BENCHMARKING THE EFFICIENCY OF PUBLIC HEALTH AGENCY IN THE CONTINENTAL U.S. AND EVALUATING ITS IMPACT ON HEALTH OUTCOMES

by

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(Under the Direction of Mu,Lan)

ABSTRACT

Studies have shown that the relationship between the performance of public health agency and health outcomes is one of the most notable gaps in public health research. This study employs data envelopment analysis (DEA) to evaluate the efficiency of public health agency in the continental U.S. as the proxy of the overall performance. The relationship between health outcomes and the efficiency public health agency is explored both in state-level and two local case studies of Alabama and Florida. Findings show that both the overall effect of the efficiency of public health agency on health outcomes and chances of improving the health of populations by appropriate operation of public health agency with suitable assignment of primary care physicians are not significant and promising. It implies that the prevalent assumption that links better public health performance with better health outcomes cannot be established, and after exploring various approaches, overall improvement of health outcomes remains challenging.

INDEX WORDS: Health outcome, public health agency; efficiency; data envelopment analysis (DEA); primary care physician supply

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CHAPTER 1

INTRODUCTON

A series of systematic reviews (Hyde et al. 2012; Beck et al. 2012; Hilliard et al. 2012; Harries et al. 2012; Dilley et al. 2012) of current public health services and systems research literatures acknowledged that “studies examining the relationship of performance of public health agencies and health status or health outcomes was one of the most notable gaps in literature”. One of the challenges of such studies, as Hyde et al. (2012) argued, is that although the prevalent assumption links better public health performance with better health outcomes, demonstrating a clear link between the two is complicated by a host of organizational, contextual, economic, political, and sociocultural factors.

Inconsistent method and standard used to measure performance of public health agencies can be another challenge. There are a substantial body of literatures providing evidences that public health performance can be reliably and accurately measured using nationally recognized instruments like the National Public Health Performance Standards (NPHPS) (Erwin 2008). However, Beaulieu et al. (2002, 2003) argued that the “gold standard” for measuring public health agencies performance has yet to be determined considering the problems of criterion validity for these instruments. Margolis et al. (1999) has shown that different public health agencies staffs have different perspectives on performance. Further, NPHPS-based measures tend to capture the performance of the whole public health system beyond just focusing on the performance of public health agencies; this makes a methodological problem for measuring the performance of the LHD per se, even as part of the "system" (Erwin 2008).

Variances in definition of performance may also challenge evaluations of the relationship between performance of public health agencies and health outcomes. NPHPS defines performance, in a public health setting, as the effectiveness of public health system in providing the ten essential public health services. Murray and Frenk (2000) defined performance as the degree of goal attainment relative to what could be achieved. Conceptually, their definition of performance is similar to the definition of efficiency which is the ability of "obtaining the maximum output for given inputs" (*A Dictionary of Economics* 2009) or "the ratio of the observed level of attainment of a goal to the maximum that could have been achieved with the observed resource" (Evans et al. 2001). These two definitions capture different dimensions of performance, and have their own advantage. Murray and Frenk's (2000) definition of performance reflects how efficiently a public health agency is operating. Their definition of performance has been adopted by the World Health Organization and frequently used to measure and compare efficiencies of public health systems of different countries in the world using efficient frontier analysis (Evans et al. 2001; Afonso and Aubyn 2005). Compared with Murray and Frenk's (2000) definition of performance, NPHPS's definition of performance emphasizes on whether desired public services have been adequately provided. Although NPHPS-based measure(s) of performance can evaluate the effectiveness of public health system in protecting and improving the health of populations, it tells little about whether the public health system is functioning in the best possible manner with the least waste of resources to produce public health service.

An unclear definition of performance will probably make the result of this study less comparable to other researches evaluating the same relationship of interest but adopting different definitions of performance. Considering the scale and breadth of the term "performance," this study measures the efficiency of public health agencies since it is more clear and distinct. Another more important reason for measuring the efficiency of public health agencies is that although the efficiency of other sectors of the public health system like hospitals (Ozcan and Luke 1993), nursing homes (Vitaliano and Toren 1994; Chattopadhyay and Ray 1996), and even physicians (Chilingerian 1995) are frequently evaluated, little is known about the efficiency at which public health agencies produce public health services. Only one publication examining the efficiencies of public health agencies has been found, in which Mukherjee et al. (2010) explored efficiencies of local health departments (LHDs) operating in the U.S. using data envelopment analysis (DEA). However, they didn't evaluate the relationship between health outcomes and the efficiency of LHDs in their study. Given the increasing costs of health care as well as the transforming health care reimbursement mode from pay-for-service towards pay-for-performance or value-based payment in the United States, understanding the relationship between health outcomes and the efficiency at which public health agencies are operating may help to reduce the waste of public health resources, provide implications of effective allocations of public health resources, and further improve the health of populations.

Health outcome can be defined by as "changes in individuals attributable to the care they received" (Donabedian 1966), and are usually measured by five D's, namely death (mortality), disease, disability, discomfort, and dissatisfaction (White 1967). As Halverson (2000) argued that “public health is more than just what the LHD provides” (Halverson 2000), health outcomes can be seen as “outputs” of the entire public health system which is defined by the Centers for Disease Control and Prevention (CDC) as “a network of all public, private, and voluntary entities that contribute to the delivery of essential public health services within a jurisdiction”. To better understand health outcomes, this study evaluates health outcomes not only from the efficiency of public health agencies, but also from primary care physician supply. Primary care physician supply is chosen among all other entities in the public health system primarily for two reasons. First, it is recognized as the most important form of health care for maintaining population health because it is relatively inexpensive, can be more easily delivered than specialty and inpatient care, and if properly distributed it is the most effective in preventing disease progression on a large scale (Guagliardo 2004). Second and the more important reason is that although there is considerable evidences of the association between health outcomes and primary care, few of them tried to understand health outcomes via an integral perspective of public health agencies and primary care. Integrating public health and primary care didn’t draw much attention until recently. Evidence from the Institute of Medicine (IOM) showed that “integrating primary care and public health can enhance the capacity of both sectors to carry out their respective missions and link with other stakeholders to catalyze a collaborative, intersectoral movement toward improved population health" (IOM 2012).

As a result, two overall questions this study tries to answer are: (1) is there any significant impact of the efficiency of public health agency on health outcomes?; (2) how the efficiency of public health agency and primary care physician supply together may affect health outcomes? Correspondingly, this study is expected to achieve two objectives:

- First, this study will provide additional empirical evidence of the relationship between health outcomes and the efficiency of public health agency.
- Second, if the relationship of interest in objective one is found, then we attempt to evaluate health outcomes from an integral perspective of the efficiency of public health agency and primary care physician supply; if the relationship of interest does not exist, the absence of such a relationship will be explained.

The following of this paper is organized in the following order: literature review is included in the next chapter; study design and methodology will be discussed in chapter three; analysis and discussion are provided in chapter four; and finally, chapter five gives the conclusion and the plan of future research.

CHAPTER 2

LITERACTURE REVIEW

2.1 Public health system in the United States

Public health systems in the U.S. are commonly defined as a "dynamic network in which all public, private, and voluntary entities that contributes to the delivery of essential public health services within a jurisdiction" (CDC). According to the CDC, the public health system includes all flowing sectors:

- Public health agencies at state and local levels
- Health care providers
- Public safety agencies
- Human service and charity organizations
- Education and youth development organizations
- Recreation and arts-related organizations
- Economic and philanthropic organizations
- Environmental agencies and organizations

Public health agencies, collaborating with other sectors of the public health system, are responsible for providing the ten Essential Public Health Services (EPHS), as listed below:

1. Monitor health status to identify and solve community health problems.
2. Diagnose and investigate health problems and health hazards in the community.

3. Inform, educate, and empower people about health issues.
4. Mobilize community partnerships and action to identify and solve health problems.
5. Develop policies and plans that support individual and community health efforts.
6. Enforce laws and regulations that protect health and ensure safety.
7. Link people to needed personal health services and assure the provision of health care when otherwise unavailable.
8. Assure competent public and personal health care workforce.
9. Evaluate effectiveness, accessibility, and quality of personal and population-based health services.
10. Research for new insights and innovative solutions to health problems.

(Source: The Centers for Disease Control and Prevention)

the Commonwealth Fund showed that Americans spent $2.7 trillion or $8,508 per capita in 2013, compared to $5,669 per person in Norway and $5,643 in Switzerland, the next highest-spending counties (Schoen et al. 2013). The OECD's *Health at a Glance 2013* report found that life expectancy in the United States was lower than the average in the 34 countries of the Organization for Economic Cooperation and Development (OECD). "While life expectancy in the U.S. has been growing over the last several decades, it has grown more slowly than in the other countries" (OECD 2013). Likewise, *Bloomberg* ranks the U.S. health care system at 46th among that of total 48 countries (Bloomberg 2013).

2.2 Public health agencies and health

"When health was no longer simply an individual responsibility, it became necessary to form public boards, agencies, and institutions to protect the health of citizens"(IOM 1988, p62) .

The history of development of public health system could date back to seventeenth century when public efforts started to evoke to protect citizens against dread disease such as the plague, cholera, and smallpox at that time. In the late seventeenth century, several European cities appointed public authorities to adopt and enforce isolation and quarantine measures (and to report and record death from the plague). By the end of the eighteenth century, several cities, including Boston, Philadelphia, New York, and Baltimore, had established permanent councils to enforce quarantine and isolation rules (IOM 1988, p57). The following "great sanitary awakening" and sanitary reform movement in early nineteenth century stimulated a new advance development in public health. Edwin Chadwick, a London lawyer and secretary of the Poor Law Commission in 1838, in his General Report on the Sanitary Conditions of the Labouring Population of Great Britain, proposed the establishment of a national board of health, local boards in each district, and the appointment of district medical officers. Many of Chadwick's idea were adopted in the Public Health Act of 1848 which is believed to have great influence in later developments in public health in England and the United States.

Similar studies were taking place in the same period in the United States. John Griscom published *The Sanitary Condition of the Labouring Population of New York* in 1848, which eventually led to the establishment of the first public agency for health in the United States, the New York City Health Department, in 1866. In 1850, Lemuel Shattuck, a Massachusetts bookseller and statistician, recommended a comprehensive public health system for the state in his famous *Report of the Massachusetts Sanitary Commission*, which has come to be considered one of the most farsighted and influential documents in the history of the American public health system. Many of the principles and activities Shattuck proposed later came to be considered fundamental to public health. And he established the fundamental usefulness of keeping records and vital statistics (National Research Council 1988).

During the same period when the first health department was established in New York City, boards of health were established in Louisiana, California, the District of Columbia, Virginia, Minnesota, Maryland, and Alabama. (National Research Council 1988, p61) Since then, health department and board of health began to be set up among the whole United States. By the end of the nineteenth century, 40 states and several local areas had established health departments. Up to 1945, Emerson and Luginbuhl reported there were 1200 local health departments in the United States. By 2010, the National Association of County & City health officials (NACCHO) reported total 2565 local health departments in the United States, and all 50 states and the District of Columbia have their own state health departments in its *2010 National Profile of Local Health Departments*.

Nowadays, health departments are responsible of assuring the quality and delivery of health services, assessing and monitor population health, and developing policies to protect and promote public health. Generally speaking, public health agencies are responsible for providing epidemiological and environmental public health services as well as responding to public health emergency and disaster. An observable trend can be found that many of local health department (LHD) expand their role and also provide clinical services to the public when comparing *National Profile of Local Health Department* reports provided by the National Association of County & City Health Officials (NACCHO).

The National Public Health Performance Standards (NPHPS) provides framework to access capacity and performance of public health agencies on the basis of ten EPHS. Instead of the public health agencies per se, NPHPS based measures have their eyes on the whole public health system and reflect the idea that public health is more than just what LHD provides.

NPHPS has been generally employed to measure local health department performance. Multiple studies revealed that jurisdictional size the strongest predictor of performance of health departments (Richards et al. 1995; Freund and Liu 2000; Kennedy 2003; Zahner and Vandermause 2003). However, jurisdiction size associated with improved performance varies across studies. Several studies found LHDs serving more than 50,000 populations usually had better performance than those serving populations less than 50,000 (Suen et al. 1995; Turnock et al. 1994; Turnock, Handler, and Miller 1998). While other studies showed that performance for LHDs serving populations less than 25,000 dropped off particularly (Suen and Magruder 2004; Turnock et al. 1995). Mays et al. (2006) showed that LHD per capita spending was the most consistent predictor of performance. Higher performance was generally noted for LHDs that have higher expenditures per capita. LHDs that have higher staff per population served were also found performing better (Mauer, Mason, and Brown 2004).

2.3 Primary care and health

"The term 'primary care' is thought to data back to about 1920, when the Dawson Report was released in the United Kingdom. That report, an official 'white paper', mentioned 'primary health care centres', intended to become the hub of regionalized services in that country" (Cited in Starfield et al, 2005). While primary care came to be the cornerstone of the health service systems in the United Kingdom as well as in many other countries, it didn't gain much attention in the United States until couple decades later. In the early decades of 20 century, instead of developing primary care, the U.S. had better interested in increasing specialization of its physician workforce. Primary care wasn't recognized as a specialty in the U.S. until family physicians, working with international colleagues, established standards for credentialing the new "specialty" of family practice. They concerned over that the survival of generalist physicians would be threatened by the disproportionate increase in the supply of specialty in the United States which might lead to the detriment of generalist practice. Two reports from the Institute of Medicine (IOM) (IOM 1978, 1996) defined primary care as "the provision of integrated, accessible health care services by clinicians who are accountable for addressing a large majority of personal health care needs, developing a sustained partnership with patients, and practicing in the context of family and community." And it is recognized as "first-contact access for each new need; long-term person-(not disease) focused care; comprehensive care for most health need; and coordinated care when it must be sought elsewhere" world-wide (WONCA 1991). Definitions of primary care physicians vary from country to country, in the United States, primary care physicians include family and general practitioners, general internists, and general pediatricians. These three types of physicians constitute the primary care physician workforce and have been shown to provide the highest levels of primary care characteristics in their practices (Weiner and Starfield 1983).

Importance of primary care to health in the United States has been well documented. At state-level analyses, Shi (1992, 1994) found that those states with higher ratios of primary care physicians to population had better health outcomes, including lower rates of all causes of mortality, even after controlling for sociodemographic measures (percentages of elderly, urban, and minority, income, unemployment, etc.). Vogel and Ackerman (1998) showed that the supply of primary care physicians was associated with an increase in life span and with reduce low birth-weight rates. In addition to its association to morality and life expectancy, primary care is also found associated with morbidity. Shi and colleagues found that the supply of primary care physicians was significantly associated with reduction of low birth weight at the state level (Shi et al, 2003a). While comparing the impacts of supply of primary care physicians and supply of specialist physicians on health, Shi et al found that the supply of primary care physicians was significantly associated with lower all-cause mortality at state level, whereas a greater supply of specialty of primary care physicians was association with higher mortality (Shi et al, 2003b).

County-level analyses confirmed the positive influence of an adequate supply of primary care physicians by showing that all-cause mortality, heart disease mortality, and cancer mortality were lower where the supply of primary care physicians was greater (Starfield, Shi, and Macinko 2005). Shi and colleagues examined urban areas and nonurban areas separately (Shi et al, 2005). They found that nonurban counties with a greater number of primary care physicians had 2 percent lower all-cause mortality, 4 percent lower heart disease mortality, and 3 percent lower cancer mortality than did nonurban counties with a smaller number of primary care physicians. While in urban areas, the relationship appeared more complex. Authors explained that such inconsistent relationships between urban and nonurban areas might result from the less degree of income inequality and greater racial differences in urban areas. Campbell et al conducted a county-level research in Florida examining supply of primary care physicians and cervical cancer mortality (Campbell et al. 2003). They found that each one per 10,000 population increase in supply of family physicians was associated with a decrease in mortality of 0.65 per 100,000 populations. The positive effect of primary care was also found in the significant relationship between reduced mortality and the supply of general internists.

Primary care also has significant implication in health disparity. Shi (1999) found that areas with abundant primary care resources and high income inequality have a 17 percent lower postneonatal mortality rate (compared with the population mean), whereas the postneonatal mortality rate in areas of high income inequality and few primary care resources was 7 percent higher. In another research, Shi et al. (2004) found that the supply of primary care physicians in the U.S. states has a larger positive impact on low birth weight and infant mortality in areas with high social inequality than it does in areas with less social inequality.

2.4 Integrating primary care and public health

In 2010, the Institute of Medicine (IOM) was asked by the Centers for Disease Control and Prevention (CDC) and the Health Resource and Services Administration to convene a committee to study and prepare a report providing recommendation on how they, as national agencies, could work collectively to improve health through the integration of primary care and public health (IOM 2012). To better understand what is “integrating primary care and public health”, key terms should be defined in the first place.

Primary care refers to "the provision of integrated, accessible health care services by clinicians who are accountable for addressing a large majority of personal health care needs, developing a sustained partnership with patients, and practicing in the context of family and community" (IOM 1996, p.1). Be careful that primary care should be distinguished from primary health care though they are often used interchangeably. The former, primary care, refers to family medicine services typically provided by physicians to individual patients and is person-oriented, longitudinal care (Shi 2012; Muldoon, Hogg, and Levitt 2006). Primary health care, in contrast, is a broader concept intended to describe both individual-level care and population-focused activities that incorporate public health elements (Shi 2012).

Public health has been defined as "the combination of sciences, skills, and beliefs that is directed to the maintenance and improvement of the health of all the people through collective or social actions, and the programs, services, and institutions involved emphasize the prevention of disease and the health need of the population as a whole" (*A Dictionary of Epidemiology* 2009). The IOM offered a condensed definition of public health as "what society does collectively to assure the condition for people to be healthy" (IOM 1996, p.19).

Integration of primary care and public health can be defined as the linkage of programs and activities to promote overall efficiency and effectiveness and achieve gains in population health (IOM 2012).

Under such context, primary care and public health are found presently operating largely independently, and should be viewed as "two interacting and mutually supportive components" of a health system designed to improve the health of populations (cited in IOM 2012). However, they have complementary functions and share the common goal of ensuring a healthier population. Generally, primary care physicians work on clinical frontier. They treat and educate individual patient to prevent diseases. Although primary care physicians usually see the bigger picture of disease, they can do little to reduce diseases on their own. One reason of this is they can't address the environment factors that affect the diseases. In contrast, public health agencies are able to collect local environmental data. They monitor patients at population level and develop policy to improve community health. However, since they don't see individual patients, much of their effort can easily go off. But by working together, primary care and public health can each achieve their own goals and simultaneously have a greater impact on the health of population than either of them would have working independently.

2.5 Governance of public health agencies

The relationship between state health agencies and local public health agencies differs across the state. For a local public health agency, if it is leaded by state employees, it is classified as "state" governance local public health agency; if it is leaded by local employees, it is classified as "local" governance local public health agency; and if state employees and local employees share the leadership, it is classified as "shared" governance local public health agency. And according to the classification criteria developed by the Association of State and Territorial Health Officials (see the ASTHO Profile of State Public health (2010), p.26 for detail), each state can be classified into four governance structures based on the relationship between state health agency and local public health agencies within the state. For instance, if the state does not have local public health agencies that serve at least 75 percent of the state's population, such state is classified as have "centralized" governance structure.

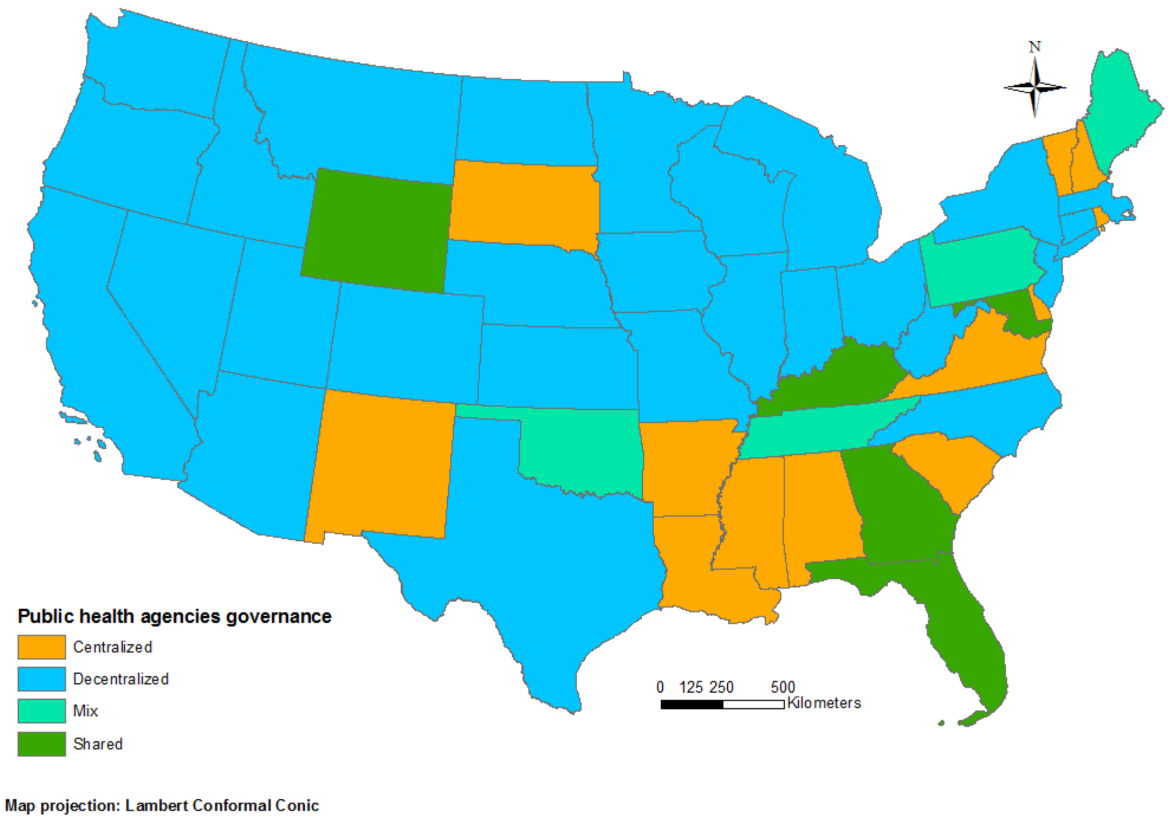


Figure 1 Governance of state and territorial public health agencies in the continental U.S.

CHAPTER 3

STUDY DESIGN AND METHODOLOGY

3.1 Study design: the outline

The relationship between health outcomes, the efficiency of public health agency, and primary care physician supply is evaluated on both state level and local level. In state-level analysis, it is ideally to measure the efficiency of state and territorial public health agencies. However, it cannot be done due to unavailable data. Therefore, we measure the efficiency of state in utilizing local public health resources as the proxy of the efficiency of state and territorial public health agencies. And we are interested in evaluating how the efficiency of state and territorial public health agencies along with primary care physician supply may affect health outcomes.

In local-level analysis, efficiencies of local health department (LHD) are evaluated. Ideally, to better understand the relationship between health outcomes, the efficiency of LHD, and primary care physician supply under different governance types, four case studies should be implemented. Correspondingly, four states representing the four governance types are chosen, namely Alabama for “centralized”, California for “decentralized”, Florida for “shared”, and Tennessee for “mix” governance. The selection of these four states is subjected to three considerations. First, there should be consistency in administrative divisions of LHDs. This consideration tries to mitigate confounders resulting from organizational differences among LHDs with different administrative divisions. Second, administrative division of LHDs should match reported units of health outcomes and primary care physician supply. Given that health outcomes and primary care physician supply are commonly reported by county, administrative division of LHDs is restricted to county in this study. Third, selected states should have high response rate in *2010 National Profile of Local Health Department* survey. This consideration aims to ensure reliable sample size in each case study. Balancing all three considerations, four states mentioned above were selected into the case study. Unfortunately, preliminary analyses show that only Alabama and Florida provide sufficient information for further analyses. As a result, local-level analyses are only implemented in Alabama and Florida in this study.

Another important issue needed to be addressed is that unlike former study by Mukherjee et al. (2010) which put all LHDs in the United States in the same cohort and compared efficiencies of LHDs in different states directly, four different cohorts are set up for each of four case studies. Each of these four cohorts only contains LHDs within the objective state to be analyzed. The motivation of creating such cohorts is to mitigate potential confounders that can be attributable to differences in the host of organizational, contextual, economic, political, and sociocultural factors in different states.

A two-step analysis scenario is applied to both state-level analysis and local-level analysis:

- Step 1: measuring efficiencies at which public health agencies (for instance, LHDs) were operating.
- Step 2: exploring the association between health outcomes, efficiencies of public health agencies, and primary care physician supply.

DEA is employed to measure efficiencies of public health agencies (see section 3.2 for a brief introduction of DEA). Data used in this study are obtained from the *2010 National Profile of Local Health Department* (see section 3.3 for detail). Section 3.4 discusses settings of DEA in this study. And section 3.5 concentrates on methodologies used to exploring the association between health outcomes, efficiencies of public health agencies, and primary care physician supply.

3.2 Data envelopment analysis

Data Envelopment Analysis (DEA) is a non-parametric method of efficiency analysis that employs linear programming to estimate the "best practice" or most efficient production frontier of a set of peer entities called Decision-Making Units (DMUs), which can be any production units such as hospitals. It was developed by Charnes, Cooper, and Rhodes (1978) based on the earlier work of Farrell's (1957). DEA has been frequently used in benchmarking to measure relative technical efficiency which concerned with "obtaining the largest possible level of output for a given quantity of inputs" (*A Dictionary of Epidemiology* 2009). As described by Debreau (1951) and Farrell (1957), relative technical efficiency can be measured as "one minus the maximum equiproportionate reduction in all input that still allows the production of given output, a value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency" (Debreau 1951; Farrell 1957) or simply the ratio of the observed input and the minimum input under the assumption of fixed output. The term "relative" reflects that the efficiency of each DMU is evaluated based on other DMUs in the cohort. Figure 1 explains the input-oriented technical efficiency for a single-output and two-input case.

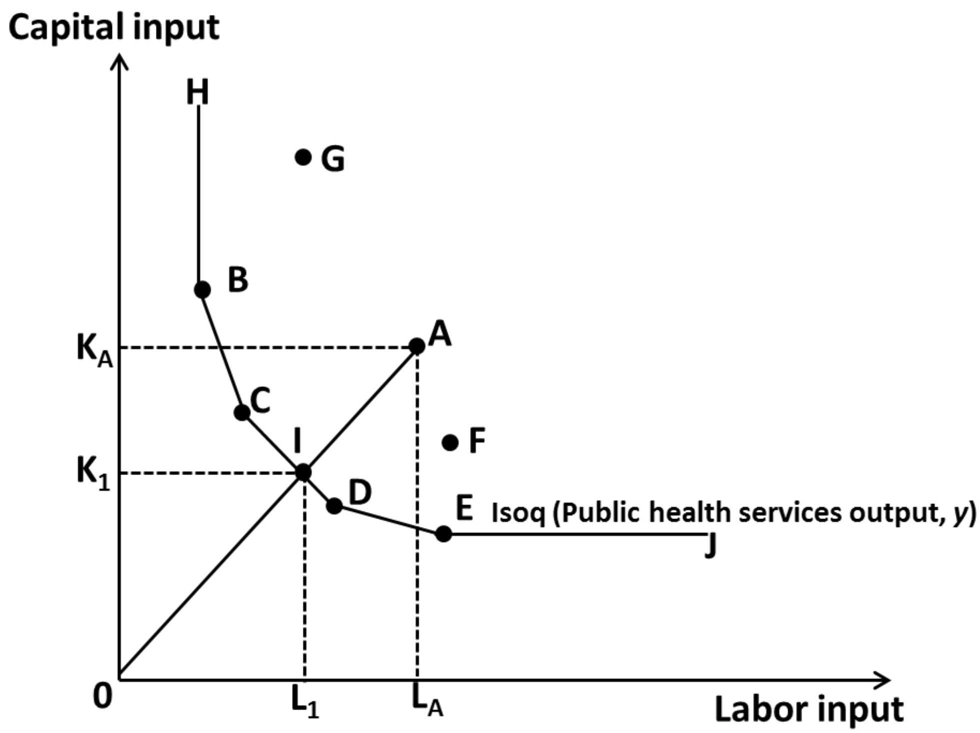


Figure 2 Input oriented efficiency for single-output and two-input case. (*redraft version from Mukherjee et al. 2010*)

Suppose A, B, C, D, E, F, and G represent seven LHDs that consume varying amounts of two inputs (labor and capital) to produce one output (public health services) of level y. HBCDEJ represents the efficient frontier corresponding to output level y. B, C, D, and E lie on the efficient frontier and represent efficient LHDs. A, F, and G are enveloped by the efficient frontier, and therefore represent inefficient LHDs since they need to consume greater amounts of inputs to produce an output of level y. Now we are interested in the efficiency of the LHD A. In this case, point I represents an efficient optimum of LHD A. In other words, it is possible for

LHD A to equiproportionately reduce the input bundle to point I and still produce the given amount of output. Employing Debreau and Farrell's measure, the technical efficiency for LHD A can be measured as the ratio of 0I (the minimum input) and 0A (the observed input).

DEA is also able to deal with multiple-output and multiple-input scenarios. In fact, the capability of dealing multiple-output and multiple-input case is one of the notable strength of DEA. Another characteristic of DEA that is favorable to this study is that no priori assumptions of the production function for DMUs are needed. Such an empirical-oriented characteristic makes DEA a suitable tool to evaluate the efficiencies of nonprofit sectors.

The original DEA developed by Charnes, Cooper, and Rhodes (1978) are commonly referred to as the CCR model. Basically, the CCR model assumes constant return to scale (CRS) in the production process. Unfortunately, the CRS assumption is only appropriate when all DMUs are operating at an optimal level. Imperfect competition, constraints on finance, etc. may cause a DMU to be not operating at optimal scale. To address this issue, Banker, Charnes, and Cooper (1984) suggested an extension of the CCR model to account for the variable returns to scale (VRS) situation. This extended model is now commonly referred to as the BCC model. The CCR model and the BCC model are two basic models of DEA. Many extensions based on these two models have been developed, which greatly strengthen the utility of DEA in efficiency analysis.

Basic DEA models were initially developed assuming all data is strictly positive. It is not unusual in practice that data do not satisfy this assumption. There are situations where some data may be zero or even missing. Thanassoulis et al. (2008) provided a detailed discussion on this issue. "Basically, zero outputs are not a problem in standard efficiency models such as the

CRS and VRS model, irrespective of the model orientation" (Thanassoulis et al. 2008, p309). However, "zero inputs can be problematic in DEA, since at least one unit with a zero input will always be CRS or CRS efficient irrespective of the levels of its remaining inputs or outputs" (Thanassoulis et al. 2008, p310). Technically, when the DMU assessed has a zero value of an input *k*, all its peers should also have a zero value on that input *k*. Thus, "at least one DMU with zero value on input *k* will be a peer to the DMU assessed and so will be Pareto efficient [,] irrespective of what values such a peer has on outputs or input other than *k*" (Thanassoulis et al. 2008, p310).

DEA has been frequently employed in a variety of fields since it was initially introduced. The first application of DEA in health care began with H. David Sherman's Doctoral dissertation in 1981 in which Sherman applied DEA to evaluate the performance of medical and surgical departments in 15 hospitals (Chilingerian and Sherman 2011). In 1983, in the first publication of health application using DEA, Nunamaker used DEA to study nursing services (Nunamaker 1983). By 1997, there were 91 DEA studies in health care (Hollingsworth et al. 1999). Systematic reviews of application of DEA in health care sectors have been provided by Hollingsworth et al. (1999), Hollingsworth (2003), Chilingerian and Sherman (2004), and Worthington (2004).

3.3 Data preprocessing

Data used in this study are from the *2010 National Profile of Local Health Department* dataset provided by the Interuniversity Consortium for Political and Social Research. This dataset was originally collected by the National Association of County and City Health Officials in its *2010 National Profile of Local Health Department* survey (Leep 2012) (hereafter "2010 survey").

In the 2010 survey, NACCHO sent questionnaires to all 2,565 local health departments in the U.S. of which 2107 or 82% responded (NACCHO 2010). Via these questionnaires, NACCHO attempted to collect information of LHDs in the United States including: governance type and organizational structure, information on employees and workforces, fiscal information such as revenue and expenditure, availability of public health services, and more.

Data preprocessing process were conducted in three steps: (1) excluding missing data and "bad" data, (2) reconstructing data for DEA estimation, and (3) excluding "bad" data. Missing data were basically resulted from the failure or rejection in response to questions in the 2010 survey. For instance, some LHDs did not provide information of the expenditure of the most recent fiscal year. Since these LHDs cannot provide useful information of the expenditure, these LHDs are excluded in the analysis regardless of whether they are able to provide other useful information or not. Same criterion is applied to the judgment of other information.

After excluding missing data, employees and workforces data as well as data of availability of public health services are reconstructed for DEA estimation later. In terms of information on workforces and employees, NACCHO collected full-time equivalent numbers of 12 common public health occupations employed by LHDs. Based on their duties and nature, these twelve public health occupations were reclassified into five public health workforces in this study, namely (1) public health managers, (2) public health physicians/nurses, (3) public health epidemiologists/sanitarians, (4) public health administrative/clerical employees, and (5) other public health employees (see "Appendix III" for details of public health occupation reclassification).

In terms of the availability of public health services, each LHD was requested to provide information of whether 87 different public health services were provided. NACCHO also identified if a particular public health service was provided internally or was contracted out. Based on their nature, these 87 public health services can be further classified into two categories: (1) clinical public health services, and (2) epidemiological/environmental public health services. Clinical public health services include immunizations, screening for disease and conditions, treatment for communicable diseases, maternal and child health services such as family planning and prenatal care, and other medical care services including comprehensive primary care, home health care, oral health, and behavioral and mental health services. In contrast, epidemiological/environmental public health services include various epidemiology and surveillance activities (e.g. surveillance of infectious diseases); population-based primary prevention services (e.g., obesity or substance abuse); regulation, inspection and licensing services (e.g. public drinking water inspection); and other environmental health services like hazardous waste disposal, pollution prevention, and land use planning. See "Appendix IV" for classifications of clinical public health services and epidemiological/environmental public health services.

The last step in data preprocessing is to exclude "bad" data. To clarify that unlike missing data, "bad" data here does not refer to data that are subjected to severe biases or any other data collection problem. In fact, these "bad" data are good in nature but can be problematic to DEA. Specifically, data considered as "bad" data in this study are those have a value of zero after step two discussed above. For instance, some LHDs reported that they did not hire any public health manager. In other words, their "FTE public health managers" inputs are zero. As discussed in section 3.2, inputs with a value of zero can be problematic to DEA since LHDs that have input(s) with a value of zero will be estimated as efficient regardless of whether they are really efficient or not since it is likely that no other LHDs show chances of improvement. In a conceptual standpoint of health department, a value of zero may be a result of a conscious management decision of not using some inputs or not producing some outputs. In other words, LHDs that didn't employ public health managers were operating in different schema(s) compared with those had public health manager(s). As a result, resulting efficiencies of LHDs in different operation schemas should not be compared with each other directly.

3.4 Measuring the efficiency of public health agency

This analysis treats a typical public health agency as a decision-making unit which consumes multiple inputs to produce multiple outputs. According to definition of technical efficiency, if a public health agency consumes fewer amounts of inputs to produce a given amount of outputs, it is considered operating more efficiently. Since the production function of public health agencies is usually unknown, this analysis allows variable-return-to-scale and therefore employs the BCC model to measure their technical efficiency.

DEA is applied to both state-level analysis and local-level analysis. Take its application in local-level analysis as an example, to measure efficiency of LHDs, this analysis assumes that a typical LHD consumes six inputs including five labor inputs and one capital input to produce the outputs. Specifically, five labor inputs are (1) full-time equivalent (FTE) public health managers,

(2) FTE public health physicians/nurses, (3) FTE public health epidemiologists/sanitarians, (4) FTE public health clerical employees, and (5) FTE other public health employees. The expenditure of the most recent fiscal year is incorporated as capital input.

Consuming these six inputs, the LHD is expected to produce three outputs including (1) number of different internally provided epidemiological/environmental public health services; (2) number of different internally provided clinical public health services; and (3) its jurisdiction size. To clarify that epidemiological/environmental public health service and clinical public health service are taken as two different outputs because the labor intensity it takes to provide these two categories of public health services may be different. Moreover, only the availability of public health services that produced internally are considered as outputs since the availability of contracted-out public health services is not a natural indicator of the productivity of LHDs.

Technically, the ideal output of LHDs should be the quantity of public health services provided. However, this information is not included in *2010 National Profile of Local Health Department* data because it is not directly observable and measurable. The jurisdiction size and the number of different of public health services provided are used as proxies for the scale and breadth of public health services provided in this study since Santerre (2009) argued that a greater population is likely to have greater need in both the quantity and the variety of public health services.

Banker et al. (1989) suggested a rule of thumb of sample size for DEA. Suppose p denotes for the number of inputs and q is the number of outputs in DEA, then the sample size n should satisfy the condition where $n \geq \max\{p \times q, 3(p + q)\}$ (Banker et al. 1989). For instance, if all six inputs and three outputs are incorporated in DEA, a sample size greater than twenty-four units is preferred.

Efficiency scores resulted from DEA are consider biased (Simar and Wilson 1998). Technically, DEA efficiency scores are likely to overestimate the true efficiency of DMUs. While several methods have been developed to address this issue, this study employs the bootstrap technique in DEA which was initially introduced by Simar and Wilson (1998) to perform bias correction on raw DEA efficiency scores (also see Simar and Wilson 2000a, 2000b, 2007; Kneip et al. 2008 for details).

Application of DEA in state-level analysis is similar. The same setting of inputs and outputs in local-level analysis is adopted. One significant difference is that, in state-level analysis, all local inputs and outputs are aggregated to state level. As a result, estimating efficiencies of these two levels of analysis have different practical meanings. In local-level analysis, estimating efficiency is efficiency of local public health agency (i.e. local health department) in serving populations in its jurisdiction. It measures the capability of local public health agency in utilizing labor and capital resources to serve its population. If a local public health agency is able to use fewer labor and capital resources to provide certain public health services to certain populations, it has higher efficiency. In state-level analysis, estimating efficiency quantify the utilization of local public health resources (i.e. labor and capital resources) to serve populations in each federal state. This efficiency is evaluated as the proxy of the efficiency of state or territorial public health agency (e.g. state public health department) since data of state or territorial public health agencies are not available in this study.

Technical efficiency and bias correction process are implemented using “FEAR” package and “Benchmarking” package in R.

3.5 Exploring the association between health outcomes, the efficiency of public health agency, and primary care professionals supply

Health outcomes explored in this analysis are three types of mortality that are reported by county including all-causes mortality, cancer mortality, and heart-diseases mortality. All-causes mortality has been commonly used as health status indicator in studies of primary care physician supply and health (see Bergner and Rothman 1987; Kawachi et al. 1999). Cancer mortality and heart-diseases mortality are also explored since they are the top two causes of death in the United States, and are amenable to prevention by public health and primary care. All mortality data were derived from the Centers for Disease Control and Prevention (CDC) compressed mortality files via the CDC Wonder system which can directly calculate age-adjusted mortality using the 2000 standard U.S. population. All mortality data are reported as cases per 100,000 populations. To mitigate extreme cases issue, instead of using mortality data for a single year, all three mortality rates are estimated based on five-year data collected during the period 2006-2010.

Primary care physician supply data used in this analysis were obtained from the Area Health Resource File released by the Health Resources and Services Administration. These data are reported as the number of primary care physicians per 100,000 populations.

Six socio-environmental variables are also incorporated in this analysis to facilitate the interpretation of the relationship of interest. Income inequality, median household income, the percentage of children in poverty, and the percentage of uninsured population are used to explain the socioeconomic aspect. Environmental aspect is captured by daily fine particular matters (micrograms per cubic meter) and the percentage of population exposed to water exceeding a violation limit. These six socio-environmental factors have been adopted by the *County Health Rankings & Roadmap* program for long to evaluate health rankings of counties throughout the whole United States.

Socio-environmental variables data were derived from different data sources. Specifically, income inequality is measured by the Gini coefficient index[1] using 2006-2010 American Community Survey data provided by the U.S. Census Bureau and is available via the American FactFinder system. Median household income data are also derived from 2006-2010 American Community Survey data via the American FactFinder system. The percentage of children in poverty and the percentage of uninsured population data are originally from Small Area Income and Poverty Estimates dataset. Daily fine particular matters mater data are maintained in CDC WONDER Environmental Data system. And the percentage of population exposed to water exceeding a violation limit data for each county are provided by Safe Drinking Water Information System (SDWIS).

Table.1 lists all explanatory variables in this analysis along with the data sources and their original providers (excluding efficiency scores of LHDs). Many data used in this analysis are estimated based on multi-year data to ensure data reliability. Due to data limitation, these data are not exactly from the same year. Fortunately, given that most single-year data are from either 2010 or 2011, they are considered from the same time period in this analysis.

[1] Gini coefficient index measures the extent to which the distribution of income or consumption expenditure among individuals or household within an economy deviates from a perfectly equal distribution. A Gini index of 0 represents perfect equality, while an index of 1 implies perfect inequality. (Source: THE WORLD BANK. http://data.worldbank.org/indicator/SI.POV.GINI)

Table 1 Data Collection

Category	Data	Year(s)	Data Source	Original Data Source
Health outcome	All-causes mortality	2006-2010	Compressed Mortality File	The U.S. Department of Health and Human Services (US DHHS) Centers for Disease Control and Prevention (CDC) National Center for Health Statistics (NCHS) Office of Analysis and Epidemiology
	Cancer mortality	2006-2010		
	Heart-diseases mortality	2006-2010		
Primary care factor	Primary Care Physician supply	2011	Area Health Resource File	American Medical Association (AMA)
Socio-environmental factors	Income inequality (Gini index)	2006-2010	American FactFinder	2006-2010 American Community Survey
	Median household income	2006-2010		
	% children in poverty	2011	County Health Ranking & Roadmap	Small Area Income and Poverty Estimates Small Area Health Insurance Estimates
	% uninsured population	2010		
	PM2.5	2006-2010	CDC WONDER Environmental Data	NASA Marshall Space Flight Center Universities Space Research Association
	% Population exposed to drinking water exceeding a violation limit	FY2012	County Health Ranking & Roadmap	Safe Drinking Water Information System

Several statistical analyses are employed to explore the association between health outcomes, the efficiency of public health agencies, and primary care physician supply (see figure 3). Bivariate analysis is applied to test correlations between three types of mortality, the efficiency of public health agencies, and primary care physician supply.. Based on the results of bivariate analysis, multiple regression analysis is employed to learn the independent contribution of each explanatory variable to the prediction of health outcomes.

Bivariate analysis and regression analysis help us to understand how the typical value of the dependent variable changes when an independent variable varies (while other independent variables are held fixed). Beyond that, we are also interested in whether health outcomes of populations living in the jurisdictions of public health agencies that operate in “high” efficiencies different from health outcomes of populations living in the jurisdictions of public health agencies that operate in “low” efficiencies? One-way ANOVA is employed to helping us to understand this.

One issue still remains: how to define “high” and “low” efficiencies? Remember that technical efficiency estimated by DEA is a relative term since the technical efficiency of a given DMU is calculated based on benchmark(s) (learn from data) in the cohort. It is possible that one thumb of rule to define “high” and “low” efficiencies in one cohort may not be suitable for another. This study employs TwoStep cluster analysis in SPSS to classify “high” and “low” efficiencies. Specifically, TwoStep cluster analysis is implemented to identify the optimal number of cluster in the dataset adopting the Schwarz Bayesian criterion (BIC) as the default clustering criterion.

Two-way factorial ANOVA analysis is employed to evaluate how the interaction between the efficiency of public health agency and primary care physician supply may affect health outcomes. “Technically, two-way factorial ANOVA analysis compares the mean differences between groups that have been split on two independent variables (factors). The primary purpose of a two-way ANOVA is to understand if there is an interaction between the two independent variables on the dependent variable."[2] As a result, it helps us to understand changes in health outcomes from an integral perspective of efficiencies of public health agencies and primary care physician supply.

All statistical referencing are implemented in SPSS. Bivariate analysis is implemented using the "Bivariate Correlation" function. Multiple regression analysis is implemented using the "Linear Regression" function. One-way ANOVA analysis is implemented by running the "One-Way ANOVA" function. TwoStep cluster analysis is implemented using the "TwoStep Cluster Analysis". And finally, "Univariate" function is employed for two-way factorial ANOVA test.

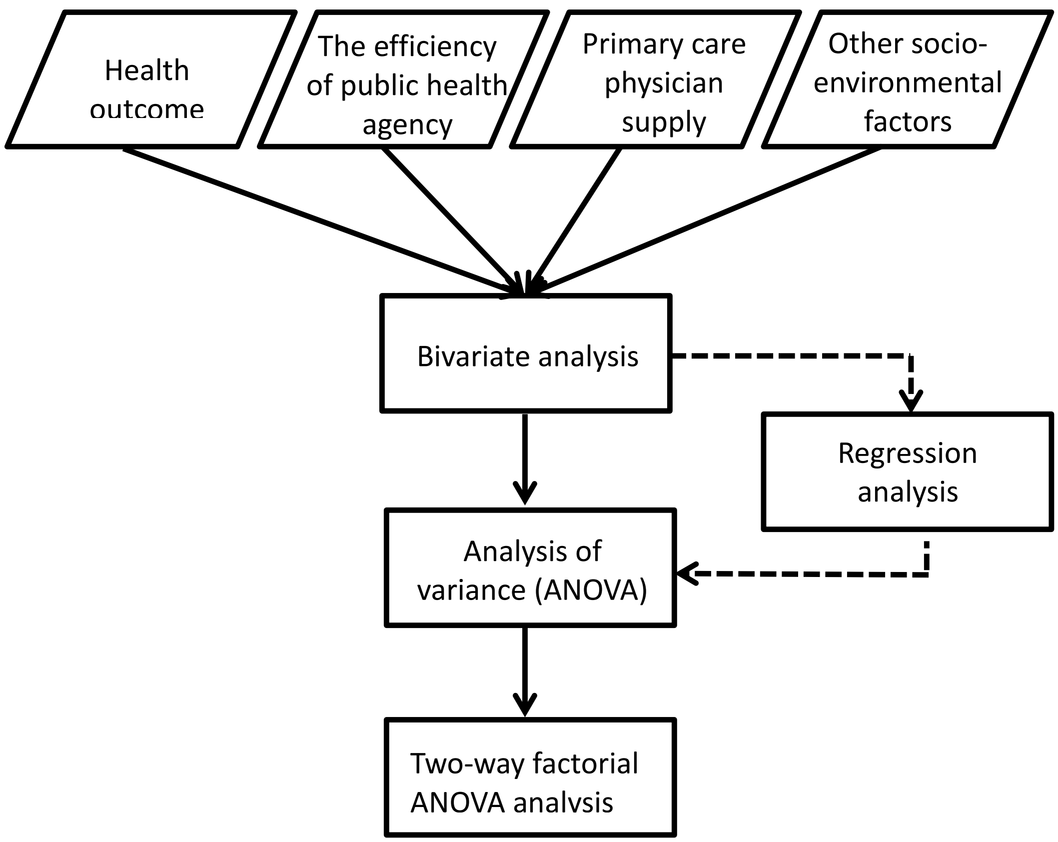


Figure 3 Flowchart of statistical analyses in this study.

[2] Cited from Laerd Statistics: https://statistics.laerd.com/spss-tutorials/two-way-anova-using-spss-statistics.php

3.6 Cartography schemes in this study

For consistency, the quantile classification, one of the most common classification methods used in demonstrating the prevalence of health outcomes, is adopted in all maps in this study. It gives us a straight impression of the rankings of health outcomes in the cohort (e.g. what health outcomes rank the top 20%). For color symbols, red always denotes worse scenarios while green represents better scenario. For instance, states with higher all-causes mortality will be denoted in red while states with higher primary care physician supply are in green.

CHAPTER 4

ANALYSIS AND DISCUSSION

4.1 State-level analysis

In state-level analysis, efficiencies of 49 states in the continental U.S. in utilizing local public health resources are estimated. The effect of estimating efficiencies and primary care physician supply to populations in their jurisdictions on health outcomes is then evaluated. The analysis is implemented in following five processes. In section 4.1.1, prevalence of selected health outcomes including all-causes mortality, heart-diseases mortality, and cancer mortality in the continental U.S. are described. In section 4.1.2, we will discuss estimating efficiencies of states in utilizing local public health resources in the continental U.S.. Correlations between selected health outcomes, estimating efficiencies, primary care physician supply, and other socio-environmental variables are tested in section 4.1.3. Discriminant analysis is employed to test whether higher efficiencies (or higher primary care physician supply) are associated with different health outcomes from those of lower efficiencies (or lower primary care physician supply) in section 4.1.4. Then in section 4.1.5, we test the interaction between estimating efficiency and primary care physician supply. The effect of such interaction on health outcomes will also be analyzed. The summary of state-level analysis is in section 4.1.6.

4.1.1 Prevalence of selected health outcomes, primary care physician supply, and other socio-environmental factors in the continental U.S.

Figure 4 shows the prevalence of age-adjusted all-causes mortality, age-adjusted heart-diseases mortality, and cancer mortality in the continental U.S., all based on standard population 100,000. The color of red denotes states with highest age-adjusted mortality rates, and green denotes states with lowest age-adjusted mortality rates. For all-causes mortality, the highest rate is found in Mississippi with 973.398 per 100,000 populations in the period of 2006 to 2010, while the lowest rate is found in Minnesota with 665.202 per 100,000 populations in the period of 2006 to 2010. The average age-adjusted all-causes mortality rate of the continental U.S. in the same period is 786.102 per 100,000 populations. In terms of cancer mortality, the highest rate is found in Kentucky with 209.499 per 100,000 populations in the period of 2006 to 2010, while the lowest rate is found in Utah with 131.254 per 100,000 populations. The average age-adjusted cancer mortality of the continental U.S. in the same period is 178.741 per 100,000 populations. Heart diseases are more severe causes of death since in average 189.084 per 100,000 populations died of heart diseases in the period of 2006 to 2010 in the continental U.S.. Mississippi is found suffering the most severe heart-diseases mortality in the period of 2006 to 2010 with 268.171 people per 100,000 populations died of heart diseases. Minnesota again has the least age-adjusted heart-diseases mortality rate of 126.639 per 100,000 populations.

Alabama, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Kentucky, West Virginia, and their adjacent states suffer more severe all-causes mortality than other states. New England region, New York, New Jersey, Minnesota, North Dakota, Utah, Colorado, and

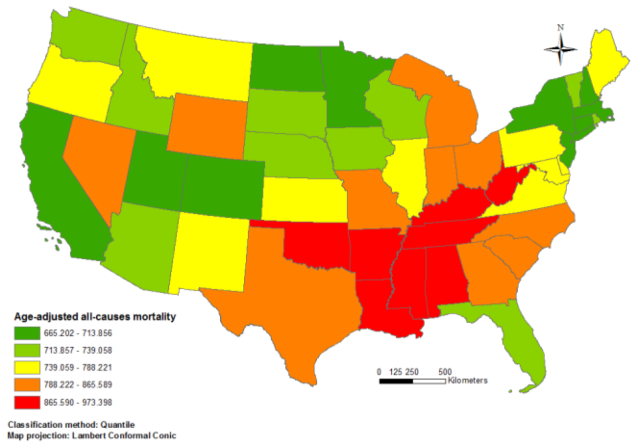
California are found to be healthier and safer. Similar spatial patterns can be found on age-adjusted cancer mortality rate and age-adjusted heart-diseases mortality rate. It seems to be a consistent pattern that Alabama, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Kentucky, and West Virginia have the highest mortality rates of both cancer mortality and heart-diseases mortality. However, not everywhere in the New England region enjoy the "being healthier privilege". Only Connecticut are still found rated top in the continental U.S. in terms of cancer mortality though the entire New England region was still doing better than its adjacent area when it comes to heart-diseases mortality. Generally, the Mountain census region and the West North Central census region have lower age-adjusted cancer mortality rate and age-adjusted heart-diseases mortality rate than other areas in the continental U.S..

Clustering patterns shown in figure 5 provide evidences of findings discussed above. The Western Atlantic area and the Eastern Atlantic area were found the hotspots of all three types of mortality.

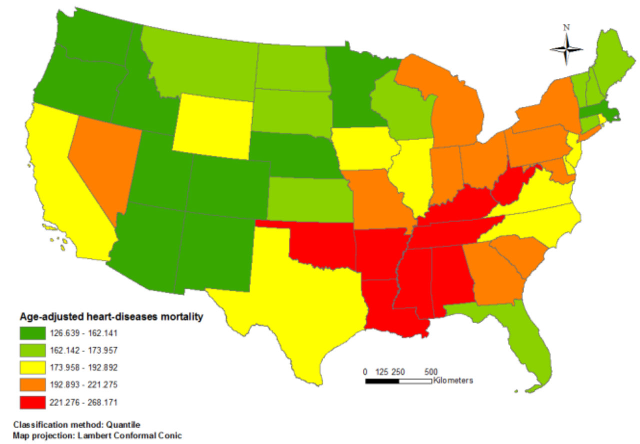
Primary care physician supply varies state by state. The highest rate of primary care physicians per 100,000 populations is found in Washington D.C. with 117.2 FTE primary care physicians available per 100,000 populations (or a population to FTE primary care physician ratio of 853:1). Mississippi is found having the least primary care physician supply with only 52.6 FTE primary care physicians available per 100,000 populations (or a population to primary care physician ratio of 1,901:1). In average, 75.6 primary care physicians per 100,000 populations were available in the continental U.S. (or a population to primary care physician ratio of 1,323:1). According to Appendix A to Part 5 of the 42 Code of Federal Regulations (CFR) (*Criteria for Designation of Areas Having Shortages of Primary Medical Care Professionals,* 1980), a geographic area will be classified as Primary Medical Care Health Professional Shortage Area if the area has a population to FTE primary care physician ratio of equal or greater than 3,500:1. To this point, none of states in the continental U.S. as geographic areas should be classified as Primary Medical Care Health Professional Shortage Area.

The spatial distribution of primary care physicians (per 100,000 populations) somehow explains the spatial pattern of three types of mortality (see figure 6b). Generally, the West South Central region, the East South Central region, and the South Atlantic region had fewer primary care physicians per 100,000 populations compared with the primary care physician supply in the New England region and its adjacent area. Such patterns show consistency with the spatial patterns of three types mortality discussed above. Every rule has an exception. For instance, Florida had relatively lower rates of three types of mortality. A reasonable expectation is that Florida should also have a higher level of primary care physician supply like what it was in the New England region. However, primary care physician supply in Florida is below the average (with 70.1 primary care physicians per 100,000 populations). The implication of such fact might be that health issues are related to a host of different factors in addition to health care resources.

Actually, previous researches have already linked health outcomes with social and physical environments where the population live in. Figure 7a to figure 7f show six socio-environmental factors that may help to understand spatial variance of health outcomes in the continental U.S.. From the spatial distribution of median household income in the continental U.S., it is visually detectable that areas have highest mortality rates are generally areas that have lowest median household incomes. Similar patterns are also found in the spatial distribution of income inequality (Gini coefficient index), percentage of uninsured populations, percentage of children in poverty, and average daily fine particulate matters (pm2.5). Statistical referencing will be used to validate their relationships latter.



(a)



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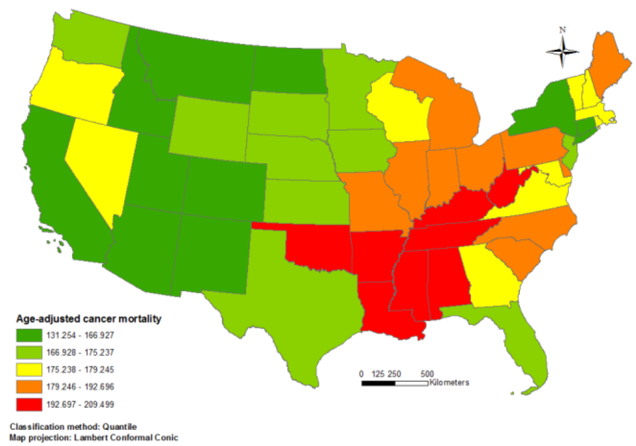
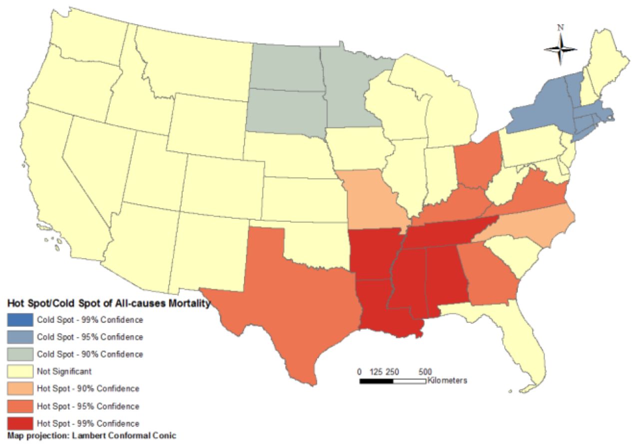
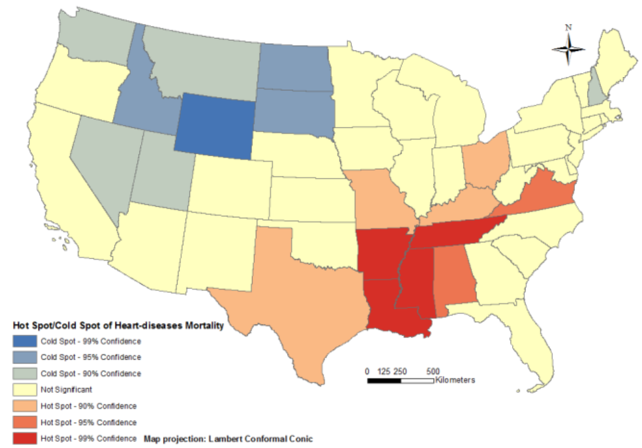


(c)

Figure 4 Age-adjusted all-causes mortality (a), heart-diseases mortality (b), and cancer mortality (c) of states in the continental U.S. in the period of 2006 to 2010.



(a)



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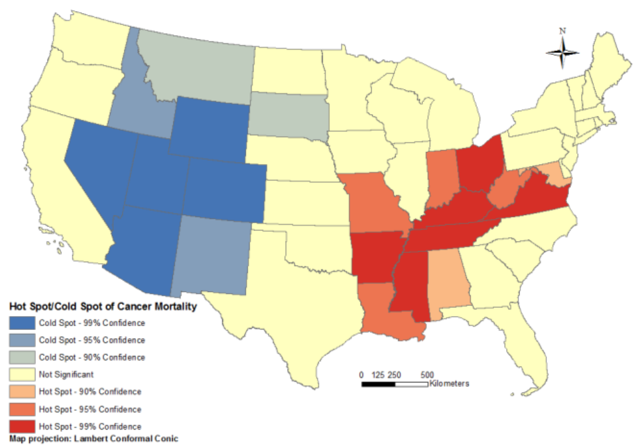
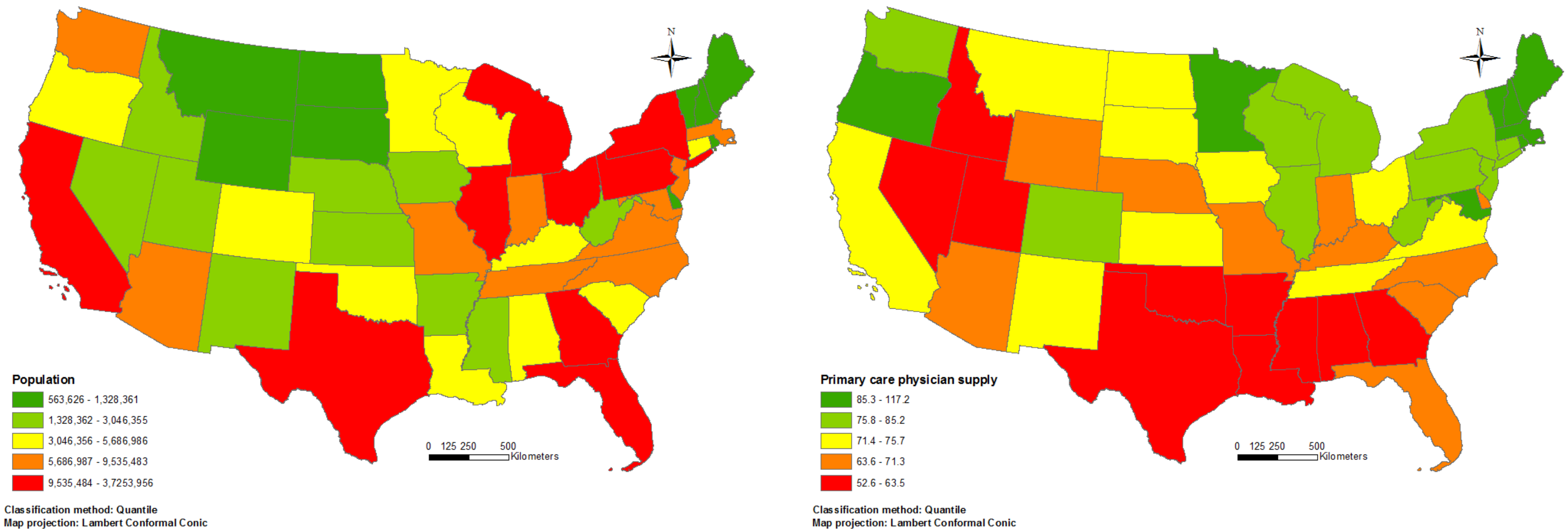


(c)

Figure 5 Hot Spot/Cold Spot of all-causes mortality (a), heart-diseases mortality (b), and cancer mortality (c) of states in the continental U.S. in the period of 2006 to 2010.



(a) (b)

Figure 6 Population (a) and primary care physicians (per 100,000 populations) (b) in states in the continental U.S. in 2011.

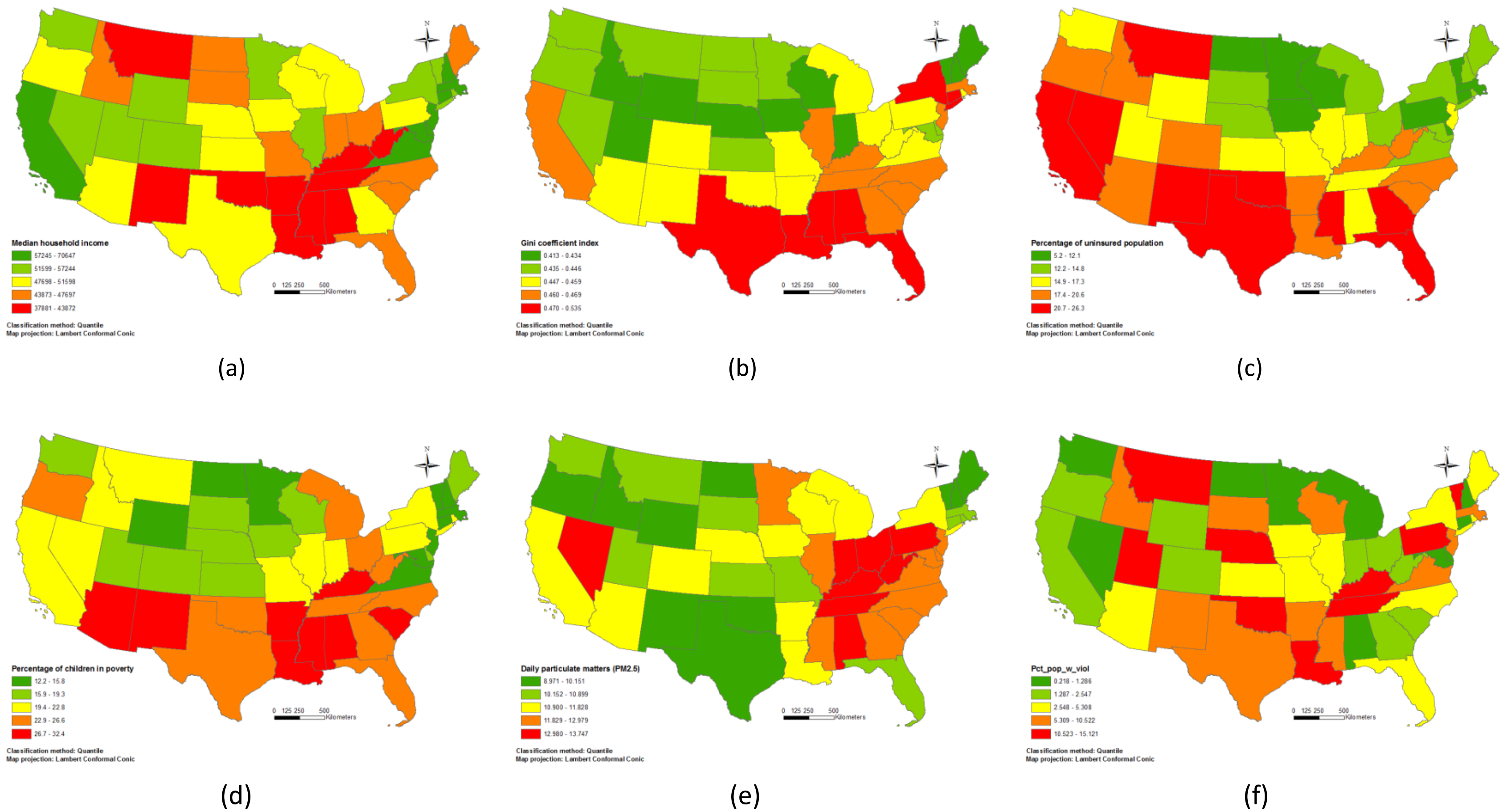


Figure 7 The spatial distribution of socio-environmental factors in the continental U.S. in the period of 2006 to 2010. (From a to f, these socio-environmental factors are: median household income (a), income inequality (Gini coefficient index) (b), percentage of uninsured population (c), percentage of children in poverty (d), average daily fine particulate matters (pm2.5) (e), and percentage of population exposed to drinking water exceeding a violation limit (f). Generally, the color of green denotes better situations while the color of red represents worse cases. For instance, states with high median household income are in green and state with low median household income are in red.)

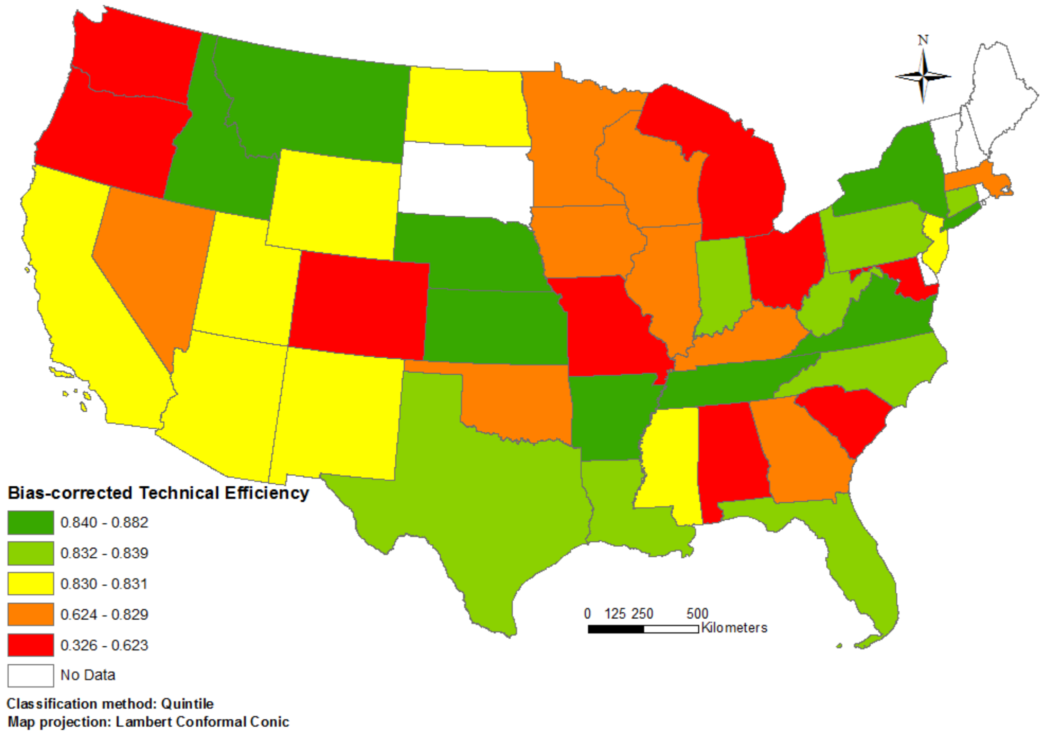
__4__.1.2 Efficiencies of states in the continental U.S. in utilizing local public health resources

Following the discussion in chapter three, especially in section 3.4 on study design and method, efficiencies of states in utilizing local public health resources are evaluated as a proxy of efficiencies of state and territorial public health agencies due to data limitation. These estimating efficiencies quantify utilizations of local public health resources to serve their populations in states in the continental U.S..

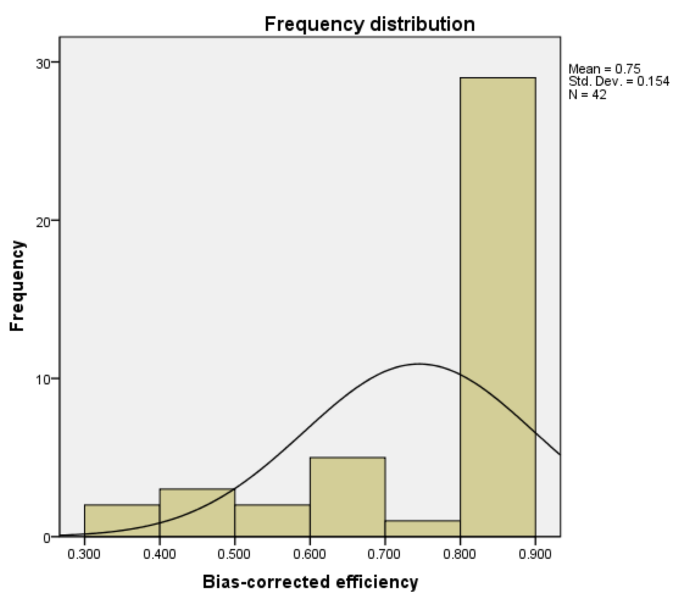
Figure 8 (a) depicts bias-corrected efficiencies of state in the continental U.S. in utilizing local public health resources, and figure 8 (b) shows their distribution. Due to data limitation, seven states are excluded in this analysis. Therefore, there are 42 states in the cohort to be analyzed. Among all forty-two states in the cohort, Kansas was found operating the most efficient with an efficiency of 0.882. It indicates that in Kansas utilized the least local public health labor forces and expenditures to serve a given amount of populations and to provide certain numbers of public health services compared with other states in the cohort. Maryland was found that least efficient state with an efficiency of 0.326. In average, states in the cohort utilized local public health resources with an efficiency of 0.745. Generally, the Pacific coastline region, the East North Central region, southern Mountain region were found utilizing local public health resources in less efficient ways. It means that states in these regions employed more local public health workforces and spent much more money to serve a certain amount of populations.

Understanding estimating efficiencies is not always a straightforward process. States had higher efficiencies mean that these states needed fewer local public health resources to serve populations living in their jurisdictions compared with those had lower efficiencies.

However, no easy equal mark can be drawn between “higher” efficiencies and “better” or between “lower” efficiencies and “worse”. This is exactly what we try to figure out in this exploratory study.



(a)



(b)

Figure 8 Efficiencies of states in utilizing local public health resources in the continental U.S. in 2010.

4.1.3 Bivariate and regression analysis: health outcomes, the efficiency of state in utilizing local public health resources, primary care physician supply, and other socio-environmental factors

Bivariate analysis is employed to learn the correlations between health outcomes, efficiencies of state in utilizing local public health resources, primary care physician supply, and other socio-environmental factors. Table 2 shows the correlation results.

From table 2, we learn that there is no statistically significant correlation between all three types of mortality and the efficiency of state in utilizing local public health resources. Same situation are found between percentage of population exposed to drinking water exceeding a violation limit and all three types of mortality. As we expect, higher primary care physician supply, higher median household income, lower rate of uninsured population, and lower proportion of children in poverty, and lower level of average daily fine particulate matters are generally associated with lower all-causes mortality. Primary care physicians supply is found negatively correlated with age-adjusted all-causes mortality and age-adjusted heart-diseases mortality. However, no statistically significant correlation is found between age-adjusted cancer mortality and primary care physician supply. It shows consistency with previous findings that higher primary care physician supply is generally linked with better health outcomes. Although increasing the primary care physician supply may significant reduce all-causes mortality and heart-diseases mortality, no significant effect is detectable on cancer mortality. Median household income is negatively, and the percentage of children in poverty; and average daily particulate matters (pm2.5) are positively correlated with all three types of mortality, and the correlations are all statistically significant. Income inequality is found has statistically significant correlations with heart-diseases mortality and cancer mortality rather than all-causes mortality. In contrast, percentage of uninsured population is only found statistically significantly correlated with all-causes mortality.

Table 2 State-level analysis: correlations between health outcomes, the efficiency of state in utilizing local public health resources, primary care physician supply, and other socio-environmental factors

Health outcome / Explanatory variables	**Age-adjusted all-causes mortality**	**Age-adjusted heart-diseases mortality**	**Age-adjusted cancer mortality**
Efficiency of state in utilizing local public health resources	-	-	-
Primary care physician supply	-.550**	-.440**	-
Median household income	-.706**	-.483**	-.474**
Income inequality (Gini coefficient index)	-	.453**	.331*
Percentage of uninsured population	.391*	-	-
Percentage of children in poverty	.699**	.612**	.478**
Average daily fine particulate matters (pm2.5)	.503**	.552**	.593**
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
*: significant at 0.05 level; **: significant at 0.01 level; “-”: no significant correlation			

Based on the results of bivariate analyses, multiple regression analysis is employed to explore how explanatory variables may help to predict the variation of health outcomess. Each of the three types of mortality is incorporated as dependent variable in the model while their corresponding significantly correlated explanatory variables are fitted into the model as independent variables. Table 3 shows results. Although all five explanatory variables in the all-causes mortality model were found statistically significantly correlated with all-causes mortality, primary care physician supply, percentage of uninsured population, and percentage of children in poverty were found less important in predicting all-causes mortality (not significant in the regression model). Median household income and average daily particulate matters (pm2.5) together are able to explain approximately 68.3% of the variation of all-causes mortality in the continental. Prediction models of heart-diseases mortality and cancer mortality share many common characteristics. Regression model of heart-diseases mortality implies that median household income, income inequality, and average daily fine particulate matters (pm2.5) are the most important factors among all other explanatory variables employed in this study. In addition to these three factors, the regression model of cancer mortality also reveals percentage of children in poverty a significant factor in explaining the prevalence of cancer mortality in the continental U.S..

In summary, in regression analysis, we do not find any statistically significant correlation between efficiencies of states in utilizing local public health resources and all three types of mortality on state level. But as we expected, higher primary care physician supply are associated with lower mortality. And median household income and average daily fine particulate matters (pm2.5) seem to be the strongest indicators of health outcomes.

Table 3 State-level analysis: multiple regression models of health outcomes and explanatory variables

Explanatory variables \ Health outcome	**Age-adjusted all-causes mortality**	**Age-adjusted heart-diseases mortality**	**Age-adjusted cancer mortality**
(Constant)	906.968**	-42.738	100.790
Efficiency of state in utilizing local public health resources	-	-	-
Primary care physician supply	-	-	-
Median household income	-.007**	-.002**	-.002**
Income inequality (Gini coefficient index)	-	525.005**	294.985*
Percentage of uninsured population	-	-	-
Percentage of children in poverty	-	-	-1.723*
Average daily fine particulate matters (pm2.5)	22.293**	7.413*	5.698**
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
R	.836	.757	.781
Adjusted R square	.683	.573	.611
Sig. of the overall model	.000**	.000**	.000**
Sig. of variables: *: significant at 0.05 level; **: significant at 0.01 level; "-": no significant correlation			

4.1.4 Analysis of variance between groups: does the efficiency of state in utilizing local public health resources and primary care physician supply matter?

From regression analyses in section 4.1.3, we learned that efficiencies at which local public health resource were utilized may not be helpful to explain prevalence of all three types of mortality in the continental U.S.. However, we are still interested to see whether states utilize local public health resources more efficiently may lead to different health outcomes from those with less efficiently. One-way ANOVA has been employed to achieve this task. Methodology and technical detail has been discussed in section 3.5.

Also discussed in section 3.5, TwoStep cluster analysis is employed to identify the optimal number of group in the cohort. The result (see figure 9) indicates that two clusters is optimal to describe the distribution of efficiencies at which local public health resources were utilized in the continental U.S.. Specifically, cluster “1” is a cluster of lower efficiencies and cluster “2” is a cluster of higher efficiencies. The “Cluster Size” graph shows that majority of states are classified into the “higher” efficiencies group (in red) while approximately 28.6% of states in the cohort had significant lower efficiencies (in blue). Adopting this classification, one-way ANOVA is run to test whether higher efficiencies matters.

No significant difference is found on all three types of mortality and primary care physician supply between “higher” efficiencies group and “lower” efficiencies group (see table 4). When it comes to socio-environmental factors, significant difference is found on percentage of population exposed to drinking water exceeding a violation limit between “higher” and “lower” efficiencies group. From table 5, we learned that “lower” efficiencies are associated with lower percentage of population exposed to drinking water exceeding a violation limit, and vice versa. This finding seems to be unreasonable at the first glance, but can be understood that higher input of local public health resources, thus possibly lower efficiency, may lead to higher drinking water quality.

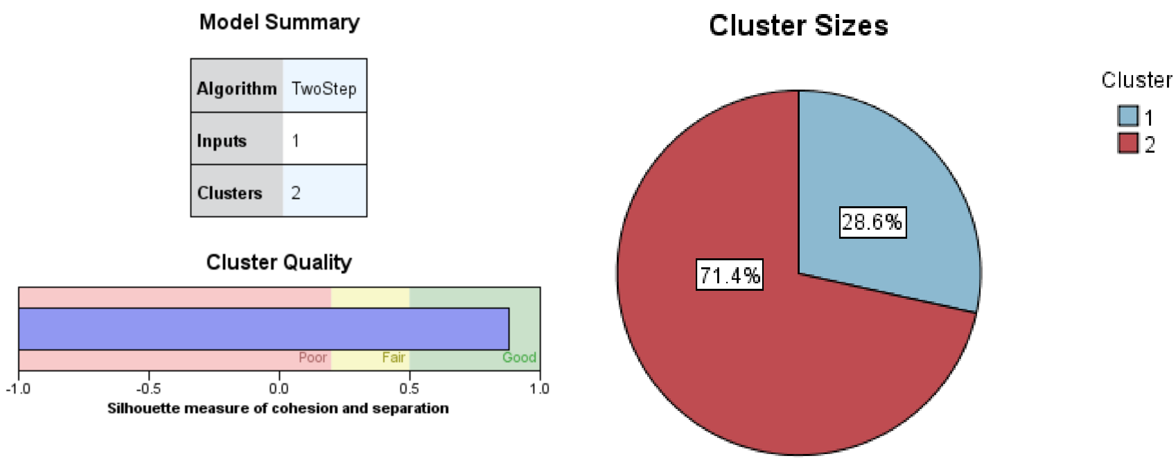


Figure 9 State-level analysis: TwoStep Cluster Analysis result for the efficiency of state in utilizing local public health resources. ("1" denotes cluster of lower efficiencies. "2" denotes cluster of higher efficiencies)

Table 4 State-level analysis: one-way ANOVA analysis result (grouping by "High" and "Low" efficiencies)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	.146	.704
Age-adjusted heart-diseases mortality	.006	.941
Age-adjusted cancer mortality	.884	.353
Primary care physician supply	2.775	.104
Median household income	.157	.694
Income inequality (Gini index)	.118	.733
Percentage of uninsured population	.452	.505
Percentage of children in poverty	.036	.850
Average daily particulate matters (PM2.5)	.192	.663
Percentage of population exposed to drinking water exceeding a violation limit	6.058	.018

Table 5 State-level analysis: descriptive analysis of percentage of population exposed to drinking water exceeding a violation limit in “higher” and “lower” efficiencies of state in utilizing local public health resources

Variable: “Percentage of population exposed to drinking water exceeding a violation limit”

Groups	Mean	Median	Std. Deviation
"Lower" efficiencies group	2.91	1.73	4.04
"Higher" efficiencies group	6.47	5.93	4.31

Similarly, TwoStep cluster analysis also derives that two clusters is optimal to describe the distribution of primary care physician supply in the continental U.S.. Specifically, cluster “1” is the cluster of lower primary care physician supply and cluster ”2” is the cluster of higher primary care physician supply. From the “Cluster Sizes” graph, we learned that 59.5% states in the continental U.S. had higher primary care physician supply while primary care physician supply in the other 40.5% states in the continental U.S. is significantly lower.

In consistence with what we found in bivariate analysis, as shown in table 6, higher primary care physician were associated with lower all-causes mortality and heart-diseases mortality. However, no significant difference in cancer mortality was found between “higher” primary care physician supply group and “lower” primary care physician supply group.

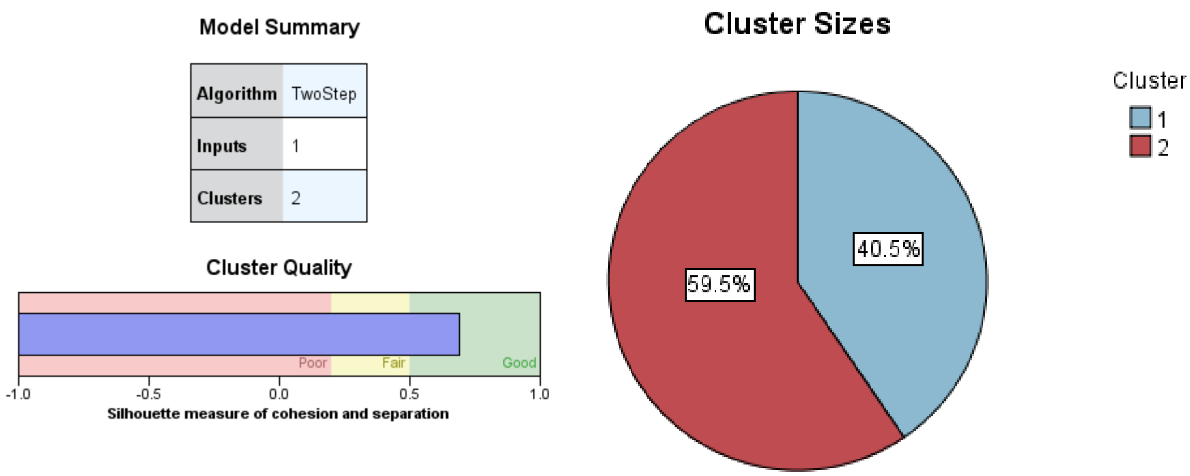


Figure 10 State-level analysis: TwoStep Cluster Analysis result for primary care physician in the continental U.S. ("1" denotes cluster of lower primary care physician supply. "2" denotes cluster of higher primary care physician supply)

Table 6 State-level analysis: one-way ANOVA analysis result (grouping by "Higher" and "Lower" primary care physician supply)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	17.298	.000
Age-adjusted heart-diseases mortality	8.709	.005
Age-adjusted cancer mortality	2.130	.152

4.1.5 Two-way factorial ANOVA analysis: how the interaction between the efficiency of state in utilizing local public health resources and primary care physician supply may impact health outcomes

In section 4.1.4, we learned that no significant difference in all three types of mortality and primary care physician supply was found between higher and lower efficiencies of state in utilizing local public health resources. In this section, two-way factorial ANOVA analysis[3] is employed to help us to understand whether there is an interaction between efficiencies at which local public health resources were utilized and primary care physician supply, and how such interaction (if exists) may impact health outcomes.

Table 7 shows that two-way factorial ANOVA result for all-causes mortality. The effect of the efficiency of state in utilizing local public health resources on all-causes mortality is not significant. In other words, higher and lower efficiencies may yield the same effect on all-causes mortality. This finding is consistent with what we learned in section 4.1.4. Although the effect of primary care physician supply on all-causes mortality is significant, no statistically significant interaction is found between the efficiency of state in utilizing local public health resources and primary care physician supply. Figure 11 can help to understand this. Figure 11a shows that in higher primary care physician supply is associated with lower all-causes mortality regardless of how efficiently the state utilizes local public health resources. Figure 11b does show some interesting patterns: (1) when primary care physician supply was higher, all-causes mortality is stable regardless of how efficiently local public health resources are utilized (in fact, higher efficiencies are associated with slightly higher all-causes mortality though it may not be

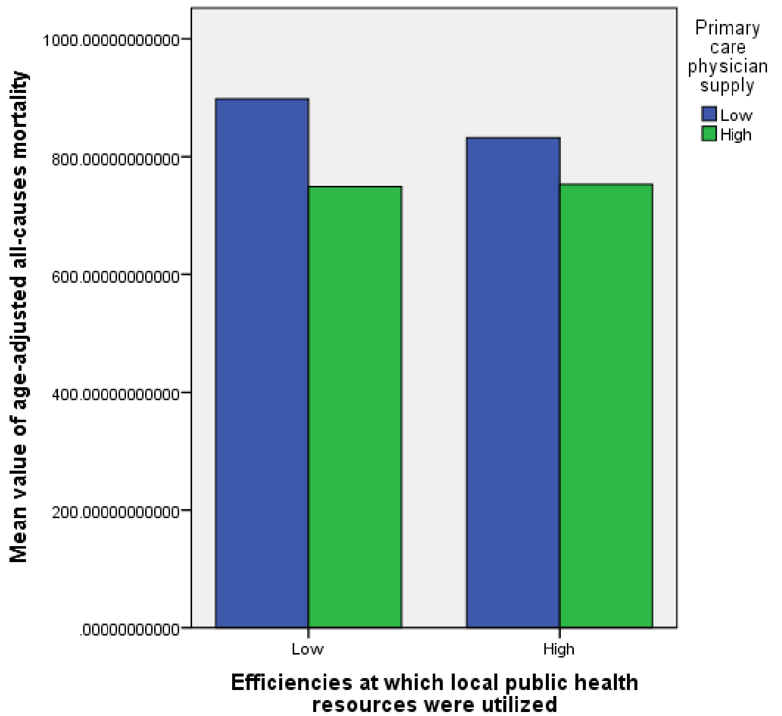
[3] See section 3.5 for introduction of two-way factorial analysis

significant); (2) however, when primary care physicians is lower, states with lower all-causes mortality utilizes local public health resources more efficiently. Although these patterns are proved to be not significant (since the interaction between the efficiency of state in utilizing local public health resources and primary care physician supply is not significant), they somehow imply that when primary care physician supply is low, it is possible to lower all-causes mortality if local public health resources are utilized more efficiently.

Table 7 State-level analysis: interaction between the efficiency of state in utilizing local public health resources and primary care physician supply, and its impact on all-causes mortality

Source	F	Sig.
Group Efficiencies	1.405	.243
Group Primary care physician supply	19.103	.000
Group Efficiencies * Group Primary care physician supply	1.757	.193

a. R Squared = .345 (Adjusted R Squared = .293



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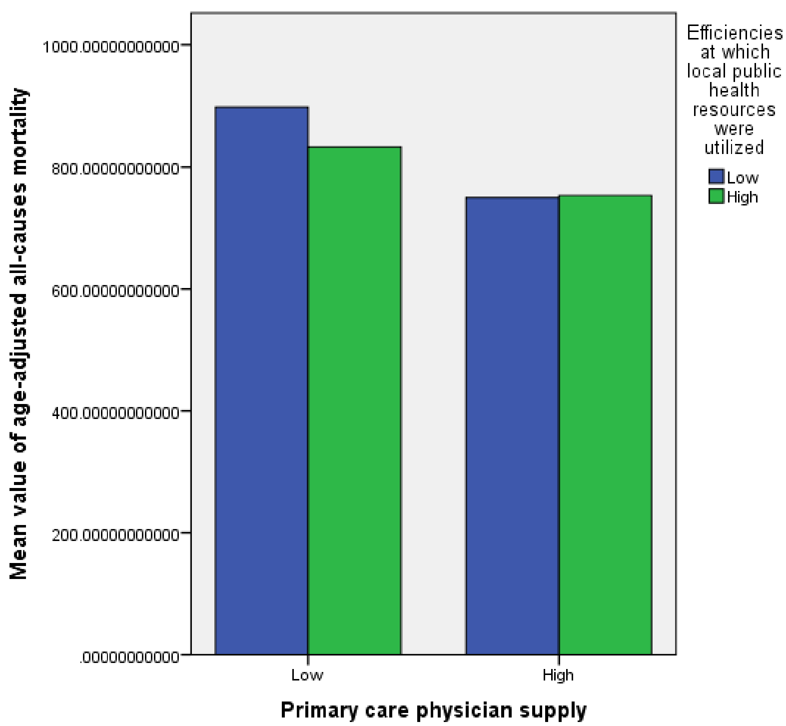


(b)

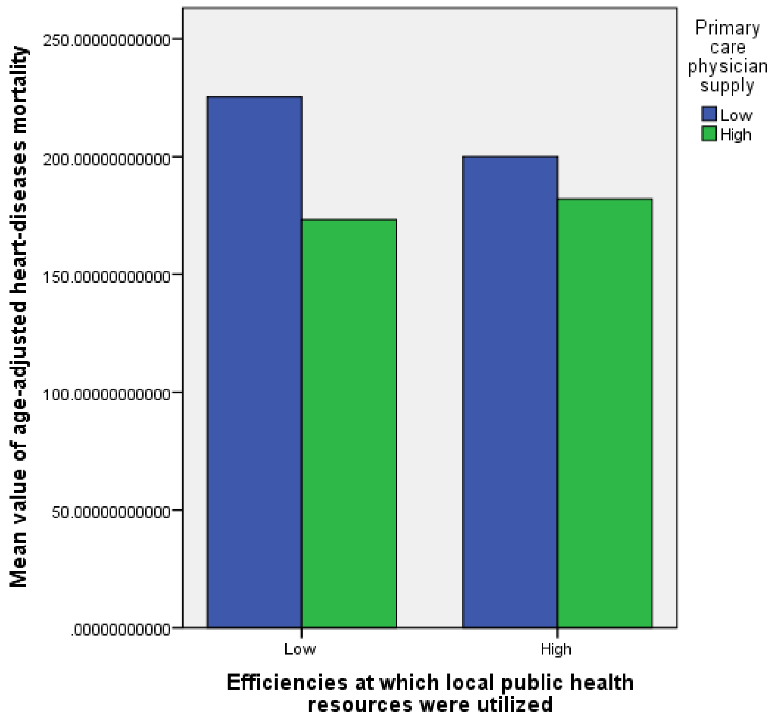
Figure 11 State-level analysis: interaction plot of efficiencies of state in utilizing local public health resources and primary care physician supply for all-causes mortality

Similar patterns are found for heart-diseases mortality (see table 8). No significant difference in heart-diseases mortality is found between “higher” efficiencies group and “lower” efficiencies group, though higher and lower primary care physician supply are associated with statistically significant different heart-diseases mortality. And lack of significant interaction between the efficiency of state in utilizing local public health resources and primary care physician supply indicates that the effect of primary care physician supply on heart-diseases mortality is not affected by the efficiency of state in utilizing local public health resources. Interaction plots in figure 12 demonstrate this. Figure 12a reveals that higher primary care physician supply is generally associated with lower heart-diseases mortality regardless of how efficiently local public health resources were utilized. Figure 12b implies that when primary care physician supply was lower, states with lower heart-diseases mortality utilizes local public health resources more efficiently. In contrast, when primary care physician supply is high, states with lower all-causes mortality utilizes local public health resources less efficiently.

Table 8 State-level analysis: interaction between the efficiency of state in utilizing local public health and primary care physician supply, and its impact on heart-diseases mortality

Source	F	Sig.
Group Efficiencies	.659	.422
Group Primary care physician supply	11.798	.001
Group Efficiencies * Group Primary care physician supply	2.774	.104

a. R Squared = .345 (Adjusted R Squared = .293



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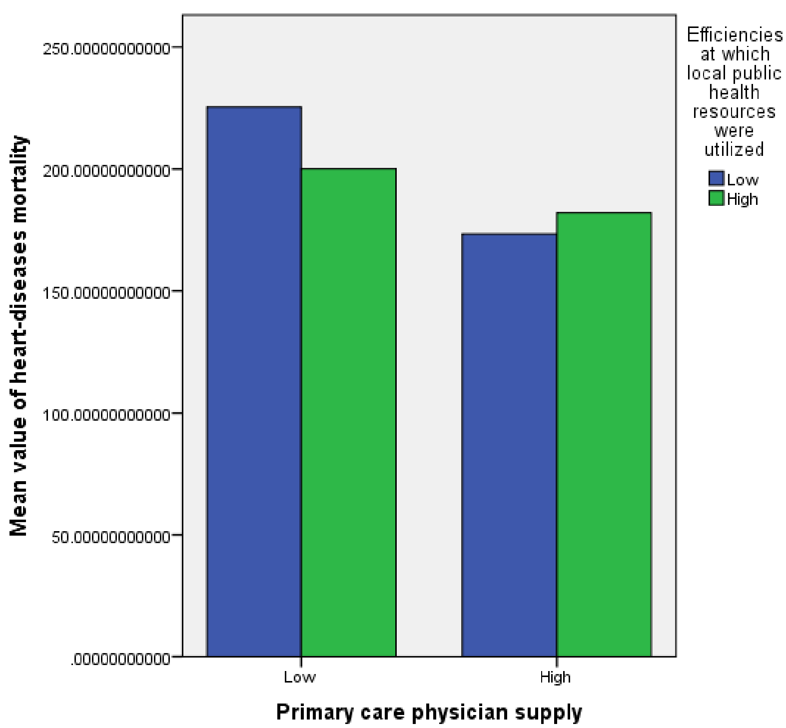

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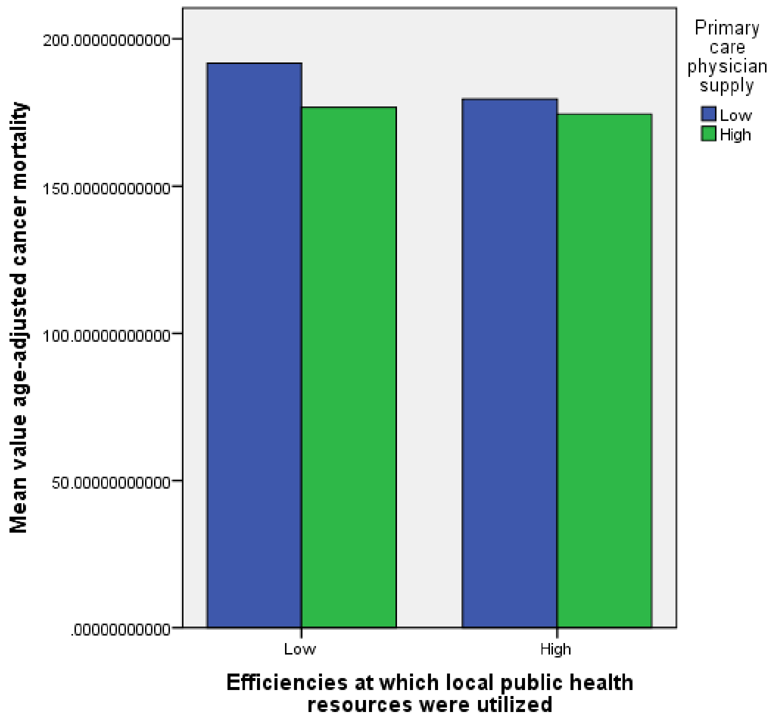
Figure 12 State-level analysis: interaction plot of efficiencies of state in utilizing local public health resources and primary care physician supply for heart-diseases mortality

For cancer mortality, none of the relationships of interest is significant (see table 9). This is consistent with what we found in section 4.1.3. From the interaction plots (figure 13), some patterns we find here are similar to what we found above for all-causes mortality and heart-diseases mortality. First, higher primary care physician supply is associated with lower cancer mortality no matter how efficiency local public health resources are utilized. Second, the efficiency of state in utilizing local public health resources seems to have a greater effect on cancer mortality when primary care physician supply is lower than it will have when primary care physician supply is higher. Being different from what we found for all-causes mortality and heart-diseases mortality, utilizing local public health resources more efficiently may always benefit the reduction of cancer mortality.

Table 9 State-level analysis: interaction between the efficiency of state in utilizing local public health resources and primary care physician supply, and its impact on cancer mortality

Source	F	Sig.
Group Efficiencies	1.691	.201
Group Primary care physician supply	3.212	.081
Group Efficiencies * Group Primary care physician supply	.802	.376

a. R Squared = .098 (Adjusted R Squared = .027)



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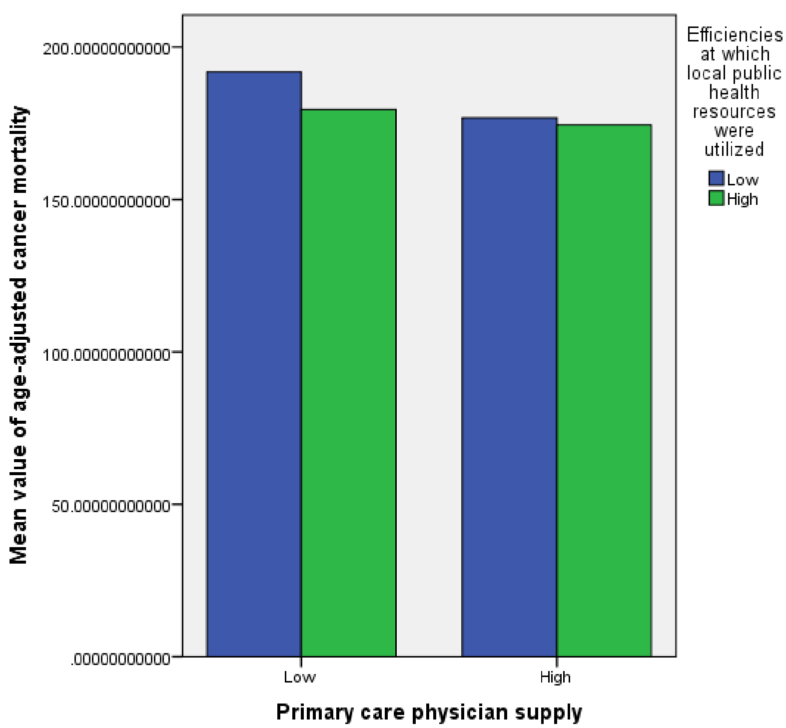


(b)

Figure 13 State-level analysis: interaction plot of efficiencies of state in utilizing local public health resources and primary care physician supply for cancer mortality.

4.1.6 Summary of state-level analysis

In state-level analysis, we described the prevalence of three types of mortality, the efficiency of state in utilizing local public health resources, primary care physician supply, and other socio-environmental factors in the continental U.S.. Associations between them were also tested statistically.

Prevalence of three types of mortality share many common patterns. For all three types of mortality, higher mortality rates are found in the West south Central area and the East South Central area. Upper West North Central area and the New England area were found with lower all-causes mortality and heart-diseases mortality. And generally, the Western United States had less cancer mortality then the Eastern United States.

Spatial distribution of primary care physician supply and other socio-environmental factors like median household income may help understand the prevalence of three types of mortality. Visually, higher mortality areas correspond with area with lower primary care physician supply and lower median household income, and vice versa. However, the spatial distribution of the efficiency of state in utilizing local public health resources seems to be less helpful.

Statistical analyses confirm that there is no significant effect of the efficiency of state in utilizing local public health resources on all three types of mortality. As we expect, higher primary care physician supply is significantly associated with lower all-cause mortality and heart-diseases mortality though its effect on cancer mortality is not significant. Other than that, median household income and average daily particulate matters (pm2.5) are the strongest indicators of the prevalence of all three types of mortality evaluated in the analysis.

Unfortunately, no statistical evidence demonstrates chances to improve the health of populations by appropriate operation of state and territorial public health agency with suitable assignment of primary care physicians. Nevertheless, one potential patterns is worth noticing: when primary care physician supply is low, utilizing local public health resources in more efficient way may help to lower all three types of mortality; however, when primary care physician supply is high, utilizing local public health resources more efficiently may worsen all-causes mortality and heart-diseases mortality but may benefit the reduction of cancer mortality.

4.2 Local-level analysis --- case study of Alabama

Alabama was selected as the representative of "centralized" governance of state and local public health agencies. Using similar methods for state-level analysis, case study of Alabama is implemented in the following processes. In section 4.2.1, the prevalence of selected health outcomes including all-causes mortality, heart-diseases mortality, and cancer mortality in Alabama are described. Efficiencies of LHDs in Alabama are analyzed in section 4.2.2. In section 4.2.3, we will discuss statistical analyses results. Findings in case study of Alabama are summarized in section 4.2.4.

4.2.1 Prevalence of selected health outcomes, primary care physician supply, and other socio-environmental factors in Alabama.

Health outcomes vary county by county in Alabama. For all-causes mortality, the highest rate was found in Walker County which suffered the most as 1178.288 out of 100,000 populations died of all causes in the period of 2006 to 2010 while the lowest rate was found in Shelby County with average 742.232 out of 100,000 populations died of all causes in the period of 2006 to 2010. For heart-diseases mortality, the highest mortality rate was found in Greene County with 393.296 per 100,000 populations died of heart diseases. Lauderdale County suffered the least from heart-diseases mortality with 179.977 per 100,000 populations died of heart diseases. Although the Greene County suffered the most severe heart-diseases mortality in the period of 2006 to 2010, it was found suffering the least cancer mortality (with 151.296 per 100,000 populations died of cancer in the same period). And Macon County was found having the highest cancer mortality rate in the period of 2006 to 2010.

Figure 14 shows the prevalence of all-causes mortality (figure 14a), heart-diseases mortality (figure 14b), and cancer mortality (figure 14c) in Alabama in the period of 2006 to 2010. The color of red denotes those counties with highest mortality rates and green denotes counties with the lowest mortality rates. From the prevalence of three types of mortality, we found that major cities and their adjacent area generally had lower mortalities. And there seems to be a cluster of counties with high mortality including the Lowndes County, the Wilcox County, the Dallas County, and the Perry County. Hot Spot Analysis is employed to help us to understand whether some places really have higher (or lower) mortalities than other places in Alabama (see figure 15a to 15c). The Marion County, the Fayette County, the Winston County, the Dallas County, the Perry County, and their adjacent areas were found having significant higher all-causes mortality. While the Limestone County, the Dale County, the Henry County, the Geneva County, and their adjacent areas were found having significant lower all-causes mortality. Although we found that major cities and their adjacent area generally had lower all-causes mortality, these patterns seem not to be significant. Hot spot patterns of cancer mortality and heart-diseases mortality share many common patterns with what we found of all-causes mortality. Interestingly, the Greene County, the Sumter County, and their adjacent areas were found the hot spots of heart-diseases mortality and cold spots of cancer mortality in the same time.

The spatial distribution of primary care physician supply seems to be less helpful to understand the prevalence of mortality in Alabama (see figure 16b). High mortality clustering areas in Alabama are not necessary to associated with lower primary care physician supply, and vice versa. However, from the spatial distribution of county population, we found that greater population may be associated with higher primary care physician supply. It implies that the variable-return-to-scale effect may exist. In other words, when population increases, the need of primary care physicians can increase in a geometric ratio.

Median household income (figure 17a) and income inequality (figure 17b) seem to be still helpful here as high mortality clustering areas in Alabama were generally associated with lower median household income and greater income inequality, and vice versa. Spatial distribution of percentage of uninsured population and percentage of children in poverty are illustrated in figure 18a and figure 18b, respectively. The spatial distribution of percentage of uninsured population shows a different pattern from those of other socio-environmental factors indicating that the decision of buying insurance can be affected by multiple factors. The spatial pattern of percentage of children in poverty is similar to those of median household income indicating that there might be strong connection between these two factors. A distinctive spatial pattern is found for average daily fine particulate matters (pm2.5) (see figure 19a). It is detectable that the air quality became better gradually from north to south. However, percentage of population exposed to drinking water exceeding a violation limit (see figure 19b) might be helpless here since rates of majority of counties in Alabama were zero.

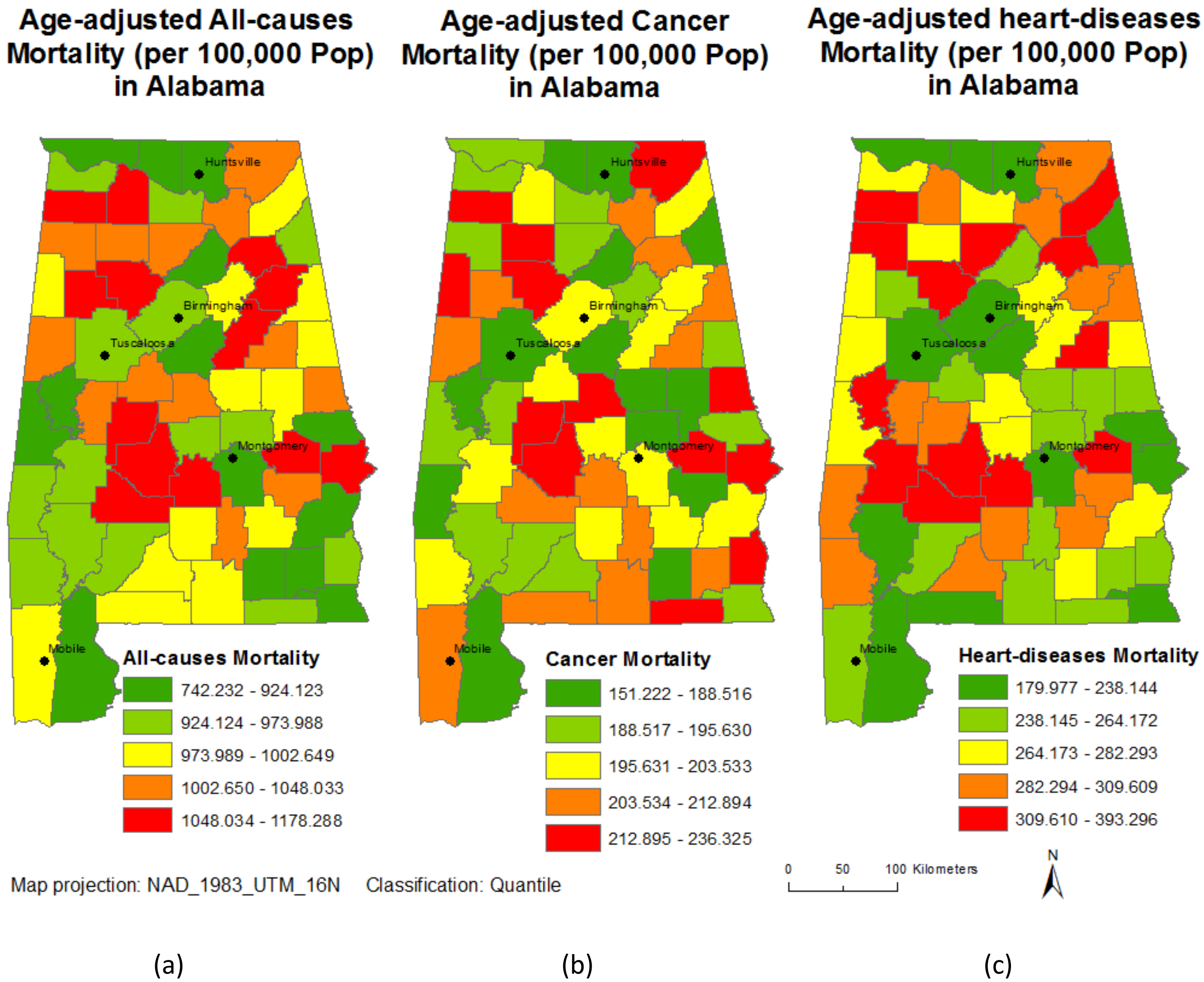


Figure 14 Local-level analysis (Alabama): spatial distribution of all-causes mortality (a), heart-diseases mortality (b), and cancer mortality (c) in Alabama in the period of 2006 to 2010.

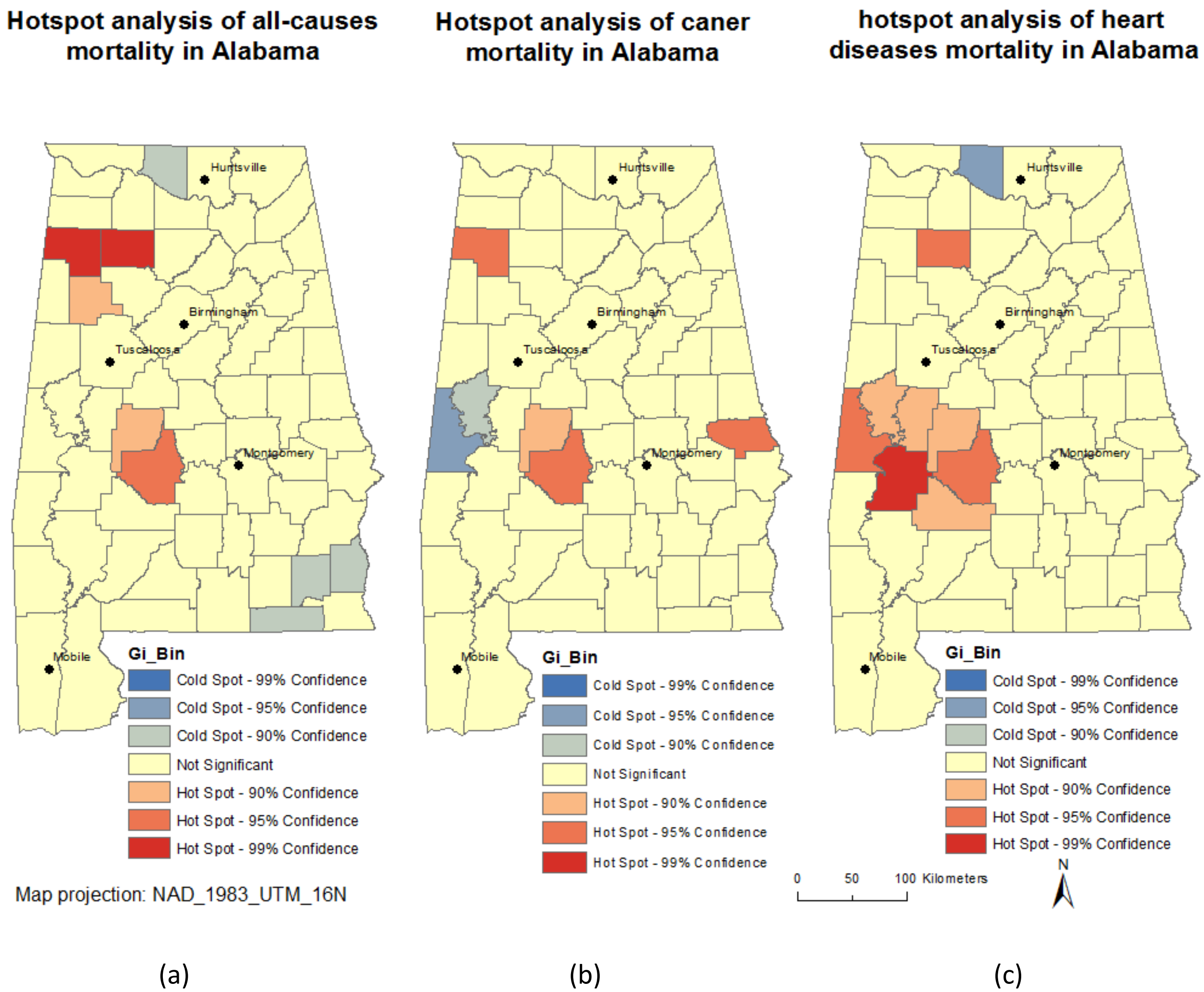


Figure 15 Hotspots of all-causes mortality (a), heart-diseases mortality (b), and cancer mortality (c) in Alabama in the period of 2006 to 2010.

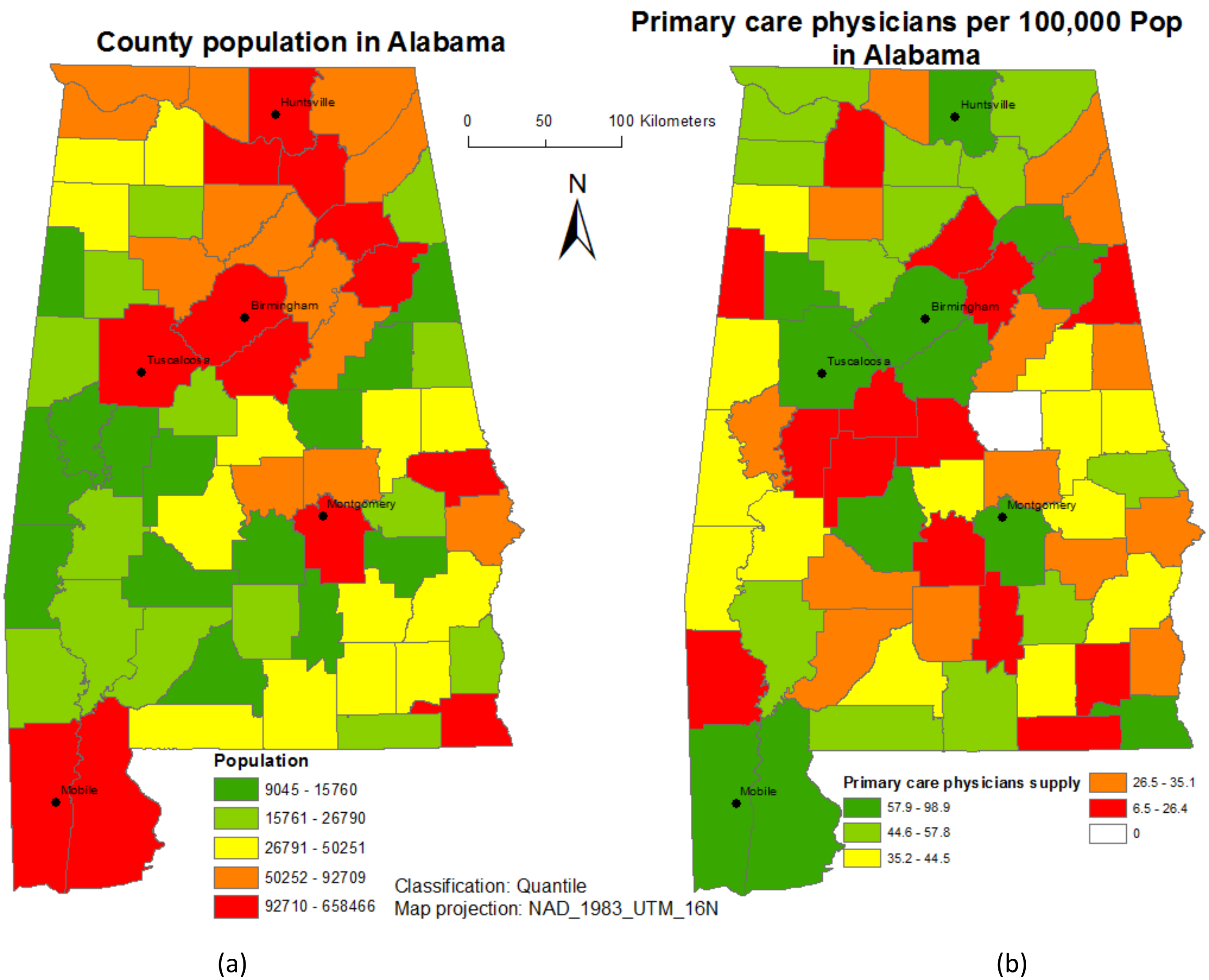
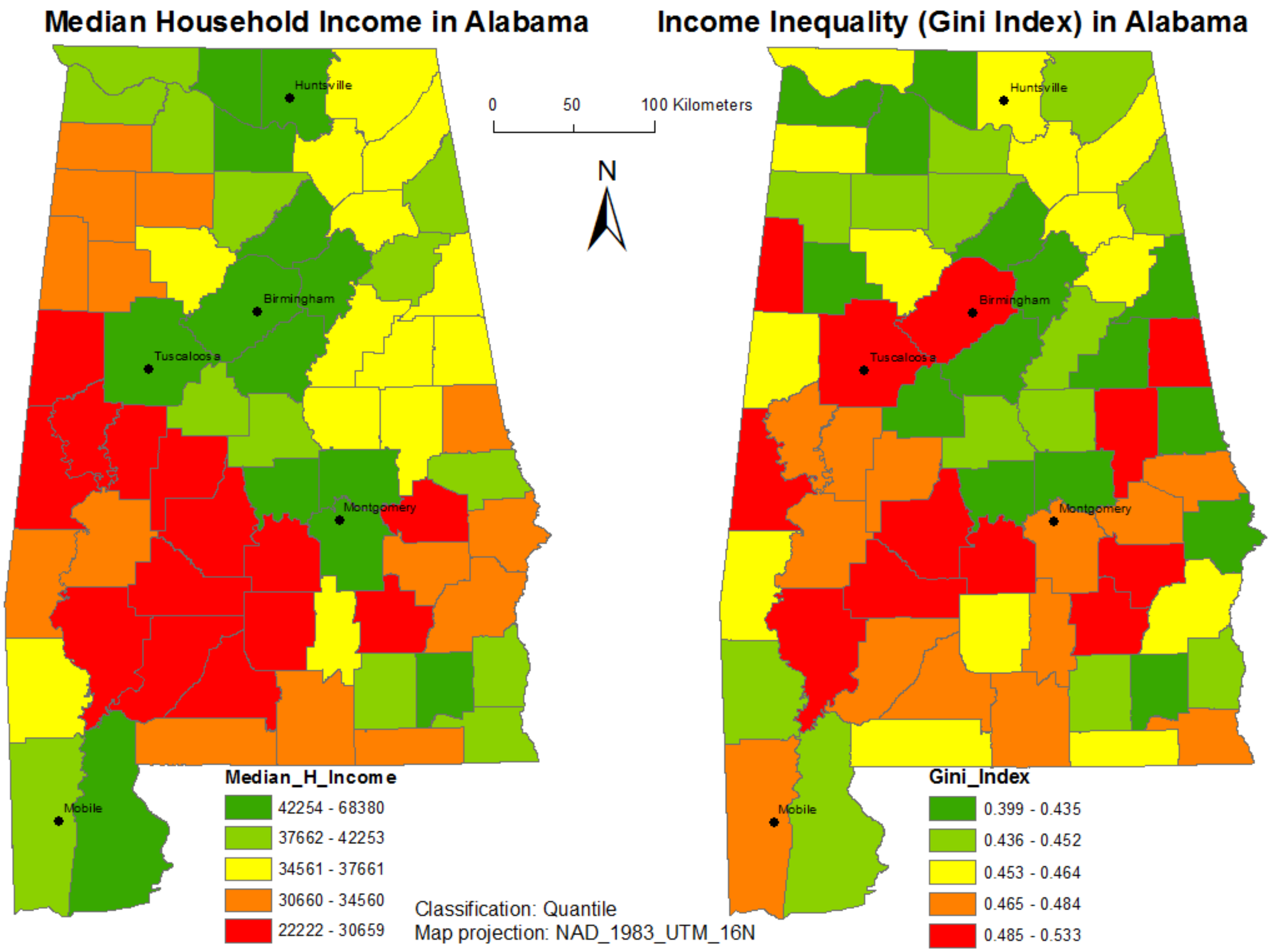


Figure 16 Local-level analysis (Alabama): spatial distribution of county population (a) and primary care physician supply (b) in Alabama in the period of 2006 to 2010.



(a) (b)

Figure 17 Local-level analysis (Alabama): spatial distribution of median household income (a) and income inequality (b) in Alabama in the period of 2006 to 2010.

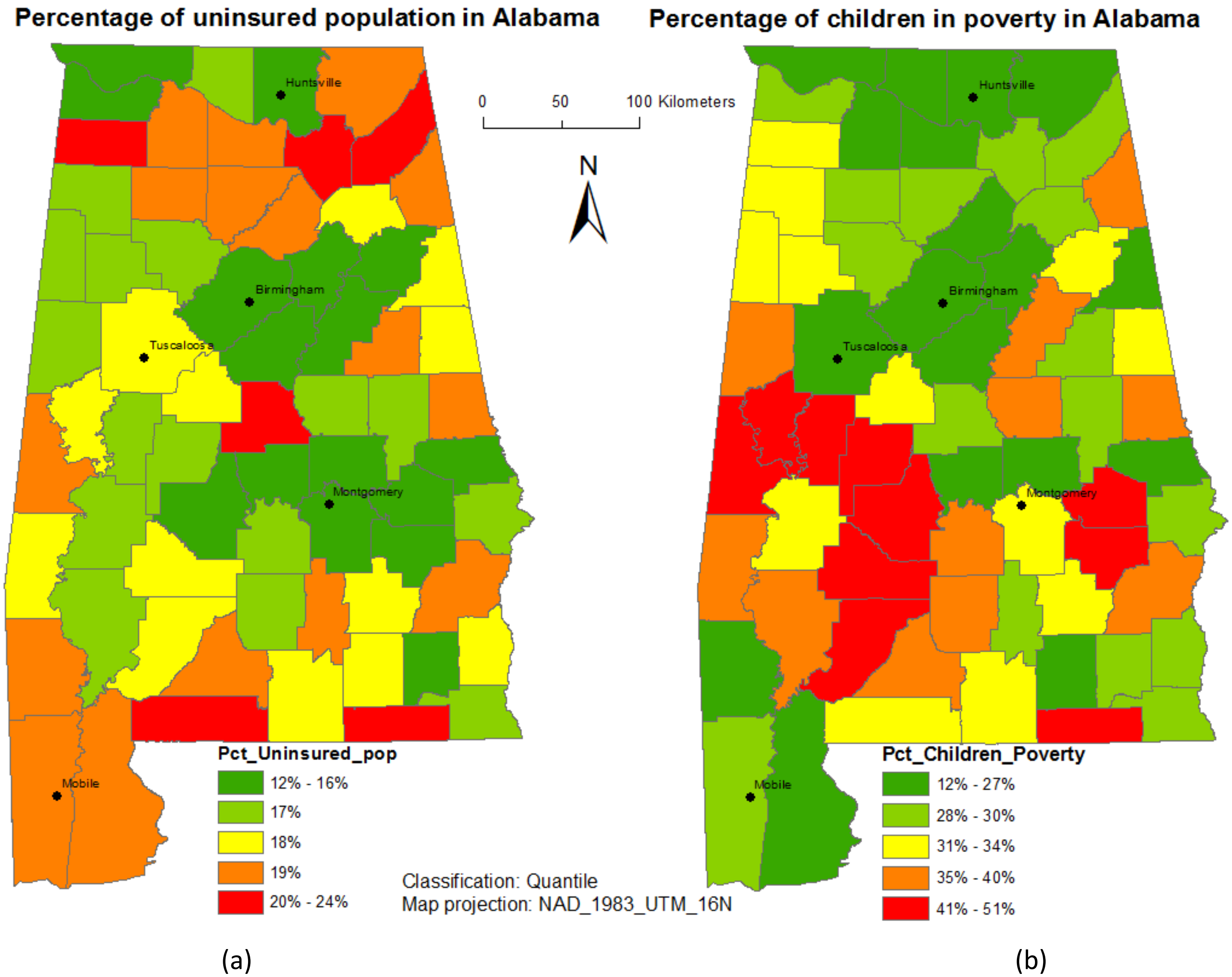


Figure 18 Local-level analysis (Alabama): spatial distribution of percentage of uninsured population (a) and percentage of children in poverty (b) in Alabama in the period of 2006 to 2010.

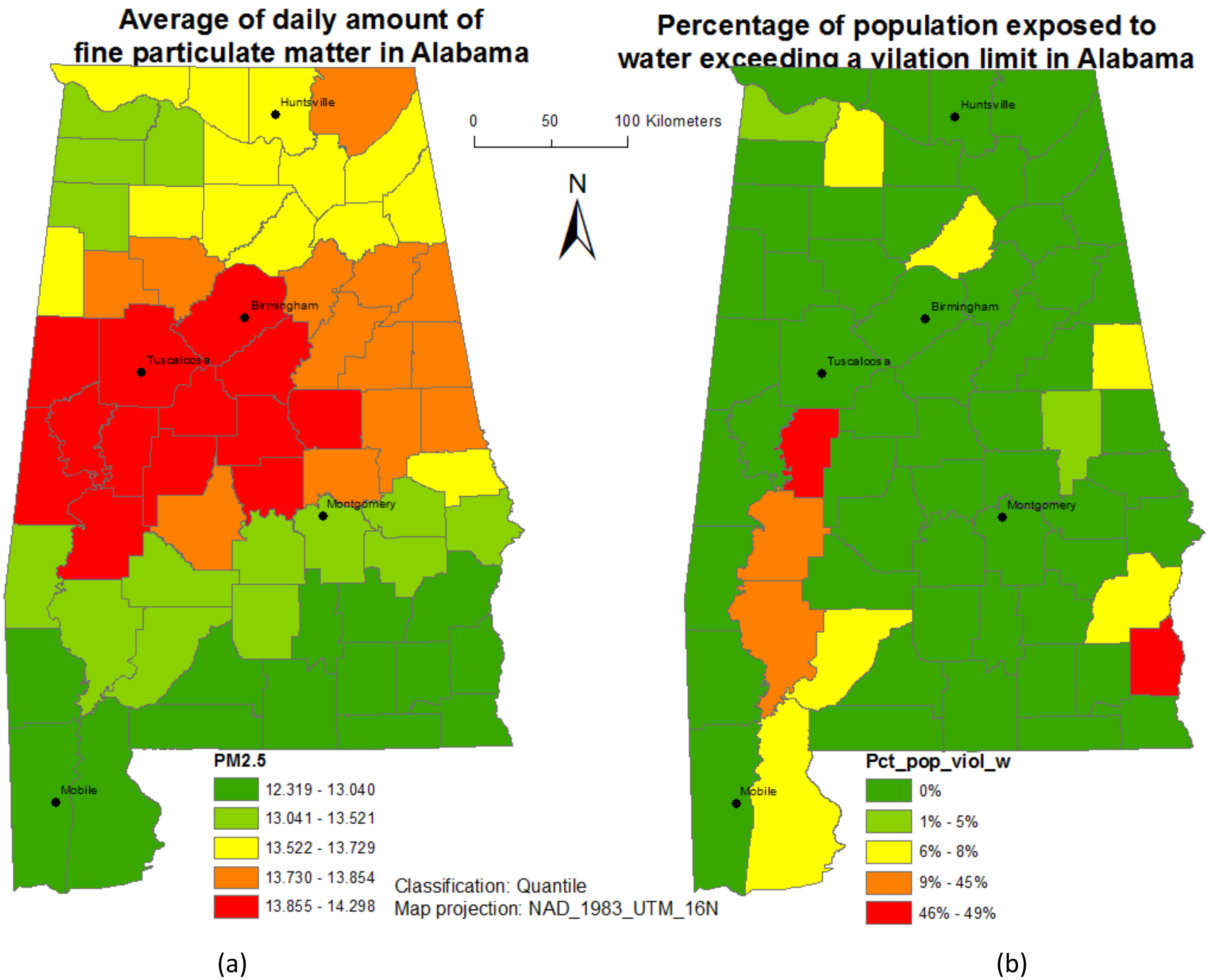


Figure 19 Local-level analysis (Alabama): spatial distribution of average daily fine particulate matters (pm2.5) (a) and percentage of population exposed to drinking water exceeding a violation limit (b) in the period of 2006 to 2010.

4.2.2 Efficiencies of local health departments in Alabama.

After data processing (see section 3.3), only 36 out of total 67 LHDs in Alabama provide sufficient information for DEA and following analyses. Fortunately, non-parametric tests prove that distributions of population, all-causes mortality, heart-diseases mortality, and cancer mortality of the 36 LHDs sample have no significant difference from those of the total 67 LHDs “population” (see table 10). It indicates that the sixty-seven LHDs sample can be used as the representative of the total 67 LHD “population” in population, all-causes mortality, heart-diseases mortality, and cancer mortality.

Table 10 Local-level analysis (Alabama): summary of test of distributions of 36 LHDs sample and 67 LHDs population

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of population is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.928	Retain the null hypothesis
2	The distribution of all-causes mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.638	Retain the null hypothesis
3	The distribution of heart-diseases mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.803	Retain the null hypothesis
4	The distribution of cancer mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.633	Retain the null hypothesis
Asymptotic significances are displayed. The significance level is 0.05				

Table 11 shows characteristics of 36 LHDs incorporated in the analysis. Characteristics vary greatly among LHDs. The largest LHD served 319,510 populations while the smallest LHD served only 9162 populations. Similar patterns were found on other LHD characteristics. For instance, total expenditures of the most recently fiscal year had great variances between LHDs (as the standard deviation is large).

We found that among 36 LHDs within the cohort, 20 LHDs did not employ public health managers. 11 LHDs only employed part-time public health managers. Only five LHDs needed full-time public health managers to supervise their daily operation. This is understandable since all 67 county-based local health departments (LHDs) in Alabama were leaded by state employees and the state public health department oversees and leads the operation of LHDs. Considering the effect of public health manager of LHDs might be limited in Alabama, public health manager is excluded from the labor inputs in DEA. As a result, four labor inputs and one capital input were incorporated in DEA including (1) FTE public health physicians/nurses, (2) FTE public health epidemiologists/sanitarians, (3) FTE public health administrative/clerical employees, (4) other public health employees, and (5) total expenditures of the most recent fiscal year. Three outputs remain the same, namely (1) number of different clinical public health services, (2) number of different clinical public health services, and (3) the jurisdiction size. Given that n = 36 is larger than three folds of the sum of the number of inputs and the number of outputs (= 21), the sample size used in this analysis satisfies the Banker et al.'s rule discussed in section 3.3.

Table 11 Local-level analysis (Alabama): descriptive statistics of LHD characteristics (36 LHDs sample)

LHD characteristics	Maximum	Minimum	Mean	Median	SD
Jurisdiction size	319,510	9162	57895.5	35,511	64,150.2
Total Expenditures	9,800,000	581,522	3,121,163.9	2,882,899	2,098,943.2
FTE Public Health Managers	7	0	0.5	0	1.2
FTE Public Health Physicians/Nurses	40.5	1	9.4	8.5	8.5
FTE Public Health Epidemiologists/Sanitarians	16	0.5	3.1	2	3.3
FTE Public Health Administrative/ Clerical Employees	29	2	9.1	7	6.8
FTE Other Employees	36	0.3	5.3	4	6.5
# of different clinical public health services	18	11	19.6	14	3.5
# of different epidemiological/ environmental public health services	38	11	22.9	21	6.3

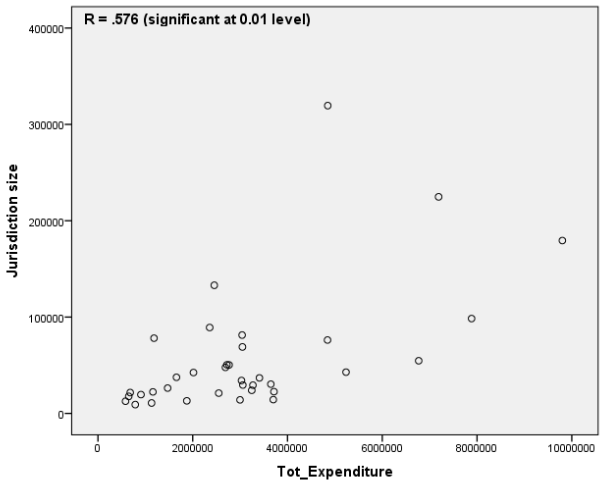
Bivariate analyses between these LHD characteristics indicates the jurisdiction size, total expenditures of the most recent fiscal year, and four public health workforces are significantly correlated with each other (see table 12). The relationships between them are also demonstrated in figure 20a to figure 20f. We found that greater jurisdiction size is generally associated with higher expenditures. Such a positive relationship is also suitable between jurisdiction size and other four public health workforces. One pattern worth of noticing is that the correlation between jurisdiction size and FTE public health epidemiologists/sanitarians is very high. It implies that the primary duty of LHDs in Alabama might be epidemiological and environmental surveillance.

Table 12 Local-level analysis (Alabama): correlation table of LHDs characteristics

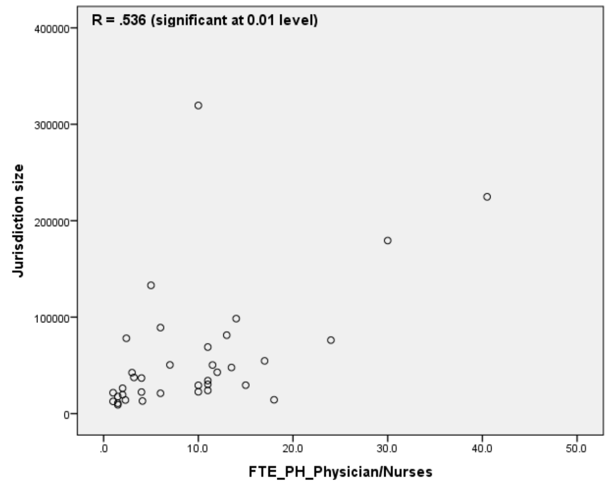
	Jurisdiction size	Total expenditures	FTE Public Health Physicians/ Nurses	FTE Public Health Epidemiologists/ Sanitarians	FTE Public Health Administrative/ Clerical Employees	FTE Other Public Health Employees	# of different clinical Services	# of different epid/envi services
Jurisdiction size	1	.576**	.536**	0.964**	0.724**	.528**	-.314	-.069
Total expenditures		1	.822**	.643**	.849**	.528**	-.050	0.122
FTE Public Health Physicians/Nurses			1	.540**	. 730**	. 667**	.032	.045
FTE Public Health Epidemiologists/Sanitarians				1	.781**	.509**	-.267	-.037
FTE Public Health Administrative/Clerical Employees					1	.631**	-.104	.034
FTE Other Public Health Employees						1	.024	-.250
# of different clinical services							1	.071
# of different epi/env services								1

**: significant at 0.01 level

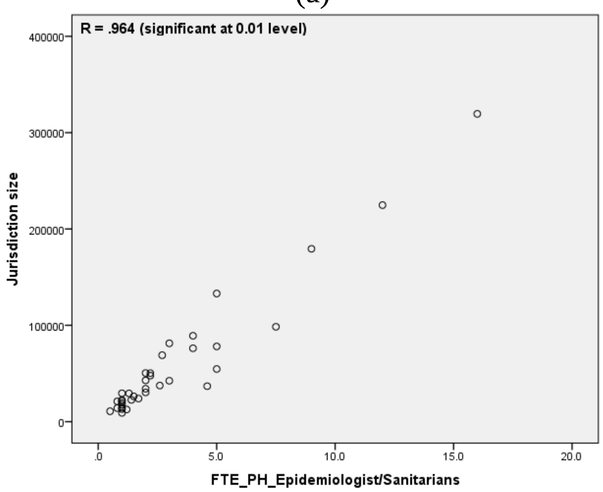
Figure 20 Local-level analysis (Alabama): scatter plots between jurisdiction size and other LHD characteristics



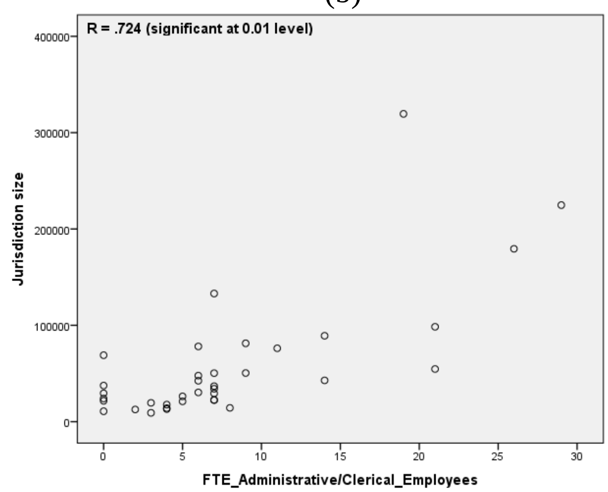
(a)



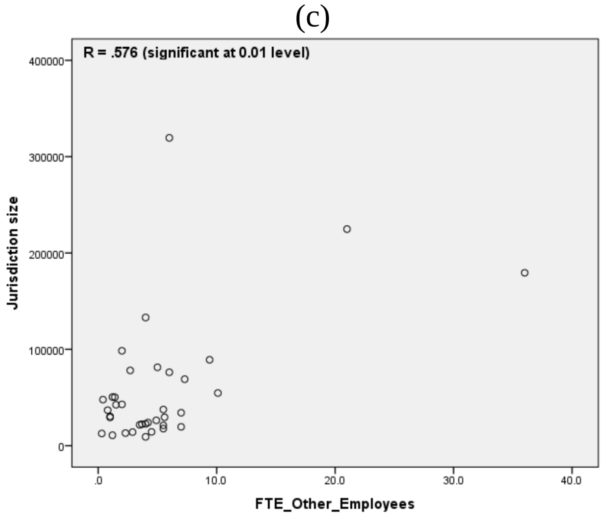
(b)



(c)



(d)

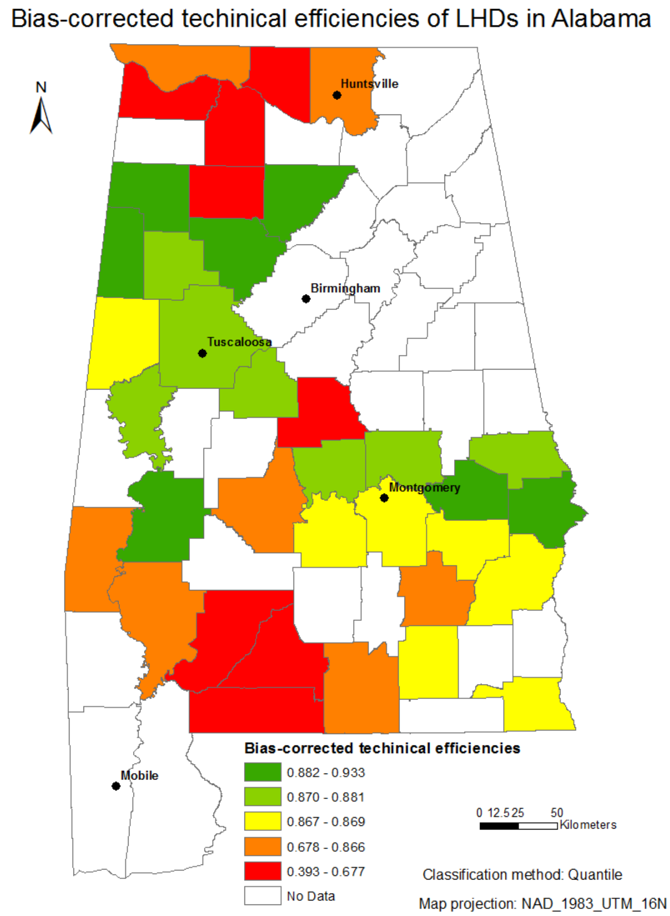


(f)

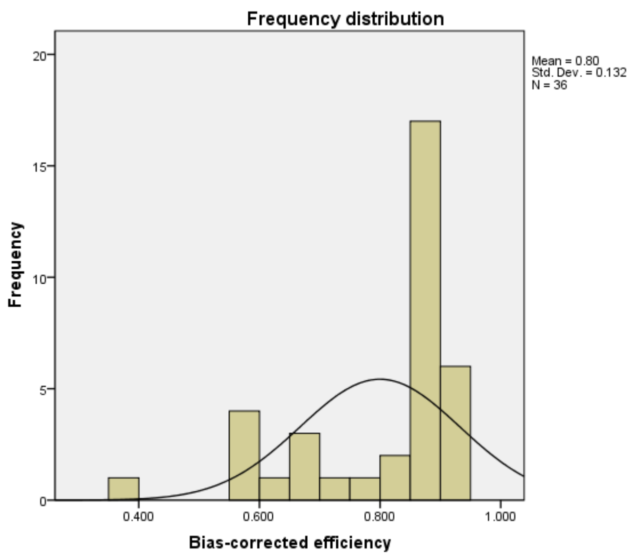
Figure 21(a) shows estimated efficiencies of 36 LHDs in Alabama, and figure 21(b) shows the frequency distribution of them. The color of red denotes for highest efficiencies and green denotes for lowest efficiencies. Among these thirty-six LHDs, those located in central Alabama were operating in higher efficiencies compared with those located on north and south Alabama. Unfortunately, these 36 LHDs are discontinued in space making demonstrating spatial distributions of efficiencies of LHDs in Alabama less reliable.

The estimating efficiency measures how efficiently a LHD operates to serve its jurisdiction. Generally, if a LHD utilized fewer workforces or less money to serve given populations and to provide certain public health services, it is considered operating more efficiently. A LHD will also be considered operating more efficiently if it can serve greater populations and provide more public health services utilizing less workforces and money.

Higher efficiencies does not always mean better, and vice versa. For instance, even though a LHD is rated less efficient, if it can provide sufficient public health services which results in better health outcomes, it is considered operating in a better way. Statistical tests in the next few sections help us to understand how efficiencies of LHDs may impact health outcomes.



(a)



(b)

Figure 21 Local-level analysis (Alabama): efficiencies of LHDs in Alabama in 2010.

4.2.3 Statistical analyses (Alabama): health outcomes, the efficiency of LHD, primary care physician supply, and other socio-environmental factors

The same statistical analyses as those in state-level analyses are implemented to explore the association between health outcomes, the efficiency of LHDs, primary care physician supply, and other socio-environmental factors in Alabama. Bivariate analysis (see table 13) shows that there is no statistically significant correlation between the efficiency of LHDs and all three types of mortality. Primary care physician supply is found negatively correlated with heart-diseases mortality. In terms of other socio-environmental factors, median household income is found negatively correlated with all-causes mortality and heart-diseases mortality, and percentage of children in poverty is found positively correlated with all-causes mortality and heart-diseases mortality. However, no statistically significant correlation is found between cancer mortality and explanatory variables incorporated in this study. Regression analysis (see table 14) reveals that median household income is the strongest indicator of the prevalence of all-causes mortality. And primary care physician supply and percentage of children in poverty together are able to explain approximately 45.3% of the prevalence of heart-diseases mortality in Alabama.

One-way ANOVA analysis (see table 16) shows that there is no significant difference in all three types of mortality and primary care physician supply between populations served by LHDs with "higher" efficiencies and those served by LHDs with "lower" efficiencies. Interestingly, significant lower percentage of uninsured populations is found in populations served by LHDs with "higher" efficiencies (see table 16). However, no statistically significant difference is found in all three types of mortality between populations with "higher" and "lower" primary care physician supply, though the difference in heart-diseases mortality is just not significant.

Unfortunately, we are not able to find any interaction between the efficiency of LHD and primary care physician supply in two-way factorial ANOVA analysis (see figure 18).

Table 13 Local-level analysis (Alabama): correlations between three types of mortality, efficiencies of LHDs in Alabama, primary care physician supply, and other socio-environmental factors

Explanatory variables	Age-adjusted all-causes mortality	Age-adjusted heart-diseases mortality	Age-adjusted cancer mortality
The efficiencies of LHD	-	-	-
Primary care physician supply	-	-.372*	-
Median household income	-.466**	-.570**	-
Income inequality (Gini coefficient index)	-	-	-
Percentage of uninsured population	-	-	-
Percentage of children in poverty	.458**	.614**	-
Average daily fine particulate matters (pm2.5)	-	-	-
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
*: significant at 0.05 level; **: significant at 0.01 level; "-": no significant correlation			

Table 14 Local-level analysis (Alabama): multiple regression models of health outcomes and explanatory variables.

Health outcome / Explanatory variables	Age-adjusted all-causes mortality	Age-adjusted heart-diseases mortality	Age-adjusted cancer mortality
(Constant)	1167.710**	181.606**	-

The efficiencies of LHD	-	-	-
Primary care physician supply	-	-	-
Median household income	-.007**	-.002**	-
Income inequality (Gini coefficient index)	-	-	-
Percentage of uninsured population	-	-	-
Percentage of children in poverty	-	3.767*	-
Average daily fine particulate matters (pm2.5)	-	-	-
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
R	.466	.696	-
Adjusted R square	.194	.453	-
Sig. of the overall model	.000**	.000**	-
Sig. of variables: *: significant at 0.05 level; **: significant at 0.01 level; "-": no significant correlation			

Table 15 Local-level analysis (Alabama): one-way ANOVA analysis result (grouping by efficiencies)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	.361	.552
Age-adjusted heart-diseases mortality	.339	.564
Age-adjusted cancer mortality	.606	.442
Primary care physician supply	1.553	.221
Median household income	.487	.490
Income inequality (Gini index)	.309	.582
Percentage of uninsured population	7.159	.011
Percentage of children in poverty	.006	.940
Average daily particulate matters (PM2.5)	.678	.416

Percentage of population exposed to drinking water exceeding a violation limit	.153	.698

Table 16 Local-level analysis (Alabama): descriptive analysis of percentage of uninsured population in "higher" and "lower" efficiencies of state in utilizing local public health resources

Variable: "Percentage of uninsured population"

Groups	Mean	Median	Std. Deviation
"Lower" efficiencies group	18.20	18.40	1.55
"Higher" efficiencies group	16.77	16.93	1.39

Table 17 Local-level analysis (Alabama): one-way ANOVA analysis result (grouping by primary care physician supply)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	.148	.703
Age-adjusted heart-diseases mortality	3.685	.063
Age-adjusted cancer mortality	.011	.916

Table 18 Local-level analysis (Alabama): interaction between the efficiency of LHDs in Alabama and primary care physician supply and its impact on health outcomes

	All-causes mortality		Heart-diseases mortality		Cancer mortality	
Source	F	Sig.	F	Sig.	F	Sig.
Group the efficiency of LHDs	.532	.471	1.431	.240	.590	.448
Group Primary care physician supply	.324	.573	4.787	.036*	.012	.912
Group the efficiency of LHDs * Group Primary care physician supply	-	.-	-	-	-	-
* Significant at 0.05 level						

4.2.4 Summary of case study of Alabama

In case study of Alabama, a cohort including 36 LHDs was used as a representative sample of the total 67 LHDs in Alabama. Prevalence of three types of mortality reveal that major cities and their adjacent areas generally have better health outcomes. Hotspot analyses show clusters of significant higher mortality rates in the Marion County, the Fayette County, the Winston County, the Dallas County, the Perry County, and their adjacent areas. Statistical analyses show that there is no significant effect of the efficiency of LHDs in Alabama on all-causes mortality, heart-diseases mortality, and cancer mortality. Due to the interaction between the efficiency of LHDs and primary care physician supply does not exist, no evidence or potential pattern shows how such interaction may affect health outcomes.

4.3 Local-level analysis --- case study of Florida

Florida was selected as the representative of “shared” governance of state and local public health agencies. Local employees and state employees share the responsibility of all 67 county-based local health departments (LHDs) in Florida. Using the same methods for case study of Alabama, case study of Florida is implemented in the following processes. In section 4.3.1, the prevalence of selected health outcomes including all-causes mortality, heart-diseases mortality, and cancer mortality in Alabama are described. Efficiencies of LHDs in Florida are analyzed in section 4.3.2. In section 4.3.3, we will discuss statistical analyses results. Findings in case study of Alabama are summarized in section 4.3.4.

4.3.1 Prevalence of health outcomes, primary care physician supply, and other socio-environmental factors in Florida.

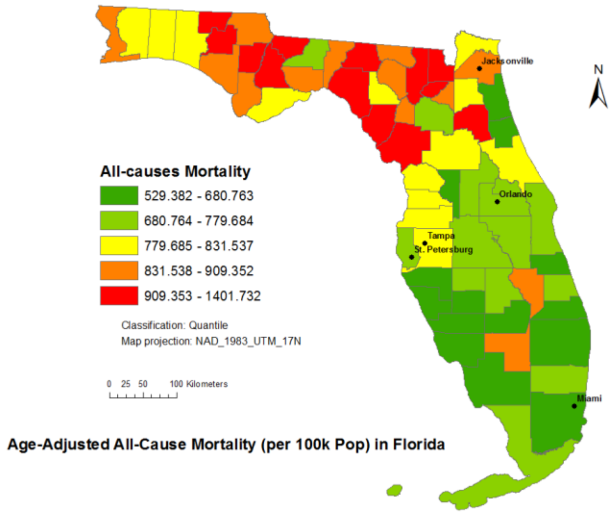
The prevalence of all-causes mortality, heart-diseases mortality, and cancer mortality in Florida (see figure 22), we found that generally populations living in north Florida were suffering from more severe mortality than their peers living in south Florida. Hotspot analyses confirm these patterns (see figure 23). South Florida is found the “cold spots” of all-causes mortality and cancer mortality. And north Florida is proved to have significant higher mortality since “hot spots” are found there. For heart-diseases mortality, although the clustering pattern is less distinct than those of all-causes mortality and cancer mortality, the “hot spots” found in north Florida reveals a severe issue of heart diseases there,

Primary care physician supply somehow demonstrates a similar pattern (see figure 24): populations living in north Florida is found having less primary care physician supply than populations living in south Florida. An interesting pattern is found when taken the spatial distribution of populations in Florida into account: primary care physician supply (per 100,000 populations) increases where the population increases. It indicates that the need of primary care physician supply to population has an increasing return-to-scale effect. In other words, the need of primary care physicians increases when the population increases.

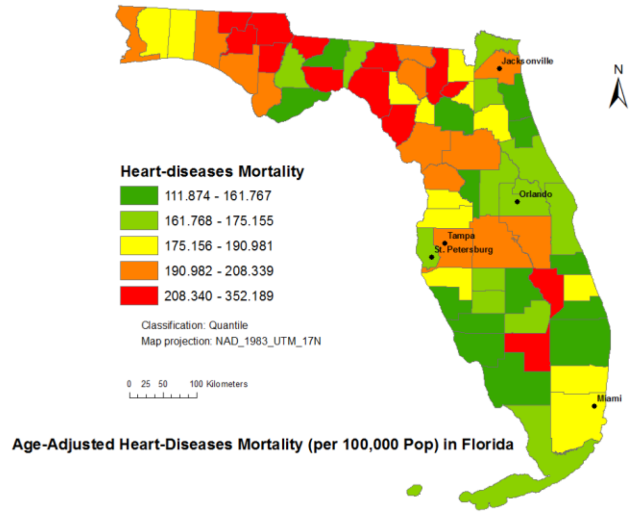
Median household income seems to be able to help to explain the prevalence of mortalities and their clustering patterns in Florida since regions with higher mortalities are likely to be areas that had lower median household income (see figure 25a). However, income inequality might be less helpful. Although we expect that high income inequality may be associated with high mortalities, it appears that areas had greater income inequality are located in “cold spots” of mortalities.

Percentage of uninsured population was found lower in north Florida where “hot spots” of mortalities locate and higher in south Florida where was the “cold spot” of mortalities (see figure 26a). Such patterns are understandable since “hot spots” areas of mortalities appear to be poorer and may have a greater need of insurance coverage. And spatial pattern of percentage children in poverty is identical to those of median household income (see figure 26b).

Daily fine particulate matter (pm2.5) was found the most severe in west-north corner of Florida and “dilute” towards to the south (figure 27a). Considering the prevalence of mortalities, it is reasonable to hypothesize that air quality may have a notable contribution on health outcomes. Given majority of areas in Florida provides good quality drinking water (see figure 27b), this factor may not be helpful in this study.



(a)



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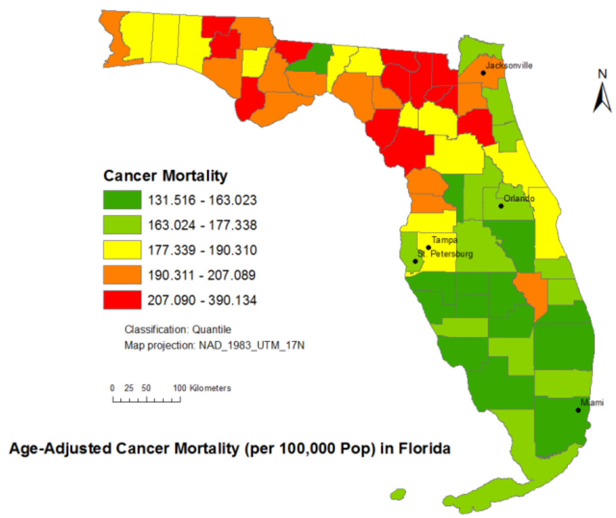
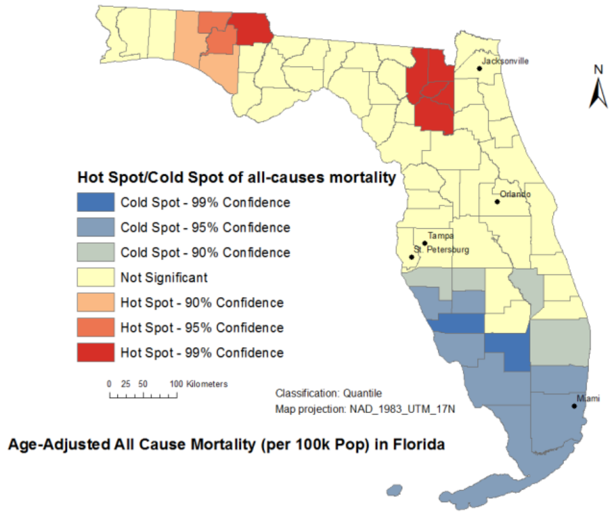
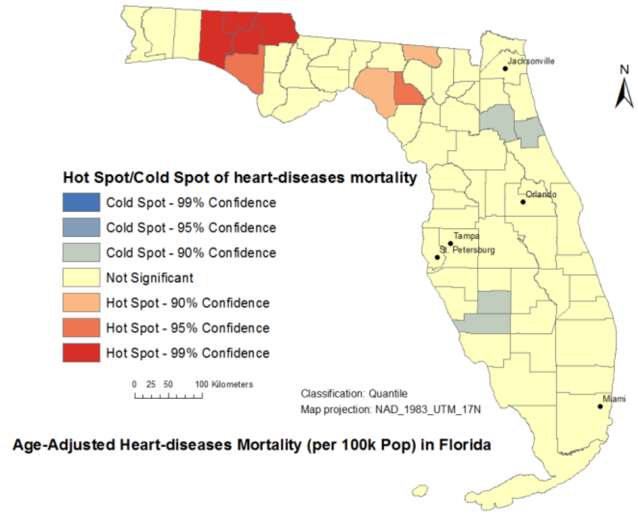


(c)

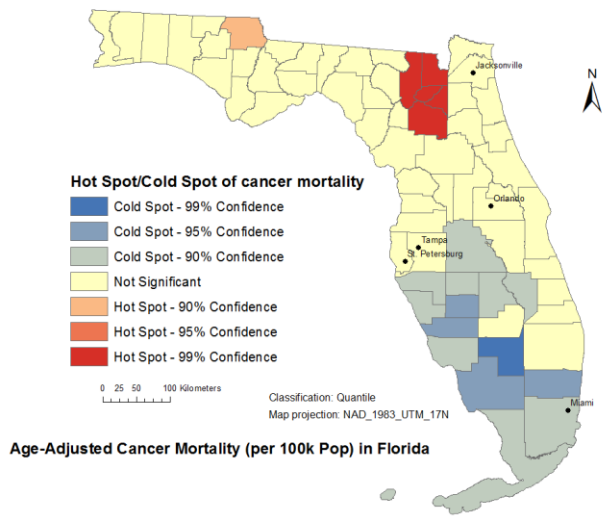
Figure 22 Local-level analysis (Florida): prevalence of all-causes mortality (a), heart-diseases mortality (b), and cancer mortality (c) in Florida in the period of 2006 to 2010.



(a)

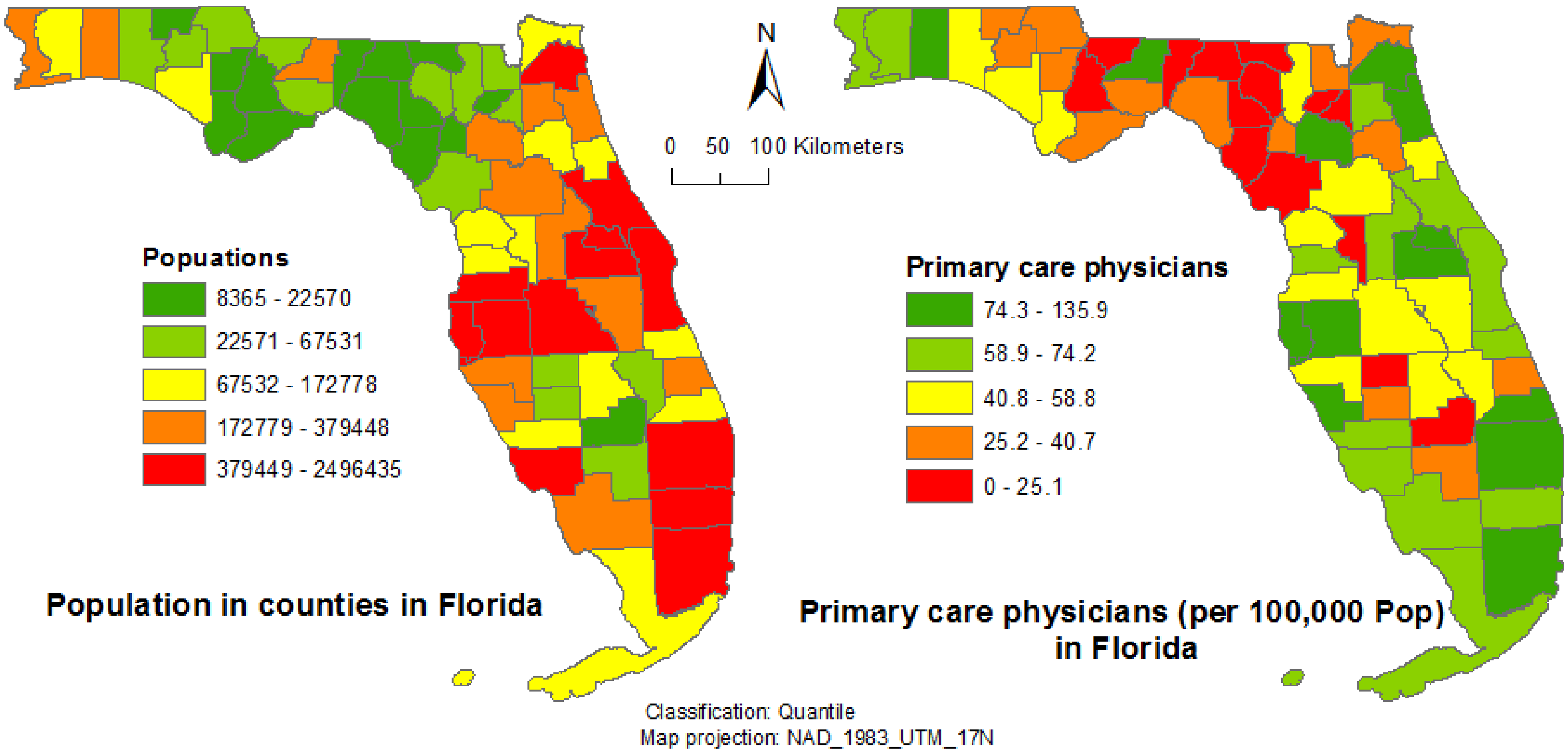


(b)



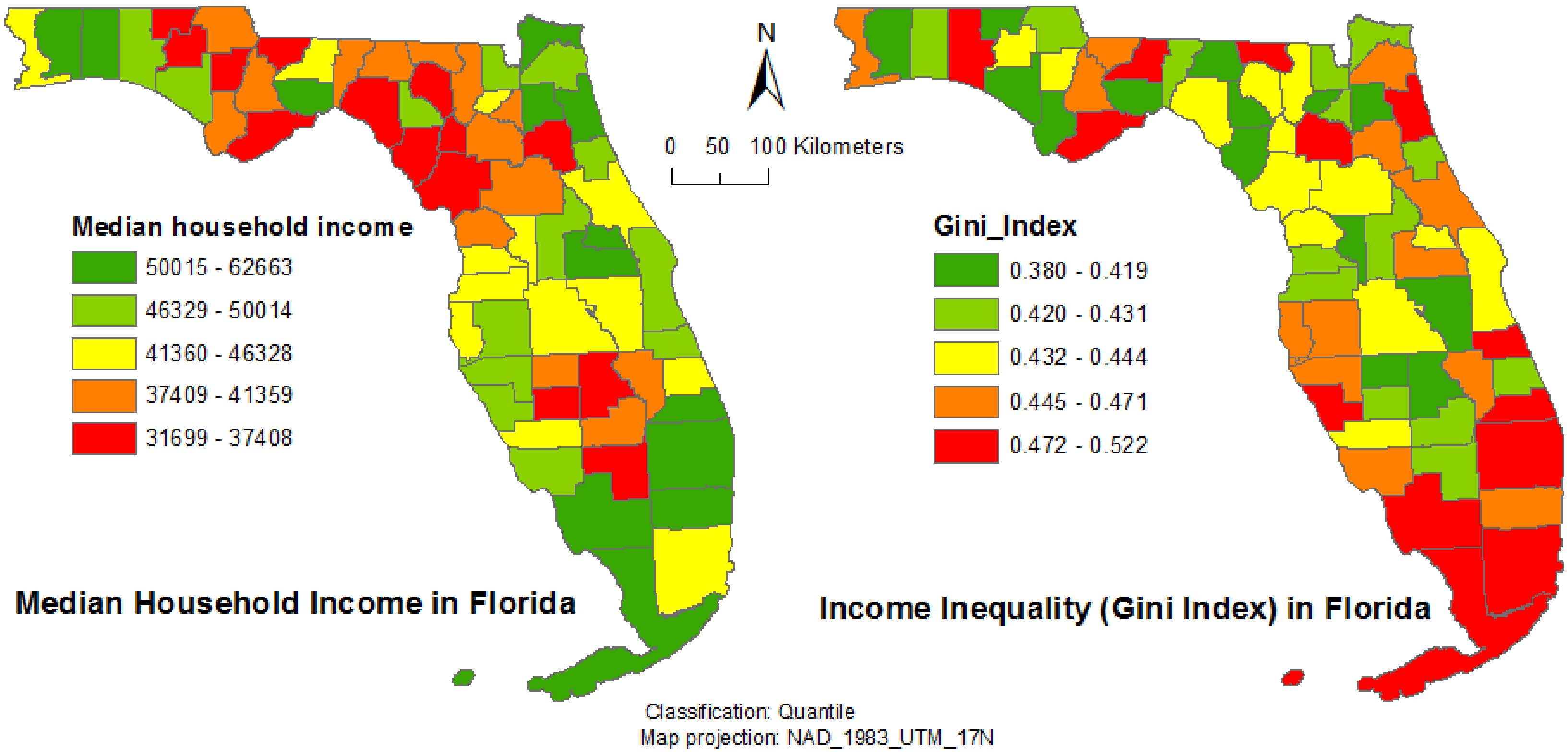
(c)

Figure 23 Local-level analysis (Florida): Hotspots of all-causes mortality (upper left), heart-diseases mortality (upper right), and cancer mortality (lower central) in Florida in the period of 2006 to 2010.



(a) (b)

Figure 24 Local-level analysis (Florida): spatial distribution of population (a) and primary care physician supply (b) in Florida in the period of 2006 to 2010



(a) (b)

Figure 25 Local-level analysis (Florida): spatial distribution of median household income (a) and income inequality (b) in Florida in the period of 2006 to 2010.

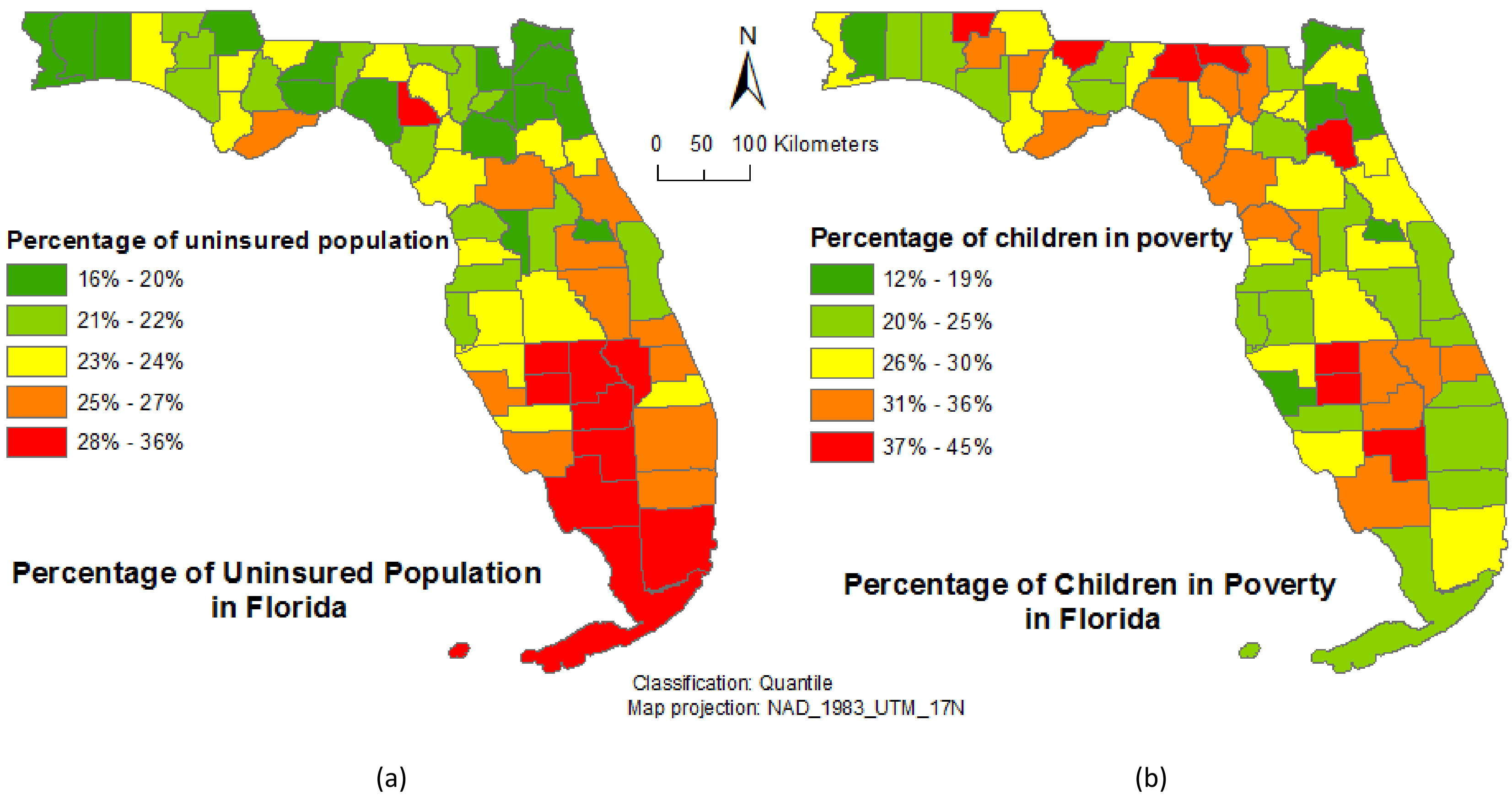
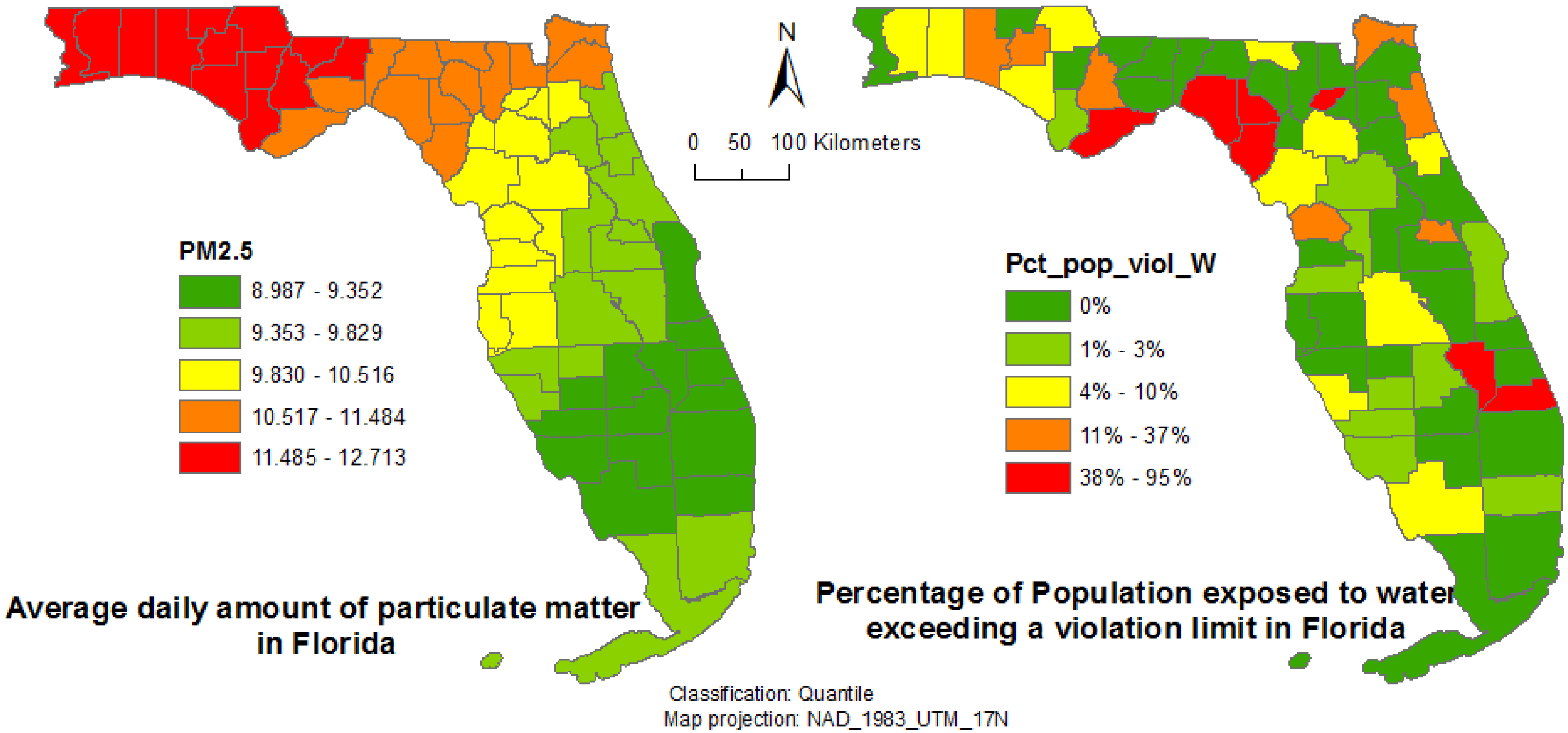


Figure 26 Local-level analysis (Florida): spatial distribution of percentage of uninsured population (a) and percentage of children in poverty in Florida (b) in the period of 2006 to 2010



(a) (b)

Figure 27 Local-level analysis (Florida): spatial distribution of average daily fine particulate matters (pm2.5) (a) and percentage of population exposed to drinking water exceeding a violation limit (b) in Florida in the period of 2006 to 2010.

4.3.2 Efficiencies local health departments in Florida.

After data processing (see section 3.3), only 47 out of total 67 LHDs in Alabama provide sufficient information for DEA and following analyses. Fortunately, non-parametric tests prove that distributions of population, all-causes mortality, heart-diseases mortality, and cancer mortality associated with the forty-seven LHDs sample have no significant difference from those of the total 67 LHDs "population" (see table 19).

Table 19 Local-level analysis (Florida): test of distributions of thirty-six LHDs sample and sixty-seven LHDs population

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of population is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.704	Retain the null hypothesis
2	The distribution of all-causes mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.904	Retain the null hypothesis
3	The distribution of heart-diseases mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.858	Retain the null hypothesis
4	The distribution of cancer mortality is the same across categories of Group	Independent-Samples Mann-Whitney U Test	.804	Retain the null hypothesis
Asymptotic significances are displayed. The significance level is 0.05				

Table 20 shows the descriptive statistics of 47 LHDs in the analysis. Note than characteristics vary greatly among LHDs. The largest LHDs served 1,265,293 people while the smallest LHD only served 11,175 people. Great differences can also be found in employment of five reclassified public health workforces. For public health managers, the LHD with the greatest need of public health managers employed 49.8 FTE public health managers to oversee its operation. However, except for those LHDs that considered public health manager unnecessary, some LHDs only employed part-time public health manager(s) for the same purpose. Similar patterns can be found on other public health workforces. These patterns indicate that total expenditures as well as public health workforces are distributed unevenly among LHDs. It is also possible that total expenditures and public health workforces were allocated according to some functions of other LHDs characteristics (e.g. jurisdiction size). Unlike other LHD characteristics discussed above, the distributions of the number of different clinical public health services and the number of different epidemiological/environmental public health services are steadier.

Table 20 Local-level analysis (Florida): descriptive statistics of LHD characteristics

LHD characteristics	Maximum	Minimum	Mean	Median	SD
Jurisdiction size	1,265,293	11,175	262,641.8	138,660	325,974.9
Total Expenditures	69,278,611	1,028,506	13,895,438.1	7,467,586	16,281,799.2
FTE Public Health Managers	49.8	0.4	11.0	6.5	12.1
FTE Public Health Physicians/Nurses	150	2.4	34.3	22	35.3
FTE Public Health Epidemiologists/Sanitarians	102	1	17.7	9	21.8
FTE Public Health Administrative/ Clerical Employees	273	4	63.1	32	66.8
FTE Other Employees	120	0.3	25.0	14.5	30.6
# of different clinical public health services	25	11	19.6	21	3.5
# of different epidemiological/ environmental public health services	41	16	27.9	27	5.6

Bivariate analysis of LHD characteristics somehow confirms these patterns. From the correlation table of LHD characteristics (see table 21), we find that jurisdiction size, total expenditures, and five public health workforces are statistically significantly correlated with each other. The relationships between them are also demonstrated in figure 28a to figure 28f. Positive relationships exist between jurisdiction size and six LHD characteristics. A reasonable explanation is that the expenditures and the employment of public health workforces are functions of the jurisdiction size. In other words, LHDs with larger jurisdiction size had greater expenditures as well as greater needs of public health workforces.

Although statistically significant correlations are found between jurisdiction size, total expenditure, and public health workforces, nearly no statistically significant relationship is detected between two types of public health services and other LHD characteristics. A weak but statistically significant correlation does exist between FTE public health managers and number of different clinical public health services. Other than that, a medium correlation exists between number of different clinical public health services and number of different epidemiological/environmental public health services. It tells us that where there are greater needs of epidemiological/environmental public health services, there are also possible to have greater needs of clinical public health services.

Table 21 Local-level analysis (Florida): correlation table of LHD characteristics

	Jurisdiction size	Total expenditures	FTE Public Health Managers	FTE Public Health Physicians/ Nurses	FTE Public Health Epidemiologists/ Sanitarians	FTE Public Health Administrative/ Clerical Employees	FTE Other Public Health Employees	# of different clinical Services	# of different epid/envi services
Jurisdiction size	1	.955**	.718**	.768**	0.941**	0.715**	.824**	.166	.141
Total expenditures		1	.699**	.857**	.913**	.694**	.817**	.272	.243
FTE Public Health Managers			1	.556**	.682**	.553**	.610**	.292**	.171
FTE Public Health Physicians/Nurses				1	.716**	.791**	.809**	.263	.156
FTE Public Health Epidemiologists/Sanitarians					1	.681**	.701**	.191	.151
FTE Public Health Administrative/Clerical Employees						1	.732**	.194	.069
FTE Other Public Health Employees							1	.095	.158
# of different clinical services								1	.439**
# of different epi/env services									1
**: significant at 0.01 level									

Figure 28 Local-level analysis (Florida): scatter plots between jurisdiction size and other LHD characteristics

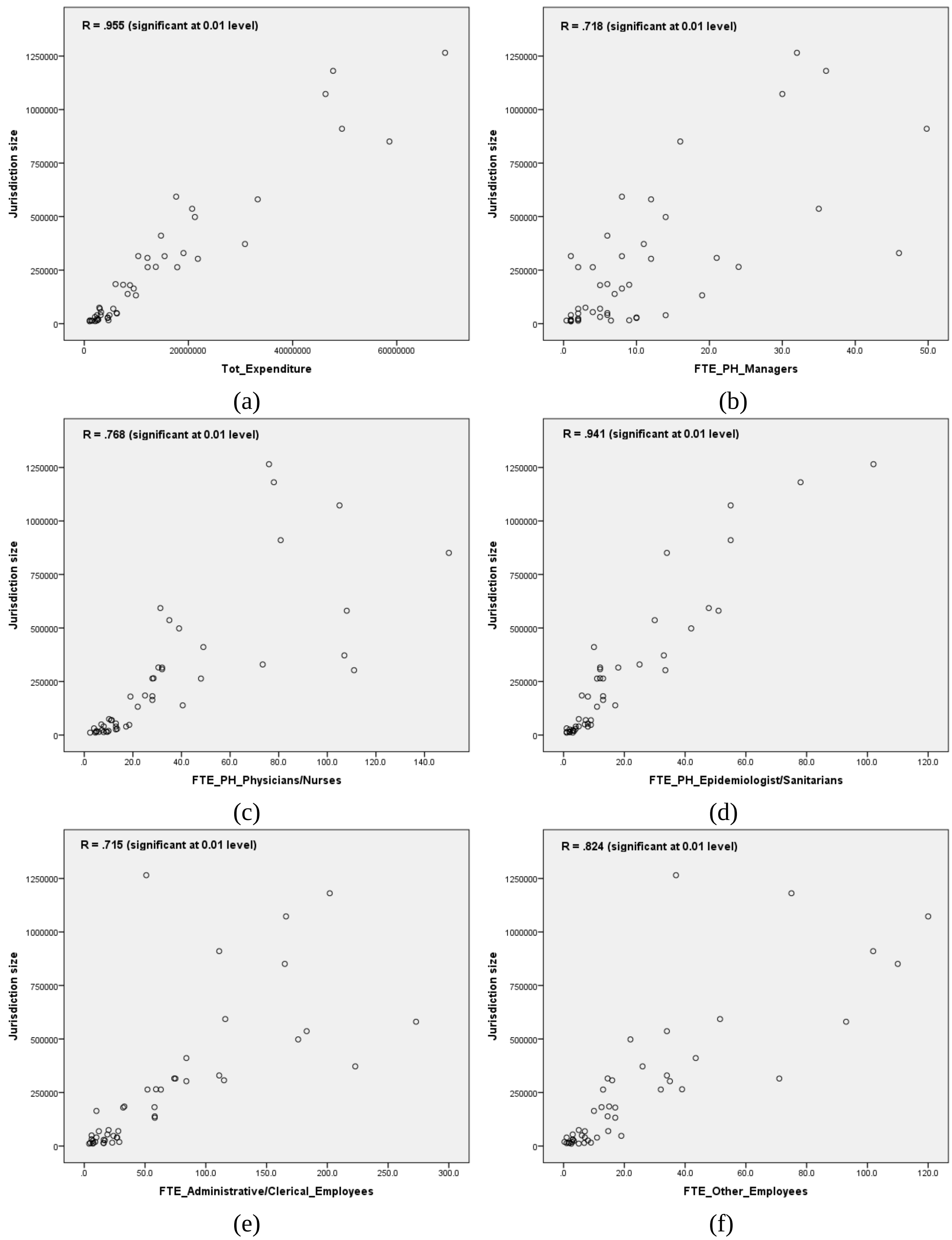
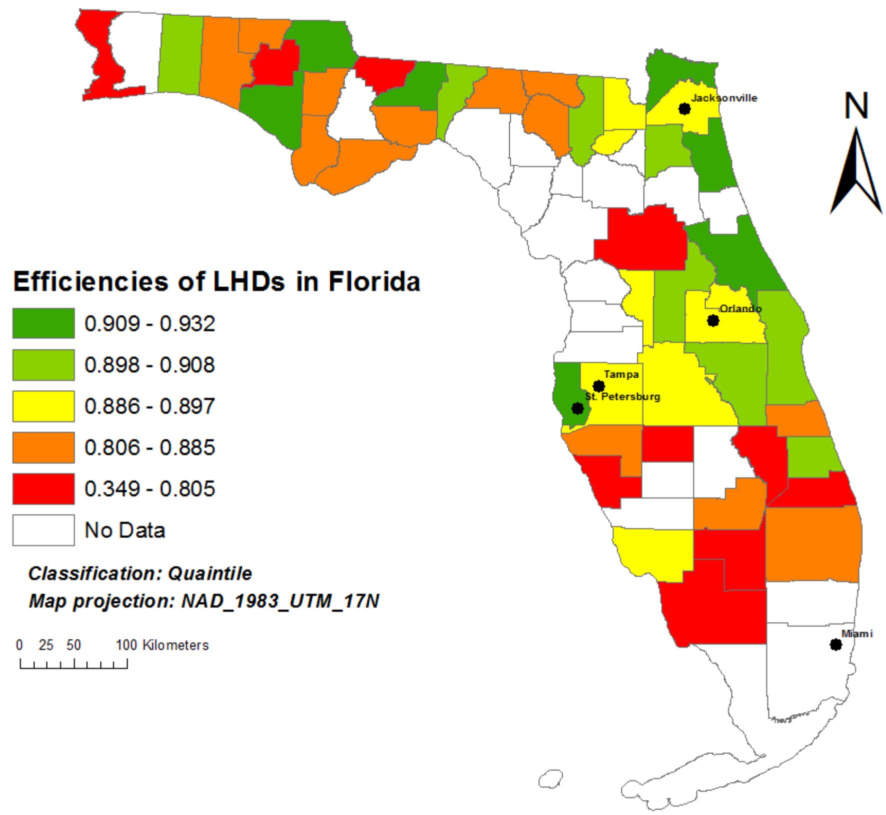
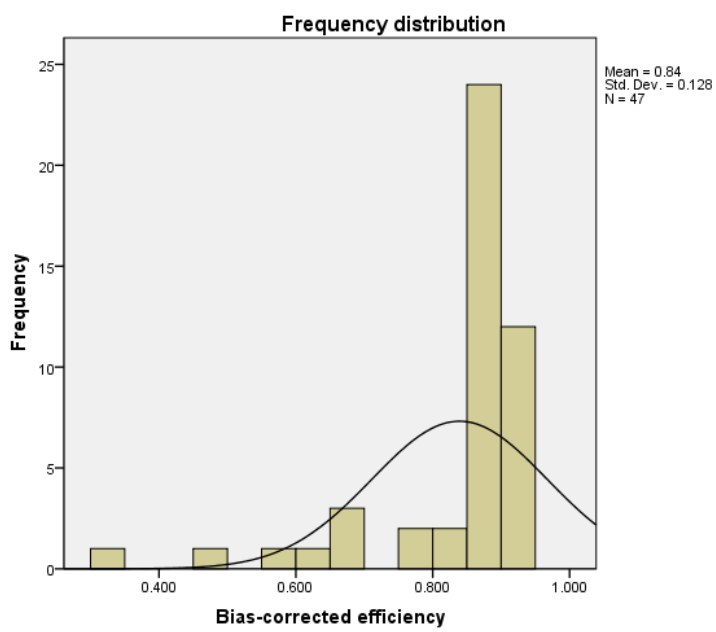


Figure 29(a) shows estimating efficiencies of 47 LHDs in Florida, and figure 29(b) shows the frequency distribution of them. The color of red denotes lowest efficiencies, and green denotes highest efficiencies. No significant spatial pattern is found for efficiencies of LHDs in Florida though it seems like LHDs near Jacksonville and Orlando were more efficient than other LHDs especially those in the south.



(a)



(b)

Figure 29 Local-level analysis (Florida): efficiencies of LHDs in Florida in 2010.

4.3.3 Statistical analyses: health outcomes, the efficiency of LHD, primary care physician supply, and other socio-environmental factors

Bivariate analysis (see table 22) shows that there is no statistically significant correlation between the efficiency of LHD and all three types of mortality. Primary care physician supply and median household income are found negatively correlated with all three types of mortality. A positive correlation is found between average daily fine particulate matters (pm2.5) and health outcomes. Interestingly, although we expected that higher income inequality may associate with worse health outcomes, it appears to be the other way around in Florida. Regression analysis confirms that median household income is the strongest indicator of the prevalence of all-causes mortality, heart-diseases mortality, and cancer mortality (see table 23). Income inequality and average daily fine particulate matters (pm2.5) are also proved to be other strongest indicators. However, primary care physician supply seems to be less important when taken other socio-environmental factors into account.

One-way ANOVA analysis (see figure 24) shows that there is no statistically significant difference in all three types of mortality and primary care physician supply between populations served by LHDs with “higher” and “lower” efficiencies. Nevertheless, populations served by LHDs with “higher” efficiencies are found with significant lower percentage of uninsured populations (see table 25), lower percentage of children in poverty (see table 26), and lower percentage of populations exposed to drinking water exceeding a violation limit (see table 27). And as what we expect, “higher” and “lower” primary care physician supply are found associated with significant difference in all-causes mortality, heart-diseases mortality, and cancer mortality (see table 28).

No statistically significant interaction between the efficiency of LHD and primary care physician supply is found in two-way ANOVA analysis (see table 29).

Table 22 Local-level analysis (Florida): correlations between three types of mortality, the efficiency of LHD, primary care physician supply, and other socio-environmental factors

Explanatory variables	Age-adjusted all-causes mortality	Age-adjusted heart-diseases mortality	Age-adjusted cancer mortality
Efficiencies of LHDs	-	-	-
Primary care physician supply	-.488**	-.484**	-.332*
Median household income	-.499**	-.626**	-.319*
Income inequality (Gini coefficient index)	-.465**	-.483**	-.314*
Percentage of uninsured population	-	-	-.296*
Percentage of children in poverty	-	-.449**	-
Average daily fine particulate matters (pm2.5)	.571**	.514**	.414**
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
*: significant at 0.05 level; **: significant at 0.01 level; "-": no significant correlation			

Table 23 Local-level analysis (Florida): multiple regression models of health outcomess and explanatory variables.

Health outcome / Explanatory variables	Age-adjusted all-causes mortality	Age-adjusted heart-diseases mortality	Age-adjusted cancer mortality
(Constant)	1179.881**	398.063**	390.630**
The efficiencies of LHD	-	-	-
Primary care	-	-	-

physician supply			
Median household income	-.006*	-.003**	-.002**
Income inequality (Gini coefficient index)	-1420.284**	-441.156**	-
Percentage of uninsured population	-	-	-4.171**
Percentage of children in poverty	-	3.767*	-
Average daily fine particulate matters (pm2.5)	50.531**	10.747*	-
Percentage of population exposed to drinking water exceeding a violation limit	-	-	-
R	.723	.769	.531
Adjusted R square	.489	.563	.250
Sig. of the overall model	.000**	.000**	.000**
Sig. of variables: *: significant at 0.05 level; **: significant at 0.01 level; "-": no significant correlation			

Table 24 Local-level analysis (Florida): one-way ANOVA analysis result (grouping by the efficiency of LHD)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	.069	.794
Age-adjusted heart-diseases mortality	.117	.734
Age-adjusted cancer mortality	.014	.905
Primary care physician supply	.313	.579
Median household income	2.823	.100
Income inequality (Gini index)	.310	.580
Percentage of uninsured population	7.037	.011
Percentage of children in poverty	7.957	.007
Average daily particulate matters (pm2.5)	.491	.487
Percentage of population exposed to drinking water exceeding a violation limit	4.436	.041

Table 25 Local-level analysis (Florida): descriptive analysis of percentage of uninsured population in “higher” and “lower” efficiencies of LHDs in Florida

Variable: “Percentage of uninsured population”

Groups	Mean	Median	Std. Deviation
"Lower" efficiencies group	26.86	25.00	5.34
"Higher" efficiencies group	22.60	22.45	3.65

Table 26 Local-level analysis (Florida): descriptive analysis of percentage of children in poverty in “higher” and “lower” efficiencies of LHDs in Florida

Variable: “Percentage children in poverty”

Groups	Mean	Median	Std. Deviation
"Lower" efficiencies group	34.14	36.00	7.89
"Higher" efficiencies group	26.63	26.00	6.27

Table 27 Local-level analysis (Florida): descriptive analysis of percentage of population exposed to drinking water exceeding a violation limit in “higher” and “lower” efficiencies of LHDs in Florida

Variable: “Percentage of population exposed to drinking water exceeding a violation limit”

Groups	Mean	Median	Std. Deviation
"Lower" efficiencies group	23.00	1.8	39.37
"Higher" efficiencies group	6.67	0.78	13.21

Table 28 Local-level analysis (Florida): one-way ANOVA analysis result (grouping by primary care physician supply)

Dependent variables	F	Sig.
Age-adjusted all-causes mortality	15.471	.000
Age-adjusted heart-diseases mortality	18.853	.000
Age-adjusted cancer mortality	5.389	.025

Table 29 Local-level analysis (Florida): interaction between the efficiency of LHD and primary care physician supply and its impact on health outcomes

	All-causes mortality		Heart-diseases mortality		Cancer mortality	
Source	F	Sig.	F	Sig.	F	Sig.
Group the efficiency of LHDs	.059	.810	.094	.760	.010	.923
Group Primary care physician supply	5.414	.025*	7.396	.009**	1.145	.291
Group the efficiency of LHDs * Group Primary care physician supply	.319	.575	.161	.690	.609	.440
* Significant at 0.05 level						

4.3.4 Summary of local-level analysis of Florida

The prevalence of three types of mortality in Florida share many common patterns. High mortality rates are more likely to be found in the north Florida while “cold spots” of mortalities can be found in south Florida. Statistical analyses reveal that there is no significant effect of the efficiency of LHD on all-causes mortality, heart-diseases mortality, and cancer mortality. And no statistical evidence demonstrates how the interaction between the efficiency of LHD and primary care physician supply may affect health outcomes.

4.4 The effect of the efficiency of public health agency on health outcomes

Does the efficiently of public health agency have significant effect(s) on health outcomes? The simple answer is no. We tested both the effect of the efficiency of state and territorial public health agency and the effect of the efficiency of local health department on all-causes mortality, heart-diseases mortality, and cancer mortality. However, neither of them is found significant in this study.

The estimating efficiency of public health agency quantifies the capability of public health agency in using fewer public health workforces to provide more public health services with less expenditure. Higher efficiency indicates that a public health agency has higher productivity. Lower efficiency indicates that a public health agency needs greater public health spending (including labor workforce and capital expenditure) per public health service. From a thirteen-year period study, Mays and Smith (2011) showed evidence that increases in public health spending per capita can benefit the declines in preventable deaths (Mays & Smith, 2011). Inconsistent with their findings, the absence of statistically significant association between the efficiency of public health agency and health outcomes in this study implies that the prevalence of health outcomes over different populations may be too complex to be explained by variances of public health spending on these populations.

However, statistically significant linear correlations between populations served by the public health agency and its full-time-equivalent workforces and expenditure are found in both case studies Alabama and Florida (see sections 4.2.2 and 4.3.2). Such finding confirms the general expectation that public health spending is based on jurisdiction size (measured by population). As a result, public health spending per capita of public health agencies among a cohort (e.g. within Florida) may not be significantly different. Although some public health agencies were found having significant higher public health spending (those in “lower” efficiencies group) compared with others (those in “higher” efficiencies group), the absence of significant difference in health outcomes between them imply that public health spending is not an effective indicator of the prevalence of health outcomes among jurisdictions served by different public health agencies.

4.5 Understanding health outcomes from an integral perspective of efficiency of public health agency and primary care physician supply

Although increases in primary care physician supply has been found associated with declines in all-causes mortality, heart-diseases mortality, and cancer mortality, no statistically significant interaction between the efficiency of public health agency and primary care physician supply on health outcomes in either state-level analysis in the continental U.S. and county-level case study in Florida. Such an interaction was not even detected in the case study of Alabama.

All of these analysis results demonstrate that improving the health of populations by appropriate assignment of primary care physicians and the operation of public health agency still remains changeling.

4.6 Strongest indicators of health outcomes

Strength of explanatory variables in explaining the prevalence of health outcomes varies from one health outcomes to another. It is found in both state-level analysis and the case study of Florida that greater percentage of the prevalence of all-causes mortality and heart-diseases mortality could be explained by explanatory variables incorporated in this study, but cancer mortality could not. The extreme case was found in the case study of Alabama where none of explanatory variables showed statistical significant correlation with cancer mortality.

Among all explanatory variables incorporated in this study, median household income, income inequality, and average daily fine particulate matters are found the most important indicators of health outcomes in state-level analysis and case study of Florida.

CHAPTER 5

CONCLUSION AND FUTURE STUDY

5.1 Conclusion

This study aims to provide additional empirical evidence of the impact of performance of public health agency on health outcomes. Given inconsistent definitions of performance of public health agency among previous researches, this study first defines and measures the efficiency of public health agency, as one dimension of the overall performance, and explores its association with health outcomes. The estimating efficiency of public health agency in this study refers to the capability of the public health agency in utilizing fewer public health workforces to provide certain amount of public health services with less expenditure. Data envelopment analysis (DEA), which has been frequently used to evaluate efficiencies of other public health sectors, is employed to evaluate efficiencies of state and territorial health departments in the continental U.S. and local health departments in Alabama and Florida respectively. Higher estimating efficiency means that a public health agency has higher productivity(since it needs lower public health spending per capita to provide certain amount of public health services, while lower estimating efficiency indicates that a public health agency has greater public health spending per public health services. We first visually explored these associations of interest visually, and then statistically tested the hypothesized associations.

Due to lack of statistically significant correlation, the effect of the efficiency of public health agency, as one important dimension of the overall performance of public health agency on health outcomes cannot be established. No significant effect of the efficiency of public health agency on health outcomes indicates that how efficiently a public health agency operates to serve its jurisdiction does not have decisive impact on the health of populations. It is possible that once the basic need is satisfied, whether a public health agency operates in higher or lower efficiency does not make a significant effect on health outcomes. How public health resources are allocated can be another contributor of the absence of significant effect of the efficiency of public health agency on health outcomes. From both case study of Alabama and case study of Florida, we find that local public health workforces and expenditure are linear correlated with the jurisdiction size of the public health agency. Such a pattern makes efficiencies of public health agencies in each cohort homogeneous, which, in return, contributes to the absence of significant effect of the efficiency of public health agency on health outcomes.

Primary care physician supply, as we expect, is found negatively correlated with the prevalence of health outcomes. Being consistent with findings in previous researches, higher primary care physician supply is generally associated with better health outcomes.

This study also tried to evaluate health outcomes from an integral perspective of efficiency of public health agency and primary care physician supply. However, no significant effect of the interaction between the efficiency of public health agency and primary care physician supply on health outcomes is found in this study. The absence of significant effect of the efficiency of public health agency on health outcomes may contribute to the absence of significant effect of the interaction between the efficiency of public health agency and primary care physician supply on health outcomes. Lack of cooperation between public health agency and primary care sectors until recently also explains the absence of significant effect of interaction between them on health outcomes. Unfortunately, we are not able to confirm whether the interaction of the efficiency of public health agency and primary care physician supply does not have significant impact on health outcomes indeed. Actually, a few tendencies are still worth of noticing. In state-level analysis, we find that when primary care physician is high, populations served by public health agencies with higher efficiency have worse health outcomes compared with populations served by public health agencies with lower efficiencies. However, when primary care physician is low, populations served by public health agencies with higher efficiencies have better health outcomes than populations served by public health agencies with lower efficiencies. A completely opposite pattern is found in case study of Florida. When primary care physician supply is high, populations served by public health agencies with lower efficiencies have better health outcomes; while primary care physician is low, populations served by public health agencies with higher efficiencies are found have worse health outcomes.

Interestingly but not surprisingly, median household income and air quality are found the most important indicators of health outcomes on both state level and local level. Higher median household income and better air quality are associated with better health outcomes. Income inequality, however, although is found statistically significantly correlated with health outcomes, their associations are inconsistent associations are found on state level and on local level.

The bottom line is that the prevalent assumption that better public health performance leads to better health outcomes cannot be established. And it cannot be significantly tested and proven that appropriate operation of public health agency and suitable assignment of primary care physician can help to improve health outcomes. After exploring various approaches at different geographic levels, socioeconomic and environmental factors still do a better job than our most interested public health performance in explaining the variation in health outcomes. With that being said, the overall improvement of health outcomes remain challenging.

5.2 Limitation

As an exploratory analysis, we acknowledge that there are many limitations in this tudy. First, this study tests the effect of efficiency of public health agency on mortality only. Effect of efficiency of public health agency on other health outcomes (e.g. disability, discomfort, etc.) has not yet been explored, and thus making the current conclusion of the effect of the efficiency of public health agency and health outcomes less comprehensive.

Another limitation of this study is the evaluation of primary care physicians. In this study, primary care physician supply to a community is simply evaluated by head counting primary care physicians working in that community. Such evaluation can cause bias since populations in a certain community are very likely to receive treatment from primary care physicians resident in other communities. County based head counting measure may either overestimate or underestimated primary care physician supply to population living in the county. The Dartmouth Atlas of Health Care provides a more accuracy mean to evaluate primary care physician supply to a the defined jurisdiction using the Primary Care Service Area (PCSA), a total different geographical unit compared to the jurisdiction of LHDs (in this study, county).

Although evaluation based on PCSA is not employed in this study, it will be a valuable addition for future studies.

Third, only public health agencies under “centralized” and “shared” governance structure are explored by case study of Alabama and Florida in this study. The other two governance structure, namely “decentralized” and “mix” governance structure, have not been explored due to limitation on data. As a result, we are not able to tell whether governance structure may affect the effect of the efficiency of public health agency on health outcomes or not.

Four, this study explores the association between the performance of public health agency and health outcomes directly. It is possible that there is no immediate effect of the performance of public health agency on health outcomes. Instead, the performance of public health agency may affect media that could significantly affect health outcomes. For instance, the performance of public health agency may affect the percentage of people smoke, while the percentage of people smoke can affect health outcomes in return.

Fifth, only health outcomes of the whole population are evaluated in this study. No extra effort has been taken to explore how the performance of public health agency may affect health outcomes of difference races and population groups.

5.3 Future study

This study points to at least six meaningful future studies. First, although no significant effect of the efficiency of public health agency on three types of mortality has been found, some general tendencies between the two phenomena are observed, and it is still worthwhile to test the effect of efficiency of public health agency on other types of health outcomes.

Second, in addition to the efficiency, future study should also explore the effect of the effectiveness of public health agencies (as another important dimension of performance) on health outcomes. Further, the association of the efficiency and the effectiveness of public health agency might also give us some inspiration on public health management.

Third, future study can evaluate how efficiency of public health agency change in time may affect health outcomes.

Fourth, this study tells little about the efficiency of local public health system (LPHS). Future studies may incorporate national recognized instrument such as NPHPS with the efficiency analysis to explore the relationship between effectiveness and efficiency of LPHS as well as their impact on health outcomes.

Fifth, only the effect of the efficiency of public health agency under “centralized” and “shared” governance structure of state and local public health departments are explored in this study. Future study should also explore the effect of the efficiency of public health agency under other two governance structures, namely “decentralized” and “mix”.

Sixth, future study should also explore the effect of the performance of public health agency on health outcomes of difference races and population groups.

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Appendix I

Technical description of DEA

This section provides technical description of basic DEA models (CCR and BCC models).

Common DEA notations (Ben-Arieh and Gullipalli 2012):

DEA	Data Envelopment Analysis
DMU	Decision Making Unit, a unit which consume inputs and produce outputs
DMU_0	DMU under evaluation or test DMU
n	Total number of DMUs under evaluation
m	Total number of input variables
s	Total number of output variables
*	Optimal solution value
v_i	Input multiplier variable of ratio model, i = 1,2,3,…,m
u_r	Output multiplier variable of ratio model, r = 1,2,3,…,s
X	Matrix representation of input variables
Y	Matrix representation of output variables
X_{ij}	Represents input variables of DMU_j, i = 1,2,3,…,m
Y_{rj}	Represents output variables of DMU_j, r = 1,2,3,…,m

Consider there are n DMUs to be evaluated. Each DMU consumes varying amount of m different inputs to produce s different outputs. Specifically, for a particular DMU_j, X_{ij} denotes for the amount of input *i* it consumes and Y_{rj} denotes for the amount of output r it produces.

The input-oriented CCR model was introduced by Charnes, Cooper, and Rhodes (1978) in the "ratio-form" in which the ratio of outputs to inputs is used to measure the relative efficiency of DMU_0 (the DMU under evaluation) relative to the ratios of all DMUs (include itself). In mathematical programming, the CCR model is given as (Charnes, Cooper, and Rhodes 1978):

$$Max\ h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_r x_{i0}} \qquad (1)$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_r x_{i0}} \leq 1; \quad i = 1, \dots, n.$$

$$u_r, v_i \geq 0;\ r = 1, \dots, s; i = 1, \dots, m.$$

"One problem for above "ratio-form" in (1) is that it yields infinite solution. That is if (u*, v*) is optimal, then (au*, av*) is also optimal for all a > 0. To avoid this problem, the constraint $vxi\ =\ 1$ is imposed, which provides" (Coelli 1996):

$$Max\ (\mu y_{r0}) \qquad (2)$$

subject to

$$\sum_r u_r y_{r0} - \sum_i v_r x_{i0}\ \leq 0$$

$$\sum_i v_r x_{i0}\ = 1$$

$$u_r, v_i \geq 0$$

Using the duality in linear programming, an equivalent envelopment form of (2) can be derived as (*Handbook on Data Envelopment Analysis* 2011):

$$\emptyset^* = min\emptyset \qquad (3)$$

subject to

$$\sum_i x_{ij} \leq \emptyset x_{i0} \quad i = 1,2,\dots,m;$$

$$\sum_i y_{rj}\lambda_j \geq y_{r0} \quad r = 1,2,\dots,s;$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n.$$

While (3) for CCR model assumes constant return to scale, it can be easily modified to account for the variable return to scale by adding an additional constraint. So the input oriented mathematical programming form for "BBC" model can be given as (Banker, Charnes, and Cooper 1984):

$$\emptyset^* = min\emptyset \qquad (4)$$

subject to

$$\sum_i x_{ij} \leq \emptyset x_{i0} \quad i = 1,2,\dots,m$$

$$\sum_i y_{rj}\lambda_j \geq y_{r0} \quad r = 1,2,\dots,s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0$$

Mathematical programming form (3) and (4) listed above are specialized for input-oriented DEA models. Output-oriented DEA models have similar but different mathematical programming forms. They are not listed here because this study employs input-oriented DEA model only.

Strengths and Limitations of DEA

The widely application of DEA suggests DEA can be a powerful tool when used wisely. A few of the characteristics make it powerful (TRICK 1998):

- DEA can handle multiple inputs and multiple outputs models.
- A priori assumption of a functional form relating inputs to outputs is not required.
- DMUs are directly compared against a peer or combination of peers.
- Inputs and outputs can have different units. For example, input 1 could be in the unit of number of FTE employees, while input 2 could be in the unit of dollars of expenditures. No priori tradeoff between the two is required.

Even though DEA has been approved to be a powerful tool, uses should use it carefully since DEA is inevitably subjected to a number of limitations:

- Since DEA is an extreme point technique, noise such as measurement error, zero values, missing values can cause significant problems.
- DEA is good at estimating “relative” efficiency of a DMU but it converges very slowly to “absolute” efficiency. That is, it can tell you how well you doing compared to your peer but not compared to a “theoretical maximum”, and thereby not good at telling you how efficiently you actually are.

- Since DEA is a nonparametric technique, the distribution of DEA estimators are usually unknown which makes statistically hypothesis difficult. Although researcheshas approved the asymptotic distribution of DEA (Korostelev, Simar, and Tsybakov 1995; Kneip, Park, and Simar 1998; Banker 1993), estimators statistical inference on DEA estimator should be assess cautiously.
- DEA estimation results are subject to bias. The raw DEA efficiency score are usually overestimates the true efficiency (Simar and Wilson 1998, 2000a, 2000b, 2007). Following correction procedure is essential.

Appendix II

Supplemental statistical referencing

This section includes supplemental statistical referencing of the study. Table 34 shows correlations between health outcomes, estimating efficiencies, primary care physician supply, and other explanatory variables on state level. Table 35 shows correlations between health outcomes, estimating efficiencies, primary care physician supply, and other explanatory variables for case study of Alabama. Table 36 shows correlations shows correlations between health outcomes, estimating efficiencies, primary care physician supply, and other explanatory variables for case study of Florida.

Table 30 State-level analysis: full table of correlations between health outcomes, efficiencies at which local public health resources were utilized by state, primary care physician supply, and other socio-environmental factors

Correlations

		AAR_All_Causes_Mortality	AAR_Cancer_Mortality	AAR_Heart_Diseases_Mortality	Bias-corrected technical efficiency	Primary care physician supply	Median_H_Income	Gini_Index	Pct_Uninsured_Pop	Pct_Children_Poverty	PM2.5	Pct_pop_w_viol
AAR_All_Causes_Mortality	Pearson Correlation	1	.811**	.850**	-.016	-.550**	-.706**	.225	.391*	.699**	.503**	.264
	Sig. (2-tailed)		.000	.000	.922	.000	.000	.152	.010	.000	.001	.091
	N	42	42	42	42	42	42	42	42	42	42	42
AAR_Cancer_Mortality	Pearson Correlation	.811**	1	.791**	-.111	-.129	-.474**	.331*	.029	.478**	.593**	.139
	Sig. (2-tailed)	.000		.000	.486	.416	.002	.032	.854	.001	.000	.380
	N	42	42	42	42	42	42	42	42	42	42	42
AAR_Heart_Diseases_Mortality	Pearson Correlation	.850**	.791**	1	.022	-.440**	-.483**	.453**	.253	.612**	.552**	.220
	Sig. (2-tailed)	.000	.000		.892	.004	.001	.003	.106	.000	.000	.161
	N	42	42	42	42	42	42	42	42	42	42	42
Bias-corrected technical efficiency	Pearson Correlation	-.016	-.111	.022	1	-.303	-.160	.102	.159	.096	-.111	.416**
	Sig. (2-tailed)	.922	.486	.892		.051	.310	.521	.314	.544	.484	.006
	N	42	42	42	42	42	42	42	42	42	42	42
Primary care physician supply	Pearson Correlation	-.550**	-.129	-.440**	-.303	1	.578**	.070	-.684**	-.562**	-.125	-.246
	Sig. (2-tailed)	.000	.416	.004	.051		.000	.658	.000	.000	.432	.117
	N	42	42	42	42	42	42	42	42	42	42	42
Median_H_Income	Pearson Correlation	-.706**	-.474**	-.483**	-.160	.578**	1	-.026	-.444**	-.754**	-.081	-.278
	Sig. (2-tailed)	.000	.002	.001	.310	.000		.872	.003	.000	.612	.075
	N	42	42	42	42	42	42	42	42	42	42	42
Gini_Index	Pearson Correlation	.225	.331*	.453**	.102	.070	-.026	1	.150	.449**	.363*	-.016
	Sig. (2-tailed)	.152	.032	.003	.521	.658	.872		.342	.003	.018	.920
	N	42	42	42	42	42	42	42	42	42	42	42
Pct_Uninsured_Pop	Pearson Correlation	.391*	.029	.253	.159	-.684**	-.444**	.150	1	.667**	.040	.063
	Sig. (2-tailed)	.010	.854	.106	.314	.000	.003	.342		.000	.802	.694
	N	42	42	42	42	42	42	42	42	42	42	42
Pct_Children_Poverty	Pearson Correlation	.699**	.478**	.612**	.096	-.562**	-.754**	.449**	.667**	1	.401**	.111
	Sig. (2-tailed)	.000	.001	.000	.544	.000	.000	.003	.000		.008	.485
	N	42	42	42	42	42	42	42	42	42	42	42
PM2.5	Pearson Correlation	.503**	.593**	.552**	-.111	-.125	-.081	.363*	.040	.401**	1	-.009
	Sig. (2-tailed)	.001	.000	.000	.484	.432	.612	.018	.802	.008		.956
	N	42	42	42	42	42	42	42	42	42	42	42
Pct_pop_viol_w	Pearson Correlation	.264	.139	.220	.416**	-.246	-.278	-.016	.063	.111	-.009	1
	Sig. (2-tailed)	.091	.380	.161	.006	.117	.075	.920	.694	.485	.956	
	N	42	42	42	42	42	42	42	42	42	42	42

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 31 Local-level analysis (Alabama): full table of correlations between health outcomes, efficiencies at which local public health resources were utilized by state, primary care physician supply, and other socio-environmental factors.

Correlations

		AAR_All_Causes_Mortality	AAR_Heart_Diseases_Mortality	AAR_Cancer_Mortality	Bias-corrected techinical efficiencies	Primary care physician supply	Median_H_Income	Gini_Index	Pct_Uninsured_Pop	Pct_Children_Poverty	PM2.5	Pct_pop_viol_w
AAR_All_Causes_Mortality	Pearson Correlation	1	.567**	.703**	.100	-.178	-.466**	.054	.181	.458**	.180	-.101
	Sig. (2-tailed)		.000	.000	.562	.300	.004	.754	.292	.005	.293	.557
	N	36	36	36	36	36	36	36	36	36	36	36
AAR_Heart_Diseases_Mortality	Pearson Correlation	.567**	1	.033	.136	-.372*	-.570**	.202	.240	.614**	.286	.158
	Sig. (2-tailed)	.000		.849	.428	.026	.000	.238	.159	.000	.091	.358
	N	36	36	36	36	36	36	36	36	36	36	36
AAR_Cancer_Mortality	Pearson Correlation	.703**	.033	1	.114	-.048	-.144	-.034	.027	.094	.006	.004
	Sig. (2-tailed)	.000	.849		.509	.782	.401	.843	.877	.587	.973	.981
	N	36	36	36	36	36	36	36	36	36	36	36
Bias-corrected techinical efficiencies	Pearson Correlation	.100	.136	.114	1	.087	.098	.090	-.271	-.003	.203	-.035
	Sig. (2-tailed)	.562	.428	.509		.615	.569	.603	.110	.986	.235	.837
	N	36	36	36	36	36	36	36	36	36	36	36
Primary care physician supply	Pearson Correlation	-.178	-.372*	-.048	.087	1	.202	.014	-.204	-.072	-.169	-.067
	Sig. (2-tailed)	.300	.026	.782	.615		.238	.934	.233	.679	.323	.700
	N	36	36	36	36	36	36	36	36	36	36	36
Median_H_Income	Pearson Correlation	-.466**	-.570**	-.144	.098	.202	1	-.595**	-.461**	-.851**	.122	-.129
	Sig. (2-tailed)	.004	.000	.401	.569	.238		.000	.005	.000	.480	.454
	N	36	36	36	36	36	36	36	36	36	36	36
Gini_Index	Pearson Correlation	.054	.202	-.034	.090	.014	-.595**	1	.082	.594**	-.217	.131
	Sig. (2-tailed)	.754	.238	.843	.603	.934	.000		.635	.000	.204	.445
	N	36	36	36	36	36	36	36	36	36	36	36
Pct_Uninsured_Pop	Pearson Correlation	.181	.240	.027	-.271	-.204	-.461**	.082	1	.278	-.209	.032
	Sig. (2-tailed)	.292	.159	.877	.110	.233	.005	.635		.101	.221	.852
	N	36	36	36	36	36	36	36	36	36	36	36
Pct_Children_Poverty	Pearson Correlation	.458**	.614**	.094	-.003	-.072	-.851**	.594**	.278	1	-.058	.102
	Sig. (2-tailed)	.005	.000	.587	.986	.679	.000	.000	.101		.737	.555
	N	36	36	36	36	36	36	36	36	36	36	36
PM2.5	Pearson Correlation	.180	.286	.006	.203	-.169	.122	-.217	-.209	-.058	1	.069
	Sig. (2-tailed)	.293	.091	.973	.235	.323	.480	.204	.221	.737		.687
	N	36	36	36	36	36	36	36	36	36	36	36
Pct_pop_viol_w	Pearson Correlation	-.101	.158	.004	-.035	-.067	-.129	.131	.032	.102	.069	1
	Sig. (2-tailed)	.557	.358	.981	.837	.700	.454	.445	.852	.555	.687	
	N	36	36	36	36	36	36	36	36	36	36	36

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 32 Local-level analysis (Florida): full table of correlations between health outcomes, efficiencies at which local public health resources were utilized by state, primary care physician supply, and other socio-environmental factors.

Correlations

		Age-adjusted all-causes mortality	Age-adjusted heart-diseases mortality	Age-adjusted cancer mortality	Efficiencies of LHDs	Primary care physician supply	Median household income	Income inequality (Gini index)	Percentage of uninsured population	Percentage of children in poverty	Average daily fine particulate matters (PM2.5)	Percentage of population exposed to drinking water exceeding a violation limit
Age-adjusted all-causes mortality	Pearson Correlation	1	.822**	.915**	-.066	-.480**	-.499**	-.465**	-.252	.267	.571**	.158
	Sig. (2-tailed)		.000	.000	.660	.001	.000	.001	.087	.070	.000	.289
	N	47	47	47	47	47	47	47	47	47	47	47
Age-adjusted heart-diseases mortality	Pearson Correlation	.822**	1	.641**	-.094	-.484**	-.626**	-.483**	-.080	.449**	.514**	.073
	Sig. (2-tailed)	.000		.000	.531	.001	.000	.001	.592	.002	.000	.627
	N	47	47	47	47	47	47	47	47	47	47	47
Age-adjusted cancer mortality	Pearson Correlation	.915**	.641**	1	.007	-.332*	-.319*	-.314*	-.296*	.098	.414**	.257
	Sig. (2-tailed)	.000	.000		.965	.023	.029	.032	.044	.514	.004	.081
	N	47	47	47	47	47	47	47	47	47	47	47
Efficiencies of LHDs	Pearson Correlation	-.066	-.094	.007	1	.153	.272	-.122	-.442**	-.430**	.048	-.197
	Sig. (2-tailed)	.660	.531	.965		.306	.065	.413	.002	.003	.751	.184
	N	47	47	47	47	47	47	47	47	47	47	47
Primary care physician supply	Pearson Correlation	-.480**	-.484**	-.332*	.153	1	.637**	.475**	-.220	-.670**	-.299*	-.044
	Sig. (2-tailed)	.001	.001	.023	.306		.000	.001	.138	.000	.041	.771
	N	47	47	47	47	47	47	47	47	47	47	47
Median household income	Pearson Correlation	-.499**	-.626**	-.319*	.272	.637**	1	.201	-.331*	-.819**	-.341*	-.043
	Sig. (2-tailed)	.000	.000	.029	.065	.000		.174	.023	.000	.019	.776
	N	47	47	47	47	47	47	47	47	47	47	47
Income inequality (Gini index)	Pearson Correlation	-.465**	-.483**	-.314*	-.122	.475**	.201	1	.167	-.124	-.232	.259
	Sig. (2-tailed)	.001	.001	.032	.413	.001	.174		.261	.407	.117	.078
	N	47	47	47	47	47	47	47	47	47	47	47
Percentage of uninsured population	Pearson Correlation	-.252	-.080	-.296*	-.442**	-.220	-.331*	.167	1	.554**	-.496**	.103
	Sig. (2-tailed)	.087	.592	.044	.002	.138	.023	.261		.000	.000	.491
	N	47	47	47	47	47	47	47	47	47	47	47
Percentage of children in poverty	Pearson Correlation	.267	.449**	.098	-.430**	-.670**	-.819**	-.124	.554**	1	.106	.030
	Sig. (2-tailed)	.070	.002	.514	.003	.000	.000	.407	.000		.480	.840
	N	47	47	47	47	47	47	47	47	47	47	47
Average daily fine particulate matters (PM2.5)	Pearson Correlation	.571**	.514**	.414**	.048	-.299*	-.341*	-.232	-.496**	.106	1	-.040
	Sig. (2-tailed)	.000	.000	.004	.751	.041	.019	.117	.000	.480		.790
	N	47	47	47	47	47	47	47	47	47	47	47
Percentage of population exposed to drinking water exceeding a violation limit	Pearson Correlation	.158	.073	.257	-.197	-.044	-.043	.259	.103	.030	-.040	1
	Sig. (2-tailed)	.289	.627	.081	.184	.771	.776	.078	.491	.840	.790	
	N	47	47	47	47	47	47	47	47	47	47	47

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix III

Public health workforce reclassification

NACCHO defines the most common public health occupations as the following table

(source: *National Profile of Local Health Departments, 2010 Codebook*):

Public health occupation	Definition
Public health managers	Health service managers, administrators, health directors overseeing the operations of the agency or of a department or division. Include the top agency executive in this category regardless of education or licensing.
Public health physician	Physician who identifies persons or groups at risk of illness or disability and develops, implements and evaluates programs or interventions designed to prevent, treat or improve such risks. May provide direct medical services.
Public health nurse	Registered nurse conducting public health nursing (e.g., school nurse, community health nurse, nurse practitioner).
Environmental health worker	Environmental health specialists, scientists, and technicians, including registered and other sanitarians.
Epidemiologist	Conducts on-going surveillance, field investigations, analytic studies and evaluation of disease occurrence and disease potential and makes recommendations on appropriate interventions.
Health educator	Designs, implements, evaluates, and provides consultation on educational programs and strategies to support and modify health-related behaviors of individuals, families, organizations, and communities and to promote the effective use of health programs and services.
Nutritionist	Dietician developing, implementing and evaluating strategies to assure effective interventions related to nutrition and physical activity behaviors, the nutrition environment, and food and nutrition policy. May directly provide nutritional counseling.
Public health informatics specialist	Also known as public health information systems specialists or public health informaticists.

Public information specialist	Also known as public information officer.
Behavioral health professional	Behavioral health professional (e.g., public health social workers, HIV/AIDS counselors, mental health and substance abuse counselors, and community organizers)
Emergency preparedness staff	Staff members whose regular job duties involve preparing for (e.g., developing plans, procedures, and training programs) and managing the local public health response to all-hazards events.
Administrative or clerical personnel	Support staff providing assistance in agency programs or operations.

These twelve most common public health occupations are classified into five public health workforces in this study as the following table:

Public health workforce	**Include:**
Public health manager	• Public health manager
Public health physician/nurses	• Public health physician • Public health nurse
Public health epidemiologists/sanitarians	• Environmental health worker • Epidemiologists
Public health administrative/clerical employees	• Administrative or clerical personnel
Other public health employees	• Health educators • Nutritionists • Public health informatics specialist • Public information specialist • Behavioral health professionals • Emergency preparedness staffs

Since public health managers are commonly employed to oversee the operation of the LHDs, itself is reclassified as "public health managers". Public health nurses and physicians are reclassified as "public health physicians/nurses" considering they usually work together to provide clinical public health services. Environmental health workers and epidemiologists are closely relevant to epidemiological/environmental public health services. Here, they are reclassified as “public health epidemiologists/sanitarians”. Administrative or clerical personnel are staffs providing assistance in agency programs or operations. It itself is classified as “public health administrative or clerical employees”. Health educators, nutritionists, public health informatics specialists, public information specialists, behavioral health professionals, and emergency preparedness staffs are reclassified as “other public health employees” since they are not the most common workforces for a typical LHD.

Appendix IV

Public health activities reclassification

NACCHO listed total eight-seven public health services in its 2010 national survey (see *National Profile of Local Health Departments, 2010 Codebook*). This study reclassifies these public health activities into epidemiological/environmental public health services and clinical public health services as the following table:

Epidemiological/environmental public health services	**Clinical public health services**
I. Epidemiology and Surveillance Activities (1)Communicable/ infectious disease (2)Chronic disease (3)Injury (4)Behavioral risk factors (5)Environmental health (6)Syndromic surveillance (7)Maternal and child health II. Population-based Primary Prevention Activities (1)Injury (2)Unintended pregnancy (3)Chronic disease programs (4)Nutrition (5)Physical activity (6)Violence (7)Tobacco (8)Substance abuse (9)Mental illness III. Regulation, Inspection and/or Licensing Activities (1)Mobile homes (2)Campgrounds & RVs (3)Solid waste disposal sites	I. Immunization: (1)Adult Immunizations (2)Childhood Immunizations II. Screening for diseases/conditions (1)HIV/AIDS (2)Other STDs (3)Tuberculosis (4)Cancer (5)Cardiovascular disease (6)Diabetes (7)High blood pressure (8)Blood lead III. Treatment for communicable diseases (1)HIV/AIDS (2)Other STDs (3)Tuberculosis IV. Maternal and Child Health (1)Family planning (2)Prenatal care (3)Obstetrical care (4)WIC (5)MCH home visits (6)EPSDT

(4)Solid waste haulers (5)Septic systems (6)Hotels/motels (7)Schools/daycare (8)Children's camps (9)Cosmetology businesses (10)Body art (tattoos, piercings) (11)Swimming pools (public) (12)Tobacco retailers (13)Smoke-free ordinances (14)Lead inspection (15)Food processing (16)Milk processing (17)Public drinking water (18)Private drinking water (19)Food service establishments (20)Health-related facilities (21)Housing (inspections) IIII. Other Environmental Health Activities (1)Indoor air quality (2)Food safety education (3)Radiation control (4)Vector control (5)Land use planning (6)Groundwater protection (7)Surface water protection (8)Hazmat response (9)Hazardous waste disposal (10)Pollution prevention (11)Air pollution (12)Noise pollution (13)Collection of unused pharmaceuticals V. Other Activities (1)Animal control (3)Occupational safety and health (4)Veterinarian public health activities (4)Laboratory services (5)Outreach and enrollment for medical insurance (include Medicaid) (6)School health (7)Asthma prevention and/or management	(7)Well Child Clinic V. Other Health Services (1)Comprehensive primary care (2)Home health care (3)Oral health (4)Behavioral/mental health services (5)Substance abuse services VI. Other Activities (1)Emergency medical services (2)School-based clinics (clinical) (3)Correctional health (4)Vital records (5)Medical examiner's office

Appendix V

ACRONYM AND ABBREVATION

DEA Data Envelopment Analysis

DMU Decision Making Unit

LHD Local Health Department

NPHPS National Public Health Performance Standards

CDC The Centers for Disease Control and Prevention

NACCHO National Association of County and City Health Officials

ICPSR Inter-university Consortium for Political and Social Research

FTE Full Time Equivalent