	.02	.034	***
Multi-county	.019	.003	5.44	0	.012	.026	***
Constant	.074	.044	1.70	.102	-.016	.164	

Mean dependent var	0.115	SD dependent var	0.034
R-squared	0.482	Number of obs	398.000
F-test	26.692	Prob > F	0.000
Akaike crit. (AIC)	-1798.211	Bayesian crit. (BIC)	-1730.441

**** p<.01, ** p<.05, * p<.1*

Linear regression

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	18.398	15.576	1.18	.248	-13.561	50.357	
Uninsured	111.454	263.035	0.42	.675	-428.249	651.156	
Primary care physicians	138751.09	65807.682	2.11	.044	3724.883	273777.3	**
Preventable hospitalizations	.005	.007	0.71	.481	-.009	.018	
High school	-359.718	290.9	-1.24	.227	-956.595	237.159	
Unemployed	-477.323	266.558	-1.79	.085	-1024.255	69.609	*
Poverty	729.79	515.962	1.41	.169	-328.877	1788.457	
Median income	.006	.004	1.75	.091	-.001	.014	*
Population	0	0	1.34	.191	0	0	
Age	-143.614	129.457	-1.11	.277	-409.237	122.01	
Race	661.23	136.197	4.85	0	381.776	940.684	***
Hispanic	116.678	112.355	1.04	.308	-113.856	347.211	
Full-time equivalents	-16.993	15.612	-1.09	.286	-49.026	15.039	
City	46.402	37.458	1.24	.226	-30.456	123.259	
City County	0	.	.	.	.	.	
County	89.196	44.692	2.00	.056	-2.505	180.897	*
Multi-county	73.858	38.097	1.94	.063	-4.31	152.027	*
Constant	-399.096	415.393	-0.96	.345	-1251.412	453.219	

Mean dependent var	185.504	SD dependent var	213.725
R-squared	0.452	Number of obs	351.000
F-test	15.858	Prob > F	0.000
Akaike crit. (AIC)	4583.997	Bayesian crit. (BIC)	4649.630

**** p<.01, ** p<.05, * p<.1*

OLS with Time Trend

Linear regression

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-.002	.002	-0.99	.331	-.007	.003	
Uninsured	-.04	.036	-1.11	.277	-.114	.034	
Primary care physicians	-46.489	6.693	-6.95	0	-60.14	-32.838	***
Preventable hospitalizations	0	0	1.67	.104	0	0	
High school	.089	.025	3.53	.001	.038	.14	***
Unemployed	-.12	.075	-1.60	.119	-.273	.033	
Poverty	.038	.035	1.10	.279	-.033	.109	
Median income	0	0	-4.28	0	0	0	***
Population	0	0	-2.51	.017	0	0	**
Age	-.155	.041	-3.80	.001	-.238	-.072	***
Race	.102	.018	5.63	0	.065	.139	***
Hispanic	-.086	.014	-6.17	0	-.114	-.058	***
Year 2010	0	.	.	.	.	.	
Year 2013	-.002	.002	-1.31	.199	-.005	.001	
Year 2016	-.003	.002	-1.68	.102	-.007	.001	
Year 2019	-.001	.003	-0.41	.684	-.008	.005	
Full-time equivalents	.001	.003	0.55	.585	-.004	.007	
City	.015	.016	0.88	.384	-.019	.048	
City County	0	.	.	.	.	.	
County	.017	.019	0.88	.388	-.023	.057	
Multi-county	.012	.02	0.61	.545	-.028	.052	
Constant	.361	.048	7.59	0	.264	.458	***

Mean dependent var	0.311	SD dependent var	0.050
R-squared	0.481	Number of obs	2745.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-10440.528	Bayesian crit. (BIC)	-10328.095

*** *p<.01, ** p<.05, * p<.1*

Linear regression

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-4.738	5.99	-0.79	.435	-16.955	7.479	
Uninsured	-255.564	149.124	-1.71	.097	-559.703	48.576	*
Primary care physicians	90584.326	19327.005	4.69	0	51166.638	130002.01	***
Preventable hospitalizations	-.001	.003	-0.28	.783	-.007	.006	
High school	-262.219	81.701	-3.21	.003	-428.849	-95.59	***
Unemployed	-725.156	205.174	-3.53	.001	-1143.61	-306.702	***
Poverty	416.316	119.12	3.49	.001	173.369	659.263	***
Median income	-.001	.001	-1.59	.122	-.003	0	
Population	0	0	2.83	.008	0	0	***
Age	-987.383	140.137	-7.05	0	-1273.194	-701.571	***
Race	1061.905	70	15.17	0	919.14	1204.67	***
Hispanic	179.647	60.313	2.98	.006	56.638	302.655	***
Year 2010	0	.	.	.	.	.	
Year 2013	-5.3	6.449	-0.82	.417	-18.453	7.853	
Year 2016	-2.126	6.826	-0.31	.757	-16.048	11.795	
Year 2019	2.098	6.859	0.31	.762	-11.892	16.087	
Full-time equivalents	-3.054	7.159	-0.43	.673	-17.656	11.547	
City	25.879	16.915	1.53	.136	-8.619	60.376	
City County	0	.	.	.	.	.	
County	79.676	15.94	5.00	0	47.166	112.185	***
Multi-county	41.057	18.275	2.25	.032	3.786	78.328	**
Constant	568.964	111.636	5.10	0	341.281	796.647	***

Mean dependent var	338.410	SD dependent var	223.809
R-squared	0.668	Number of obs	2725.000
F-test	209.649	Prob > F	0.000
Akaike crit. (AIC)	34258.762	Bayesian crit. (BIC)	34376.967

**** p<.01, ** p<.05, * p<.1*

Linear regression

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	.001	.001	0.63	.533	-.002	.003	
Uninsured	.041	.018	2.28	.03	.004	.079	**
Primary care physicians	-19.63	3.604	-5.45	0	-26.98	-12.281	***
Preventable hospitalizations	0	0	7.92	0	0	0	***
High school	.038	.014	2.72	.011	.01	.067	**
Unemployed	.038	.037	1.02	.317	-.038	.114	
Poverty	.101	.02	5.15	0	.061	.14	***
Median income	0	0	-1.48	.149	0	0	
Population	0	0	-0.05	.962	0	0	
Age	.083	.019	4.44	0	.045	.121	***
Race	.051	.009	5.65	0	.033	.07	***
Hispanic	-.059	.009	-6.75	0	-.077	-.041	***
Year 2010	0	.	.	.	.	.	
Year 2013	0	.001	0.18	.854	-.002	.003	
Year 2016	0	.001	0.39	.696	-.002	.002	
Year 2019	.002	.002	0.98	.335	-.002	.006	
Full-time equivalents	0	.001	-0.23	.818	-.002	.002	
City	.016	.004	3.93	0	.008	.024	***
City County	0	.	.	.	.	.	
County	.019	.004	5.34	0	.012	.027	***
Multi-county	.014	.004	3.84	.001	.007	.021	***
Constant	.022	.018	1.21	.237	-.015	.058	

Mean dependent var	0.112	SD dependent var	0.033
R-squared	0.498	Number of obs	2745.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	-12848.346	Bayesian crit. (BIC)	-12735.913

*** *p<.01, ** p<.05, * p<.1*

Linear regression

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	5.549	9.322	0.60	.556	-13.463	24.561	
Uninsured	3.487	194.387	0.02	.986	-392.968	399.941	
Primary care physicians	94729.371	47555.508	1.99	.055	-2260.727	191719.47	*
Preventable hospitalizations	.005	.003	1.65	.108	-.001	.012	
High school	-644.932	319.475	-2.02	.052	-1296.505	6.642	*
Unemployed	-378.076	255.158	-1.48	.149	-898.475	142.322	
Poverty	280.451	202.018	1.39	.175	-131.569	692.47	
Median income	.003	.002	1.97	.057	0	.007	*
Population	0	0	2.63	.013	0	0	**
Age	-24.133	118.233	-0.20	.84	-265.271	217.004	
Race	764.743	191.609	3.99	0	373.953	1155.533	***
Hispanic	227.633	136.567	1.67	.106	-50.898	506.164	
Year 2010	0	.	.	.	.	.	
Year 2013	2.62	5.241	0.50	.621	-8.069	13.308	
Year 2016	9.023	5.394	1.67	.104	-1.978	20.024	
Year 2019	13.394	9.092	1.47	.151	-5.149	31.936	
Full-time equivalents	9.473	12.105	0.78	.44	-15.216	34.162	
City	57.231	27.278	2.10	.044	1.597	112.865	**
City County	0	.	.	.	.	.	
County	74.544	37.551	1.99	.056	-2.042	151.13	*
Multi-county	70.353	23.715	2.97	.006	21.986	118.719	***
Constant	341.296	293.108	1.16	.253	-256.501	939.094	

Mean dependent var	182.322	SD dependent var	219.716
R-squared	0.444	Number of obs	2305.000
F-test	30.350	Prob > F	0.000
Akaike crit. (AIC)	30085.914	Bayesian crit. (BIC)	30200.771

**** p<.01, ** p<.05, * p<.1*

Fixed Effects

Regression results

Obesity prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	.002	.002	0.77	.444	-.003	.006	
Uninsured	-.02	.031	-0.65	.518	-.082	.041	
Primary care physicians	4.216	7.344	0.57	.566	-10.19	18.622	
Preventable hospitalizations	0	0	-0.90	.37	0	0	
High school	-.014	.014	-1.02	.308	-.042	.013	
Unemployed	-.047	.054	-0.87	.382	-.153	.059	
Poverty	-.076	.031	-2.44	.015	-.136	-.015	**
Median income	0	0	0.14	.888	0	0	
Population	0	0	-1.16	.248	0	0	
Age	-.081	.066	-1.24	.215	-.21	.047	
Race	.189	.093	2.04	.042	.007	.371	**
Hispanic	.065	.072	0.91	.363	-.076	.207	
Year 2010	0	.	.	.	.	.	
Year 2013	-.001	.001	-1.15	.252	-.004	.001	
Year 2016	-.001	.001	-0.92	.357	-.004	.001	
Year 2019	0	.002	0.16	.873	-.003	.004	
Full-time equivalents	-.001	.002	-0.60	.549	-.006	.003	
City	.009	.013	0.70	.483	-.016	.034	
City County	0	.	.	.	.	.	
County	.011	.033	0.33	.74	-.054	.076	
Multi-county	-.003	.036	-0.09	.928	-.074	.067	
Constant	.316	.044	7.17	0	.23	.403	***

Mean dependent var	0.311	SD dependent var	0.050
R-squared	0.016	Number of obs	2745.000
F-test	1.308	Prob > F	0.000
Akaike crit. (AIC)	-14900.414	Bayesian crit. (BIC)	-14782.063

*** *p<.01, ** p<.05, * p<.1*

Regression results

Sexually transmitted infections	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	1.828	7.654	0.24	.811	-13.186	16.841	
Uninsured	41.72	111.686	0.37	.709	-177.359	260.799	
Primary care physicians	-550.2	26332.719	-0.02	.983	-52203.509	51103.108	
Preventable hospitalizations	-.002	.002	-0.86	.388	-.005	.002	
High school	-128.954	51.37	-2.51	.012	-229.719	-28.189	**
Unemployed	-156.58	192.921	-0.81	.417	-535.007	221.846	
Poverty	-380.008	110.437	-3.44	.001	-596.637	-163.378	***
Median income	0	.001	0.09	.926	-.001	.001	
Population	0	0	-0.23	.82	0	0	
Age	11.735	233.938	0.05	.96	-447.15	470.62	
Race	72.59	331.09	0.22	.826	-576.863	722.043	
Hispanic	-288.381	256.986	-1.12	.262	-792.475	215.713	
Year 2010	0	.	.	.	.	.	
Year 2013	-3.564	4.398	-0.81	.418	-12.192	5.064	
Year 2016	.461	4.894	0.09	.925	-9.138	10.06	
Year 2019	-4.339	6.081	-0.71	.476	-16.266	7.588	
Full-time equivalents	-11.932	8.063	-1.48	.139	-27.749	3.885	
City	5.364	44.916	0.12	.905	-82.742	93.469	
City County	0	.	.	.	.	.	
County	7.103	117.986	0.06	.952	-224.335	238.541	
Multi-county	-70.041	128.14	-0.55	.585	-321.396	181.313	
Constant	456.714	157.944	2.89	.004	146.896	766.532	***

Mean dependent var	338.410	SD dependent var	223.809
R-squared	0.019	Number of obs	2725.000
F-test	1.543	Prob > F	0.000
Akaike crit. (AIC)	29794.180	Bayesian crit. (BIC)	29912.385

**** p<.01, ** p<.05, * p<.1*

Regression results

Diabetes prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	0	.001	0.29	.772	-.002	.003	
Uninsured	-.039	.021	-1.86	.064	-.079	.002	*
Primary care physicians	-7.326	4.873	-1.50	.133	-16.886	2.233	
Preventable hospitalizations	0	0	4.75	0	0	0	***
High school	.012	.009	1.25	.211	-.007	.03	
Unemployed	-.091	.036	-2.55	.011	-.161	-.021	**
Poverty	-.008	.021	-0.40	.691	-.048	.032	
Median income	0	0	-2.11	.035	0	0	**
Population	0	0	-1.12	.264	0	0	
Age	-.007	.043	-0.17	.863	-.093	.078	
Race	.05	.062	0.82	.413	-.07	.171	
Hispanic	0	.048	-0.01	.994	-.094	.093	
Year 2010	0	.	.	.	.	.	
Year 2013	0	.001	-0.08	.937	-.002	.002	
Year 2016	.001	.001	0.91	.363	-.001	.003	
Year 2019	0	.001	-0.23	.822	-.002	.002	
Full-time equivalents	-.001	.001	-0.70	.482	-.004	.002	
City	-.002	.008	-0.25	.804	-.018	.014	
City County	0	.	.	.	.	.	
County	-.003	.022	-0.12	.906	-.046	.04	
Multi-county	-.005	.024	-0.22	.828	-.052	.042	
Constant	.124	.029	4.22	0	.066	.181	***

Mean dependent var	0.112	SD dependent var	0.033
R-squared	0.167	Number of obs	2745.000
F-test	15.737	Prob > F	0.000
Akaike crit. (AIC)	-17152.010	Bayesian crit. (BIC)	-17033.659

**** p<.01, ** p<.05, * p<.1*

Regression results

HIV prevalence	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LHD expenditures (log)	-6.077	4.486	-1.35	.176	-14.879	2.724	
Uninsured	58.18	69.12	0.84	.4	-77.428	193.788	
Primary care physicians	17109.643	16942.869	1.01	.313	-16130.775	50350.06	
Preventable hospitalizations	0	.001	0.33	.742	-.002	.003	
High school	47.519	30.581	1.55	.12	-12.478	107.515	
Unemployed	-168.396	115.267	-1.46	.144	-394.54	57.747	
Poverty	-118.381	65.767	-1.80	.072	-247.41	10.649	*
Median income	-.002	0	-4.12	0	-.003	-.001	***
Population	0	0	0.21	.834	0	0	
Age	513.664	140.744	3.65	0	237.536	789.793	***
Race	2107.934	185.102	11.39	0	1744.779	2471.089	***
Hispanic	391.99	149.953	2.61	.009	97.794	686.185	***
Year 2010	0	.	.	.	.	.	
Year 2013	-5.787	2.649	-2.18	.029	-10.983	-.59	**
Year 2016	-2.644	2.936	-0.90	.368	-8.404	3.116	
Year 2019	-2.801	3.566	-0.79	.432	-9.797	4.195	
Full-time equivalents	-7.001	4.678	-1.50	.135	-16.179	2.177	
City	-128.479	66.546	-1.93	.054	-259.037	2.079	*
City County	0	.	.	.	.	.	
County	-124.167	30.79	-4.03	0	-184.573	-63.76	***
Multi-county	0	.	.	.	.	.	
Constant	-.596	74.447	-0.01	.994	-146.656	145.463	

Mean dependent var	182.322	SD dependent var	219.716
R-squared	0.153	Number of obs	2305.000
F-test	12.197	Prob > F	0.000
Akaike crit. (AIC)	22303.959	Bayesian crit. (BIC)	22413.073

*** *p<.01, *** *p<.05, ** *p<.1*

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PUBLICATIONS AND PRESENTATIONS

Elliott N. (February 2020). Reductions in Infant Mortality are Associated with Increased Local Health Department Expenditures. Poster presented at Florida International University, Miami, FL.

Elliott N. (April 2021). The Impact of Local Health Department Expenditures on Public Health Outcomes, 2010-2019. Abstract presented at Florida International University, Miami, FL.

Elliott N. (June 2021). The Funding and Performance of Local Health Systems and their Impact on Public Health Outcomes. Proposal presented at Florida International University, Miami, FL.

Elliott N. (June 2022). Local Health Department Capacity to Improve Public Health: The Impact of Public Health Accreditation and Public Health Funding. Dissertation defense presented at Florida International University, Miami, FL.

Elliott N., Arrieta A. (2022). The Effect of Public Health Accreditation on Public Health Outcomes. In review: Journal of Public Health Management & Practice.

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