Essays on Community Characteristics Associated with Potentially Preventable Hospitalizations

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Dedication

This dissertation is dedicated to my family. To my husband, Jared—Thank you for supporting me through this long process, from Masters to PhD, with a wedding and a baby thrown in the mix. You truly are “Dad of the Year” every year. To my son, Asher—Your smiles and “I love you, Mommy” in the early mornings and late at night keep me going. To my parents—Thank you for believing in me and providing wonderful examples of people living life to the fullest. I would not be where I am today without you. And to my sister, Shaelyn—I can always turn to you for perspective and a pep talk. You have been my favorite cheerleader.

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Abstract of Dissertation

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Adequate access to primary care is an integral part of any health care system. One indicator for access outcomes is potentially preventable hospitalizations (PPH), i.e., a hospitalization that occurs when a patient is hospitalized for an ambulatory care sensitive condition (ACSC). PPHs are of interest because the additional costs of caring for a patient in a hospital with an ACSC, as opposed to in a primary care setting, are substantial, for patients, payers, and hospitals. Identifying the factors associated with PPH will aid in policymaking, improve access to care, and reduce the burden on the health care system.

To address the gaps in the literature, I analyze how community-level access to care resources and state policies are associated with PPH using nationally representative data, while controlling for individual patient characteristics and community-level demographics. Multiple publicly available and restricted use data sources are linked to create a comprehensive data set that is used to investigate the relationship between PPH rates and community access to care factors. The dissertation addresses the following three objectives: (1) To determine the association between state Medicaid policies and the odds of a potentially preventable hospitalization; (2) To assess how primary care capacity and the odds of a potentially preventable hospitalization varies across the urbanization spectrum; and (3) To assess how primary care capacity and the odds of PPH varies for chronic and acute ACSCs.

The findings are summarized below:

- An analysis of state Medicaid policies does not find any significant associations between the odds of PPH and Medicaid generosity index and managed care penetration.
- Primary care physician supply and the presence of a federally qualified health center are associated with a lower odds of PPH across the urbanization spectrum.
- Physician supply, primary care and specialist, is associated with a lower odds of PPH for chronic ACSCs, while nurse practitioner and physician assistant supply is associated with a lower odds of PPH for acute ACSCs. The presence of a federally qualified health center is associated with lower odds of PPH for both chronic and acute ACSCs.

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Chapter 1: Introduction

Background

Inequalities in access to health care exist in the health care system of the United States. The Institute of Medicine (1993) defines access to care as "the timely use of personal health services to achieve the best health outcomes." Access to care can be evaluated through several metrics: potential access measures, realized access measures, and access outcomes. Potential access, measured by a person's ability to gain entry into the health care system and gain access to sites of care, is often operationalized as having insurance or a usual source of care. Realized access, measured by whether a person was actually able to receive care from a provider, is often defined as utilization of health care resources. Access outcomes, the results of adequate or inadequate potential and realized access, are operationalized through health status indicators, such as low birth weight or potentially preventable hospitalizations.

The focus of this dissertation is on one measure for access outcomes: potentially preventable hospitalizations (PPH). A PPH is a hospitalization that occurs when a patient is hospitalized for particular acute illnesses (e.g., urinary tract infection) or worsening chronic conditions (e.g., congestive heart failure) that might not have required hospitalization had these conditions been managed successfully by primary care providers in outpatient settings. PPHs are also called hospitalizations for an ambulatory care sensitive condition (ACSC) and they are variously referred to in the literature, and in this dissertation, as "preventable," "avoidable," "discretionary," or "unnecessary" hospitalizations.

PPHs are of interest for multiple reasons. For patients, being hospitalized for an

ACSC could indicate a lack of access to care, an inability to obtain timely access to care, or non-compliance with treatment regimens (Freund, Campbell, Geissler, Kunz, Mahler, Peters-Klimm, & Szecsenyi, 2013). Additionally, hospitalization itself, and the complications that may develop during hospitalization, can cause additional morbidity, loss of functional capacities, and death (Maslow & Ouslander, 2012). For hospitals and insurers, the additional costs of caring for a patient with an ACSC in a hospital, as opposed to in a primary care setting, are substantial. The hospital costs associated with PPH totaled over $30 billion in 2006 (Jiang, Russo, & Barrett, 2009). It is estimated that the government could avoid paying between $625 million and $1.9 billion in expenditures annually by reducing PPHs in the dually eligible Medicare/Medicaid population (Walsh et al., 2012). Identifying the factors associated with PPHs can help guide policy efforts at the national, state, and local levels to improve access to, and the quality of, primary care and reduce the incidence and costs associated with PPHs.

Many studies have established associations between individual patient characteristics, such as sex, race, income, and insurance status, and PPHs (Billings et al., 1993; Bindman et al., 1995; Billings, Anderson, & Newman, 1996; Schreiber & Zielinski, 1997; Pappas et al., 1997; Laditka & Laditka, 1999, 2006; Gaskin & Hoffman, 2000; DeLia, 2003; Probst, Moore, Baxley, & Lammie, 2003; Derose, 2008). There is also an extensive literature on community-level factors and indicators of potential and realized access to care, such as self-reported usual source of care and having had a primary care visit within the past 12 months, and significant associations have been found between community characteristics and potential and realized access to care (Pappas et al., 1997; Laditka & Laditka, 1999, 2006; Gaskin & Hoffman, 2000; Falik et al., 2005).

However, fewer studies have examined how community-level factors such as the primary care environment, safety net support, and health care policies for vulnerable populations are associated with access to primary care outcomes, as measured by PPH. The studies that have explored the relationship between community-level factors and PPH have been narrow in scope, focusing on a particular population, such as Medicare recipients (Parchman & Culler, 1999), or a geographic region (Derose, 2008).

Conceptual Framework

Davidson, Anderson, Wyn, and Brown (2004) developed a framework to evaluate the health care safety net and other community-level factors that influence access to health care (Figure 1). The framework builds on the well-established Andersen models (1968, 1995) of individual determinants of access to health services by systematically accounting for community-level contextual variables, including the "social, economic, structural, and public policy environment in which access occurs" (Davidson et al., 2004, 21).

The framework has three broad domains: individual-level characteristics, community-level characteristics, and health care access and outcomes. The individual-level characteristics category is adapted from the Andersen models and includes three types of variables: predisposing (an individual's predisposition to use health services); need (recognition that an individual requires medical care); and enabling (variables that help or hinder an individual's access to care). Community-level characteristics include variables that measure local, state, and federal influences on the health care market and availability of health care in an area. The framework proposes measuring five community-level characteristics: the safety net population; low-income population support; safety net support; health care market; and safety net services.

Health care access and outcomes include variables that measure potential access, realized access, and access outcomes that were previously discussed in the introduction. The individual and community characteristics in the model help to predict an individual's health care access and outcomes.

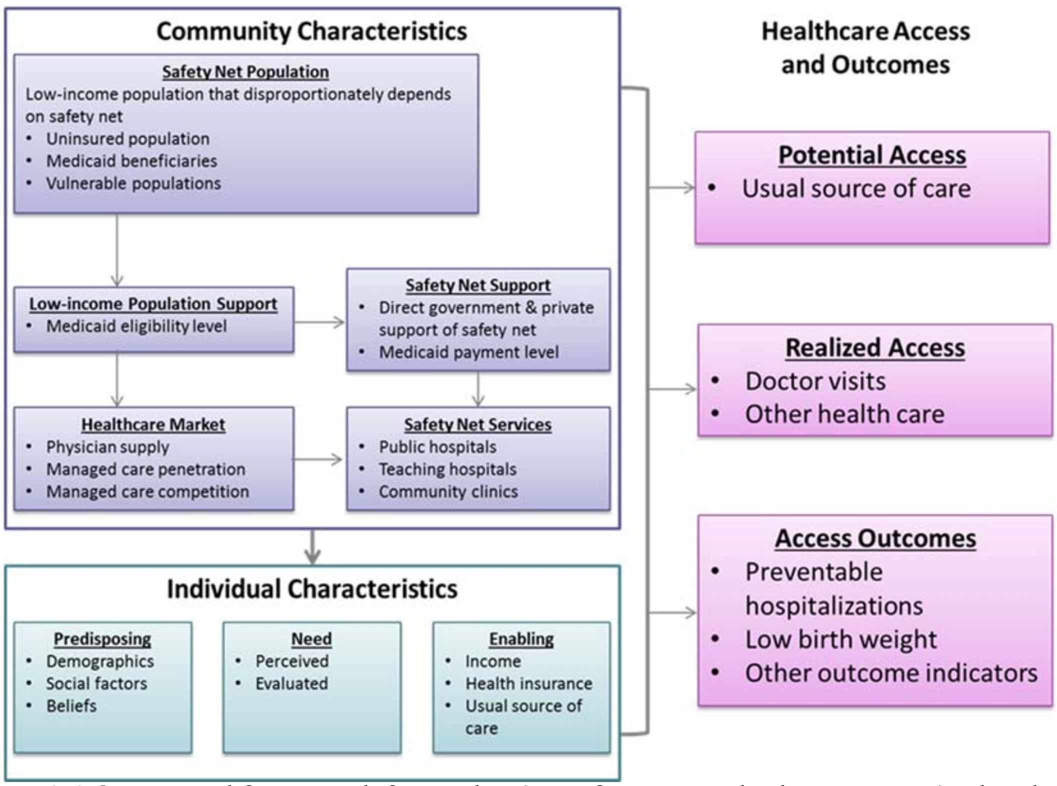

Figure 1.1 Conceptual framework for evaluating safety net and other community-level factors on access and access outcomes (Davidson, Andersen, Wyn, & Brown, 2004)

For the purposes of this dissertation, the Davidson et al. and the Andersen models are blended to create a parsimonious model of community and individual characteristics. Like the types of individual characteristics in the Andersen model, the community characteristics are categorized into the same three types of characteristics: predisposing, need, and enabling. Predisposing community characteristics encompass many area demographic measures, such as median income, elderly and minority populations, and the urban-rural continuum. Need community characteristics include designation as a medically underserved area and population health measures. An area can be designated a medically underserved area based on scores from four indicators: the percent of the population in poverty, the percent of the population aged 65 and over, the infant mortality rate, and primary care physician supply. Finally, enabling community characteristics are comprised of state Medicaid policies, physician supply, and community health center and government hospital availability.

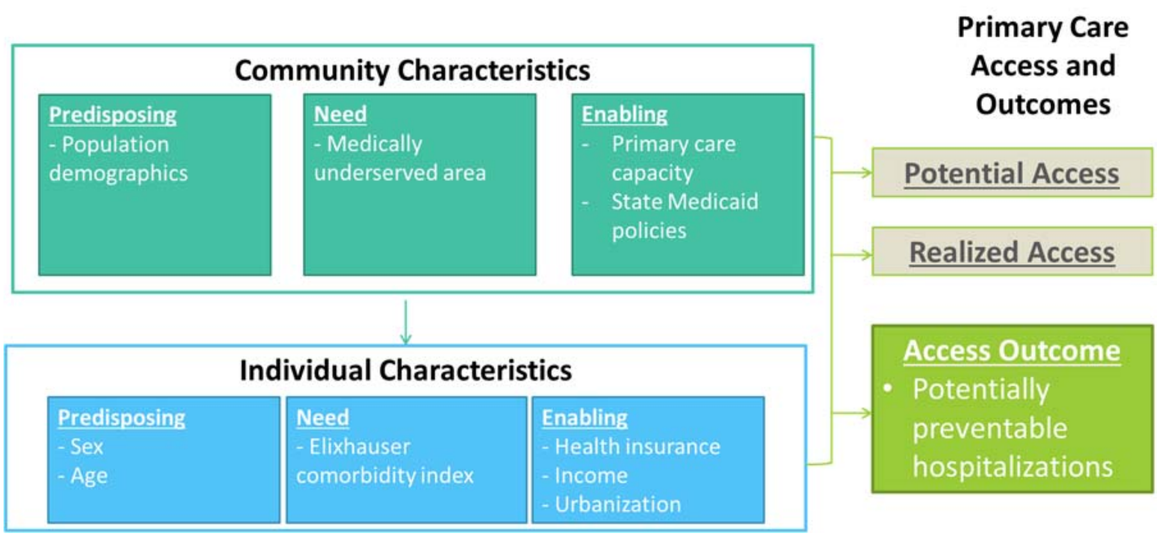

Figure 1.2 Modified conceptual framework for evaluating individual and community characteristics on potentially preventable hospitalizations (adapted from Davidson et al., 2004 and Andersen, 1968, 1995)

While this blended framework could be used to study both potential and realized primary care access, this dissertation only analyzes how individual and community characteristics affect the access outcome of potentially preventable hospitalizations.

Literature review

The following section includes a literature review of the dependent variable used in all papers—potentially preventable hospitalizations—and the individual predisposing, need, and enabling characteristics and community predisposing and need characteristics that are used as control variables. The literature on the community enabling characteristics is described in each chapter individually due to the different measures of the community enabling characteristics studied in each paper.

Potentially preventable hospitalizations

In the United States, the development and categorization of ambulatory care sensitive conditions (ACSCs) can be traced to research by Billings, Anderson, and Newman (1996) and Weissman, Gatsonis, and Epstein (1992) from the early 1990s. Weissman et al. developed a list of ACSCs through a review of the literature and clinician guidance, identifying conditions that could be effectively managed in primary care settings, thereby avoiding unnecessary hospitalizations. Conditions were evaluated using four criteria: consensus in the literature, the importance of the health problem, clinical face validity, and the ability to identify conditions in available data sources. The rationale for identifying ACSCs was to assess whether differences in primary care utilization by insurance status led to measurable differences in health outcomes. Communities with high rates of potentially preventable hospitalizations (i.e. hospitalizations for ACSCs) may have barriers to primary care that can be addressed through policy.

There have been multiple categorizations of ACSCs over the years, however one of the most widely used and accepted categorizations of ACSCs for measuring PPH is the Agency for Healthcare Research and Quality's (AHRQ) Prevention Quality Indicators (PQI), originally developed in the late 1990s. AHRQ evaluated PQIs through a review of the literature and empirical evaluation based on six criteria: face validity, precision, minimum bias, construct validity, fostering real quality improvement, and application (Davies, Geppert, McClellan, McDonald, Romano, & Shojania, 2001). There are 12 specific PQIs (see Table 1.1) for adults, which can be combined into three composite measures—overall, acute, and chronic—as a way to monitor primary care performance over time, across regions, and across populations at the national, regional, state, and provider-area levels. The composite measures improve the statistical precision of the individual PQI. Including acute and chronic composite measures allows for investigation into the different factors that influence PPH for each condition.

Table 1.1 Prevention Quality Indicators

Acute ACSCs	Chronic ACSCs
Dehydration	Diabetes with short-term complications
Bacterial pneumonia	Diabetes with long-term complications
Urinary tract infection	Uncontrolled diabetes
	Lower-extremity amputation with diabetes
	Older adults with COPD or asthma
	Younger adults with asthma
	Hypertension
	Congestive heart failure
	Angina (without procedure)

Source: Agency for Healthcare Research and Quality Prevention Quality Indicators Overview

The operationalization of PPH as hospitalizations for ACSCs is common and broadly used as a construct in the literature (Stranges & Stocks, 2010). One limitation of PPH as a construct is that it fails to account for medical comorbidities and clinical complexity in the measure itself (Maslow & Ouslander, 2012). However, using other measures of health status, such as the Elixhauser comorbidity index described below, as controls in models that assess PPH, can help overcome the limitation. The papers in this dissertation are intended to fill a gap in the literature due to the dearth of research on community-level influences in the composite measure of PPH, acute PPH, and chronic PPH using the existing research on potential access, realized access, and access to care outcomes to inform the models.

Individual predisposing, need, and enabling characteristics

The literature on individual characteristics and PPH is fairly consistent and yields the following conclusions (Weissman et al., 1992; Pappas et al.,1997; Gill, 1997; Silver et al., 1997; Blustein et al., 1998; Culler et al., 1998; Parchman & Culler, 1999; Shi et al., 1999; Friedman & Basu, 2001; Ladika, 2003; Laditka & Laditka, 2004, 2006). Individual age and minority status are positively associated with PPH, while individual education and income are negatively associated with PPH. Individuals without health insurance are more likely to have PPH than individuals with private health insurance or Medicaid coverage. Studies have found that medical comorbidities and clinical complexity are positively associated with hospitalizations, but no studies on individual characteristics and PPH have been found that control for comorbid conditions (Maslow & Ouslander, 2012).

Community predisposing and need characteristics

Predisposing and need community characteristics associated with PPH and other measures of access to care (i.e., potential and realized) have also been well established and discussed in the literature. These community characteristics include median income and vulnerable populations, for example as measured by percentages of elderly, minority, unemployed, and foreign born (Billings et al., 1993; Bindman et al., 1995; Billings et al., 1996; Schreiber & Zielinski, 1997; Pappas et al., 1997; Laditka & Laditka, 1999, 2006; Gaskin & Hoffman, 2000; Epstein, 2001; DeLia, 2003; Probst, Moore, Baxley, & Lammie, 2003; Derose, 2008). Lower income and less educated communities are more likely to have higher rates of PPH than higher income and more educated communities. Communities with high proportions of minority and elderly populations are positively associated with higher rates of PPH. The designation of a community as a medically underserved area (MUA) is positively associated with higher rates of PPH.

Data Sources

This dissertation is a secondary data analysis that uses as its base the National Hospital Discharge Survey (NHDS). The NHDS includes individual characteristics of inpatient hospitalizations and is used to identify PPHs. The NHDS is then merged with other data sets to obtain community-level predisposing, need, and enabling characteristics to build a comprehensive dataset for analysis. Refer to Appendix A for a detailed table describing all of the variables, their level of measurement, and data sources.

The National Hospital Discharge Survey (NHDS)

The NHDS, fielded by the National Center for Health Statistics (NCHS), was first conducted in 1965 and was the longest continuing national survey of hospital inpatients, collecting a nationally representative sample of inpatient discharges annually through 2010. The NHDS was a national probability sample designed to meet the need for information on characteristics of inpatient discharges from non-federal, non-institutional, short-stay hospitals in the United States. Federal, military, Department of Veteran Affairs hospitals, hospital units of institutions such as prisons, hospitals with fewer than six staffed beds, and hospitals with an average length of stay of more than 30 days were excluded from the survey.

Since 1988, the NHDS used a three-stage, stratified, clustered survey design: (1) Primary sampling units (PSUs) selected at the first stage consisted of either hospitals or geographic areas, such as counties, groups of counties, or metropolitan statistical areas in the 50 states and the District of Columbia. (2) At the second stage, hospitals were selected from within a sampled PSU (i.e., a geographical area). (3) At the third stage, discharges were selected from within sampled hospitals using systematic random sampling. In order to create nationally representative estimates, the discharge data were weighted, adjusting for non-response.

The NHDS collected data elements on the demographic characteristics of the patient (such as age and sex), clinical characteristics (primary diagnosis and up to six secondary diagnoses), utilization measures (such as days of care and up to four surgical and nonsurgical procedures), and administrative characteristics (such as expected source of payment, from which can be inferred insurance type and status), as well as some geographic data, including residential ZIP code.

The data used in these analyses are from the 2007 NHDS restricted-use file, available to researchers through the Research Data Center at NCHS. The 2007 NHDS has over 350,000 discharges, sampled from approximately 500 hospitals. Discharges from all 50 states and Washington, DC are represented in the data. The 2007 NHDS had a weighted response rate of 88 percent.

Other data sources

In order to provide a community context of an individual discharge from the NHDS, the patient's ZIP code is used to link the NHDS with other publicly available data sources. Patient ZIP code maps into ZIP code tabulation areas (ZCTAs); ZCTAs map into primary care service areas (PCSAs); PCSAs map into counties; and counties map into states.

ZCTA-level data. The United States has approximately 33,000 ZCTAs, with almost 15,000 represented in the 2007 NHDS data. The ZCTA-level dataset that is linked to the 2007 NHDS is the 2008 Population Estimates (2008 POP) dataset. The dataset, prepared under contract for the Health Resources and Services Administration (HRSA), is publicly available through The Dartmouth Atlas of Health Care (Dartmouth) website. Using census block data obtained from Claritas, a marketing information resources company, Dartmouth is able to produce ZCTA-level estimates of median income. The ZCTA-level data is linked to the NHDS data using a crosswalk also developed by Dartmouth that maps patient ZIP codes to the corresponding ZCTAs in the 2008 POP dataset. Median income from the 2008 POP dataset is used in the analysis as a proxy for individual income.

PCSA-level data. The PCSA is the most meaningful level used to study community predisposing, need, and enabling characteristics and their association with PPH. PCSAs were designed to reflect the travel of health care seekers to primary care physicians, therefore describe the communities within which people access care

(Goodman, Mick, Bott, Stukel, Chang, Marth, Poage, & Carretta, 2003). The United States has approximately 6,500 PCSAs with more than 4,400 represented in the 2007 NHDS data. The PCSA-level datasets that are linked to the 2007 NHDS are the 2007 American Medical Association (2007 AMA) and the 2007 Healthcare Market Index and Hospital Market Profiling Solution (HMI) datasets compiled by Verispan, LLC. The HMI, and its precursors, provide the frame for the NHDS. The variables from the 2007 AMA include primary care physician (PCP) and specialty physician supply, percent population aged 65 and over, percent population minority, and percent population living in a medically underserved area (MUA). The 2007 HMI is used at both the PCSA and county levels. At the PCSA level, the number of hospital beds in a PCSA has been included in the analysis. The PCSA-level data are linked to the 2007 NHDS data using a crosswalk developed by Dartmouth that maps ZCTAs into corresponding PCSAs.

County-level data. County-level data are used when predictors are not available at the PCSA level. The United States has approximately 3,100 counties with more than 2,200 represented in the 2007 NHDS data. The county-level datasets that are linked to the 2007 NHDS are the 2007 HMI and the 2015 Area Health Resources File (AHRF) compiled by HRSA. The AHRF includes data elements for years dating back to 2000. At the county level, the AHRF provides county demographics, such as percent uninsured, in poverty, foreign born, unemployed, and eligible for Medicaid, as well as the presence of a federally qualified health center (FQHC) and the number of nurse practitioners and physician assistants (NP/PAs) in a county. The 2007 HMI provides the number of emergency departments (ED) and the presence of a government hospital at the county-level.

State-level data. The state-level datasets that were linked to the 2007 NHDS are the 2007 Medicaid Statistical Information System (2007 MSIS) maintained by CMS, the 2007 State Income Eligibility Limits (2007 SIEL) published by the Kaiser Family Foundation, and data from the Census Bureau's state and county estimates for 2007. The state-level data were linked with the 2007 NHDS through state identifiers.

Exclusions and imputations

There were 365,648 records in the 2007 NHDS. The first group excluded from all analyses was children under age 18 because the ambulatory care sensitive conditions developed by the Agency for Healthcare Research and Quality that are used in the analysis apply to adults aged 18 and over. Children under age 18 have a different set of ambulatory care sensitive conditions (Friedman, Jee, Steiner, & Bierman, 1999). The second group excluded is females with deliveries because they are not hospitalized for an illness, but instead for an event that could never be a preventable hospitalization. The third group excluded is adults aged 65 and over, because they are predominately covered by Medicare and their PPHs have been studied by CMS and other investigators. The fourth group excluded is records with Medicare listed as any source of payment. People under age 65 who qualify for Medicare have end stage renal disease or a permanent disability making their health care needs and utilization very different from other patients.

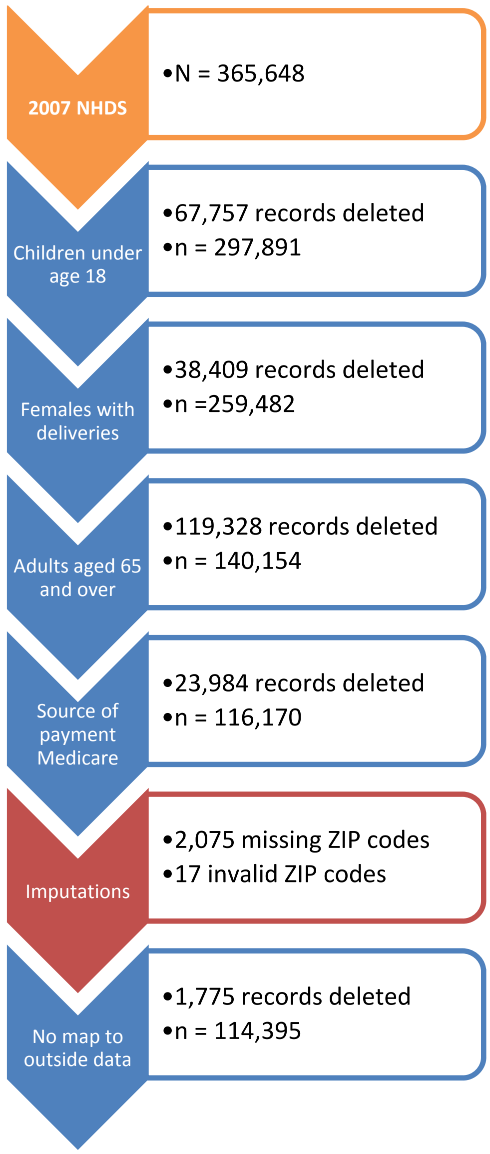

Figure 1.3 Exclusion criteria to final analytic file

After exclusions, there are 2,092 discharges with missing or invalid (including U.S. territories) ZIP codes. For discharges with a missing or invalid ZIP code, the ZIP code of the hospital is used to link to the external data sets. All NHDS data are linked to ZCTA, PCSA, and county-level data using patient ZIP code, while state-level data is linked using the state identifiers. There were 1,775 NHDS discharge records that cannot be linked to the outside data because the patient's ZIP code is not included in the outside datasets, less than two percent of total eligible NHDS discharges. The final dataset that serves as the foundation for the different analyses conducted in this dissertation includes 114,395 discharges.

Chapter 2: State Medicaid Policies Associated with Potentially Preventable Hospitalizations

Introduction

Literature review

Medicaid programs vary greatly from state to state in many ways, such as the eligibility criteria set by the states (i.e., Medicaid generosity) and health plan structure (i.e., managed care versus fee-for-service). Medicaid generosity determines the eligibility for low-income populations to apply for Medicaid and receive benefits. Plan structure can affect both access to care for patients and the reimbursement rates that health care providers receive. Because state Medicaid programs are complex and varied, the relationship between Medicaid policies and PPH has been difficult to establish. The most recent, relevant literature on Medicaid generosity and plan structure that inform the model used in this analysis is reviewed.

Medicaid generosity. One method to analyze the effect of Medicaid generosity on PPH is through expansions (and reductions) in state Medicaid program eligibility. One study, analyzing Medicaid eligibility expansion in Oregon, found that PPH increased among the Medicaid-insured and uninsured populations, while decreasing among the privately-insured population (Saha et al., 2007). The increase in PPH among the Medicaid-insured population could reflect the increased access to care and a pent up demand for health care, but the cause of the increase in the continuously uninsured population is less obvious. The decrease in the privately-insured population could be attributed to people newly eligible for Medicaid moving from private insurance to

Medicaid, a phenomenon known as "crowd out" (Cutler & Gruber, 1996). Since the newly eligible population is lower-income, the population may have been over-contributing to the PPH rate in the privately-insured population. In a study of Medicaid expansion for children in California, researchers found that the rate of PPH for children in lower-income families with public insurance or no insurance significantly declined after Medicaid expansion, however there was no change in rate for children in higher-income, privately-insured families (Cousineau, Stevens, & Pickering, 2008). The authors attributed the reduction in PPH in the lower-income population to increased access to primary care.

Another method for studying Medicaid generosity is the Medicaid generosity index developed by Brown, Wyn, and Teleki for the Commonwealth Fund and the UCLA Center for Health Policy Research in 2000. The authors used the construct, a composite measure of federal poverty level eligibility limits for infants, children, pregnant women, and parents with dependent children, to study access to care disparities. The Medicaid generosity index was proposed in the Davidson et al. framework as a measure of low-income population support, however, no studies have been found that have examined the relationship between the Medicaid generosity index and access to care.

Plan structure. The original model for Medicaid plans is the fee-for-service model. However, in the past 20 years, managed care programs have been established in all 50 states and DC as states look for ways to decrease Medicaid costs by averting unnecessary hospitalization and promoting preventive care. The significance of the relationship between Medicaid managed care penetration and PPH is not yet established in the literature. Some research has found that increases in Medicaid managed care penetration are associated with lower levels of PPH in the Medicaid-insured population (Backus, Moron, Bacchetti, Baker, & Bindman, 2002; Bindman, Chattopadhyay, Osmond, Huen, & Bacchetti, 2005). The association likely reflects the improved access to and/or quality of primary care for Medicaid beneficiaries in a managed care program. Supporting this conclusion is evidence that the rate of PPH for Medicaid fee-for-service beneficiaries is higher than that of managed care beneficiaries in the same state (Bindman et al., 2005), although that difference may be attributable to selection bias exaggerating the differences between the fee-for-service beneficiaries and the managed care beneficiaries.

However, some studies have found that increases in Medicaid managed care penetration can have negative consequences as well. The nature of the competitive bidding on Medicaid contracts by the for-profit sector can lead to the loss of market share and funding for safety-net providers (Holahan, Weiner, & Wallin, 1998), potentially leading to negative access to care outcomes for the uninsured. Finally, another study did not find a difference in PPH rates for Medicaid managed care enrollees compared with Medicaid fee-for-service enrollees, although significant differences were found in the privately insured (managed care versus fee-for-service) populations (Basu, Friedman, & Burstin, 2004). The lack of a difference in the rate of PPH between Medicaid managed care programs and Medicaid fee-for-service programs could be attributed to poor health status, diverse need, incomplete compliance at the individual level, low-quality providers, and lack of choice of provider. On the provider side, low payments for Medicaid visits could act as a barrier to care.

Additionally, Medicaid managed care penetration has been studied relative to potential and realized access to care. In an analysis of the effect of Medicaid managed care penetration on access to care for insured and uninsured populations, low-income uninsured persons reported lower access to care in states with high Medicaid managed care penetration, as opposed to states with low Medicaid managed care penetration (Cunningham, 1999). Additionally, there was a greater difference in access between insured and uninsured persons in states with high Medicaid managed care penetration. One possible explanation is that Medicaid managed care capitation payments may reduce a provider's ability to subsidize the care they deliver to the uninsured population.

Limitations. The literature on state Medicaid policies shares one major limitation: studies have been restricted to particular geographic areas, preventing a comparison across states (Backus et al., 2002; Bindman et al., 2005; Basu et al., 2004; Saha et al., 2007; Cousineau et al., 2008). The geographic restrictions can introduce bias into an analysis, as well as affect the generalizability of the results.

Hypotheses

In order to better understand the effect of state Medicaid policies on the rate of PPH, two variables of state Medicaid policies are examined: Medicaid generosity and Medicaid managed care penetration. Medicaid generosity is operationalized as a composite measure of the federal poverty level income eligibility limit for infants, children aged one through five, children aged six through 19, pregnant women, and parents with dependent children. Medicaid managed care penetration is operationalized as the percentage of Medicaid beneficiaries enrolled in a managed care program.

The three insurance groups of interest are Medicaid-insured, uninsured, and privately-insured. Previous research has found that Medicaid policies affect all three groups (Cunningham, 1999; Saha, Solotaroff, Oster, & Bindman, 2007), but no national studies have been found that employ methods that use multiple levels of contextual variables. The following hypotheses are tested:

H1: The association between the odds of PPH and the Medicaid generosity index of a state varies by insurance type (i.e., Medicaid-insured, uninsured, and privately-insured) controlling for patient and community characteristics.

H2: The association between the odds of PPH and Medicaid managed care penetration in a state varies by insurance type (i.e., Medicaid-insured, uninsured, and privately-insured) controlling for patient and community characteristics.

Methods

Study design

To assess the association of state Medicaid policies and PPH for Medicaid-insured, uninsured, and privately-insured inpatients, this paper uses the 2007 National Hospital Discharge Survey, linked with publicly available data sources. The NHDS, a national probability sample of inpatient discharges in the United States, is described in Chapter 1. This paper employs a type of hierarchical modeling: two-stage regression.

Data

To construct a two-stage model—discharge-level and state-level—there are two datasets used in the analysis. First, a discharge-level dataset that includes demographic, clinical, and administrative data about discharges and the communities in which they live.

Second, a state-level dataset that includes measures of Medicaid policies of interest and demographic characteristics about the states. The data sources used in this analysis are described in Chapter 1.

The discharge-level dataset includes variables used to control for individual and local factors that influence the likelihood of a PPH (Table 2.1). The demographic characteristics of the discharge included in the analysis are sex (reference level = female), age, Elixhauser comorbidity index, health insurance coverage (reference level = privately-insured), and ZCTA median income. Health insurance coverage is categorized as Medicaid, no insurance (consisting of self-pay and charity care), private insurance, and other insurance (consisting of other government, workers' compensation, and unknown). The Elixhauser comorbidity index is a comprehensive set of 30 comorbidity measures developed for use with large administrative hospital discharge datasets (Elixhauser, Steiner, Harris, and Coffey, 1998). Inpatients with Elixhauser comorbidities have increases in length of stay, hospital charges, and mortality. The SAS program to apply the Elixhauser comorbidity index to the NHDS discharge data was downloaded from the Agency for Healthcare Research and Quality (2015). As applied in this analysis, the Elixhauser comorbidity index ranges from zero to six and is the count of the number of Elixhauser comorbid conditions found in the secondary diagnoses on the discharge record (there were only six secondary diagnoses collected in the 2007 NHDS).

The community predisposing, need, and enabling variables included in the above dataset created for this study that were proposed in Davidson, Andersen, Wyn, and Brown's framework (2004). The variables are operationalized in the following ways. Community-level predisposing and need variables are comprised of the demographic characteristics of a community, including percentages of the population aged 65 and over, minority, living in a medically underserved area (MUA), Medicaid-eligible, living in poverty, unemployed, and foreign born. The predisposing and need characteristics at the community-level provide the context in which people are seeking health care. For example, although inpatient discharges aged 65 and over are excluded from the analysis, if a community has a large percentage of elderly then the needs of the community are much greater than in a community that has a lower percentage of elderly, possibly reducing the availability of services for other populations.

Community enabling variables include both practitioner supply and health facility supply. Practitioner variables include the supply of primary care physicians (PCPs), specialty physicians, and nurse practitioners and physician assistants (NP/PAs), each measured as providers per 100,000 population. Health facility supply consists of facilities that serve vulnerable populations, including the presence of a non-federal, non-institutional government run hospital; the presence of a federally qualified health center (FQHC); general acute care hospital beds per 1,000 population; and emergency departments (EDs) per 100,000 population uninsured.

The second dataset used in this analysis is a state-level dataset that includes the Medicaid policies of interest and demographic characteristics of the state as measures of state enabling characteristics (Table 2.2). The state-level community predisposing, need, and enabling variables were also proposed in Davidson et al.'s framework (2004). The state Medicaid generosity index measures each individual state's eligibility limits for different eligibility groups in 2007, adjusting for the number of eligible individuals in each category. Medicaid managed care penetration is operationalized as the number of

Medicaid beneficiaries in managed care programs over the total number of Medicaid beneficiaries, as reported to CMS.

In addition to the two Medicaid policy variables, the state-level predisposing and need variables include percentages of the state population living in a rural area, unemployed, minority, in poverty, and foreign born, as well as federal disproportionate share hospital payment rates. While many of the state-level predisposing and need characteristics are similar to the community-level predisposing and need characteristics (e.g., unemployed and minority populations), the concepts at the different levels are used for conceptually and qualitatively different purposes. The community-level predictors reflect factors that may influence an individual's accessibility and availability of care, while the state-level predictors control for factors that may have an influence on a state's Medicaid policies.

Variable transformations. All of the community-level practitioner supply variables, and hospital bed supply, are highly skewed to the right, so they are transformed using a log(x+1) transformation in order to maintain the meaningful zero values (i.e. no provider supply). ED supply is also highly skewed to the right, but the log(x+1) transformation does not result in a normal distribution. ED supply is therefore categorized into four groups: none, few, some, and many. Few, some, and many are categorized into terciles after excluding counties with no EDs. In three states, the number of reported Medicaid managed care participants is greater than the number of Medicaid beneficiaries, so the variable was top-coded to 100.

Table 2.1 Discharge-level dataset variable descriptions

Domain and variable	Variable definition	Unit of observation	Source
Dependent variable			
Potentially preventable hospitalization (PPH)	Binary variable denoting whether a discharge was hospitalized for a PPH.	Discharge	NHDS
Individual Predisposing			
Sex	Sex of discharge	Discharge	NHDS
Age	Age at discharge	Discharge	NHDS
Individual Need			
Elixhauser comorbidity index	Number of Elixhauser comorbid conditions	Discharge	NHDS
Individual Enabling			
Type of health insurance	Expected source of payment for discharge (Medicaid, no insurance, private insurance, other insurance--includes other government, worker's compensation, not stated, and other)	Discharge	NHDS
Income	Median income of ZCTA	ZCTA	HRSA
Community Predisposing/Need			
Percent population over age 65	The numerator is the total number of persons aged 65 years and over in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA
Percent population minority	The numerator is the total number of minority persons in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA
Percent population living in a medically underserved area (MUA)	The numerator is the total number of people living in a MUA in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA
Percent population uninsured (under age 65)	The numerator is the total number of persons under age 65 that are uninsured in a county. The denominator is the total population under age 65 of the county.	County	AHRF
Percent population eligible for Medicaid	The numerator is the total number of persons eligible for Medicaid in a county. The denominator is the total population of the county.	County	AHRF

Percent population in poverty	The numerator is the total number of persons living below the federal poverty level in a county. The denominator is the total population of the county.	County	AHRF
Percent population unemployed	The numerator is the total number of persons unemployed in the labor force in a county. The denominator is the total civilian labor force of the county.	County	AHRF
Percent population foreign born	The numerator is the total number of persons foreign born in a county. The denominator is the total population of the county.	County	AHRF
Community Enabling			
Primary care physician supply per 100,000 population	The number of primary care physicians (including OB/GYNs, pediatricians, osteopaths, and family doctors) per 100,000 population in a PCSA.	PCSA	HRSA
Specialty physician supply per 100,000 population	The number of specialty care physicians per 100,000 population in a PCSA.	PCSA	HRSA
Number of hospital beds per 1,000 population	The numerator is the total number of hospital beds in a PCSA (HMI). The denominator is the total population in the PCSA (HRSA).	PCSA	HMI/HRSA
Presence of a government hospital (non-federal, non-institutional)	Binary variable denoting presence of a non-federal, non-institutional government hospital.	County	HMI
Emergency departments (EDs) per 100,000 population uninsured: none, few, some, many	A categorical variable created from the ratio of the total number of EDs in a county (HMI) over the total number of individuals in the county that are uninsured (AHRF).	County	HMI/AHRF
Presence of a federally qualified health center (FQHC)	Binary variable denoting presence of a FQHC.	County	HRSA
NP/PA supply per 100,000 population	The numerator is the number of nurse practitioners and physician assistants in a county. The denominator is the total population of the county.	County	AHRF

Table 2.2 State-level dataset variable descriptions

Domain and variable	Variable definition	Unit of observation	Source
State Predisposing/Need			
Percent population living in rural area	The numerator is the total number of persons living in a rural area in a state. The denominator is the total population of the state.	State	Census
Percent population minority	The numerator is the total number of minority persons in a state. The denominator is the total population of the state.	State	Census
Percent population in poverty	The numerator is the total number of persons living below the federal poverty level in a state. The denominator is the total population of the state.	State	Census
Percent population unemployed	The numerator is the total number of persons unemployed in a state. The denominator is the total population of the state.	State	Census
Percent population foreign born	The numerator is the total number of persons foreign born in a state. The denominator is the total population of the state.	State	Census
Disproportionate share hospital payment rates	The numerator includes expenditures available to directly subsidize safety net hospitals in a state. The denominator is the total population of uninsured persons.	State	KFF
State Enabling			
Medicaid generosity index	Composite index of Federal Poverty Levels for Medicaid eligibility groups.	State	KFF
Medicaid managed care penetration	The numerator is the total number of individuals enrolled in a Medicaid managed care program. The denominator is the total number of individuals enrolled in Medicaid.	State	CMS

Analysis

All analyses are performed using the statistical packages SAS version 9.3 (SAS Institute, Cary, NC) and SUDAAN version 10.0 (RTI International, Research Triangle Park, NC). SUDAAN software is used to adjust for the complex sampling design and correlated data of the NHDS. Because NHDS is a sample survey, a weighting variable is used in all analyses. A Pearson correlation matrix is produced to examine bivariate correlations between each pair of continuous variables. Mean and percentage distributions of each covariate by rate of PPH and insurance group are also computed and differences among subgroups are evaluated with two-tailed *t*-tests at the alpha = 0.05 level of significance.

In order to assess the effect of state Medicaid policies on Medicaid-insured, uninsured, and privately-insured inpatient populations, two-stage multivariate regression is used to analyze the effects of the independent variables and control variables at the discharge- and state-levels. The three-stage survey design of the NHDS called for sampling PSU, hospital, and discharge levels, as described in Chapter 1. Because the design of the NHDS does not allow for state-level estimation, there is no conventional or accepted method to perform a single multilevel analysis with discharge and state levels incorporated. Therefore, the two-stage multivariate regression is employed, with a logistic regression model in stage 1 and a separate linear regression model for each insurance group in stage 2. A significance level of $p < 0.05$ is used as the criterion for rejection of the null hypothesis. Multicollinearity in the models is assessed using variance inflation factors (VIF), which quantify the severity of the multicollinearity in the model. A VIF of one for a variable indicates no multicollinearity with other variables in the model, while a VIF greater than or equal to ten indicates high multicollinearity (Allison, 1999). The logistic regression models are assessed for fit using the Chi-square goodness of fit test, recommended by Allison for ungrouped data (2014).

In stage 1, the dependent variable, PPH, is regressed on individual and community-level covariates, with dummy variables included for the 45 states in the analysis, using logistic regression with weighted observations. A likelihood ratio test is used to confirm that a model with state fixed effects fits the data better than a model without state fixed effects. In order for the model to converge, states with less than 30 observations are dropped from the analysis. The final size of the dataset is 114,346 discharge records from 45 states. The predictors of PPH that are included in this model are age, sex, Elixhauser comorbidity index, insurance group, ZCTA median income, the percentage of population aged 65 and over, that is a minority, that is living in a medically underserved area (MUA), that is uninsured (under age 65), that is in poverty, that is unemployed, that is foreign born, the supply of PCPs, NP/PAs, hospital beds, and EDs, the presence of a government hospital, and the presence of a FQHC.

In stage 2 of the analysis, the predicted log odds of PPH for each state, by insurance group of interest (Medicaid-insured, uninsured, and privately-insured), are calculated from the stage 1 results, using the mean value for each continuous predictor and the beta values for male, the presence of an FQHC and a government hospital, and many EDs. The predicted log odds for each state, by insurance group, are then converted to the predicted probabilities of PPH. The predicted probabilities of PPH for each state by insurance group are then used as the dependent variable to fit three multivariate regression models—Medicaid, no insurance, and private insurance. In the first step, the model regresses predicted probability of PPH on state Medicaid policy variables only, Medicaid generosity index and Medicaid managed care penetration. The second step then introduces controls for state-level factors that may influence a state's Medicaid policy—the percentage of population that lives in a rural area, that is a minority, that is living in poverty, that is unemployed, and the state's disproportionate share hospital payment rate.

Results

Descriptive analysis

A weighted Pearson correlation of the stage 1 variables shows two groups of very highly correlated variables (Appendix B). PCP supply and specialist physician supply are too highly correlated to be included in the logistic regression model together (rho = 0.89), so specialist physician supply is dropped from the analysis. Additionally, percent population eligible for Medicaid and percent population in poverty, both at the county level, are too highly correlated to be in the model together (rho = 0.75), so the Medicaid eligible population is dropped from the analysis. A Pearson correlation of the stage 2 state-level covariates shows that percent of the population foreign born is highly correlated with percent of the population living in a rural area (rho = -0.73), so foreign born is dropped from the analysis. Ninety-five percent of immigrants live in metropolitan areas, including central cities and suburbs, while only five percent live in non-metropolitan areas (Congressional Budget Office, 2004).

The weighted rates of PPH, unadjusted for the effects of other variables, are 14.6 percent for the Medicaid-insured group, 13.6 percent for the uninsured group, and 10.1 percent for the privately-insured group (see Table 2.3). All rates are per 100 hospitalizations. The rate of PPH for males is less than the rate for females in the no insurance group (12.35 vs. 15.10). The rate of PPH is higher in the oldest age category than in the youngest age category for all insurance groups (Medicaid: 7.78 vs. 22.39; no insurance: 9.88 vs. 16.63; private insurance: 6.86 vs. 11.55). Medicaid and privately-insured patients with at least one Elixhauser comorbid condition have a higher rate of PPH than patients without a comorbid condition (17.17 vs. 10.33 and 13.03 vs. 7.55, respectively). The Medicaid-insured have the highest average number of comorbidities for patients with a PPH, compared to the no insurance and privately-insured groups: 1.32 vs. 0.89 and 0.90, respectively (data not shown). The rate of PPH is lowest among all patients living in an area with an average income of $80,000 (Medicaid: 9.55; no insurance: 8.06; private insurance: 7.12). Patients with private insurance have a higher average income than patients in the Medicaid and no insurance groups, for all hospitalizations (data not shown).

The rate of PPH for the no insurance group is higher in communities in the fourth quartile of population aged 65 and over than it is in communities in the first quartile (15.59 vs. 11.53). For Medicaid and privately insured patients, the rate of PPH is higher in communities in the fourth quartile than the first quartile for minority population, population in a MUA, and population in poverty. For all three insurance groups, the rate of PPH is lower in the first quartile of population unemployed than in the fourth quartile (Medicaid: 11.85 vs. 16.42; no insurance: 11.28 vs. 16.50; private insurance: 9.21 vs. 11.19).

The supply of PCPs, NP/PAs, and FQHCs is highest in areas where Medicaid patients live, compared with patients with no insurance and private insurance (data not shown). For the privately insured, the rate of PPH is lower in communities in the fourth quartile than in the first quartile of nurse practitioner and physician assistant supply (8.52 vs. 10.73). The rate of PPH for the no insurance group is lower when there is an FQHC present (12.47 vs. 15.82). Medicaid patients and patients with no insurance are more likely to live in a county with a government hospital than privately insured patients (data not shown).

Table 2.4 provides means of the state PPH rates for the quartiles of the state-level variables used in the second stage state-level analysis. The two state-level variables of interest are Medicaid generosity index and Medicaid managed care penetration, both state enabling variables. The mean rate of PPH in states in the lowest quartile of Medicaid generosity index is 11.33, while in the highest quartile of Medicaid generosity the mean rate of PPH is 11.20. The mean rate of PPH for states in the lowest quartile of Medicaid managed care penetration is 9.49 and the highest quartile has a mean rate of 12.49. Graphs of the state-level variable distributions can be found in Appendix C.

Table 2.3. Rate per 100 hospitalizations of PPH by the Stage 1 individual and community predisposing, need, and enabling characteristics in the discharge-level dataset, by insurance type

	Medicaid n = 24,458		No Insurance n = 12,698		Private Insurance n = 66,313	
	Rate	SE	Rate	SE	Rate	SE
Total rate of PPH	**14.61**	**0.66**	**13.55**	**0.65**	**10.07**	**0.33**
Individual Predisposing						
Sex						
Male	13.96	0.89	12.35	0.65	9.80	0.43
Female	15.08	0.88	15.10	1.15	10.29	0.43
Age						
18-34	7.78	0.82	9.88	1.06	6.86	0.46
35-54	15.49	0.73	14.79	0.93	10.26	0.41
55-64	22.39	1.46	16.63	1.59	11.55	0.50
Individual Need						
Elixhauser Comorbidity						
Yes (at least one)	17.17	0.75	14.53	0.74	13.03	0.47
No	10.33	0.89	12.37	1.16	7.55	0.36
Individual Enabling						
Income						
Less than $20,000	22.33	4.90	*15.79*	*5.54*	*10.40*	*3.75*
$20,000-$49,999	15.67	0.83	14.52	0.82	11.12	0.53
$50,000-$79,999	12.04	0.98	12.69	1.35	9.76	0.47
Over $80,000	9.55	1.72	8.06	1.43	7.12	0.54
Community Predisposing/Need						
Population over 65						
Q1 (3.3-10.0)	15.34	1.20	11.53	1.06	9.32	0.58
Q2 (10.1-12.6)	14.99	1.20	12.27	1.12	10.67	0.57
Q3 (12.7-14.4)	16.04	1.34	15.40	1.36	10.72	0.63
Q4 (14.5-50.9)	12.66	1.11	15.59	1.56	9.65	0.62

	Medicaid		No Insurance		Private Insurance	
	Rate	SE	Rate	SE	Rate	SE
Population minority						
Q1 (0.5-13.0)	12.10	1.35	11.76	1.84	9.40	0.56
Q2 (13.1-24.5)	13.63	1.14	15.20	1.66	9.91	0.69
Q3 (24.6-42.6)	15.95	0.95	12.39	1.14	10.39	0.56
Q4 (42.7-98.0)	15.96	1.14	14.87	0.88	11.08	0.63
Population in MUA						
Q1 (0-2.7)	11.71	1.37	12.07	1.37	9.37	0.60
Q2 (2.8-15.5)	13.34	0.78	12.15	1.08	10.00	0.53
Q3 (15.6-43.9)	13.54	1.19	13.24	1.32	9.00	0.59
Q4 (44.0-100)	16.92	0.99	15.14	1.14	11.72	0.65
Population uninsured (under age 65)						
Q1 (6.6-12.1)	14.08	1.28	13.30	1.40	9.93	0.49
Q2 (12.2-14.7)	15.19	1.51	12.73	1.48	10.90	0.65
Q3 (14.8-19.2)	14.74	1.17	13.85	1.04	9.45	0.73
Q4 (19.3-38.7)	14.55	1.10	13.80	1.37	10.20	0.68
Population in poverty						
Q1 (2.4-8.6)	10.57	1.36	10.36	1.24	9.32	0.51
Q2 (8.7-12.8)	14.25	1.08	14.73	1.13	9.90	0.63
Q3 (12.9-16.2)	14.84	1.08	15.08	1.54	10.22	0.76
Q4 (16.3-41.9)	16.01	1.21	13.46	1.05	10.96	0.65
Population unemployed						
Q1 (0-6.7)	11.85	1.19	11.28	1.15	9.21	0.58
Q2 (6.8-7.8)	15.26	1.32	13.39	1.28	10.29	0.62
Q3 (7.9-9.3)	14.59	0.94	13.70	1.13	10.15	0.56
Q4 (9.4-23.0)	16.42	1.14	16.50	1.19	11.19	0.52

	Medicaid		No Insurance		Private Insurance	
	Rate	SE	Rate	SE	Rate	SE
Population foreign born						
Q1 (0-4.5)	14.56	1.20	14.07	1.27	9.89	0.62
Q2 (4.6-8.9)	14.13	1.28	16.39	1.22	10.51	0.67
Q3 (9.0-19.5)	13.65	1.27	12.09	1.10	9.69	0.60
Q4 (19.6-51.1)	15.53	1.07	11.13	1.08	10.30	0.59
Community Enabling						
PCPs per 100,000 population						
Q1 (0-55)	14.58	1.06	15.09	1.47	10.93	0.61
Q2 (56-73)	15.60	1.24	15.01	1.12	10.41	0.58
Q3 (74-97)	14.50	1.20	10.24	1.03	9.33	0.47
Q4 (98-932)	14.02	1.05	13.71	1.14	9.41	0.48
NPs/PAs per 100,000 population						
Q1 (0-41)	15.49	1.13	14.47	1.56	10.73	0.63
Q2 (42-53)	14.80	1.17	14.08	1.51	10.34	0.56
Q3 (54-77)	13.67	1.12	14.51	1.15	10.56	0.61
Q4 (78-629)	14.48	1.14	11.07	1.09	8.52	0.55
EDs per 100,000 population uninsured						
None (0)	18.01	2.45	17.06	3.65	10.82	1.60
Few (.6-4.1)	14.00	0.78	12.98	1.06	9.52	0.51
Some(4.2-8.8)	16.12	1.33	12.59	1.06	10.15	0.53
Most (8.9-607.0)	13.34	1.02	14.39	1.11	10.24	0.55
Presence of an FQHC						
Yes	14.57	0.68	12.47	0.61	9.73	0.36
No	14.73	1.43	15.82	1.41	10.69	0.66

	Medicaid		No Insurance		Private Insurance	
	Rate	SE	Rate	SE	Rate	SE
Hospital beds per 1,000 population						
Q1 (0-1.4)	13.36	1.05	12.76	1.19	9.98	0.63
Q2 (1.5-2.4)	15.55	1.12	13.34	1.43	10.35	0.58
Q3 (2.5-4.0)	13.77	0.95	14.70	1.30	9.59	0.48
Q4 (4.1-51.9)	15.45	1.31	13.44	1.09	10.36	0.62
Presence of a government hospital						
Yes	15.18	0.78	13.56	0.85	9.95	0.47
No	13.55	1.06	13.54	1.10	10.22	0.47

Note: Italicized estimates do not meet standards of reliability.

Table 2.4 Mean state rate of PPH for quartiles of Stage 2 state-level continuous variables

Second Stage Variables Sample size = 45	**Mean rate of PPH**
State Predisposing/Need	
Population in rural area	
Q1 (0.0-12.0)	11.72
Q2 (12.1-24.5)	11.52
Q3 (24.9-33.9)	11.26
Q4 (35.2-61.3)	9.96
Population minority	
Q1 (3.5-10.1)	12.41
Q2 (10.2-15.4)	9.55
Q3 (15.5-25.5)	11.53
Q4 (26.0-70.9)	11.08
Population in poverty	
Q1 (7.6-10.4)	10.44
Q2 (10.5-12.6)	11.00
Q3 (12.7-15.5)	11.18
Q4 (15.7-21.0)	11.56
Population unemployed	
Q1 (2.6-3.7)	10.23
Q2 (3.9-4.4)	12.07
Q3 (4.5-4.9)	10.32
Q4 (5.0-7.1)	11.25
Population foreign born	
Q1 (2.3-6.6)	10.66
Q2 (6.7-10.3)	10.85
Q3 (10.4-20.6)	12.45
Q4 (20.8-43.0)	10.25
Disproportionate share payment rate	
Q1 (2.9-84.3)	10.86
Q2 (92.6-178.3)	11.20
Q3 (187.0-433.9)	11.31
Q4 (447.5-1,041.9)	10.91
State Enabling	
Medicaid generosity index	
Q1 (124.8-150.0)	11.33
Q2 (150.8-166.5)	10.76
Q3 (167.5-196.3)	11.01
Q4 (200.0-276.3)	11.20
Medicaid managed care penetration	
Q1 (0.0-67.8)	9.49
Q2 (68.2-72.7)	11.30
Q3 (74.3-86.7)	11.06
Q4 (86.8-100.0)	12.49

Stage 1 Model

Including state fixed effects in the first stage regression analysis significantly improves the fit of the model (LR = 546, DF = 1, $p < 0.0001$). In the first stage, an increase in one year of age is associated with 1.02 times the odds of a PPH (95% CI = 1.02, 1.03) and an additional Elixhauser comorbid condition is associated with 1.25 times the odds of a PPH (95% CI = 1.19, 1.30) (Table 2.5). Having Medicaid insurance, as opposed to private insurance, is associated with 1.38 times the odds of a PPH (95% CI = 1.24, 1.53); having no insurance, as opposed to private insurance, is associated with 1.45 times the odds of a PPH (95% CI = 1.30, 1.61). Being male (OR = 0.85; 95% CI = 0.78, 0.93) and a higher supply of primary care providers in a community (OR = 0.65; 95% CI = 0.45, 0.93) are negatively associated with the odds that a hospitalization is a PPH. See Appendix E for more information regarding the natural log transformed variables.

Stage 2 Model

The predicted probabilities of PPH rates for each state, estimated from the stage 1 multivariate logistic regression, range from one percent to 26 percent for the Medicaid insured group; one percent to 27 percent for the no insurance group; and one percent to 21 percent for the privately-insured group. Table 2.6 displays the results of the two step regression models that estimate the impact of different state-level factors on the predicted probability of state PPH rates. In the first step of this stage, the two state enabling characteristics, Medicaid generosity index and the Medicaid managed care penetration, are included in the model. The second step includes state-level predisposing and need characteristics in addition to the two state-level enabling characteristics. None of the state-level factors explain a significant proportion of the variation in the state PPH rates.

Table 2.5 Stage 1 odds ratios (OR) with confidence intervals

Stage 1 Model	OR	Lower 95% Limit OR	Upper 95% Limit OR
Individual Predisposing			
Age	1.02*	1.02	1.03
Male	0.85*	0.78	0.93
Individual Need			
Elixhauser comorbidity index	1.25*	1.19	1.30
Individual Enabling			
Insurance			
Private Insurance	1.00	1.00	1.00
Medicaid	1.38*	1.24	1.53
No Insurance	1.45*	1.30	1.61
Other Insurance	0.96	0.79	1.18
Income	0.92*	0.90	0.95
Community Predisposing & Need			
Percent population aged 65 and over	0.99	0.97	1.01
Percent population minority	1.00	1.00	1.01
Percent population in a MUA	1.00	1.00	1.00
Percent population uninsured (under age 65)	0.98	0.96	1.00
Percent population in poverty	1.01	1.00	1.03
Percent population unemployed	0.98	0.94	1.02
Percent population foreign born	1.00	0.99	1.01
Community Enabling			
PCPs per 100,000 population (natural log)	0.65*	0.45	0.93
NPs & PAs per 100,000 population (natural log)	1.02	0.70	1.48
Beds per 1,000 population (natural log)	1.11	1.00	1.22
Government hospital located in county of residence	1.05	0.88	1.25
EDs per 100,000 population uninsured			
No EDs	1.00	1.00	1.00
Few EDs	0.86	0.63	1.18
Some EDs	0.99	0.75	1.30
Many EDs	1.01	0.80	1.27
FQHC located in county of residence	0.87	0.73	1.04
State			
45 state dummies	--	--	--

***Significant at the 5% level.**

Table 2.6 Stage 2 linear regression models

Stage 2 Models- Medicaid	State enabling		State enabling, predisposing, and need	
	ß (se)	p > |z|	ß (se)	p > |z|
State Enabling				
Medicaid eligibility index	-0.0059 (0.0145)	0.687	-0.0045 (0.0160)	0.781
Medicaid managed care penetration	0.0436 (0.0244)	0.082	0.0315 (0.0260)	0.232
State Predisposing & Need				
Percent population living in a rural area			-0.0954 (0.0514)	0.072
Percent population minority			-0.0699 (0.0539)	0.203
Percent population in poverty			-0.0128 (0.2689)	0.962
Percent population unemployed			-0.6583 (0.8405)	0.439
DSH payment rate			0.0013 (0.0025)	0.620
Pr > F	0.19		0.20	
Adjusted R^2	3.3%		7.2%	

Stage 2 Models- No insurance	State enabling		State enabling, predisposing, and need	
	ß (se)	p > |z|	ß (se)	p > |z|
State Enabling				
Medicaid eligibility index	-0.0060 (0.0151)	0.691	-0.0046 (0.0166)	0.785
Medicaid managed care penetration	0.0453 (0.0253)	0.081	0.0328 (0.0269)	0.230
State Predisposing & Need				
Percent population living in a rural area			-0.0990 (0.0533)	0.071
Percent population minority			-0.0725 (0.0558)	0.202
Percent population in poverty			-0.0133 (0.2787)	0.962
Percent population unemployed			-0.6815 (0.8712)	0.439
DSH payment rate			0.0013 (0.0026)	0.618
Pr > F	0.18		0.20	
Adjusted R^2	3.4%		7.2%	

Stage 2 Models- Private insurance	State enabling	State enabling, predisposing, and

			need	
	ß (se)	p > |z|	ß (se)	p > |z|
State Enabling				
Medicaid eligibility index	-0.0050 (0.0114)	0.663	-0.0038 (0.0125)	0.761
Medicaid managed care penetration	0.0336 (0.0191)	0.086	0.0242 (0.0203)	0.242
State Predisposing & Need				
Percent population living in a rural area			-0.0743 (0.0403)	0.073
Percent population minority			-0.0545 (0.0422)	0.205
Percent population in poverty			-0.0099 (0.2104)	0.962
Percent population unemployed			-0.5191 (0.6577)	0.435
DSH payment rate			0.0010 (0.0020)	0.629
Pr > F	0.19		0.21	
Adjusted R^2	3.2%		6.9%	

Discussion

The study hypothesizes associations between odds of PPH and state-level Medicaid generosity index and Medicaid managed care penetration in the Medicaid insured, uninsured, and privately-insured groups controlling for patient and community characteristics. No associations are found at the state-level. Possible reasons for the lack of association between state Medicaid policy factors and the likelihood of a PPH are explored below. Although the stage 2 results are not significant, the results for the stage 1 community-level model are consistent with previous studies. Prior studies of smaller geographic areas (Basu, Friedman, & Burstin, 2002) and Medicare populations (Chang, Stukel, Flood, & Goodman, 2011) have found that physician supply is negatively associated with PPH and this study supports the finding for non-elderly hospitalized adults in the United States. The finding that Medicaid and uninsured groups have a higher odds of PPH than the privately-insured group also is consistent with previous studies (Pappas et al.,1997). A potential new contribution to the literature is that Elixhauser comorbid conditions are associated with a higher odds of PPH.

A possible reason no significant effects are found in the second stage is that not all within and between state differences are able to be captured in the analysis. The state fixed effects model fits the data significantly better than the model without state fixed effects, indicating that unmeasured differences among the states contribute to the likelihood of a PPH. As noted in the analysis section, a conventional multilevel model employing discharge and state levels is not possible due to the particular sampling design of the NHDS. In order to advance knowledge in a less than ideal situation, the two stage model is fit.

An additional possible explanation for the lack of significant findings is measurement of the Medicaid policies. While Medicaid managed care penetration has been used in previous studies (Saha et al., 2007; Cousineau, Stevens, & Pickering, 2008), the variable may not accurately reflect the reality within a state. The implementation of managed care can vary greatly from state to state—mandatory versus voluntary enrollment, particular subpopulations targeted for enrollment. For example, in 2007 the managed care program in California required mandatory enrollment in a managed care program for residents of urban counties, but not rural counties. Additionally, managed care programs are often targeted at specific populations within the Medicaid program, in particular populations that are excluded from this analysis such as children with disabilities, excluded due to age, and dual eligibles, people eligible for both Medicaid and Medicare who have been excluded due to Medicare coverage. Finally, there are three types of managed care that are included in the Medicaid managed care construct: (1) comprehensive managed care, including health management organizations (HMOs), health insuring organizations (HIOs), and Program of All-inclusive Care for the Elderly (PACE); (2) prepaid health plans; and (3) primary care case management (PCCM) plans. The coverage of services varies greatly within the different managed care plans, from full managed care services in HMOs to dental-only HMOs to PCCM case management services only. The care provided by PCCMs is reported as managed care to CMS, even though most of the services provided to beneficiaries are on a fee-for-services basis. Therefore, the definition of Medicaid managed care across the states may not have been refined enough to detect an effect.

In previous studies, Medicaid eligibility generosity has generally been investigated during expansions and contractions in particular state Medicaid programs. This analysis appears to be the first to use the index developed by Brown, Wyn, and Teleki, outside of the authors' own analyses. The variable is meant to measure how much support is given to low-income populations within a state by eligibility category. Due to the exclusions in this analysis—children under age 18, females with deliveries, and dual eligibles—the only Medicaid recipient populations included in the analysis are parents with dependent children and, in a few states with Section 1115 waivers, adults aged 21 to 64 with no dependent children (Borck, Dodd, Zlatinov, Verghese, Malsberger, & Petroski, 2012). These groups make up just over one quarter of the nation's Medicaid beneficiaries. While the index is meant to measure how generous a state is in covering low-income populations in general, the federal poverty limit for infants and pregnant women may not be relevant to access to care for parents with dependent children and other working-age adults. The Medicaid generosity measure may be inadequate, or too vague, to be seen to have an impact on PPH. Other measures of generosity, such as Medicaid provider reimbursement rates and number and type of covered services, or other measures of access to care, such as potential access and realized access, could possibly reveal associations between Medicaid policies and access to care (Buchmueller, Orzol, & Short-Sheppard, 2013; Cunningham & Nichols, 2005).

Although state Medicaid policies are not found to be significantly associated with the odds of PPH, the limitations from this study may actually provide policy makers with some important insights concerning potential and realized access to care, which are instrumental to the access to care outcome of PPH. In order to compare access to care outcomes across state Medicaid programs, better measures of state Medicaid policies need to be developed and adopted by all the states. Even in the mandated reporting of administrative data to CMS, there are discrepancies in the numbers reported by states. As described in the data section, some states reported more beneficiaries in managed care programs than Medicaid beneficiaries, suggesting measurement error in the data. Other states reported more beneficiaries than eligible individuals, making their take up rate for Medicaid over 100 percent. The national estimate of Medicaid take up rate in the time period studied was 62 percent (Sommers & Epstein, 2010). Studies have suggested that administrative data by itself cannot be used to estimate Medicaid take up rates. Administrative data, in conjunction with national survey data, is often used to calculate take up rates (Sommers, Kronick, Finegold, Po, Schwartz, & Glied, 2012), but may undercount individuals with Medicaid due to respondent error. While this study does not attempt to measure take up rates, the caution against using administrative data only is relevant to the measure of Medicaid managed care penetration. While CMS gives the same reporting guidelines to all of the states and the District of Columbia, the guidelines may be interpreted differently, resulting in poor measures for statistical purposes. Unfortunately, administrative data is one of the only sources of nationally available data for information regarding Medicaid policies.

Finally, the nature of the Medicaid program itself may make it difficult to assess access to care outcomes for the Medicaid-insured population. Medicaid has covered more people annually than Medicare since the 1990s, but many people move in and out of eligibility for Medicaid within a calendar year. In fact, only 38 percent of adults covered by Medicaid were enrolled for a full year in 2008 (Borck et al., 2012). While insurance is only one enabling factor in the access to care conceptual framework, it is one of the most important factors for people to receive both the timely care required to treat acute ACSCs and the continuity of care required to keep chronic ACSCs under control.

While this study does not support an association between the Medicaid policies studied and access to care outcomes, there are policy recommendations that can be made. First, in order to study the effects of a policy, reliable data for meaningful policy constructs need to be available for research. Collecting reliable and valid measures of policy constructs needs to be addressed. First, Medicaid programs devote a very large portion of their time, effort, and budget to determining eligibility for, and paying for, covered services. Producing even the federally required data can be a challenge, and quality controls on these data are often limited or non-existent. This means that data are often lacking, or of questionable utility, when researchers attempt to assess the effects of Medicaid policy. Particularly in view of the considerable expansion of Medicaid in response to incentives in the Affordable Care Act, more resources should be allocated in Medicaid budgets to gathering more extensive and higher quality data. Second, statistical data collection needs to be prioritized and funded at the federal level. The budgets for the federal statistical agencies, the collectors of data for statistical purposes, have varied over the past ten years, making the planning and collection of survey data over time difficult to accomplish (AMSTAT News, 2015).

Second, while the Affordable Care Act has encouraged states to expand Medicaid coverage and has attempted to make private insurance more affordable for certain populations, the nature of the Medicaid program still creates a revolving door based on eligibility. For people with chronic conditions, it is especially important to maintain a relationship with a physician in order to manage the condition. While the state-level

Medicaid policies did not show significance in the second stage of the model, the first stage of the model showed that the odds of hospitalization for PPH are greater for Medicaid-insured patients than privately-insured patients. If Medicaid benefits were to be given for a minimum of one year after establishing eligibility, without requiring reports of changes in circumstances that may affect eligibility, medical care could be established and conditions could be stabilized for vulnerable populations (CMS, 2015). Additionally, 12-month continuous eligibility could reduce administrative costs associated with assessing eligibility multiple times over the course of a year.

Chapter 3: Community Primary Care Capacity Associated with Potentially Preventable Hospitalizations across the Urbanization Spectrum

Introduction

Literature review

The primary care capacity of a community is comprised of multiple parts that encompass different settings in which patients receive care, the ability of settings to provide care, and the volume of care delivered. The primary care settings include office-based physicians, both primary care and specialty; community health centers; and government hospitals, which provide primary care in emergency departments (EDs) and outpatient departments (OPDs) to populations that are unable to access health care elsewhere, or unable to choose to access health care elsewhere. The ability of settings to provide care includes measures such as physician supply and funding levels of health care facilities. The volume of care delivered can include the number of inpatient hospital days, as well as the number of emergency and outpatient department visits. Because the concept of primary care capacity is multifaceted, the literature regarding two aspects that are most relevant to the model employed in this dissertation are reviewed: provider supply and facility supply.

Provider supply. In general, previous research has found that the supply of primary care physicians (PCPs), defined as the number of PCPs per capita, in a community is negatively associated with the rate of PPH because the waiting time to see a physician may be shorter in communities with more physicians per capita and primary care is largely more accessible (Basu, Friedman, & Burstin, 2002; Chang, Stukel, Flood, & Goodman, 2011). However, there is some evidence that the link between physician supply and the rate of PPH is not significant (Probst, Moore, Baxley, & Lammie, 2003) or is only significant for particular populations, such as rural communities (Gresenz, Rogowski, & Escarce, 2006). Fewer studies have examined the relationship between specialty physician supply and the rate of PPH in a community. However, some evidence suggests that specialty physician supply may be positively associated with the rate of PPH (Basu et al., 2002). While the authors do not offer a reason why more specialty physicians may increase the rate of PPH in a community, one possible explanation could be that specialty physicians working in hospital EDs and OPDs may be more likely to admit patients than primary care physicians in an office-based setting (Carrier, Yee, & Holzwart, 2011).

No studies were found to have examined the effect of nurse practitioner and physician assistant supply on rates of PPH. However, studies have shown that the primary care outcomes in patients treated by nurse practitioners were comparable to outcomes in patients treated by physicians, as long as nurse practitioners had the same authority, responsibilities, productivity, and administrative requirements as physicians (Mundinger et al., 2000). A meta-analysis evaluating patient outcomes for nurse practitioners and physicians found that there was greater patient compliance, patient satisfaction, and resolution of pathological conditions for patients treated by nurse practitioners (Brown & Grimes, 1995). Finally, a comparison of outcomes for patients treated by nurse practitioners, physician assistants, and resident physicians found that outcomes did not differ by provider, but that nurse practitioners and physician assistants were more likely to treat the patient in a holistic manner (Rudy et al., 1998).

Facility supply. Patients can receive care in multiple types of health care facilities, from community health centers, whose purpose it is to provide primary care services, to hospital-based facilities, such as emergency departments (EDs) and government hospitals. Federally qualified health centers (FQHCs) are community health centers that serve populations or areas designated as medically underserved, are community-based and patient-directed organizations, and receive federal funding under section 330 of the Public Health Service Act. The directional relationship between the presence of FQHCs and the rate of PPH has not been established in the literature. One study found that patients receiving care in a community health center were less likely to have a PPH than patients receiving care in an office- or hospital-based setting, suggesting that the access to and quality of care in community health centers is better than in other primary care settings (Falik, Herbert, & Politzer, 2005). Additionally, the more funding a community health center receives, the more likely people are to report a usual source of care (Cunningham & Hadley, 2004). However, the presence of a community health center may not be enough to reduce the rate of PPH (Probst et al., 2003).

The association between hospital-based care and access to care outcomes (i.e., PPH) is not well established in the literature. However, there has been research about the use of EDs and government hospitals in terms of potential and realized access to care. EDs have a mandate to provide care to all populations, regardless of ability to pay, and tend to provide primary care to vulnerable populations with high barriers to office-based primary care (Cheung, Wiler, Lowe, & Ginde, 2012). Similarly, government hospitals have a mandate to provide care, regardless of ability to pay, in both inpatient and outpatient settings. Patients receiving primary care in hospital settings are sicker and less likely to have follow-up care than patients receiving primary care in office-based settings or community health centers (Forrest & Whelan, 2000). Hospitals provide a necessary primary care environment for needy populations and are important components of the safety-net system.

Urbanization spectrum. Few studies have examined the relationship between health care supply and PPH across the urbanization spectrum. One study, which focused on gradient levels of rurality, found that the odds of PPH increase with the degree of rurality (Laditka, Laditka, & Probst, 2009). A study with a trichotomous categorization of urban/rural counties (urban with a large central city, other urbanized counties, and rural counties) found that the odds of a PPH in urban counties with a large central city and rural counties were 20 percent greater than the odds in other urbanized counties (Culler, Parchman, & Przybylski, 1998). The barriers to access to care are different for rural and urban populations. Rural residents may have higher costs due to travel to seek care, possibly waiting until their condition may require hospitalization, while urban residents may have a lack of adequate ambulatory care supply or are unable to take off work to see a provider during office hours. Another study, using a dichotomous categorization of urban/rural counties, found that physician supply was negatively associated with PPH in urban counties, but was not significantly associated with PPH in rural counties (Laditka, Laditka, & Probst, 2005).

Limitations. The previous research on primary care capacity in a community shares many similar limitations. First, studies have been restricted to particular populations, such as Medicare beneficiaries (Chang et al., 2011), children (Gresenz et al., 2006), specific types of insurance (Mobley et al., 2011), or patient ages (Probst et al., 2003). Studies have also restricted the geographic area of analysis, studying discharges from one state (Basu et al., 2002; Mobley et al., 2011) or group of states (Falik et al., 2005; Bazzoli et al., 2011). Both population and geographic limitations may introduce bias into an analysis and thus affect the generalizability of the results.

Hypotheses

In order to understand the effect of provider and health care facility supply on populations across the urbanization spectrum, the NCHS urban-rural classification scheme is applied to the discharge-level data in the NHDS (Table 3.1). The urban-rural six-level classification scheme was developed to study the health variations in urban and rural counties that reflect the differences in community characteristics, including demographic, economic, physical, social, and environmental, as well as the accessibility and nature of health care resources (Ingram & Franco, 2012).

Using the 2000 census population data and the 2000 U.S. Office of Management and Budget's (OMB) definitions of metropolitan and micropolitan counties, NCHS assigned all counties and county equivalents in the United States to four metropolitan and two nonmetropolitan categories. NCHS demonstrated that the urban-rural classification scheme captures important health variations across the urbanization spectrum by analyzing restricted data from the National Vital Statistics System mortality records and the National Health Interview Survey. For example, residents of large fringe metro counties have significantly more favorable mortality than residents of large central metro counties. Significant health differences were also observed between medium metro and small metro counties, as well as micropolitan and noncore counties, in pairwise comparisons without adjusting for multiple comparisons.

Table 3.1 2006 NCHS urban-rural classification scheme (from Ingram & Franco, 2012)

Category	Classification rules	Metropolitan status
Large central metro county	Counties in MSA of 1 million or more population that: 1) contain the entire population of the largest principal city of the MSA, or 2) are completely contained within the largest principal city of the MSA, or 3) contain at least 250,000 residents of any principal city in the MSA	Metropolitan
Large fringe metro county	Counties in MSA of 1 million or more population that do not qualify as large central	
Medium metro county	Counties in MSA of 250,000-999,999 population	
Small metro county	Counties in MSA of 50,000-249,999 population	
Micropolitan county	Counties in micropolitan statistical area	Non- Metropolitan
Noncore county	Counties not in metropolitan or micropolitan statistical areas	

No studies were found that have researched the aspects of primary care capacity that may have different associations with the odds of PPH along an urbanization spectrum using nationally representative data. For the purposes of this paper, the non-MSA categories, micropolitan and noncore, are combined to create a single rural category. The components of primary care capacity that are included in the model are supply of primary care physicians, specialist physicians, nurse practitioner/physician assistants (NP/PAs), emergency departments (ED), and the presence of a federally qualified health center (FQHC) and the presence of a government hospital. The following hypotheses are tested:

H1: The association between provider supply (e.g., primary care physician supply and nurse practitioner/physician assistant supply) and the odds of PPH varies across the urbanization spectrum.

H2: The association between health care facility availability (e.g., EDs, federally qualified health centers, and government hospitals) and the odds of PPH varies across the urbanization spectrum.

Methods

Study design

In order to assess the association of provider and health care facility supply across the urbanization spectrum, this paper uses the 2007 National Hospital Discharge Survey, linked with publicly available data sources. The NHDS, a national probability sample of inpatient discharges in the United States, is described in Chapter 1.

Data

This analysis uses the augmented discharge-level dataset based on the 2007 NHDS, which includes demographic information about inpatient discharges and the communities in which they live. The dataset is described in Chapters 1 and 2.

Variables. The independent variables of interest in this analysis are PCP supply, specialist supply, NP/PA supply, ED supply, the presence of an FQHC, and the presence of a government hospital. PCP, specialist, and NP/PA supply are operationalized as providers per 100,000 population. PCP and specialist supply are measured at the PCSA level, while NP/PA supply is measured at the county level. There is not a data source that measures national NP/PA supply at the PCSA level.

ED supply is operationalized as the number of EDs per 100,000 population uninsured in a county and is categorized into no EDs, few EDs, some EDs, and many EDs. The Davidson et al. framework propose operationalizing the variable as EDs per population uninsured and living in poverty, however there is no source of data for national, county-level population uninsured and living in poverty. The decision was made to use the larger population as the denominator. On average, there are more uninsured people than people living in poverty in the United States in 2007. Although the number of EDs is available at the PCSA level, the uninsured population is only available at the county level. Therefore, EDs were aggregated to the county. The presence of an FQHC and a government hospital were both measured at the county level.

Additional control variables include discharge-level individual characteristics, such as sex, age, Elixhauser comorbidity index, type of insurance, ZCTA income, and where the individual's county of residence falls on the urbanization spectrum. Community-level characteristics, including percentages of the population over age 65, minority, in a medically underserved area (MUA), uninsured, in poverty, unemployed, and foreign born, are also used as control variables and are measured at the PCSA and county levels.

Analysis

All analyses are performed using the statistical packages SAS version 9.3 (SAS Institute, Cary, NC) and SUDAAN version 10.0 (RTI International, Research Triangle Park, NC). SUDAAN software is used to adjust for the complex sampling design and correlated data of the NHDS. Because NHDS is a sample survey, a weighting variable is used in all analyses. A Pearson correlation matrix is produced to examine bivariate correlations between each pair of continuous variables. Percentage distributions of each covariate by PPH/not PPH and urbanization classification are also computed. In order to assess the extent to which the association between community enabling characteristics and PPH varies across the urbanization spectrum, multivariate logistic regression models with interaction terms between urbanization spectrum and each provider supply and facility availability variable are fit.

A significance level of $p < 0.05$ is used as the criterion for rejection of the null hypothesis. Multicollinearity in the models is assessed using variance inflation factors (VIF), which quantify the severity of the multicollinearity in the model. A VIF of one for a variable indicates no multicollinearity with other variables in the model, while a VIF greater than or equal to ten indicates high multicollinearity (Allison, 1999). The logistic regression models are assessed for fit using the Chi-square goodness of fit test, recommended by Allison for ungrouped data (2014).

Results

Descriptive statistics

A weighted Pearson correlation of the continuous variables reveals two groups of very highly correlated variables. PCP supply and specialist physician supply are too highly correlated to be included in the logistic regression model together (rho = 0.89), so specialist physician supply is dropped from the analysis. Additionally, percent population eligible for Medicaid and percent population in poverty, both at the county level, are too highly correlated to be in the model together (rho = 0.75), so the Medicaid eligible population is also dropped from the logistic regression analysis.

The unadjusted likelihood of a hospitalization being a PPH ranges across the urbanization spectrum, from 9.4 percent in small metropolitan counties to 12.3 percent in large central metropolitan counties (Table 3.2). All rates are per 100 hospitalizations. Across the urbanization spectrum, the rate of PPH is similar for males and females. The rate of PPH for the 18-34 age group is lower than the rate of PPH for the 55-64 age group, across the urbanization spectrum (large central metro: 7.04 vs. 15.17 ; large fringe metro: 6.62 vs. 12.09 ; medium metro: 9.34 vs. 15.22 ; small metro: 8.03 vs. 14.23 ; rural: 7.00 vs. 13.09). The rate of PPH for the 18-34 age group is higher in medium metropolitan areas than in large fringe metropolitan areas (9.34 vs. 6.62); the rate of PPH for the 55-64 age group is higher in large central metropolitan areas than in large fringe metropolitan areas (15.17 vs. 12.09). The rate of PPH is higher across the urbanization spectrum for patients with at least one Elixhauser comorbid conditions (large central metro: 14.88 vs. 9.20; large fringe metro: 12.95 vs. 7.38; medium metro: 15.40 vs. 8.42; small metro: 11.91 vs. 7.25; rural: 14.92 vs. 9.28). Additionally, the average number of Elixhauser comorbid conditions is higher for patients with PPHs in large central metropolitan areas than it is for patients with PPH in large fringe metropolitan areas, small metropolitan areas, and rural areas (1.15 vs. 0.96, 0.96, and 0.93, respectively; data not shown). The rate of PPH for Medicaid hospitalizations is higher than the rate of PPH for privately insured hospitalizations in large central metropolitan areas (15.93 vs. 10.59), large fringe metropolitan areas (12.26 vs. 9.55) and medium metropolitan areas (16.23 vs. 10.10), but not in small metropolitan and rural areas. The rate of PPH for uninsured hospitalizations is higher than the rate of PPH for privately insured hospitalizations in large fringe metropolitan areas (12.68 vs. 9.55), medium metropolitan areas (14.33 vs. 10.10), and rural areas (17.17 vs. 10.92), but not in large central metropolitan and small metropolitan areas. In large central metropolitan areas, the rate of PPH is highest in the lowest income category (17.19), and lowest in the highest income category (5.92).

There are also variations in the community-level characteristics between and within the urbanization spectrum. The percentage of the population aged 65 and over in large central metropolitan and large fringe metropolitan areas is lower than the percentage of the population in medium metropolitan and rural areas (data not shown). In small metropolitan areas, the rate of PPH is higher in areas with the highest proportion of minorities and population in poverty than in areas with the smallest proportion (14.49 vs. 7.05 and 11.39 vs. 7.31, respectively). In large central metropolitan areas, the rate of PPH is higher in areas with the highest proportion of medically underserved population than in areas with the lowest proportion (15.15 vs. 10.10). Additionally, the rate of PPH in areas with the highest proportion of medically underserved is higher in large central metropolitan areas than in large fringe metropolitan areas and small metropolitan areas (15.15 vs. 11.35 and 10.87, respectively). The percentage of the population uninsured is higher in large central metropolitan areas than in large fringe metropolitan areas (data not shown). For all hospitalizations, large fringe metropolitan areas have the lowest percentage of the population in poverty (data not shown). The rate of PPH in areas with the lowest proportion of foreign born is lower in small metropolitan areas (8.29) than in all other areas (large central metro: 14.20; large fringe metro: 11.60; medium metro: 12.82; rural: 11.45).

The rate of PPH does not differ by physician supply, except for in rural areas where the rate of PPH in areas with highest physician supply is lower than the rate in areas with the lowest physician supply (8.21 vs. 13.38). Additionally, the rate of PPH in areas with highest nurse practitioner and physician assistant supply is lower than the rate in areas with the lowest nurse practitioner and physician assistant supply in small metropolitan areas (7.90 vs. 12.82) and rural areas (6.14 vs. 12.64). Large central metropolitan areas have a higher rate of PPH in areas with the larges supply of physicians and nurse practitioners and physician assistants compared with rural areas (12.35 and 12.56 vs. 8.21 and 6.14, respectively). In rural areas with a federally qualified health center the rate is PPH is lower than in rural areas without a federally qualified health center (9.08 vs. 13.37).

Table 3.2 Rate per 100 hospitalizations of PPH by individual and community predisposing, need, and enabling characteristics in the discharge-level dataset and urbanization level

	Large Central Metro		Large Fringe Metro		Medium Metro		Small Metro		Rural	
	n = 38,353		n = 38,564		n = 19,107		n = 6,680		n = 11,691	
	Rate	SE	Rate	SE	Rate	SE	Rate	SE	Rate	SE
Total rate of PPH	**12.33**	**0.36**	**10.06**	**0.65**	**12.01**	**0.48**	**9.44**	**0.72**	**12.11**	**1.02**
Individual Predisposing										
Sex										
Male	11.64	0.66	9.62	0.56	11.46	0.77	8.27	0.96	11.56	1.13
Female	12.97	0.79	10.43	0.57	12.45	0.93	10.40	0.82	12.57	1.31
Age										
18-34	7.04	0.90	6.62	0.57	9.34	0.96	8.03	1.17	7.00	1.31
35-54	13.44	0.58	10.42	0.57	11.41	0.81	7.79	0.92	13.84	1.14
55-64	15.17	0.96	12.09	0.68	15.22	1.57	14.23	1.34	13.09	1.19
Individual Need										
Elixhauser Comorbidity										
Yes (at least one)	14.88	0.92	12.95	0.50	15.40	0.80	11.91	0.97	14.92	1.18
No	9.20	0.63	7.38	0.60	8.42	0.88	7.25	0.71	9.28	1.10
Individual Enabling										
Insurance										
Private Insurance	10.59	0.49	9.55	0.48	10.10	0.73	8.37	1.03	10.92	1.07
Medicaid	15.93	0.91	12.26	1.26	16.23	1.83	10.63	1.58	13.99	1.43
No Insurance	12.48	0.99	12.68	1.16	14.33	1.11	9.99	1.88	17.17	1.94
Other Insurance	10.90	2.25	7.53	1.07	10.56	1.68	12.01	3.45	7.82	2.13
Income										
Less than $20,000	17.19	3.47	*9.69*	*5.57*	*15.77*	*5.20*	*0.00*	*0.00*	*0.00*	*0.00*
$20,000-$49,999	14.67	0.68	12.35	0.80	13.05	1.01	10.09	0.79	12.22	1.09
$50,000-$79,999	9.69	1.06	10.14	0.61	10.82	1.10	7.62	0.96	11.35	1.88
Over $80,000	5.92	0.97	8.11	0.63	6.48	1.07	*0.00*	*0.00*	*0.00*	*0.00*

	Large Central Metro		Large Fringe Metro		Medium Metro		Small Metro		Rural	
	Rate	SE	Rate	SE	Rate	SE	Rate	SE	Rate	SE
Community Predisposing/Need										
Population over 65										
Q1 (3.3-10.0)	12.11	1.51	9.07	0.69	*11.19*	*1.13*	10.89	1.63	*5.31*	*1.96*
Q2 (10.1-12.6)	13.01	0.65	10.59	0.78	12.79	1.78	8.14	0.90	12.26	2.52
Q3 (12.7-14.4)	12.72	0.68	10.48	0.93	13.34	1.01	12.07	1.10	14.08	2.08
Q4 (14.5-50.9)	11.29	0.66	10.61	0.85	10.78	1.11	6.60	0.92	11.62	1.22
Population minority										
Q1 (0.5-13.0)	11.61	1.75	9.40	0.86	11.89	1.09	7.05	0.67	10.68	1.15
Q2 (13.1-24.5)	10.07	0.99	9.89	0.59	10.70	0.89	10.54	1.83	14.97	3.36
Q3 (24.6-42.6)	10.18	1.13	10.30	0.74	13.97	0.83	11.14	1.08	14.29	1.93
Q4 (42.7-98.0)	14.31	0.81	11.55	1.21	11.99	2.67	14.49	2.49	9.57	1.88
Population in MUA										
Q1 (0-2.7)	10.10	1.53	9.45	0.69	10.83	1.27	*5.00*	*1.75*	10.28	2.03
Q2 (2.8-15.5)	10.61	0.69	10.79	0.65	11.78	1.00	9.30	1.16	9.46	1.03
Q3 (15.6-43.9)	11.10	1.16	9.76	0.96	12.57	1.25	8.59	1.20	9.21	1.24
Q4 (44.0-100)	15.15	0.90	11.35	1.24	12.21	1.40	10.87	1.27	14.16	1.50
Population uninsured (under age 65)										
Q1 (6.6-12.1)	12.91	1.06	9.83	0.74	12.63	1.09	6.20	1.50	11.27	0.79
Q2 (12.2-14.7)	16.42	1.60	10.20	0.73	10.44	1.82	10.25	2.21	11.10	1.93
Q3 (14.8-19.2)	12.15	1.09	9.97	0.96	12.25	0.87	11.39	1.41	11.03	2.28
Q4 (19.3-38.7)	10.65	0.99	10.50	1.12	11.97	1.99	8.34	1.12	14.32	2.30
Population in poverty										
Q1 (2.4-8.6)	*7.68*	*0.96*	9.22	0.61	*10.44*	*1.39*	7.31	0.42	*12.52*	*1.22*
Q2 (8.7-12.8)	11.66	1.06	11.17	0.68	10.55	0.99	*6.72*	*2.12*	11.46	1.42
Q3 (12.9-16.2)	12.42	0.67	11.36	1.72	12.91	1.00	9.10	0.93	13.18	2.40
Q4 (16.3-41.9)	12.78	1.44	12.18	2.37	13.75	1.82	11.39	1.57	11.67	1.33

	Large Central Metro		Large Fringe Metro		Medium Metro		Small Metro		Rural	
	Rate	SE	Rate	SE	Rate	SE	Rate	SE	Rate	SE
Population unemployed										
Q1 (0-6.7)	*12.44*	*5.07*	9.04	0.67	12.38	0.91	7.94	0.88	10.58	1.12
Q2 (6.8-7.8)	9.66	1.05	11.12	0.76	10.88	1.65	9.27	2.48	16.56	2.45
Q3 (7.9-9.3)	12.54	0.68	10.89	0.95	*10.91*	*1.17*	7.75	2.29	10.90	1.76
Q4 (9.4-23.0)	15.88	1.16	10.43	1.33	13.83	0.86	13.62	1.34	10.66	0.82
Population foreign born										
Q1 (0-4.5)	14.20	1.23	11.60	0.96	12.82	1.15	8.29	0.74	11.45	0.91
Q2 (4.6-8.9)	13.50	0.68	9.79	0.95	11.28	1.03	11.44	1.02	13.99	4.04
Q3 (9.0-19.5)	12.30	1.05	9.25	0.55	10.94	1.60	10.62	1.49	*19.89*	*6.50*
Q4 (19.6-51.1)	11.89	1.04	10.67	1.10	12.44	0.91	9.38	2.75	*6.43*	*4.06*
Community Enabling										
PCPs per 100,000 population										
Q1 (0-55)	11.55	1.77	10.00	0.86	13.66	1.27	11.00	1.96	13.38	1.71
Q2 (56-73)	13.39	0.83	10.50	0.88	10.33	0.87	9.77	1.10	13.21	1.26
Q3 (74-97)	12.42	0.76	9.87	0.69	11.81	1.07	8.18	0.74	10.21	1.60
Q4 (98-932)	12.35	0.63	9.92	0.65	11.59	1.28	11.19	1.38	8.21	1.05
NPs/PAs per 100,000 population										
Q1 (0-41)	12.51	1.16	10.90	0.75	12.45	1.31	12.82	2.06	12.64	1.68
Q2 (42-53)	12.43	1.74	9.16	0.78	13.50	1.03	9.02	1.14	11.45	1.67
Q3 (54-77)	11.62	0.65	9.81	0.80	11.43	1.98	10.09	1.44	14.16	1.80
Q4 (78-629)	12.56	0.85	9.40	1.08	11.22	1.02	7.90	0.94	6.14	0.92
EDs per 100,000 population uninsured										
None (0)	*0.00*	*0.00*	8.37	1.58	15.27	1.45	*11.95*	*4.13*	13.54	2.48
Few (.6-4.1)	10.94	0.95	10.29	0.82	11.35	0.81	8.27	2.01	*10.05*	*7.25*
Some(4.2-8.8)	14.01	1.07	10.40	0.68	12.52	0.93	7.76	1.02	*10.63*	*3.32*
Most (8.9-607.0)	13.38	1.05	9.68	0.87	10.72	1.13	10.11	0.83	11.90	1.19

	Large Central Metro		**Large Fringe Metro**		**Medium Metro**		**Small Metro**		**Rural**	
	SE	Rate	SE	Rate	SE	Rate	SE	Rate	SE	
Presence of an FQHC										
Yes	12.32	0.65	10.24	0.63	11.68	0.77	9.56	0.88	9.08	1.23
No	*17.50*	*6.93*	9.86	0.66	13.06	1.38	*9.18*	*1.29*	13.37	1.29
Hospital beds per 1,000 population										
Q1 (0-1.4)	10.94	1.11	9.42	0.63	12.60	1.01	9.34	1.42	12.37	2.41
Q2 (1.5-2.4)	12.63	1.48	9.33	0.85	11.99	1.38	*12.02*	*1.69*	11.74	1.78
Q3 (2.5-4.0)	12.35	0.70	11.38	0.90	10.66	1.14	6.19	0.91	11.18	1.18
Q4 (4.1-51.9)	12.85	0.79	10.96	0.94	12.56	1.69	10.50	1.09	12.84	1.32
Presence of a government hospital										
Yes	12.38	0.66	9.35	0.71	11.62	1.22	10.20	1.24	12.98	2.77
No	10.02	2.17	10.54	0.56	12.57	0.68	8.88	0.86	11.79	0.92

Note: Italicized estimates do not meet standards of reliability.

Logistic regression

Preliminary tests of the interaction terms between urbanization spectrum and provider and facility supply are not significant in the multiple logistic regression models. Therefore, a single model analyzing the main effects of community enabling characteristics, controlling for urbanization spectrum, is fit and described. No variables had a VIF higher than 2.5 and the Chi square goodness of fit test was not significant, indicating a good model fit.

The results of the logistic regression are reported in Table 3.3. The odds of a PPH versus not a PPH are less when the there is a higher supply of PCPs (OR = 0.69; 95% CI = 0.48, 0.99) and an FQHC is located within the county of residence (OR = 0.82; 95% CI = 0.71, 0.95). The odds of a PPH is lower for men compared to women (OR = 0.85; 95% CI = 0.78, 0.92), possibly due to women being more likely to have a urinary tract infection, an acute PPH. Income is negatively associated with the odds of a PPH (OR = 0.93; 95% CI = 0.90, 0.96). An increase in one year of age is associated with 1.02 times the odds of a PPH (95% CI = 1.02, 1.03) and an additional Elixhauser comorbid condition is associated with 1.25 times the odds of a PPH (95% CI = 1.19, 1.31). Additionally, compared to the privately-insured group, the Medicaid-insured (OR = 1.36; 95% CI = 1.22, 1.51) and the uninsured (OR = 1.44; 95% CI = 1.29, 1.61) are more likely to be hospitalized for a PPH than not a PPH.

None of the community predisposing or need characteristics significantly influenced the odds of a PPH after controlling for individual and community enabling characteristics. See Appendix E for more information regarding the natural log transformed variables.

Table 3.3 Odds ratios (OR) with confidence intervals

	OR	Lower 95% Limit OR	Upper 95% Limit OR
Community Enabling			
PCP supply (natural log)	0.69*	0.48	0.99
NPs & PAs supply (natural log)	0.83	0.61	1.14
Hospital bed supply (natural log)	1.09	0.98	1.21
Government hospital located in county of residence	1.01	0.84	1.21
EDs per 100,000 population uninsured			
No EDs	1.00	1.00	1.00
Few EDs	0.90	0.68	1.19
Some EDs	1.02	0.77	1.33
Many EDs	0.96	0.73	1.27
FQHC located in county of residence	0.82*	0.71	0.95
Community Predisposing & Need			
Percent population aged 65 and over	0.99	0.97	1.01
Percent population minority	1.00	1.00	1.01
Percent population in a MUA	1.00	1.00	1.00
Percent population uninsured (under age 65)	0.99	0.97	1.00
Percent population in poverty	1.01	0.99	1.02
Percent population unemployed	1.00	0.97	1.02
Percent population foreign born	1.00	1.00	1.01
Individual Predisposing			
Age	1.02*	1.02	1.03
Male	0.85*	0.78	0.92
Individual Need			
Elixhauser comorbidity index	1.25*	1.19	1.31
Individual Enabling			
Insurance			
Private Insurance	1.00	1.00	1.00
Medicaid	1.36*	1.22	1.51
No Insurance	1.44*	1.29	1.61
Other Insurance	0.96	0.78	1.19
Urbanization level			
Large central metro	1.00	1.00	1.00
Large fringe metro	0.98	0.80	1.21
Medium metro	1.01	0.84	1.21
Small metro	0.80	0.63	1.01
Rural	0.88	0.69	1.13
Income	0.93*	0.90	0.96

***Significant at the 5% level.**

Discussion

The study hypothesizes that the association between provider supply (e.g., primary care physician supply and nurse practitioner/physician assistant supply) and health care facility availability (e.g., EDs, federally qualified health centers, and government hospitals) and the odds of PPH varies across the urbanization spectrum. Although the interactions hypothesized are not significant, there are significant results that are consistent with previous studies, including the findings from Chapter 2. Prior studies of smaller geographic areas (Basu, Friedman, & Burstin, 2002) and Medicare populations (Chang, Stukel, Flood, & Goodman, 2011) have found that physician supply is negatively associated with PPH and this study supports the finding for non-elderly adults in the United States.

Additionally, the finding that the presence of a FQHC is negatively associated with the odds of PPH supports the research of Falik, Needleman, Herbert, Wells, Politzer, and Benedict (2006), who found that Medicaid beneficiaries who rely on community health centers as their usual source of care have fewer PPHs. This study expands the finding to all non-elderly adults in the United States. The finding that Medicaid and uninsured groups have a higher odds of PPH than the privately-insured group also is consistent with previous studies (Pappas et al., 1997). Consistent with the findings from Chapter 2, Elixhauser comorbid conditions are associated with a higher odds of PPH.

This study expands prior studies of PPH that have compared small geographic areas by changing both the depth and scope of the geographic areas studied. The descriptive analysis found differences both within and across the urbanization spectrum, however the differences are not found to be significantly associated with the odds of

PPH, when simultaneous controls for these variables are introduced. One possible explanation could be related to the modifiable areal unit problem. The modifiable areal unit problem consists of two components: the scale or aggregation problem and the zoning or grouping problem. The scale problem refers to the different statistical inferences that can be drawn when the same analysis is conducted at different geographic scales—e.g., state versus county versus census tract. The zone problem refers to the different statistical inferences that can be drawn when different zones of the scale can produce different results—e.g., political party affiliations in districts before and after redistricting.

The type of modifiable areal unit problem that likely affects this analysis is the scale problem. The urbanization spectrum is applied to counties depending on the county population size and metropolitan statistical area designation. However, there is still great variation within counties that is not accounted for in the county-level designations. There have been efforts to address this issue. For example, the US Department of Agriculture has developed the rural-urban community area (RUCA) codes to classify census tracts based on daily commuting, population density, and urbanization. RUCA codes are classified into ten primary codes that delineate metropolitan, micropolitan, small town, and rural areas based on the size and direction of the largest commuting flows.

The modifiable areal unit problem may also be affecting this analysis through the level of variables available for analysis. As was mentioned in the introduction, the ideal data level for community-level analysis would be at the PCSA level. However, not all meaningful constructs are available at the PCSA level, so county-level measures are used (e.g., NP/PA supply and population uninsured). Despite this issue, the variables that are significant in the model are consistent with previous research.

Although the study did not find significant differences in the association between the odds of PPH and health care provider and facility supply across the urbanization spectrum, there are still policy implications. This study finds that PCP supply does positively impact access to care outcomes, controlling for other individual and community predisposing, need, and enabling characteristics. The finding supports the call to increase the supply of primary care physicians by increasing medical school admissions and lifting the federal funding cap on residency training programs. There is a predicted doctor shortage of 46,000 to 90,000 physicians by the year 2025, and even with the Affordable Care Act increasing insurance coverage across the country, coverage alone is not enough to reduce PPH (IHS, 2015).

The study also supports the funding of federally qualified health centers as a viable source of care, able to reduce the likelihood of a PPH. In addition to policies aimed at increasing physician supply, another policy that leverages known effective primary care could include increasing the number of health centers able to serve low-income, vulnerable populations. The Affordable Care Act created the mandatory Health Center Trust Fund to expand health center funding over previous discretionary funding levels (NACHC, 2014). The Health Center Trust Fund will expire by fiscal year 2016, leaving only discretionary funding to cover operational costs and leading to a 70 percent funding reduction to all existing health centers. Additionally, the $11 billion in annual appropriations between fiscal years 2011 through 2015, meant to supplement discretionary funds, have actually been used to supplant discretionary funds (Redhead, 2015). The Health Center Trust Fund has not received an annual discretionary appropriation since fiscal year 2011. In order to secure and expand access to care, the Health Center Trust Fund should be reauthorized for fiscal years 2016 through 2020. As of November 3, 2015, the Bipartisan Budget Act of 2015, H.R. 1314 increases domestic spending by $25 billion in fiscal year 2016, however an appropriations bill has yet to be negotiated and the funding status for the Health Center Trust Fund is unknown.

Chapter 4: Differences in Associations between Community Primary Care Capacity and Acute and Chronic Potentially Preventable Hospitalizations

Introduction

Literature review

Research investigating acute and chronic PPH measures separately is less common than research employing the overall composite PPH measure. One short statistical brief (Stranges & Stocks, 2010) released by researchers with the Healthcare Cost and Utilization Project (HCUP) at AHRQ found that PPH for an acute ACSC made up 7.0 percent of all rural hospital stays, but only 3.4 percent of all urban hospital stays. Additionally, males were more likely to have a PPH for a chronic ACSC while women were more likely to have a PPH for an acute ACSC. Differences were also found by type of insurance. Compared to Medicaid stays for PPH, privately insured stays for PPH were more likely to be for an acute ACSC; but Medicaid stays for PPH were more likely to be for a chronic ACSC. Stranges and Stocks only report what they found in their statistical analyses and do not offer any explanations for the differences between PPH for acute and chronic ACSC. Other researchers have studied chronic ACSCs individually, but have not compared the acute and chronic composite measures (Bindman et al., 1995; Probst et al., 2003).

There is a large literature on the relationship between patients and physicians in the management of chronic disease (Holman & Lorig, 2000; Anderson & Knickman, 2001; Katon, Von Korff, Lin, & Simon, 2001; Rothman & Wagner, 2003). The literature suggests that primary care treatment of acute and chronic conditions is influenced by different factors. Chronic disease management and treatment requires a continued partnership and coordination between physician, patient, and community (Holman & Lorig, 2000; Anderson & Knickman, 2001; Rothman & Wagner, 2003).

The literature on the treatment of acute conditions in general is smaller than the literature on chronic conditions. The treatment of acute conditions in primary care settings has requirements that differ from chronic disease management. For example, correctly diagnosing the condition, ordering necessary treatments, and patient compliance with the treatment plan (Linder et al., 2009). Some literature suggests that fewer patients are seeking acute care in their primary care physicians offices, instead seeking treatment in emergency departments, urgent care clinics, and other non-primary care settings (Laws & Scott, 2008; Weinick, Bristol, & DesRoches, 2009; Pitts, Carrier, Rich, & Kellermann, 2010).

The intention of this paper is to fill a gap in the literature due to the dearth of research on community-level differences in acute and chronic PPH. Additional literature on community health care capacity and its association with PPH is addressed in Chapter 3.

Hypotheses

No study was found that has examined whether different sources of provider care in a community are associated differently with acute versus chronic ambulatory care sensitive conditions. However, research suggests that the management and treatment of acute and chronic conditions in primary care settings requires different resources and physician services (Holman & Lorig, 2000; Anderson & Knickman, 2001; Linder, Kaleba, & Kmetik, 2009). The following hypotheses are tested:

H1: The association between provider supply (e.g., primary care physician supply and nurse practitioner/physician assistant supply) and the odds of PPH varies by type of PPH.

H2: The association between health care facility supply (e.g., emergency departments, federally qualified health centers, and government hospitals) and the odds of PPH varies by type of PPH.

Methods

Study design

In order to assess the association of community enabling characteristics on acute and chronic ACSCs, this paper uses the 2007 National Hospital Discharge Survey, linked with publicly available data sources. The NHDS, a national probability sample of inpatient discharges in the United States, is described in Chapter 1.

Data

This analysis uses the augmented discharge-level dataset based on the 2007 NHDS, which includes demographic information about discharges and the communities in which they live. The datasets are described in Chapters 1 and 2.

Variables. The independent variables of interest in this analysis are PCP supply, specialist supply, and NP/PA supply, each of these being operationalized as providers per 100,000 population. PCP and specialist supply are measured at the PCSA level, while NP/PA supply is measured at the county level. There is not a data source that measures national NP/PA supply at the PCSA level.

Health care facility supply covariates include ED supply and presence of an FQHC and government hospital. ED supply is operationalized as the number of EDs per 100,000 population uninsured in a county and is categorized into no EDs, few EDs, some EDs, and many EDs. Although the number of EDs is available at the PCSA level, the uninsured population is only available at the county level. Therefore, EDs were aggregated to the county. The presence of an FQHC and a government hospital were both measured at the county level. Discharge-level covariates include characteristics such as sex, age, Elixhauser comorbidity index, type of insurance, income, and where the individual's county of residence falls on the urbanization spectrum. Community-level characteristics, including population over age 65, population minority, population in a medically underserved area (MUA), population uninsured, population in poverty, population unemployed, and population foreign born, are also used as control variables.

Analysis

All analyses are performed using the statistical packages SAS version 9.3 (SAS Institute, Cary, NC) and SUDAAN version 10.0 (RTI International, Research Triangle Park, NC). SUDAAN software is used to adjust for the complex sampling design and correlated data of the NHDS. Because NHDS is a sample survey, a weighting variable is used in all analyses. A Pearson correlation matrix is produced to examine bivariate correlations between each pair of continuous variables. Percentage distributions of each covariate by acute PPH, chronic PPH, and no PPH are also computed. In order to assess the association of provider supply on hospitalizations for acute and chronic ACSCs, a multinomial logistic regression model is fit.

A significance level of $p < 0.05$ is used as the criterion for rejection of the null hypothesis. Multicollinearity in the models is assessed using variance inflation factors (VIF), which quantify the severity of the multicollinearity in the model. A VIF of one for a variable indicates no multicollinearity with other variables in the model, while a VIF greater than or equal to ten indicates high multicollinearity (Allison, 1999). The logistic regression models are assessed for goodness of fit using the Chi-square goodness of fit test, recommended by Allison for ungrouped data (2014).

Results

Descriptive statistics

A weighted Pearson correlation of the continuous variables exposes two groups of very highly correlated variables. Percent population eligible for Medicaid and percent population in poverty, both at the county level, are too highly correlated to be in the model together (rho = 0.75), so the Medicaid eligible population is dropped from the logistic regression analysis. PCP supply and specialist physician supply are too highly correlated to be included in the logistic regression model together (rho = 0.89). In order to determine which variable to use, separate models with PCP supply only and specialty physician supply only are fit. The results from both models are the same: Physician supply is associated with a lower odds of being hospitalized for a chronic PPH, but not an acute PPH. Since the variables are so highly correlated and appear to measure the same effect, a single variable for physician supply, including both PCP and specialist, is used in the models.

The unadjusted likelihood of hospitalization for acute ACSCs is 3.9 percent and for chronic ACSCs is 7.6 percent (Table 4.1). All rates are per 100 hospitalizations. The rate of acute PPH is higher for females than for males (4.54 vs. 3.08), but not for chronic PPH. For chronic ACSCs, the rate of PPH increases by age (18-34: 3.83; 35-54: 8.16; 55-64: 9.60). For both acute and chronic ACSCs, the rate of PPH is higher for patients with at least one Elixhauser comorbid condition versus no comorbid conditions (5.40 vs. 2.26 and 8.90 vs. 6.15, respectively). The rate of acute PPH is higher for Medicaid patients than for privately insured patients (4.44 vs. 3.72) and the rate of chronic PPH is higher for Medicaid and uninsured patients than it is for privately insured patients (10.17 and 9.23, respectively, vs. 6.35). The rate of chronic PPH is higher for patients in large central metropolitan areas (8.78) and rural areas (7.95) than it is in large central fringe metropolitan areas (6.21) and small metropolitan areas (6.19). Additionally, the rate of chronic PPH is higher for patients in the lowest two income categories (13.11 and 8.72) than in the highest two income categories (6.43 and 4.49). There are no differences for acute PPH across the urbanization or income spectrums.

The rate of chronic PPH is higher for patients in communities with the largest minority populations, compared with the lowest minority populations (9.79 vs. 6.49). The difference is also significant for populations in the highest and lowest medically underserved areas (9.42 vs. 5.76), population in poverty (8.72 vs. 5.87), and population unemployed (9.18 vs. 6.07). There were no significant differences for the rates of acute PPH for any community predisposing or need variable.

The rate of acute PPH is higher in areas with the lowest rate of nurse practitioners and physician assistants compared with areas with the highest rate (4.56 vs. 3.43). The rate of acute PPH is lower in areas with a federally qualified health center than in areas without (3.61 vs. 4.42). There are no significant differences for the rates of chronic PPH for any community enabling variable.

Table 4.1 Rate per 100 hospitalizations of acute and chronic PPH by individual and community predisposing, need, and enabling characteristics in the discharge-level dataset

	Acute PPH n = 4,226		Chronic PPH n = 8,157	
	Rate	SE	Rate	SE
Total rate of PPH	**3.87**	**0.17**	**7.55**	**0.24**
Individual Predisposing				
Sex				
Male	3.08	0.19	7.74	0.29
Female	4.54	0.22	7.40	0.32
Age				
18-34	3.60	0.30	3.83	0.30
35-54	3.75	0.18	8.16	0.29
55-64	4.29	0.23	9.60	0.44
Individual Need				
Elixhauser Comorbidity				
Yes (at least one)	5.40	0.22	8.90	0.30
No	2.26	0.17	6.15	0.28
Individual Enabling				
Insurance				
Private Insurance	3.72	0.18	6.35	0.23
Medicaid	4.44	0.29	10.17	0.53
No Insurance	4.31	0.44	9.23	0.50
Other Insurance	3.04	0.42	6.80	0.83
Urbanization spectrum				
Large Central Metro	3.56	0.22	8.78	0.49
Large Fringe Metro	3.86	0.26	6.21	0.34
Medium Metro	4.40	0.48	7.61	0.45
Small Metro	3.25	0.35	6.19	0.48
Rural	4.15	0.53	7.95	0.68
Income				
Less than $20,000	3.28	1.05	13.11	2.57
$20,000-$49,999	4.19	0.25	8.72	0.31
$50,000-$79,999	3.63	0.22	6.43	0.38
Over $80,000	2.87	0.24	4.49	0.39

	Acute PPH		Chronic PPH	
	Rate	SE	Rate	SE
Community Predisposing/Need				
Population over 65				
Q1 (3.3-10.0)	3.39	0.28	7.43	0.60
Q2 (10.1-12.6)	4.13	0.32	7.61	0.32
Q3 (12.7-14.4)	4.36	0.26	8.01	0.44
Q4 (14.5-50.9)	3.68	0.32	7.28	0.46
Population minority				
Q1 (0.5-13.0)	3.60	0.33	6.49	0.49
Q2 (13.1-24.5)	4.31	0.36	6.77	0.42
Q3 (24.6-42.6)	4.03	0.27	7.33	0.44
Q4 (42.7-98.0)	3.61	0.29	9.79	0.49
Population in MUA				
Q1 (0-2.7)	3.98	0.31	5.76	0.38
Q2 (2.8-15.5)	3.64	0.21	6.99	0.33
Q3 (15.6-43.9)	3.59	0.29	7.20	0.42
Q4 (44.0-100)	4.15	0.32	9.42	0.47
Population uninsured (under age 65)				
Q1 (6.6-12.1)	3.89	0.26	7.27	0.38
Q2 (12.2-14.7)	4.00	0.35	8.13	0.59
Q3 (14.8-19.2)	3.75	0.29	7.60	0.43
Q4 (19.3-38.7)	3.87	0.35	7.39	0.48
Population in poverty				
Q1 (2.4-8.6)	3.67	0.27	5.87	0.37
Q2 (8.7-12.8)	3.87	0.29	7.19	0.39
Q3 (12.9-16.2)	4.08	0.34	8.01	0.42
Q4 (16.3-41.9)	3.81	0.36	8.72	0.58
Population unemployed				
Q1 (0-6.7)	3.83	0.27	6.07	0.36
Q2 (6.8-7.8)	3.87	0.35	7.44	0.48
Q3 (7.9-9.3)	3.52	0.23	8.12	0.38
Q4 (9.4-23.0)	4.29	0.29	9.18	0.45
Population foreign born				
Q1 (0-4.5)	4.02	0.35	7.34	0.42
Q2 (4.6-8.9)	4.15	0.34	7.61	0.41
Q3 (9.0-19.5)	3.85	0.24	7.02	0.46
Q4 (19.6-51.1)	3.40	0.28	8.27	0.58

	Acute PPH		Chronic PPH	
	Rate	SE		Rate
Community Enabling				
PCPs and specialists per 100,000 population				
Q1 (0-55)	4.12	0.36	7.76	0.50
Q2 (56-73)	3.93	0.24	7.87	0.42
Q3 (74-97)	3.72	0.25	7.07	0.33
Q4 (98-932)	3.63	0.23	7.51	0.38
NPs/PAs per 100,000 population				
Q1 (0-41)	4.56	0.36	7.41	0.39
Q2 (42-53)	3.65	0.31	8.02	0.64
Q3 (54-77)	3.73	0.29	7.72	0.41
Q4 (78-629)	3.43	0.21	7.13	0.40
EDs per 100,000 population uninsured				
None (0)	4.44	0.60	8.41	1.23
Few (.6-4.1)	3.53	0.24	7.21	0.46
Some(4.2-8.8)	3.86	0.26	8.13	0.39
Most (8.9-607.0)	4.03	0.31	7.21	0.35
Presence of an FQHC				
Yes	3.61	0.16	7.69	0.29
No	4.42	0.36	7.27	0.42
Hospital beds per 1,000 population				
Q1 (0-1.4)	3.89	0.29	6.90	0.37
Q2 (1.5-2.4)	3.99	0.28	7.57	0.51
Q3 (2.5-4.0)	3.79	0.32	7.19	0.34
Q4 (4.1-51.9)	3.82	0.23	8.47	0.45
Presence of a government hospital				
Yes	3.73	0.21	7.91	0.33
No	4.07	0.26	7.04	0.31

Multinomial logistic regression

The results of the multinomial logistic regression are reported in Table 4.2. Total physician supply is negatively associated with chronic PPH as compared with hospitalizations that are not a PPH (OR = 0.90; 95% CI = 0.82, 0.99). However, acute PPH, as compared with hospitalizations that are not a PPH, is not significantly different (OR = 1.02; 95% CI = 0.90, 1.16). Nurse practitioner/physician assistant supply is associated with a lower odds of a hospitalization being for an acute PPH (OR = 0.62; 95% CI = 0.42, 0.92), but not for a chronic PPH (OR = 0.92; 95% CI = 0.65, 1.31). The presence of an FQHC is associated with lower odds of a hospitalization being for an acute ACSC (OR = 0.78; 95% CI = 0.63, 0.95), and the same is true for chronic ACSCs (OR = 0.84; 95% CI = 0.72, 0.99). See Appendix E for more information regarding the natural log transformed variables.

The odds of an acute PPH is lower for men compared to women (OR = 0.65; 95% CI = 0.57, 0.74), possibly due to women being more likely to have a urinary tract infection, an acute PPH. Income is negatively associated with the odds of a PPH for only chronic ACSCs (OR = 0.91; 95% CI = 0.88, 0.94). An increase in one year of age is associated with 1.03 times the odds of a chronic PPH (95% CI = 1.03, 1.04). An additional Elixhauser comorbid condition is associated with 1.47 times the odds of an acute PPH (95% CI = 1.39, 1.55) and 1.14 times the odds of a chronic PPH (95% CI = 1.08, 1.21). Additionally, the odds for patients with a chronic PPH is 1.54 times higher if they have Medicaid (95% CI = 1.37, 1.73) compared to private insurance, and 1.6 times higher if they have no insurance (95% CI = 1.41, 1.82) compared to private insurance.

Table 4.2 Odds ratios (OR) with confidence intervals

	Acute vs. Not PPH			Chronic vs. Not PPH		
	OR	Lower 95% Limit OR	Upper 95% Limit OR	OR	Lower 95% Limit OR	Upper 95% Limit OR
Community Enabling						
Total physician supply (natural log)	1.02	0.90	1.16	0.90*	0.82	0.99
NPs & PAs supply (natural log)	0.62*	0.42	0.92	0.92	0.65	1.31
Hospital bed supply (natural log)	0.99	0.86	1.15	1.11	0.99	1.25
Presence of government hospital	1.04	0.81	1.33	1.00	0.85	1.18
EDs per 100,000 population uninsured						
No EDs	1.00	1.00	1.00	1.00	1.00	1.00
Few EDs	0.90	0.64	1.27	0.93	0.66	1.33
Some EDs	1.02	0.75	1.40	1.03	0.74	1.44
Many EDs	1.07	0.77	1.49	0.92	0.67	1.27
Presence of an FQHC	0.78*	0.63	0.95	0.84*	0.72	0.99
Community Predisposing & Need						
Percent population aged 65 and over	0.99	0.97	1.02	0.99	0.97	1.00
Percent population minority	1.00	1.00	1.00	1.00	1.00	1.01
Percent population in a MUA	1.00	1.00	1.00	1.00	1.00	1.00
Percent population uninsured (under age 65)	1.00	0.98	1.03	0.98	0.97	1.00
Percent population in poverty	1.01	0.99	1.03	1.01	0.99	1.02
Percent population unemployed	0.99	0.95	1.03	1.01	0.98	1.04
Percent population foreign born	1.00	0.99	1.01	1.01	1.00	1.01
Individual Predisposing						
Age	1.01	1.00	1.01	1.03*	1.03	1.04
Male	0.65*	0.57	0.74	0.97	0.87	1.08

	Acute vs. Not PPH			Chronic vs. Not PPH		
	OR	Lower 95% Limit OR	Upper 95% Limit OR	OR	Lower 95% Limit OR	Upper 95% Limit OR
Individual Need						
Elixhauser comorbidity index	1.47*	1.39	1.55	1.14*	1.08	1.21
Individual Enabling						
Insurance						
Private Insurance	1.00	1.00	1.00	1.00	1.00	1.00
Medicaid	1.05	0.89	1.24	1.54*	1.37	1.73
No Insurance	1.18	0.97	1.43	1.60*	1.41	1.82
Other Insurance	0.82	0.62	1.08	1.05	0.84	1.31
Urbanization level						
Large central metro	1.00	1.00	1.00	1.00	1.00	1.00
Large fringe metro	1.09	0.84	1.40	0.94	0.75	1.18
Medium metro	1.16	0.88	1.53	0.95	0.80	1.13
Small metro	0.81	0.59	1.10	0.81	0.63	1.04
Rural	0.89	0.62	1.27	0.90	0.69	1.16
Income	0.96	0.92	1.00	0.91*	0.88	0.94

***Significant at the 5% level.**

Discussion

This study hypothesizes that the associations between provider and health care facility supply and the odds of PPH vary by type of PPH. The findings support the hypothesis that provider supply is associated with PPH: First, increases in physician supply are negatively associated with the odds of hospitalization for chronic ACSC, compared with hospitalizations for other reasons. The finding is consistent with the literature that management of chronic conditions requires the involvement of patients with teams of physicians (Holman & Lorig, 2000; Anderson & Knickman, 2001; Rothman & Wagner, 2003). For example, diabetes-related conditions make up almost one half of all chronic ACSCs. Managing diabetes requires patients to eat well, test their blood sugar, and may require patients to see a range of health care providers, such as a primary care physician, diabetes specialist, optometrist, and podiatrist.

Second, increases in the supply of nurse practitioners and physician assistants are negatively associated with the odds of hospitalization for acute ACSCs, compared with hospitalization for other reasons. The finding provides additional context for research that has explored where patients with acute conditions are seeking treatment and finding that it is increasingly outside of physician's offices in settings where nurse practitioners and physician assistants are likely to be employed (Laws & Scott, 2008; Weinick, Bristol, & DesRoches, 2009; Pitts, Carrier, Rich, & Kellermann, 2010). The acute conditions classified as ACSCs are urinary tract infection (UTI), bacterial pneumonia, and dehydration. UTI and bacterial pneumonia can be easily treated with antibiotics and dehydration may require intravenous fluids. Both treatments can ordered by nurse practitioners and physician assistants.

Third, the presence of a federally qualified health center is negatively associated with the odds of hospitalization for both acute and chronic ACSCs, compared with hospitalization for other reasons. This finding is consistent with Chapter 3 of this dissertation, and with research that found the presence of an FQHC reduces PPH for the Medicaid population (Falik, Needleman, Herbert, Wells, Politzer, & Benedict, 2006).

Policies to increase physician supply and fund FQHCs have been discussed in Chapter 3 and are similarly applicable. However, the findings from this analysis reveal another vector in health care delivery that can be enhanced through policy: nurse practitioners and physician assistants. Expanding and standardizing the independent practice and prescribing authority for nurse practitioners and physician assistants across states could increase people's ability to access care.

The current policies regulating the practice of both nurse practitioners and physician assistants vary widely from state to state. In 2007 and today, nurse practitioner scope of practice and prescribing authority varies widely from state to state. Scope of practice ranges from independent practice without physician supervision or involvement, practice in collaboration with a physician, and a requirement of physician supervision. Specific practice authorities also vary across states, as in a nurse practitioner's ability to diagnose, refer, and order tests. All states allow nurse practitioners to prescribe, but requirements for physician involvement vary and additional limitations may also be applied.

The laws regulating physician assistants are similarly complex and vary from state to state. The term describing the legal practicing authority are described as both "licensure" and "certification." The scope of practice and prescriptive authority for physician assistants are sometimes set by state medical boards, while in other states are set by the supervising physician. The number of physician assistants that can be supervised by a single physician also varies from state to state, as do the chart co-signature requirements.

In addition to expanding the scope of practice, another policy could be for states to adopt mutual recognition agreements for licenses of nurse practitioners and physician assistants across the country. Mutual recognition agreements could increase practitioner mobility, enabling nurse practitioners and physician assistants to move to locations that have provider shortages. In order to maximize the benefits to access to care provided by a nurse practitioner or physician assistant, states need to reevaluate current laws and regulations in order to balance access to care and patient safety.

Chapter 5: Conclusions

Chapters 2 through 4 of this dissertation sought to identify the community characteristics associated with potentially preventable hospitalizations (PPH). In order to assess the association, a nationally representative sample of inpatient discharges was augmented with available secondary datasets to provide a community context setting for PPH. In Chapter 2, a two-stage regression model was employed to study the effects of two Medicaid policies—Medicaid generosity index and Medicaid managed care penetration—on the likelihood of PPH in three populations: the Medicaid insured, the uninsured, and the privately insured. While no significant associations were found with the Medicaid policies, physician supply in primary care services areas is significantly associated with a lower likelihood of PPH. Previous studies have found that physician supply is negatively associated with PPH, however they have been limited to smaller geographic areas (Basu, Friedman, & Burstin, 2002) and Medicare populations (Chang, Stukel, Flood, & Goodman, 2011). The analysis in Chapter 2 supports the finding for all non-elderly hospitalized adults in the United States. The finding that Medicaid and uninsured groups have a higher odds of PPH than the privately-insured group also is consistent with previous studies (Pappas et al., 1997).

In Chapter 3, a multiple logistic regression model sought to address whether the association between provider and health care facility supply and the likelihood of PPH varied across the urbanization spectrum. No interactions were found between urbanization level and provider and health care facility supply, but in a model controlling for urbanization, physician supply and the presence of a federally qualified health center were found to be negatively associated with the odds of a PPH. Consistent with Chapter 2 and previous studies (Basu, Friedman, & Burstin, 2002; Chang, Stukel, Flood, & Goodman, 2011), the analysis in Chapter 3 found that physician supply is negatively associated with PPH for non-elderly adults in the United States. Additionally, the finding that the presence of a FQHC is negatively associated with the odds of PPH supports prior research that found that Medicaid beneficiaries who rely on community health centers as their usual source of care have fewer PPHs (Falik, Needleman, Herbert, Wells, Politzer, & Benedic,t 2006). This study expands the finding to all non-elderly hospitalized adults in the United States who have an FQHC in their county. Again, the finding that Medicaid and uninsured groups have a higher odds of PPH than the privately-insured group is also consistent with previous studies (Pappas et al., 1997).

Finally, in Chapter 4, a multinomial logistic regression model looked for variation in the association between provider and health care facility supply and the likelihood of a PPH for an acute ACSC and a PPH for a chronic ACSC. Physician supply was found to be negatively associated with the odds of a chronic PPH, while nurse practitioner and physician assistant supply was found to be negatively associated with the odds of an acute PPH. Federally qualified health centers were negatively associated with the odds of both acute and chronic PPHs. These findings are supported by prior research. There is a large literature on management of chronic conditions showing that the involvement of patients with teams of physicians is necessary to control disease (Holman & Lorig, 2000; Anderson & Knickman, 2001; Rothman & Wagner, 2003). The finding that nurse practitioner and physician assistant supply is associated with reduced likelihood of PPH provides additional context for research that has explored where patients with acute conditions are seeking treatment and finding that it is increasingly outside of physician's offices in settings where nurse practitioners and physician assistants are likely to be employed (Laws & Scott, 2008; Weinick, Bristol, & DesRoches, 2009; Pitts, Carrier, Rich, & Kellermann, 2010). Third, the finding on the association between the presence of a federally qualified health center and PPH is consistent with Chapter 3 of this dissertation, and with research that found the presence of an FQHC reduces PPH for the Medicaid population (Falik, Needleman, Herbert, Wells, Politzer, & Benedict, 2006). Finally, all analyses in Chapters 2 through 4 find that Elixhauser comorbid conditions are associated with a higher odds of PPH, a potential new contribution to the literature.

The analyses in this dissertation are guided by the conceptual framework, described in Chapter 1, adapted from Davidson, Andersen, Wyn, and Brown (2004). The purpose of the framework is to identify contextual variables that are hypothesized to influence access to care, thus strengthening the external validity of the results. The findings in this dissertation, in turn, validate the "community" determinants of access to care proposed in the framework. However, some of the limitations described by Davidson et al. in their original paper are still a problem and have affected this research. For example, the data for many of the community characteristics, such as local government funding, volume of services provided by local health departments, and AIDS incidence rates, are not available on a national scale at geographically meaningful units of observation (e.g., PCSAs).

The findings summarized above all have a workforce component in their policy implications. While the following policies are not directly related to the findings, an effort is made to evaluate different policies used increase health care capacity. In all papers, physician supply is found to be associated with a lower odds of hospitalization for a PPH. The Affordable Care Act (ACA) does include some workforce development policies, including redistributing Graduate Medical Education (GME) training positions and prioritizing primary care and general surgery in states with the lowest resident physician-to-population ratios; supporting the training of health professionals through grants and loans; addressing the potential shortage of nurses by increasing the capacity of training programs; and supporting the development of programs that train providers to focus on primary care medical homes, team management of chronic disease, and integration of mental health and physical health services.

Although policies have been enacted through the ACA, their outcomes may have not been desired or anticipated. For example, in the past, the GME redistribution policy for specialties and geographic locations has not has the intended effect. In 2003, the Medicare Prescription Drug, Improvement, and Modernization Act redistributed approximately 3,000 GME positions in an effort to increase physician supply in rural areas and the number of primary care physicians. Although the net number of primary care physicians increased, the relative growth of specialty physicians was twice as large, diverting potential primary care physicians to specialty training (Chen, Xierali, Piwnica-Worms, & Phillips, 2013). Additionally, of the 304 hospitals that received additional GME positions, only 12 were rural and received fewer than three percent of the redistributed positions.

The current tangle of federal and state regulations that govern the practice of physicians, nurse practitioners, and physician assistants also needs to be addressed. Mutual recognition agreements between states could enable practitioners to more easily set up an office in areas of need and facilitate the practice of telemedicine across state lines, allowing health care providers to deliver care to patients in medically underserved areas. The delivery of health care is changing and regulations need to adapt to new modes of diagnosis and treatment.

While interest in telemedicine has been growing in the medical, health insurance, and government communities, how to effectively harness the ability of telemedicine to positively impact the delivery of health care is still being studied. A systematic review of 20 years of cost-effectiveness studies of telemedicine found no conclusive evidence that telemedicine is cost-effective when compared to traditional medicine (Mistry, 2012). There are also risks associated with telemedicine that need to be explored further, including lack of a physical examination and how to develop a patient-physician relationship (Daniel & Sulmasy, 2015).

Another policy that leverages known effective primary care could include increasing the number of health centers able to serve low-income, vulnerable populations. The ACA created the mandatory Health Center Trust Fund to expand health center funding over previous discretionary funding levels (NACHC, 2014). The Health Center Trust Fund will expire by fiscal year 2016, leaving only discretionary funding to cover operational costs and leading to a 70 percent funding reduction to all existing health centers. Additionally, the $11 billion in annual appropriations between fiscal years 2011 through 2015, meant to supplement discretionary funds, have actually been used to supplant discretionary funds (Redhead, 2015). The Health Center Trust Fund has not received an annual discretionary appropriation since fiscal year 2011. In order to secure and expand access to care, the Health Center Trust Fund needs to be reauthorized for fiscal years 2016 through 2020.

In addition to the provider and health care facility supply implications, this dissertation also demonstrates both the power and limitations of secondary data. By finding linkages within data sets that permit merging and augmenting the data, richer analyses can be conducted. However, secondary data from administrative sources do have significant limitations when used in statistical analysis. Administrative data are collected for the purpose of monitoring and managing non-statistical programs—e.g. state reporting on Medicaid enrollment and expenditures to CMS—and some fields are more likely to be more accurate than others (Billings, 2003).

With the use of secondary data, researchers are also limited to what is available so therefore analyses suffer from omitted variable bias. The studies in this dissertation assess the access to care outcome of potentially preventable hospitalizations, but there are multiple uncaptured variables that affect the outcome. Discharge-level variables, such as potential and realized access to care, health status, compliance, and quality of care, are not able to be measured from the administrative data sources used in the analyses.

Additionally, secondary data limit the level of analysis. While primary care service areas are a validated construct created to analyze the distribution of health professionals, primary care services, and access to primary care, not all administrative data are available at the primary care service area level. For a number of predictors, the smallest area at which they are available is at the county level, which is not as granular or as conceptually meaningful as the primary care service area level. However, despite all of the limitations of working with administrative data, all three papers support the conceptual framework that underlies the models.

This dissertation raises some questions that should be addressed through future data collection activities and research. The link between realized access and access to care outcomes should be explored further outside of the Medicare and Medicaid populations, especially in light of the expansion of health insurance through the ACA. To most people, the ACA is understood as an expansion of health insurance; and making health insurance more available to populations is a major component of the legislation. However, the policies in the ACA that expand the workforce development and fund community sources of primary care are also integral to reducing PPH in the nation. Insurance cover is not access to care—it is an important component of access to care, but insurance alone is not enough to reduce PPH. Continuing to research the intersections of individual and community predisposing, need, and enabling factors and access to care under the new ACA legislation is necessary to understand the health care system.

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Appendices

Appendix A – Variable descriptions

Table A.1 Variable descriptions and sources

Domain and variable	Variable definition	Unit of observation	Source
Dependent variable			
Potentially preventable hospitalization (PPH)	Binary variable denoting whether a discharge was hospitalized for a PPH.	Discharge	NHDS
Individual Predisposing			
Sex	Sex of discharge	Discharge	NHDS
Age	Age at discharge	Discharge	NHDS
Individual Need			
Elixhauser comorbidity index	Number of Elixhauser comorbid conditions	Discharge	NHDS
Individual Enabling			
Health insurance	Expected source of payment for discharge (Medicaid, no insurance, private insurance, other insurance--includes other government, worker's compensation, not stated, and other)	Discharge	NHDS
Urbanization level	Urban-rural classification scheme developed by the National Center for Health Statistics. Includes designations for large central metro, large fringe metro, medium metro, small metro, micropolitan, and noncore.	Discharge	NHDS
Income	Median income of ZCTA	ZCTA	HRSA
Community Predisposing/Need			
Percent population over age 65	The numerator is the total number of persons aged 65 years and over in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA
Percent population minority	The numerator is the total number of minority persons in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA
Percent population living in a medically underserved area (MUA)	The numerator is the total number of people living in a MUA in a PCSA. The denominator is the total population of the PCSA.	PCSA	HRSA

Percent population uninsured (under age 65)	The numerator is the total number of persons under age 65 that are uninsured in a county. The denominator is the total population under age 65 of the county.	County	AHRF
Percent population eligible for Medicaid	The numerator is the total number of persons eligible for Medicaid in a county. The denominator is the total population of the county.	County	AHRF
Percent population in poverty	The numerator is the total number of persons living below the federal poverty level in a county. The denominator is the total population of the county.	County	AHRF
Percent population unemployed	The numerator is the total number of persons unemployed in the labor force in a county. The denominator is the total civilian labor force of the county.	County	AHRF
Percent population foreign born	The numerator is the total number of persons foreign born in a county. The denominator is the total population of the county.	County	AHRF
Percent population living in rural area	The numerator is the total number of persons living in a rural area in a state. The denominator is the total population of the state.	State	Census
Percent population unemployed	The numerator is the total number of persons unemployed in a state. The denominator is the total population of the state.	State	Census
Percent population uninsured	The numerator is the total number of persons uninsured in a state. The denominator is the total population of the state.	State	Census
Percent population minority	The numerator is the total number of minority persons in a state. The denominator is the total population of the state.	State	Census
Percent population foreign born	The numerator is the total number of persons foreign born in a state. The denominator is the total population of the state.	State	Census
Percent population eligible for Medicaid	The numerator is the total number of persons on for Medicaid in a state. The denominator is the total population of the state.	State	CMS

Percent population in poverty	The numerator is the total number of persons living below the federal poverty level in a state. The denominator is the total population of the state.	State	Census
Disproportionate share hospital payment rates	The numerator includes expenditures available to directly subsidize safety net hospitals in a state. The denominator is the total population of uninsured persons.	State	KFF
Community Enabling			
Primary care physician supply per 100,000 population	The number of primary care physicians (including OB/GYNs, pediatricians, osteopaths, and family doctors) per 100,000 population in a PCSA.	PCSA	HRSA
Specialty physician supply per 100,000 population	The number of specialty care physicians per 100,000 population in a PCSA.	PCSA	HRSA
Number of hospital beds per 1,000 population	The numerator is the total number of hospital beds in a PCSA (HMI). The denominator is the total population in the PCSA (HRSA).	PCSA	HMI/HRSA
Presence of a government hospital (non-federal, non-institutional)	Binary variable denoting presence of a non-federal, non-institutional government hospital.	County	HMI
Emergency departments (EDs) per 100,000 population uninsured: none, few, some, many	A categorical variable created from the ratio of the total number of EDs in a county (HMI) over the total number of individuals in the county that are uninsured (AHRF).	County	HMI/AHRF
Presence of a federally qualified health center (FQHC)	Binary variable denoting presence of an FQHC.	County	HRSA
NP/PA supply per 100,000 population	The numerator is the number of nurse practitioners and physician assistants in a county. The denominator is the total population of the county.	County	AHRF
Medicaid payments per enrollee	The numerator is the total Medicaid expenditures in a state. The denominator is the number of Medicaid recipients in a state.	State	CMS

Health maintenance organization (HMO) penetration	The percent of insured persons enrolled in an HMO plan in a state.	State	KFF
Medicaid generosity index	Composite index of Federal Poverty Levels for Medicaid eligibility groups.	State	KFF
Medicaid managed care penetration	The numerator is the total number of individuals enrolled in a Medicaid managed care program. The denominator is the total number of individuals enrolled in Medicaid.	State	CMS

Appendix B – Correlation tables

Table B.1 Discharge-level Pearson correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Age	1														
2. Elixhauser comorbidity index	0.15	1													
	<.0001														
3. Median income, in 10,000s	0.05	-0.09	1												
	<.0001	<.0001													
4. PCPs per 100,000 population	0.01	0.02	0.07	1											
	0.007	<.0001	<.0001												
5. Specialists per 100,000 population	0.00	0.02	0.07	0.89	1										
	0.4724	<.0001	<.0001	<.0001											
6. NPs & PAs per 100,000 population	0.00	0.02	0.07	0.37	0.41	1									
	0.7024	<.0001	<.0001	<.0001	<.0001										
7. Hospital beds per 1,000 population	-0.01	0.03	-0.18	0.59	0.66	0.22	1								
	0.0011	<.0001	<.0001	<.0001	<.0001	<.0001									
8. Percent population 65 and older	0.07	-0.01	-0.21	0.09	0.02	0.04	0.08	1							
	<.0001	0.0498	<.0001	<.0001	<.0001	<.0001	<.0001								
9. Percent population minority	-0.03	0.07	-0.15	0.12	0.16	0.02	0.16	-0.39	1						
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001							
10. Percent population living in an MUA	-0.01	0.04	-0.42	-0.08	-0.06	-0.08	0.11	0.16	0.19	1					
	0.0282	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001						
11. Percent population under 65 uninsured	-0.05	0.00	-0.10	-0.18	-0.09	-0.22	0.00	-0.21	0.21	0.23	1				
	<.0001	0.9665	<.0001	<.0001	<.0001	<.0001	0.8758	<.0001	<.0001	<.0001					
12. Percent population on Medicaid	-0.02	0.07	-0.41	0.04	0.02	-0.06	0.12	-0.05	0.46	0.36	0.11	1			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
13. Percent population in poverty	-0.04	0.06	-0.53	0.00	0.00	-0.02	0.18	-0.01	0.33	0.47	0.29	**0.75**	1		
	<.0001	<.0001	<.0001	0.4463	0.1851	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
14. Percent population unemployed	-0.01	0.07	-0.27	-0.02	-0.02	-0.13	0.03	-0.09	0.37	0.23	0.00	0.54	0.54	1	
	0.0006	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.9137	<.0001	<.0001		
15. Percent of population foreign born	-0.01	0.04	0.17	0.12	0.13	-0.03	-0.02	-0.30	0.51	-0.06	0.43	0.33	0.07	0.11	1
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Table B.2 State-level Pearson correlations

	1	2	3	4	5	6	7	8
1. Percent of state living in rural area	1							
2. Percent population minority	-0.36	1						
	0.01							
3. Percent population in poverty	0.30	0.22	1					
	0.03	0.12						
4. Percent of state unemployed	0.04	0.14	0.47	1				
	0.80	0.32	0.00					
5. Percent population foreign born	-0.74	0.23	-0.15	-0.05	1			
	<.0001	0.12	0.29	0.74				
6. Disproportionate share hospital payment rate	0.04	0.14	0.06	0.25	-0.11	1		
	0.77	0.35	0.69	0.08	0.43			
7. Eligibility generosity index	-0.04	0.21	-0.17	0.16	0.08	0.31	1	
	0.78	0.15	0.23	0.27	0.57	0.03		
8. Percent of Medicaid beneficiaries in managed care	-0.27	0.01	0.03	-0.18	0.15	-0.20	-0.11	1
	0.05	0.93	0.84	0.21	0.30	0.15	0.45	

Appendix C – State distributions by state-level variables

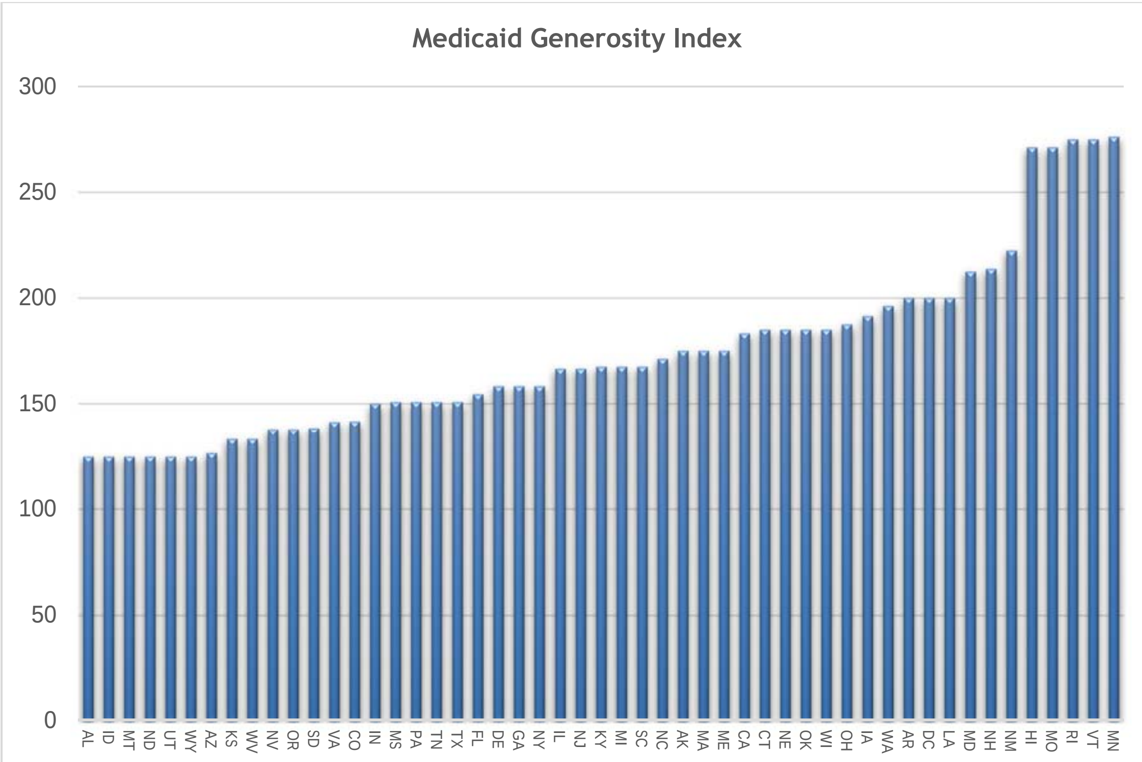

Figure C.1

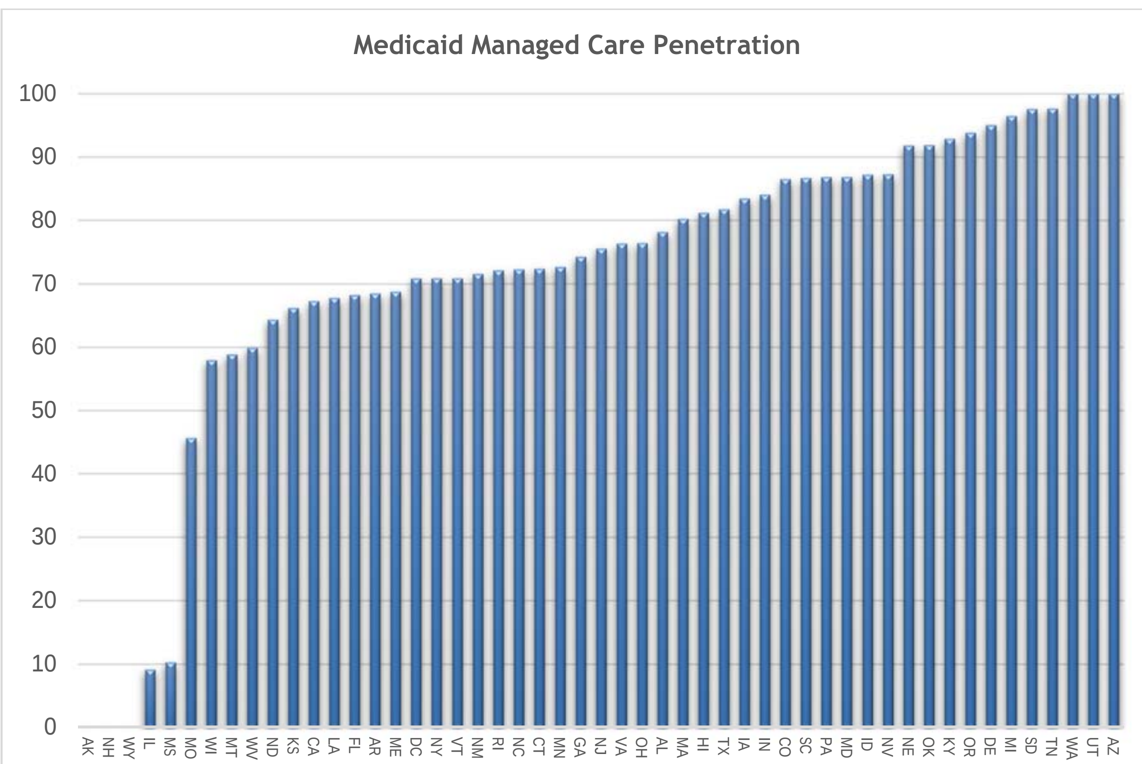

Figure C.2

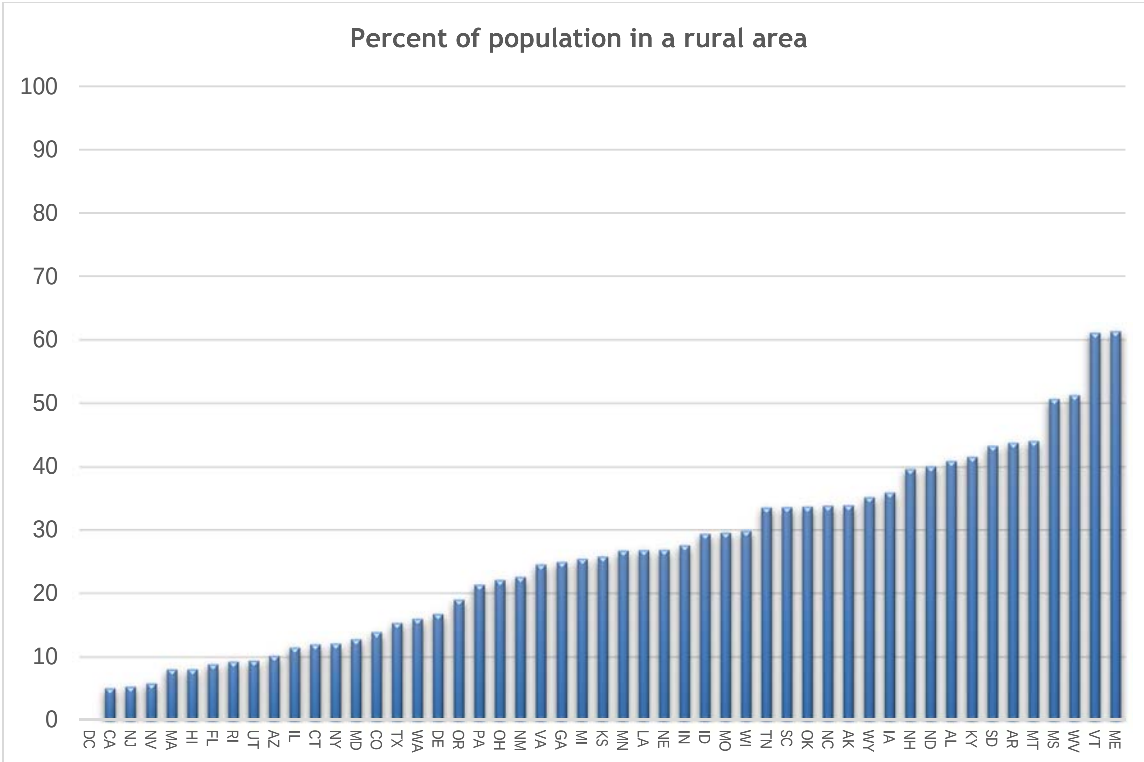

Figure C.3

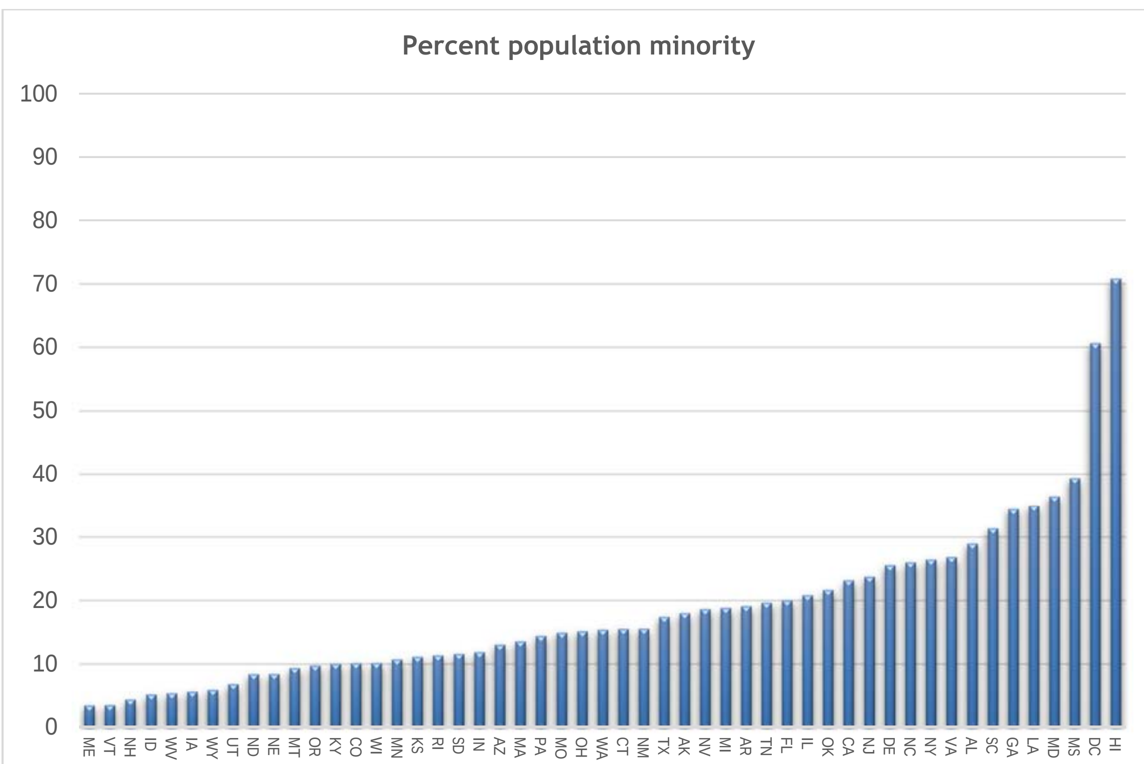

Figure C.4

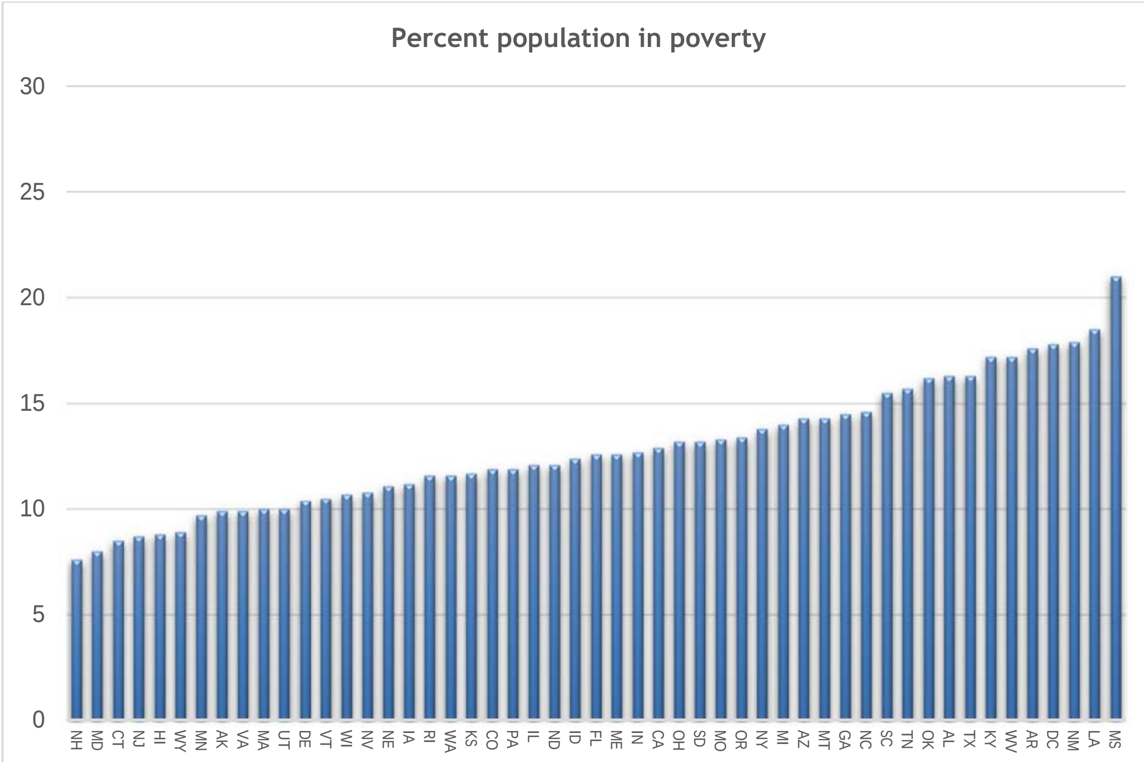

Figure C.5

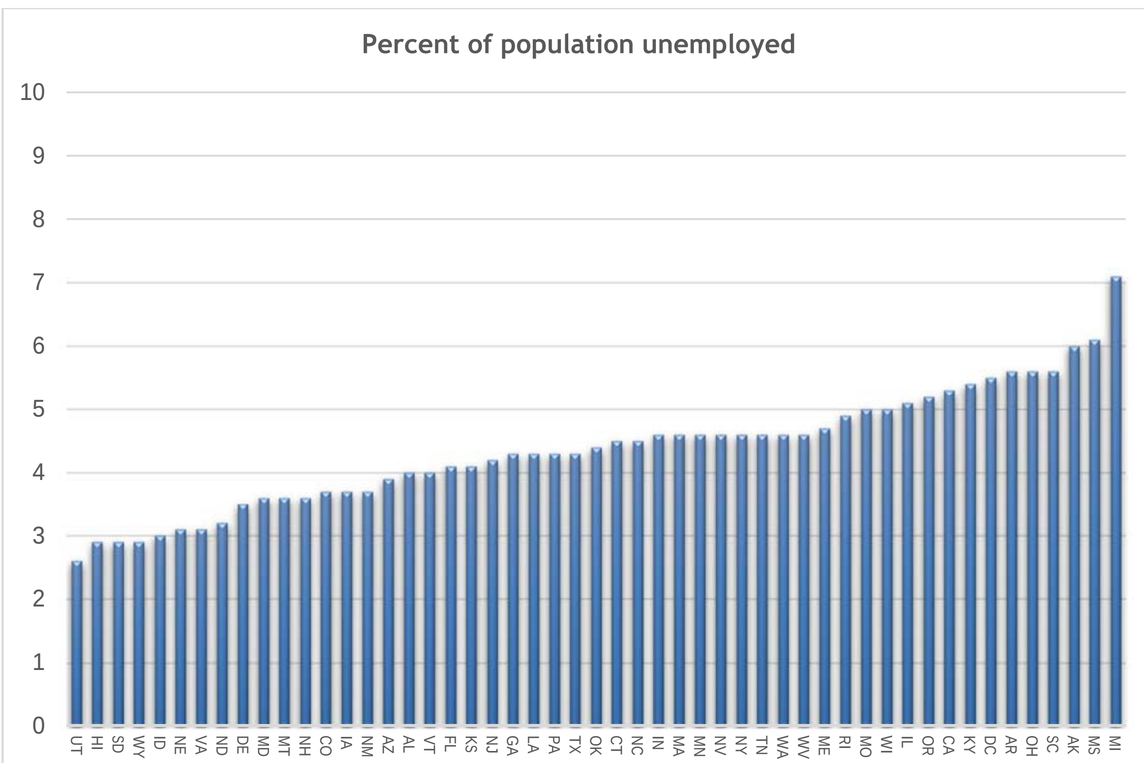

Figure C.6

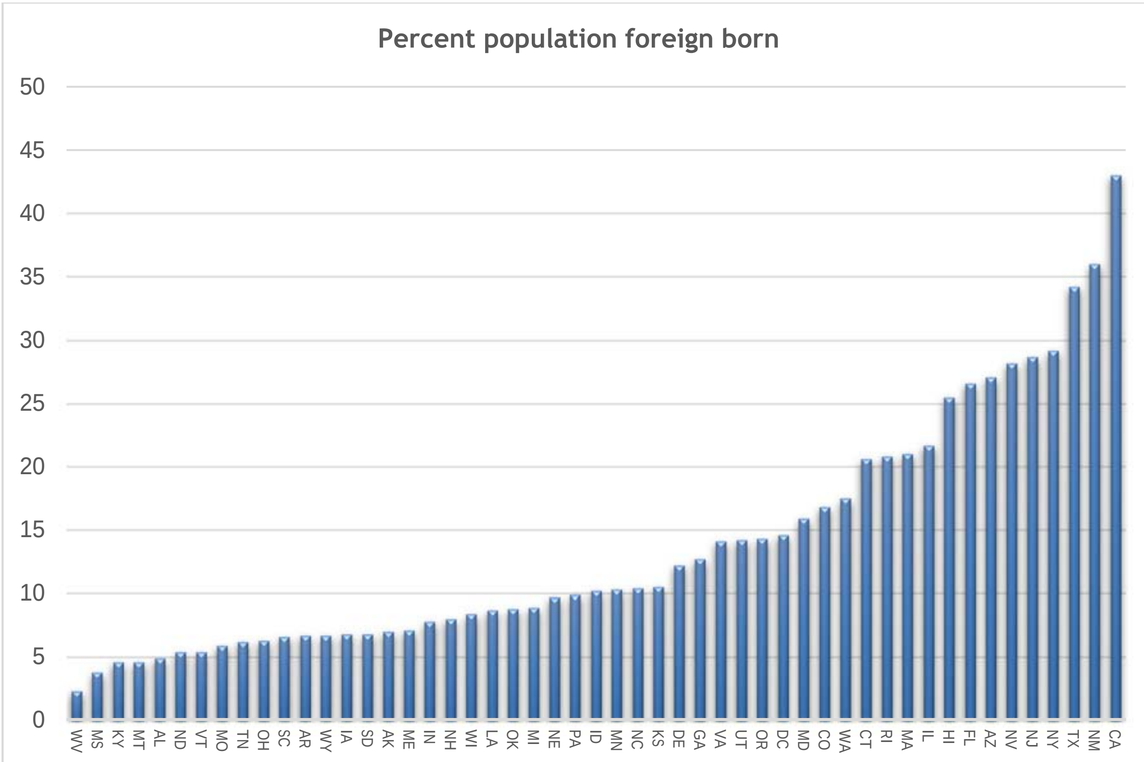

Figure C.7

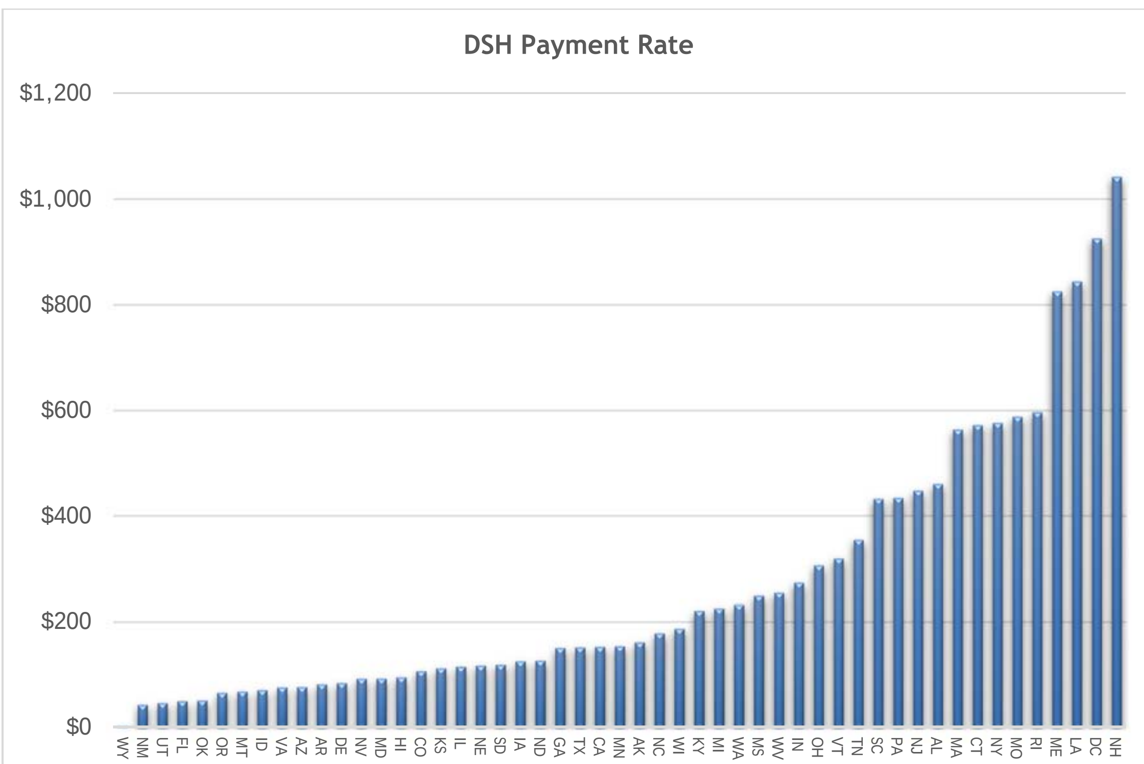

Figure C.8

Appendix D – Predicted probabilities by state from Chapter 2

Table D.1 Predicted probability of PPH for states, by insurance type

State	Medicaid	No insurance	Private insurance
AL	11%	11%	8%
AR	8%	8%	6%
AZ	12%	12%	9%
CA	14%	15%	11%
CO	12%	12%	9%
CT	9%	9%	7%
DC	15%	15%	11%
DE	10%	10%	7%
FL	14%	14%	10%
GA	13%	14%	10%
HI	7%	7%	5%
IA	13%	13%	10%
IL	14%	14%	10%
IN	9%	9%	7%
KS	7%	7%	5%
KY	10%	11%	8%
LA	13%	13%	10%
MA	6%	6%	4%
MD	14%	15%	11%
ME	6%	7%	5%
MI	12%	12%	9%
MN	10%	11%	8%
MO	8%	8%	6%
MS	1%	1%	1%
MT	6%	6%	4%
NC	10%	11%	8%
NH	16%	16%	12%
NJ	18%	19%	14%
NM	13%	13%	10%
NY	11%	12%	9%
OH	15%	15%	11%
OK	10%	10%	7%
OR	21%	22%	17%
PA	11%	12%	8%
RI	8%	8%	6%
SC	11%	11%	8%
TN	12%	12%	9%
TX	12%	13%	9%
UT	26%	27%	20%
VA	13%	13%	10%
VT	16%	16%	12%
WA	10%	11%	8%
WI	12%	12%	9%
WV	11%	11%	8%
WY	7%	8%	5%

Appendix E – Interpretation of Natural Log Transformed Variables

In order to interpret the log transformed variables in the logistic regressions, the beta values are re-transformed using the method described by the Institute for Digital Research and Education at the University of California, Los Angeles (2015). The interpretation of natural log transformed independent variables is that a one percent change in the independent variable is associated with a ($\beta/100$) change in the dependent variable.

Chapter 2

Table E.1 Transformation of log transformed variables from Chapter 2

Variable	Β	SE	Transformation
PCP supply (natural log)	-0.434*	0.188	-0.0043
NPs & PAs supply (natural log)	0.017	0.193	0.0002
Hospital bed supply (natural log)	0.099*	0.049	0.0010

***Significant at the 5% level.**

- A one percent increase in physician supply is associated with a 0.0043 unit decrease in the likelihood of a PPH, *ceteris paribus*.
- A one percent increase in hospital bed supply is associated with a 0.001 unit increase in the likelihood of a PPH, *ceteris paribus*.

Chapter 3

Table E.2 Transformation of log transformed variables from Chapter 3

Variable	Β	SE	Transformation
PCP supply (natural log)	-2.393*	0.314	-0.0239
NPs & PAs supply (natural log)	-0.185	0.182	-0.0019
Hospital bed supply (natural log)	0.085	0.053	0.0009

***Significant at the 5% level.**

- A one percent increase in physician supply is associated with a 0.0239 unit decrease in the likelihood of a PPH, *ceteris paribus*.

Chapter 4

Table E.3 Transformation of log transformed variables from Chapter 4

Variable	β	SE	Transformation
Acute ACSC			
PCP supply (natural log)	-0.020	0.204	-0.0002
NPs & PAs supply (natural log)	-0.479*	0.129	-0.0048
Hospital bed supply (natural log)	-0.009	0.075	-0.0001
Chronic ACSC			
PCP supply (natural log)	-0.103*	0.051	-0.0010
NPs & PAs supply (natural log)	-0.079	0.176	-0.0008
Hospital bed supply (natural log)	0.015	0.060	0.0002

***Significant at the 5% level.**

- A one percent increase in nurse practitioner and physician assistant supply is associated with a 0.0048 decrease in the likelihood of being hospitalized for an acute ACSC, *ceteris paribus*.
- A one percent increase in physician supply is associated with a 0.001 unit decrease in the likelihood of being hospitalized for a chronic ACSC, *ceteris paribus*.