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Professional Associations

- **Sigma Theta Tau, member,** 2012-present.
- **American Nurses Association,** 2004-present.
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Community Activities

- School Sector Working Group, Member — 2012 - Present
  "Live Well Sioux Falls" Community Transformation Grant
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- **Group Visits: FNP Health Assessment & Health Promotion in Primary Care,** University of Maryland Dean's Teaching Scholars Award: $5,000, 2011.

- **Geographic Information Systems to Support Quality Improvement in Health**, University of Maryland School of Nursing, Alumni grant: $15,000, 2009.

- **Penn North Community Health Clinic**, Baltimore, MD. With Harry Schwarz, LCSW, Tai Sophia Institute; Open Society Institute grant: $100,000, 2001.

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Special Awards

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ABSTRACT

Title of Dissertation: Quantifying Neighborhood-Level Social Determinants of Potentially Preventable Emergency Department Visits in Maryland

Name: Gina C. Rowe, Doctor of Philosophy, 2013

Dissertation Directed by: Meg Johantgen

Background: Potentially preventable hospital admissions (PPAs) and emergency department (ED) visits (PPVs) are those that might have been prevented if patients had received better primary care. A significant number of ED visits in the United States and about a third of those in Maryland are "ambulatory care sensitive," or potentially preventable. Geographic variation in PPV rates reflects community-level differences in primary care access, social determinants of health-seeking behavior, and health disparities. Higher rates are noted in poor communities and vulnerable populations.

Purpose: To compare and explain the geographic variance in Maryland PPV rates for total and uninsured populations and test the predictive value of regression models developed using generalized linear regression and geographic information systems. Analysis of geographic variance in PPV rates across the Baltimore metropolitan statistical area (MSA) used neighborhood-level social determinants to determine whether social capital can mediate the negative impact of living in a disadvantaged neighborhood on PPV rates.

Methods: Two cross-sectional, ecologic regression analyses of secondary data aggregated to the zip code tabulation level were conducted. Generalized linear and geographic regression models were built using SPSS and ArcGIS statistical software, and results were compared to determine which model(s) best explained geographic variance in PPV rates. Social capital measures were obtained from the Baltimore Ecosystem Study.

Results: In Maryland, geographic hot spots of increased PPV rates were highly correlated for uninsured and total populations, but uninsured PPV rates were more clustered in urban areas. Poisson and geographically weighted regression (GWR) models explained the most PPV rate variance. Significant predictors were per capita income, female-headed households, and level of education. In the Baltimore MSA, Poisson and GWR models predicted 85-86% of PPV rate variance; relative poverty and female-headed households were significant predictors but percent uninsured and per capita primary care physicians were not. Social capital was a significant partial mediator of all measures of neighborhood disadvantage reviewed.

Conclusion: Communities with high social capital may offer health-protective benefits to residents, even mediating the negative impact of living in a disadvantaged neighborhood. Reducing PPVs requires consideration of population-level health-seeking behaviors and promotion of neighborhood-level social capital, particularly for single mothers.

Quantifying Neighborhood-Level Social Determinants of Potentially Preventable Emergency Department Visits in Maryland

by
Gina C. Rowe

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, Baltimore in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
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DEDICATION

To the people of Baltimore City and the great state of Maryland, who with much charm, wit and grace have taught me all I know about nursing, public health and health care.

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CHAPTER 1
The Mediating Impact of Social Capital on Neighborhood-Level Social Determinants of Potentially Preventable Emergency Department Visits in Maryland

1.1 Introduction to Dissertation Research

Potentially preventable emergency department visits (PPVs) and hospital admissions (PPAs) are those that might have been prevented if patients had received better or higher quality primary care (Agency for Healthcare Research and Quality [AHRQ], 2001; Johnson, et al., 2012; Maslow & Ouslander, 2012; Steiner, 2010). This conceptualization has developed in response to the need to measure the impact of a lack of access to primary care within a particular health service delivery area as well as to explore health disparities at the population level. In fact, PPAs and PPVs are often used as a proxy measure for lack of access to care in a geographic area or among a subset of the population. In the U.S. over 8% of all emergency department (ED) visits and 10% of all hospitalizations are estimated to be potentially preventable (Johnson, et al., 2012; Stranges and Stocks, 2010). PPV and PPA rates vary geographically and reflect differences in primary care access characteristics (e.g., health services, built environment) and social determinants of health, such as income and education (Johnson, et al., 2012; Magan, Alberquilla, Otero & Ribera, 2011). While traditional statistical and graphical techniques can be used to examine geographical differences, advances in Geographic Information Systems (GIS) software and data have made these analyses more feasible for researchers and community planners.

This dissertation includes three completed manuscripts. The first manuscript is a literature review linking social determinants of health, primary care access, and PPVs and PPAs. The second manuscript is a spatial investigation of predictors of variance in the PPV rates for the total and uninsured populations in Maryland comparing generalized linear and

geographically weighted regression models. The third manuscript seeks to identify factors that best explain variance in PPV rates in the greater Baltimore Metropolitan Statistical Area (MSA), using indicators of social capital and social determinants aggregated to the neighborhood (ZCTA) level. A brief overview of the background and significance is presented first.

1.2 Background and Significance

1.2.1 Potentially Preventable Hospital Admissions (PPAs) Associated with Community Characteristics

In 2008, over one in ten hospital admissions was potentially preventable; 39% were for acute and 61% for chronic conditions (Stranges & Stocks, 2010). PPAs indicate both inadequate primary care access and health care system inefficiency, as care delivered in hospitals is more expensive than primary care (Moy, Barrett & Ho, 2011; Russo, Jiang & Barrett, 2007). PPA rates are higher in poor communities (Moy, et al.; Stranges & Stocks, 2010; Wier, Merrill & Elixhauser, 2009) and communities with less access to coordinated primary care (Bindman, et al., 1995). PPA rates in the U.S. decreased between 2004 and 2007, but excess PPA in poor areas (the difference in PPA rates between relatively poor and wealthy communities) still accounted for over 910,000 hospitalizations in 2007, at a cost of over $6.7 billion (Moy, et al.). Overall PPA rates were 22% higher in the bottom quartile of zip codes stratified by median income, and PPA rates for 45-64 year olds in these poorest communities were over 50% higher than rates in more well-off neighborhoods (Wier, et al.). Hospitalizations for those living in the poorest communities were about 45 percent more likely to be potentially preventable than hospitalizations for those living in wealthier communities (Stranges & Stocks).

1.2.2 Potentially Preventable Emergency Department Visits (PPVs) also Associated with Community Characteristics

From 1991 to 2009, total U.S. ED visits increased 44%, from 88.5 to 127.3 million, and the ED visit rate increased 18%, from 351 to 415 visits per 1,000 people (American Hospital Association [AHA], 2011). Meanwhile, total U.S. EDs decreased from 5,108 in 1991 to 4,594 in 2009 (AHA, 2009). More adults surveyed in 2011 about visiting an ED listed lack of access to other providers (79.7%) than listed seriousness of the medical problem (66.0%) as a reason for their last ED visit (Gindi, Cohen & Kirzinger, 2012). About 48.6 million Americans, or 15.7%, are currently without health insurance (DeNavas-Walt, Proctor & Smith, 2012), and even as coverage expands, there is concern regarding the ability of current primary care providers to meet growing demand and provide adequate access to primary care. These trends have led to ED overcrowding and renewed interest in strategies to reduce ED overuse (DeLia & Cantor, 2009; O'Shea, 2007; Taylor, 2011). The U.S. Government Accountability Office investigated six areas with ED overcrowding (Atlanta, Boston, Cleveland, Los Angeles, Miami and Phoenix) and learned that crowding was more likely to occur in large cities and areas with high population growth and/or high percentages of uninsured people (2003). Concerns also focus on non-urgent ED visits, which are costly and expected to increase as more people become insured under the Affordable Care Act (DeLia & Cantor; O'Shea; Taylor).

U.S. PPV estimates vary based on location, population and how such visits are defined. Most studies to date have focused on specific diagnoses and/or local or regional samples (Dulin, et al., 2010a; Ginde, Espinola & Camargo, 2008; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Menchine, Weichmann, Peters & Arora, 2012; Murday & Corley, 2008; Oster & Bindman, 2003: Plescia, Koontz & Laurent, 2001). Over half of U.S.

pediatric ED visits are estimated to be "non-urgent" (Berry, Brousseau, Brotanek, Tomany-Korman & Flores, 2008), and up to three-fifths of ED visits for Medicare patients are "potentially preventable" (Sadownik & Ray, 2012). Young Americans aged 20-29 years receive 22% of all their health care in the ED (Fortuna, Robbins, Mani & Halterman, 2010). In 2008, the National Hospital Ambulatory Medical Care Survey (NHAMCS) reported that 8% of U.S. ED visits were non-urgent, meaning that the patient could be seen in 2-24 hours (Centers for Disease Control and Prevention [CDC], 2011). In a separate analysis of 2007-2009 NHAMCS data, Johnson, et al. (2012) classified 8.4% of U.S. ED visits as potentially avoidable based on diagnoses classification as ambulatory care sensitive conditions (ACSC). Use of this classification scheme for PPVs is growing. The national rate of adult PPV for ACSC was fairly steady between 1997 and 2007, at about 8-10% of visits (Tang, Stein, Hsia, Maselli & Gonzales, 2010). PPV rates for ACSC among adults with Medicaid and Medicare, however, have steadily increased for over a decade (Cunningham, 2011; DeLia & Cantor, 2009; Tang, et al.; Zuckerman & Shen, 2004).

1.2.3 Ambulatory Care Sensitive Conditions (ACSC)

The Agency for Healthcare Research and Quality (AHRQ) uses the number of visits for ambulatory care sensitive conditions (ACSC) - diagnoses such as asthma, diabetes, and acute conditions that should not require hospitalization if properly managed in primary care - as a tool to monitor local safety net provider ability to meet the healthcare needs of low-income, vulnerable populations (AHRQ, 2003). In the past decade others have adopted this methodology to measure PPAs and PPVs. High PPA rates have been associated with lack of access to community health centers or other primary care in Colorado (Burns, Mcgloin & Westfall, 2005) and with Medicaid insurance coverage but not minority status or rural or

urban residence in South Carolina (Probst, Moore, Baxley & Lammie, 2003). Nationally, PPA for ACSC vary by as much as 20 times between high- and low-income areas in the U.S. (Billings, et al. 1996). Total U.S. PPV rates have also been shown to vary by payer category; of total adult PPVs in 2007, 15% were made by those who were uninsured, 26% were made by those with private insurance, 22% were made by those with Medicaid, and 31% were made by those with Medicare (Tang, Stein, Hsia, Maselli & Gonzales, 2010). A list of ACSC as defined by AHRQ and the related International Statistical Classification of Disease (ICD-9) codes is attached in Appendix A.

1.2.4 Need for Informed Decision-Making to Meet Growing Needs for Primary Care

As the ACA is implemented and approximately 32-34 million more people obtain health insurance coverage by 2019, total hospital and ED visits and those for ACSC are expected to increase (Draper, 2011; Goodman, 2010; Katz, 2010). ED use and costs increased 7% and 17%, respectively, after health care reform in Massachusetts (DeLia & Cantor, 2009). Preventable hospitalizations also increased in Oregon after Medicaid coverage expansion (Saha, Solotaroff, Oster & Bindman, 2007). Under the ACA, health centers are to expand and play a vital role in providing access to vulnerable populations; about $11 billion in funds over 5 years is earmarked for health center operation, construction and expansion (Draper, 2011). Well-situated health centers have the potential to minimize PPA and PPV by increasing primary care access and care coordination (Draper; Felland, Hurley & Kemper, 2008). Health inequities and primary care barriers are also implicated in higher PPA and PPV rates among minorities, low-income, and uninsured and Medicaid populations (Johnson, et al., 2012; Oster and Bindman, 2003; Laditka, Laditka & Mastanduno, 2003). These barriers

may stem from factors intrinsic to healthcare delivery or the physical and social environments where people live.

1.2.5 Social Determinants of Health and Social Capital's Potential Mediating Influence

Social determinants of health, such as socioeconomic status (SES), education, housing, transportation, insurance, minority status, discrimination, and social or environmental stressors, have been linked to health disparities (Koh, et al., 2010; Braveman, Cubbin, Egerter, Williams & Pamuk, 2010). Neighborhood SES characteristics (e.g., income, crime, unemployment rates) have been correlated to general health (Kawachi & Berkman, 2003), cardiovascular health (Diez Roux, et al., 2001; Foraker, et al., 2008; Sundquist, et al., 2005), diabetes (Auchincloss, et al., 2009), atherosclerosis (Moore, Diez Roux, Nettleton, Jacobs, & Franco, 2009), obesity (Escaron, 2009; Lopez, 2007; Lovasi, et al., 2009; Lovasi, Hutton, Guerra & Neckerman, 2009), and mental health (Galea, Ahern, Rudenstine, Wallace and Vlahov, 2005).

At the aggregate or neighborhood level, lower rates of income and education and higher proportions of minority populations have been associated by some studies with less access to primary care or higher PPA and PPV rates. Multiple studies with aggregate income measures have concluded that rates of PPAs/PPVs are higher in areas of lower income (Billings, Anderson & Newman, 1996; Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Finnegan, Gao, Pasquale & Campbell, 2010; Liu & Pearlman, 2009, McLafferty & Grady, 2004; Murday & Corley, 2008;Waidmann & Rajan, 2000; Zhan, Miller, Wong & Meyer, 2004; Zlotnick, 2004). Several studies have also found higher PPA/PPV rates in areas with higher rates of people with less education (Laditka, Laditka & Probst, 2005; Waidman & Rajan, 2000; Zhan et al., 2004) and higher proportions of

minorities (Chang, et al., 2008; Liu & Pearlman, 2009; Murday & Corley, 2008; Waidmann & Rajan, 2000.

Community-level social capital is thought to positively impact multiple aspects of community well-being and health and to moderate health disparities (Carlson & Chamberlain, 2003; Kawachi, Kennedy & Wilkinson, 1999), perhaps mediating the impact of living in a poor or disadvantaged neighborhood. Interest in studying social capital's effects on health has grown exponentially in the past 20 years (Kawachi, Subranmanian & Kim, 2008), largely due to its potential to mediate the negative impact of living in a poor, socially disorganized community. Yet, consensus on theoretical and operational definitions of social capital is lacking in both the sociological and health literature (Carlson et al.; Egan, Tannahill, Petticrew & Thomas, 2008; Lyles, 2009); no single definition or standard measure has yet emerged (Kawachi, et al., 2008).

The concept of social capital is rooted in social disorganization theory, which grew out of the early twentieth century ethnographic field work and ecological analysis of urban sociologists affiliated with the University of Chicago. The works of early "Chicago School" scholars, such as W.I. Thomas, Florian Znaniecki, Roderick McKenzie, Robert Park and Ernest Burgess, still impact urban sociology almost a century later. Key assumptions are that social disorganization is caused by rapid social changes and breakdown of community social controls and is characterized by areas of economic disadvantage and high crime. Shaw and McKay found inverse relationships between areas of low socioeconomic status and social organization and high crime and disease rates in multiple U.S. cities (1969/1942). W.J. Wilson later described concentrated economic and social disadvantage in poor, black urban areas resulting from the larger societal processes of that time, e.g., racial segregation,

suburban flight, job loss, and family disruption (1987). Robert Sampson extended social disorganization theory to include a new concept, social or collective efficacy, to explain why some communities, just as deprived and poor as their peers, are able to leverage informal controls and neighborhood cohesion to reduce crime (Sampson & Groves, 1989; Sampson, Morenoff & Gannon-Rowley, 2002; Sampson, Raudenbush & Earls, 1997). Collective efficacy is "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (Sampson, et al., 1997, p. 918). Sampson et al. viewed social disorganization and collective efficacy at opposite ends of the spectrum and posited that communities with high collective efficacy could mediate the negative impact of disorganization on crime and other aspects of community well-being.

Modern researchers are now applying social capital to study effects of neighborhood social structure on health outcomes (Pitkin Derose, 2008; Browning & Cagney, 2003; Kawachi & Berkman, 2003; Yen & Syme, 1999). Social disorganization theory and collective efficacy have always been firmly rooted in consideration of aggregate community or neighborhood processes impacting social behaviors. Social capital, however, traces conceptual derivation back to two schools of thought: 1) as a type of capital residing in the individual's and community's "social networks" (Bourdieu, 1979; Lin, 1999), or 2) as a multidimensional characteristic of communities roughly akin to "social cohesion" (Sampson, 1997, Wilkinson, 1996). The former is a "structural" and the latter a "cognitive" dimension of social capital, and reunion of both branches may be needed in order to accurately measure the concept (Lee & Kim, 2012; Kawachi, Subramanian & Kim, 2010). One definition that is conceptually sound, measurable, reliable and valid must be chosen for social capital, a multifactorial concept with multiple theoretical and operational definitions. Kawachi's (Kawachi,

Subramanian & Kim, 2010) and Kim's (Lee & Kim, 2012) definition of social capital, as an aggregate community trait, with a "cognitive" dimension of social cohesion and including some structural dimensions of social networks, in an aggregate survey of multiple components (social relationships, support, networks, organization membership, community involvement, norms & values, reciprocal activities, trust), seems most appropriate for public health. This Harvard-based research group has published the most work to validate and disseminate instruments to measure social capital. These instruments, however, can be costly and time-consuming to administer.

1.3 Manuscript 1 is presented in chapter 2: Community Level Determinants of Potentially Preventable Hospital and Emergency Department Visits in the United States: A Review

My first aim was to perform a narrative review of studies attempting to explain geographic variation in PPA or PPV in the U.S. at the aggregate level, using administrative units - states, counties, communities or census tracts - as the relevant units of analysis. In this manner, focus is placed on primary care characteristics and population-level social determinants of health-seeking behaviors. Search strategies included keyword searches in CINAHL and Medline and originally resulted in analysis of 23 studies attempting to explain geographic variance in PPAs, PPVs and various measures of primary care access, for which PPAs and PPVs are often used as proxy variables. Synthesis across studies was difficult, due to use of multiple differing geographic units of analysis, differing outcome measures and definitions, and differing explanatory variables. The studies of divergent measures of primary care access (e.g., self-reported health, use of healthcare, problems with access, breast exam in past year, early prenatal care, end-stage renal disease, etc.) were particularly difficult to amalgamate into a coherent review and indeed raised questions regarding the true nature of

the relationship between primary care access and PPAs and PPVs. Therefore, the manuscript included in Chapter 2 is a more focused analysis of 14 of these 23 studies, examining PPAs and PPVs only. The 14 studies reviewed were conducted in a various settings: single (8) or multiple (3) states; individual cities (1), regions (1) and within the national Veteran's Administration system (1). All 14 studies were descriptive: either cross-sectional (5), ecologic (7) or with both cross-sectional and ecologic components (2). Modeling and statistical analyses used were geospatial modeling and hot spot analysis (2), factor analysis (2) and regression analyses (12).

All 14 studies sought to identify and explain areas of increased need for primary care demonstrated by geographical variance in PPA and PPV rates, but firm conclusions about characteristics to explain increased PPA/PPV rates remains elusive. Several factors contributed to challenges in comparing results for these studies, including differing levels of data aggregation, definitions, operationalization and measurement of both outcomes and explanatory variables across studies. Geographic units of analysis included census block groups, census tracts, communities, zip codes, hospitals and hospital statistical areas, states, regions and urban versus rural measures. Outcome measures included PPA or PPV for ACSC, ACSC-related charges, repeat hospitalizations, and total ED utilization. Twelve of the 14 studies examined PPA/PPV for ACSC but ACSC definitions and conditions included varied widely, from single conditions (e.g., low back pain, asthma), to 6-12 conditions, to the full list as defined by AHRQ.

1.3.1 Multiple Explanatory Variables

Of the 14 studies reviewed, 12 included predictive measures of both primary care access ("supply" measures such as primary care physicians per population, hospital beds) and

social determinants ("demand" measures or socioeconomic factors such as census variables and measures of diversity), but explanatory variables used varied considerably across studies. On the "supply" side, numbers of primary care providers was negatively associated with PPA/PPV rates (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Dulin, et al., 2010; Hossain & Laditka, 2009; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Laditka, Laditka & Probst, 2005; Murday & Corley, 2008; Pitkin Derose, 2008; Zhan, Miller, Wong & Meyer, 2004). Several studies also indicated that higher PPA/PPV rates are more common in areas lacking community or safety net clinics (Hossain & Laditka, 2009; Pitkin Derose, 2008) or where distances to primary care clinics is greater (Finnegan, Gao, Pasquale & Campbell, 2010). Some studies concluded that PPA/PPV rates are higher in areas with large proportions of the population with public or no insurance (Chang, et al., 2008; Dulin, et al., 2010; Liu & Pearlman, 2009; Murday & Corley, 2008), but others found no association with insurance status (Chen, et al., 2009; Pitkin Derose, 2008).

1.3.2 Knowledge Gaps Identified

In spite of differences in definitions and measures of outcomes and explanatory variables, common findings across studies were that PPA rates were higher in geographical areas of lower income, lower average education, and fewer primary care physicians and community clinics, and also may be higher in areas with less social capital. Some studies associated higher rates of no insurance or public insurance status to higher PPA/PPV rates, but others did not. Likewise, some studies indicated that areas with large proportions of minorities were at increased risk for higher PPA/PPV rates, but others found no such association, or negative associations between minority status and increased rates. Far fewer studies examined PPV versus PPA rates and none examined PPV rates for all ACSC or used

regression to examine relationships at administrative units smaller than counties. Only one study looked at the association between social capital and PPA (Pitkin DeRose, 2008). No studies examined relationships between social capital and PPV rates.

Use of proxy measures for social capital facilitates analysis due to public accessibility of these data. But it is becoming clear that proxy variables and social capital measures without reliability and validity will likely continue to produce mixed results in research on associations between social capital and healthcare access, healthcare-seeking behaviors, and PPA/PPV rates.

1.4 Chapter 3 presents Manuscript 2: Geographic Variance in Maryland's Preventable Emergency Department Visits: Comparison of Explanatory Models

My second aim was to conduct a spatial investigation of predictors of variance in the PPV rates for the total and uninsured populations in Maryland using generalized linear and geographically weighted regression models, using a sample of total Maryland PPV for ACSC for fiscal 2008 and 2009, aggregated to the ZCTA level. In Maryland, about 715,000 residents, or about 14% of those under age 65, were uninsured in 2007-2008 (Maryland Health Care Commission, MHCC, 2010). Maryland ED visits increased from 1.5 to 2.4 million from 1990 to 2007 (Salamon, Cowdry, & Barclay, 2007). Little is published about PPA/PPV rates for overall and vulnerable populations in Maryland. In 2010 the PPA rate for ACSC for Medicare enrollees in Maryland was 62.7 per 1,000, down from 78.3 per 1,000 in 2000 and at the 50th percentile for all states (Dartmouth Atlas of Healthcare, 2013). Disparities are noted in Maryland Medicaid beneficiaries for PPA for ACSC, with African Americans experiencing higher rates than whites, at an annual excess cost of over $22 million for six common ACSC: hypertension, diabetes, adult asthma, dehydration, urinary tract infection and congestive heart failure (O'Neil, et al., 2010). Race is a risk marker, not a

risk factor, for PPA/PPV; i.e., race-based disparities quantify a high-priority problem but offer little in the way of actionable public health interventions. Identifying health disparities is an important start, but policy-makers need more information about modifiable risk factors, etiology of the problem, and potential solutions in order to know how to address disparities with evidence-based public health practices.

A third of all ED visits in Maryland are consistently classified as non-emergent and an additional 5-9% of visits as emergent but likely avoidable if the underlying condition had been treated earlier (Salamon, Cowdry & Barclay, 2007; Barclay, 2007; Schur, Mohr & Zhao, 2003). Rates of PPV for ACSC in Baltimore City were 294 to 333 per 1,000 in fiscal years 2002-2007, significantly higher than such rates in Baltimore County, Anne Arundel County, Harford County, the District of Columbia and Maryland overall for all age groups (Gresenz, Ruder & Lurie, 2009). Using the total ACSC method to define PPV, statewide rates for PPV in fiscal years 2008 and 2009 were lower, at about 19% of all non-admitted ED visits, and 80% of these were made by persons with insurance (Rowe, n.d.). Examination of place-based health disparities in PPV may offer insights into potential etiology and strategies to decrease such rates.

1.4.1 Conceptual Model Underlying Study

Flaskerud and Winslow's (1998) Vulnerable Populations Conceptual Model (VPCM) was used to guide the conceptualization and analyses for Manuscript 2. The model explains health disparities in vulnerable populations through proposed relationships between (1) low socioeconomic and environmental resource availability, such as access to care, (2) increased relative risk, and (3) impaired health outcomes such as morbidity and premature mortality. Empirical evidence supports the relationships described by the VPCM (Flaskerud, et al.,

2002; Flaskerud & Winslow), and its propositions have been tested (Bay, Kreulen, Shavers & Currier, 2006; Carr, 2006; Dyer, 2003; Flynn, Budd & Modelski, 2008; Rodehorst, Wilhelm, & Stepans, 2006) and blend well with what is known about health disparities, differential risks and differential resource availability in vulnerable populations (Flaskerud, 2002; Flaskerud, et al., 2002; Flaskerud & McQuiston, 2003; Kim, Flaskerud, Koniak-Griffin, & Dixon, 2005; Kim, Koniak-Griffin, Flaskerud, & Guarnero, 2004). Resource availability for residents of the ZCTAs was operationalized as aggregate social census and provider characteristics (per capita income and education levels reported by the U.S. Census Bureau and per capita primary care physician rates reported by the Health Resources Services Administration). Relative risk was operationalized as PPV rates.

1.4.2 Summary of Findings

Manuscript 2 aimed to: 1) compare the distribution of PPV in Maryland for the total populations and those uninsured; 2) explain the geographic variance in these, using socio-demographic census and provider variables aggregated to the ZCTA level; and 3) test the predictive value of two types of regression models developed using FY 2008 data in the FY 2009 dataset. Ordinary least squares (OLS) and geographically weighted regression (GWR) models in ArcGIS 10.0 and Poisson and negative binomial models in SPSS were fitted to the FY 2008 data on PPV for ACSC. Model performance was then evaluated using the FY 2009 data. Results demonstrated that geographic hot spots of increased PPV rates were highly correlated for uninsured and total populations, but uninsured PPV rates were more clustered in urban areas. The Poisson regression model best fit the data and predicted 52% and 46% of variance in FY 2009 total and uninsured PPV rates (AIC = 2052, 1069),

respectively. The GWR model also predicted 40% and 46% of variance in total and uninsured PPV rates, respectively, but fit the data less well (AIC = 2296, 1340).

At the ZCTA level, significant predictors of increased PPV rates in both the total and uninsured populations were percent of female-headed households, per capita income and percent of people with a high school diploma. Percent of vacant houses, disability, and cars per population were also significant predictors in the total but not the uninsured population. Number of primary care physicians per population, owner occupied housing rate and percent of houses in linguistic isolation were not significant predictors of PPV rates. GIS models also indicated that a significant predictor was missing from the explanatory variables included. New measures of population-level social and behavioral determinants of health are needed to understand and address PPV. The significant predictors identified here (percent of female-headed households, per capita income, percent of high school graduates) indicate that social determinants and social resources are key components in understanding how to decease PPV rates. (Rowe, n.d.).

1.5 Manuscript 3 is presented in Chapter 4: Social Capital, Neighborhood Disadvantage, and Potentially Preventable Emergency Department Visits in Metropolitan Baltimore

The third manuscript explores relationships between social determinants and PPV rates and the mediating influence of social capital, using the greater Baltimore Metropolitan Statistical Area (MSA) as the setting, with indicators of social capital and social determinants aggregated to the neighborhood (ZCTA) level. The specific aims were: 1) to identify the social determinants of health (e.g., poverty, income, education, female-headed households, percent minorities, insurance status) that best explained variance in PPV rates at the neighborhood (ZCTA) level in the greater Baltimore MSA, and 2) to determine if social

capital mediates the effects of poverty or other significant social determinants on PPV rates at this level.

1.5.1 Conceptual Framework for Studying Community Social Capital and PPVs

In Manuscript 2 a need to study an as-yet unexamined community-level social determinant of PPV rates was identified and led to an investigation of the concept of social capital. Manuscript 3 employs the social capital scale and data on social capital collected by the Baltimore Ecosystem Study (BES). The BES scale draws on questions from Kawachi and Kim's Social Capital Community Benchmark Survey and Sampson's validated collective efficacy measures (social cohesion) to capture data on multiple social capital dimensions (Walker, 2003). The survey's face, content and nomological validity can be validated in the same way used by Lee and Kim (2012), although convergent validity cannot be tested unless compared to another tool. The BES survey incorporates elements of both structural and cognitive social capital, measured at the aggregate community level, and had good evidence of internal consistency validity (Vemuri, Grove, Wilson, & Burch, 2011) when applied to that study's data.

Communities with high levels of social capital may offer health-protective benefits to their residents, even mediating the negative health impacts of living in a low-SES neighborhood on PPV rates. According to social disorganization theory, social processes at the population level result in increased residential mobility, weakened social controls and differential social determinants of health related to poverty. Health-seeking behaviors are primarily dictated by population social determinant characteristics (e.g., income, education, insurance status). It is hypothesized that community-level social capital can mediate the negative impact of poverty on PPV rates, perhaps simply by bolstering individual social

supports and resources. At the individual level, more social support may translate into more options for transportation, child care, health information, and social resources to facilitate timely primary care access, versus ignoring health needs until crisis states arise and emergent care is needed.

1.5.2 Summary of Findings

Based on previous analyses at the state-wide level, I hypothesized that aggregate rates of income, education and single-parent families would explain approximately 30% of the variance in PPV rates at the ZCTA level in the Baltimore Metropolitan Statistical Area. I also hypothesized that social capital would have a moderating effect on these social determinants. The study was a cross-sectional ecological analysis of geographic variation in per capita rates of PPV for ACSC in the 130 zip code tabulation areas (ZCTAs) of the Baltimore metropolitan statistical area (Baltimore City and County, Anne Arundel, Howard, Harford, and Carroll Counties). Geographically weighted and generalized linear models were built using ArcGIS 10.0 and SPSS 19 to examine potential social health determinant predictors (e.g., per capita income and other census variables related to educational levels, single-parent households, insurance and home ownership) of these PPV rates. Social determinant data were obtained from the Census Bureau, PPV data were obtained from the Maryland Health Services Cost Review Commission (MHSCRC) and social capital data were obtained from the BES. Bivariate analyses of each predictor were examined. Once the best models were fitted to the social determinant predictors, social capital was introduced to the models and analyzed as a potential mediating variable.

Social capital was found to have a mediating influence on all social determinant predictors examined. At the neighborhood or ZCTA level, the most significant predictor of

increased PPV rates was relative poverty, operationalized as percent of people with income less than twice the poverty level. By itself relative poverty explained 72% of neighborhood-level variance in PPV rates. The rate of female-headed households by itself explained 68% and social capital by itself explained 24% of PPV rate variance. Social capital was a partial mediator of both relative poverty and percent of households receiving public assistance and a full mediator of percent uninsured. The model with the best fit to the data (AIC = 515.36) explained 86% of the PPV rate variance; relative poverty, percent of households receiving public assistance, social capital and the interaction term between female-headed households and social capital were significant predictors of the variance in PPV rates. Multiple design, measurement and data issues were addressed in building appropriate statistical models, but certain limitations still apply to the results, including the cross-sectional design of the study, limitations of the tool used to measure social capital, clustering of both outcome and explanatory variables, and the ecologic fallacy which prohibits application of findings at the community level to individual level behavior.

Communities with high social capital offer health-protective benefits to residents and may mediate the negative impact of living in a disadvantaged neighborhood. Reducing PPVs requires consideration of population-level health-seeking behaviors and further investigation of the mediating effect of neighborhood-level social capital on poverty and other measures of neighborhood disadvantage. Strategies to reduce PPVs should consider ways to cultivate neighborhood-level social capital

1.6 Conclusions and implications for future research

Chapter 5 summarizes conclusions and practice, research and policy implications. Interest in reducing potentially preventable emergency department visits is increasing as

healthcare reform places renewed emphasis on prevention, access to quality care in appropriate venues, and cost containment. As medical homes become more common, fostering social capital at the community level is a potential strategy to facilitate better primary care access and more desirable health-seeking behavior at the population level.

CHAPTER 2
Community Level Determinants of Potentially Preventable Hospital and Emergency Department Visits in the United States: A Review[1]

2.1 Introduction

Potentially preventable hospital admissions (PPAs) and emergency department (ED) visits (PPVs) are those that might have been prevented if patients had received better or higher quality primary care (Agency for Healthcare Research and Quality [AHRQ], 2001; Johnson, et al., 2012; Maslow & Ouslander, 2012; Steiner, 2010). This conceptualization has developed to help understand the lack of access to primary care providers as well as to explore health disparities at the population level. In fact, PPAs and PPVs are often used as a proxy measure for lack of access to care in a geographic area or among a subset of the population. In the U.S. over 8% of all ED visits and 10% of all hospitalizations are estimated to be potentially preventable (Johnson, et al., 2012; Stranges and Stocks, 2010). PPA and PPV rates vary geographically and reflect differences in primary care access characteristics (e.g., health services, built environment) and population-level social determinants of health, such as income, education, and social capital (Johnson, et al., 2012; Magan, Alberquilla, Otero & Ribera, 2011). While traditional statistical and graphical techniques can be used to examine geographical differences, advances in Geographic Information Systems (GIS) software and data have made these analyses more feasible for researchers and community planners. This paper explores and summarizes the literature on geographic variation in PPA and PPV rates in the United States (U.S.) and associated community level factors. The review is limited to studies utilizing statistical or spatial models to explain geographic variance in these rates at aggregate levels.

1. G. Rowe, Accepted for peer review by *Health & Place* in November 25, 2013.

2.1.1 PPAs are associated with community characteristics

In 2008, over one in ten hospital admissions in the U.S. was potentially preventable; 39% were for acute and 61% for chronic conditions (Stranges & Stocks, 2010). PPAs indicate both inadequate primary care access and health care system inefficiency, as care delivered in hospitals is more expensive than primary care (Moy, Barrett & Ho, 2011; Russo, Jiang & Barrett, 2007). PPA rates are higher in poor communities (Moy, et al.; Stranges & Stocks; Wier, Merrill & Elixhauser, 2009) and communities with less access to coordinated primary care (Bindman, et al., 1995). PPA rates in the U.S. decreased from 1617 to 1510 visits per 100,000 population between 2004 and 2007, but excess PPA in poor areas (the difference in PPA rates between relatively poor and wealthy communities) still accounted for over 910,000 hospitalizations in 2007, at a cost of over $6.7 billion (Moy, et al.). Overall PPA rates were 22% higher in the bottom quartile of zip codes stratified by median income, and PPA rates for 45-64 year olds in these poorest communities were over 50% higher than rates in more well-off neighborhoods (Wier, et al.). Hospitalizations for those living in the poorest communities were more likely to be potentially preventable (11.7%) than hospitalizations for those living in wealthier communities (8.1%) in 2008 (Stranges & Stocks).

2.1.2 PPVs are also associated with community characteristics

From 1991 to 2009, total U.S. ED visits increased 44%, from 88.5 to 127.3 million, and the ED visit rate increased 18%, from 351 to 415 visits per 1,000 people (American Hospital Association [AHA], 2011). Meanwhile, total U.S. EDs decreased from 5,108 in 1991 to 4,594 in 2009 (AHA, 2009). These trends have led to ED overcrowding and renewed interest in strategies to reduce ED overuse (DeLia & Cantor, 2009; O'Shea, 2007; Taylor,

2011). The U.S. Government Accountability Office (2003) investigated six areas with ED overcrowding (Atlanta, Boston, Cleveland, Los Angeles, Miami and Phoenix) and learned that crowding was more likely to occur in large cities and areas with high population growth and/or high percentages of uninsured people.

Concerns also focus on non-urgent ED visits, which are costly and expected to increase as more people become insured under the Affordable Care Act (DeLia & Cantor; O'Shea; Taylor). About 48.6 million Americans, or 15.7%, are currently without health insurance (DeNavas-Walt, Proctor & Smith, 2012). Even as coverage expands, there is concern regarding the ability of current primary care providers to meet growing demand and provide adequate access to primary care. More adults surveyed in 2011 about visiting an ED listed lack of access to other providers (79.7%) than listed seriousness of the medical problem (66.0%) as a reason for their last ED visit (Gindi, Cohen & Kirzinger, 2012).

U.S. PPV estimates vary based on location, population, and how such visits are defined. Most studies to date have focused on specific diagnoses and/or local or regional samples (Ginde, Espinola & Camargo, 2008; Menchine, Weichmann, Peters & Arora, 2012; Oster & Bindman, 2003; Plescia, Koontz & Laurent, 2001). Over half of U.S. pediatric ED visits are estimated to be "non-urgent" (Berry, Brousseau, Brotanek, Tomany-Korman & Flores, 2008), and up to three-fifths of ED visits for older Medicare patients are "potentially preventable" (Sadownik & Ray, 2012). Young Americans aged 20-29 years receive 22% of all their health care in the ED (Fortuna, Robbins, Mani & Halterman, 2010). In 2008, the National Hospital Ambulatory Medical Care Survey (NHAMCS) reported that 8% of U.S. ED visits were non-urgent, meaning that the patient could be seen in 2-24 hours (Centers for Disease Control and Prevention [CDC], 2011). In a separate analysis of 2007-2009

NHAMCS data, Johnson, et al. (2012) classified 8.4% of U.S. ED visits as potentially avoidable based on diagnoses classification as ambulatory care sensitive conditions (ACSC). Use of this classification scheme for PPVs is growing. The national rate of adult PPV for ACSC was fairly steady between 1997 and 2007, at about 8-10% of visits (Tang, Stein, Hsia, Maselli & Gonzales, 2010). PPV rates for ACSC among adults with Medicaid and Medicare, however, have steadily increased for over a decade (Cunningham, 2011; DeLia & Cantor, 2009; Tang, et al.; Zuckerman & Shen, 2004).

2.1.3 Ambulatory care sensitive conditions (ACSC)

The Agency for Healthcare Research and Quality (AHRQ) uses the number of visits for ambulatory care sensitive conditions (ACSC) - diagnoses such as asthma, diabetes, and acute conditions that should not require hospitalization if properly managed in primary care - as a tool to monitor local safety net provider ability to meet the healthcare needs of low-income, vulnerable populations (AHRQ, 2003). In the past decade others have adopted this methodology to measure PPAs and PPVs. High PPA rates have been associated with lack of access to community health centers or other primary care in Colorado (Burns, Mcgloin & Westfall, 2005) and with Medicaid insurance coverage but not minority status or rural or urban residence in South Carolina (Probst, Moore, Baxley & Lammie, 2003). Nationally, PPA rates for ACSC vary by as much as 20 times between high- and low-income areas in the U.S. (Billings, Anderson & Newman, 1996). Total U.S. PPV rates have also been shown to vary by payer category; of total adult PPVs in 2007, 15% were made by those who were uninsured, 26% were made by those with private insurance, 22% were made by those with Medicaid, and 31% were made by those with Medicare (Tang, Stein, Hsia, Maselli & Gonzales, 2010).

2.1.4 Informed decision-making to meet growing primary care needs

As the ACA is implemented and approximately 32-34 million more people obtain health insurance coverage by 2019, total hospital and ED visits and those for ACSC are expected to increase (Draper, 2011; Goodman, 2010; Katz, 2010). ED use and costs increased 7% and 17%, respectively, after health care reform in Massachusetts (DeLia & Cantor, 2009). Preventable hospitalizations also increased in Oregon after Medicaid coverage expansion (Saha, Solotaroff, Oster & Bindman, 2007). Under the ACA, health centers are to expand and play a vital role in providing access to vulnerable populations; about $11 billion in funds over 5 years is earmarked for health center operation, construction and expansion (Draper, 2011). Well-situated health centers have the potential to minimize PPA and PPV by increasing primary care access and care coordination (Draper; Felland, Hurley & Kemper, 2008). Health inequities and primary care barriers are also implicated in higher PPA and PPV rates among minorities, low-income, and uninsured and Medicaid populations (Johnson, et al., 2012; Oster and Bindman, 2003; Laditka, Laditka & Mastanduno, 2003). These barriers may stem from factors intrinsic to healthcare delivery and/or the physical and social environments where people live. Multivariate geographic health care data analyses for decision support are needed now more than ever.

Multiple regression analyses of demographic and socioeconomic data related to PPA rates published in the 1990s identified income, race and insurance status as explanatory variables at the individual level, but few analyses were performed at the small area level (i.e., counties, zip codes or census tracts) during this time period (Davies, et al., 2001; Shi, et al., 1999). Interest in effects of place on health and use of geographic information system (GIS) technologies have both grown tremendously during the 21st century, providing additional

capacity to conduct spatial analyses and regression modeling of factors related to health at the neighborhood or other aggregate level (Berke, 2010). This paper reviews studies that attempt to explain geographic variation in PPA or PPV rates in the U.S. at the aggregate level, using communities, census tracts, counties, and states as the relevant units of analysis. In this way focus is placed on primary care characteristics and/or population-level social determinants of health-seeking behaviors.

2.2 Literature Review

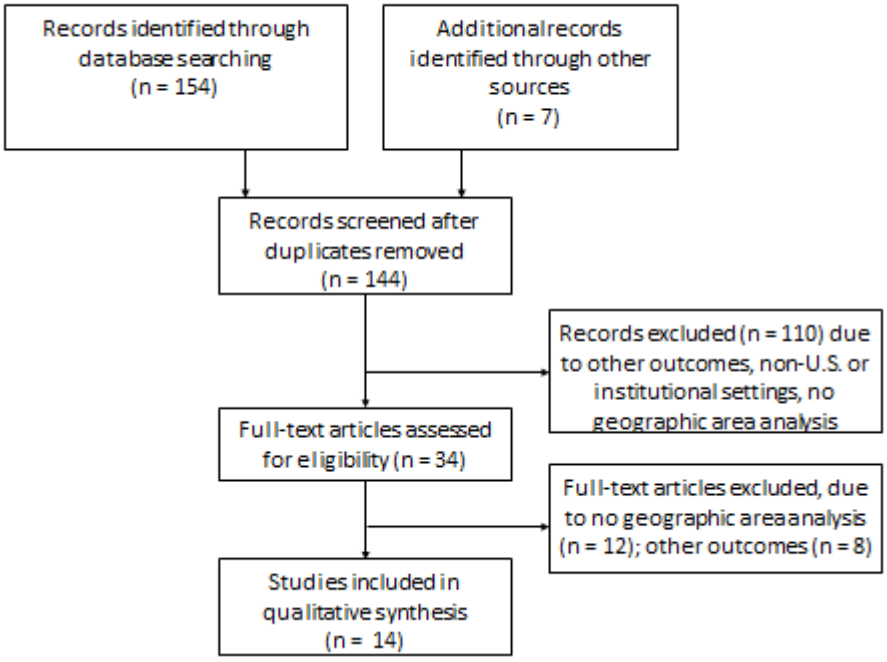
The purpose of this review is to summarize the literature on geographic variance in PPA and PPV rates among community-based populations, specifically focusing on statistical and spatial modeling of predictors and outcomes at the aggregate level.

2.2.1 Search strategies

Keywords selected included *ambulatory care, ambulatory care sensitive conditions, emergency service, emergency department visits, preventable hospital or hospitalization, health service misuse, geographic, geographic information systems, medically underserved areas primary health care*. Databases searched included the Cumulative Index to Nursing and Allied Health Literature (CINAHL) and Medline. A librarian assisted with keyword selection for database searches. Inclusion criteria included published articles seeking to explain predictors of geographic variation in PPA or PPV rates in the U.S. from 2001 to present (since the development of Quality Indicators, including PPA and PPV rates, by the Agency for Healthcare Research and Quality). Exclusion criteria included exploration of predictors of the outcomes of interest in other countries, in institutionalized populations, and based on individual characteristics without consideration of geographic context. Studies in other countries were excluded due to marked differences in health service delivery between

the U.S. and both developed and developing countries elsewhere. Studies of institutionalized populations (e.g., nursing home residents) were excluded due to different contextual influences on health-seeking behaviors between these populations in comparison to community-dwelling populations. Studies based on individual characteristics without geographic context have been reviewed in detail elsewhere and are briefly summarized above. A summary of the steps in the literature search and determination of articles for inclusion in the review appears in Figure 2.1.

Figure 2.1: *Summary of literature search and determination of articles for inclusion*



In all, titles and abstracts of 144 articles were reviewed and screened for inclusionary and exclusionary criteria; of these 34 articles were retrieved and read in full to determine the level of analysis (i.e., individual, census tract, hospital, county, state, regional) and appropriateness for inclusion. The final review includes 15 articles published between 2003 and 2010. Two articles by essentially the same group of authors on the same study,

published in the same journal (Dulin et al., 2010a; Dulin, et al., 2010b), are included together as one item, resulting in a total of 14 studies summarized. Ten studies examined predictors of PPAs, three studies investigated predictors of PPVs, and one study examined both outcome variables.

2.3 Results

The 14 studies are summarized in Table 2.1 and were conducted in a variety of settings: single states (eight); multiple states (three); individual cities (one), regions (one) and within the national Veteran's Administration system (one).

Table2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits*

Preventable Hospitalizations					
Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Chang, et al., 2008 Tennessee	Cross-sectional 10% random sample 217,911 inpatient discharges Individual: SD[b]; County-level: hospital characteristics	Logistic regression [HCUP[c] NIS[d] hospital in-patient discharge records, 2002-04; 2004 Area Resource File (ARF[e])]	Individual level: age, race, ethnicity, gender, insurance, health status, illness severity Hospital/county level: ED[f] vs. non-ED[f], Charleson index, urban vs. rural, percent in poverty, PCP[g]s per 1,000 population, region *(Both PCA[a] & SD[b])*	Potentially avoidable hospitalizations (PAH[h]s), based on acute and chronic ACSC[i] (Region, County)	Greater odds of PAH[h]s if public insurance or self-pay, minority race, in rural areas, in middle of the state, and in counties with higher proportion in poverty & fewer PCP[g]s; greater odds of PAH[h]s for chronic concerns in blacks but acute concerns in whites.
Chen, et al., 2009 United States: 4 regions: South, Midwest, Northeast, West	Ecologic Hospital charge data from 442 rural hospitals in 4 regions Hospital and County-level	Generalized estimating equation regression model [HCUP[c] NIS[d] hospital in-patient discharge records, 2002; 2002 ARF[e] and AHA[j] survey]	Hospital size, regional variables, other controls: hospital ownership. County-level variables, e.g., percent of population 65 & older, percent white, median household income, unemployment rate, PCP[g] per 10,000 population, mortality rate, # of rural health clinics, un-insurance rate. *(Both PCA[a] & SD[b])*	1) Total charges ($) for all ACSC[i]-related hospitalizations (ACSH[k]); 2) ACSC[i]-related charges as a percent of total hospital charges (4 U.S. Regions)	Rural hospitals in the South had the highest proportion of ACSC[i]-related charges (20.1%), followed by the Midwest (17.9%), Northeast (15.6%), and West (13.7%). This partly coincides with geographic variation in population SES[12] and PCP[g] supply; the South has the smallest PCP[g]-to-pop ratio, lowest per capita income and highest poverty rate.

Table2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits (cont.)*

Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Finegan, et al., 2010 Veterans hospitals in U.S.	Cross-sectional U.S. Veterans healthcare system Hospital and Individual-level	Multiple linear regression [1997-2007 veterans healthcare system data]	Case mix Low income veterans Patient travel time *(Both PCA[a] & SD[b])*	Hospitalization rates due to ACSC[i] (ACSH[k]) (Hospital/City)	Total ACSH[k] decreased by 58% but significant geographic variation remained; higher ACSH[k] among low-income veterans and those with travel times > 30 minutes to nearest VA provider.
Laditka, Laditka, & Probst, 2005 948 counties in 20 states	Ecologic 642 urban & 306 rural counties in 20 states County-level	Multivariate OLS regression, separate models for urban and rural areas [Safety Net Monitoring Initiative, AHRQ[m], ARF[e], AHA[j], Claritas, U.S. Census, FBI[n] Crime Reports, CMS[o], HRSA[p], EPA[q]]	Primary Care/Area Characteristics: rates of primary care physicians and short-term hospital beds per population, percent investor-owned hospitals, community health center numbers, ED[f] visit rate, Medicaid generosity Environmental quality: percent annual days with unhealthy air Aggregate Individual Risk: percent minority; high school education; FHH[r]; low or high income households; crime rate; disability, chronic obstructive pulmonary disease, diabetes, liver, heart disease death rates *(Both PCA[a] & SD[b])*	Hospitalization rates for ACSC[i] (ACSH[k]) for children (0-17 years old), younger adults (18-39 years old) & mid-adult (40-64 years old) (County)	Urban Models: Physician supply significantly associated with lower ACSH[k] rates in all age groups, with largest effect on ACSH[k] risk reduction in children. In adults, percent Hispanic, Native American, high income, and physician supply were associated with lower ACSH[k] rates. Lower education and more hospital beds associated with higher ACSH[k] risks. Rural Models: Physician supply not a significant predictor of ACSH[k] rate.

Table 2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits (cont.)*

Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Laditka, Laditka, & Probst, 2009 Counties in 8 states	Ecologic 8 states County-level	Multiple linear regression	Rurality *(PCA[a])*	ACSC[i] hospitalization (ACSH[k]) rates (County)	ACSH[k] rates for children did not vary with rurality. Adjusted adult rates generally increased with level of rurality.
Hossein & Laditka, 2009 South Carolina	Ecologic N = 46 counties, 2001 population > = 18 years old County-level	Spatial structural equation modeling & confirmatory factor analysis for latent variable identification	Population (poverty, ethnicity, income, unemployment); Physician practice behavior (supply of physicians & beds); Population tendency to use healthcare (rural residence, HMO[t] penetration, elective procedures); Prevalence (disability, mortality, marker & chronic conditions) *(Both – PCA[a] and SD[b])*	Hospitalization rates for 12 adult ACSC[i]: diabetes & complications, asthma, urinary tract infection, chronic obstructive pulmonary disease hypertension, dehydration, bacterial pneumonia, angina, congestive heart failure. (County)	Cluster analysis identified similar areas of higher hospitalization rates for 11 of 12 ACSC[i]. Counties with high rates had less primary care access and no community health centers as well as unhealthful lifestyles, inadequate physician practice behaviors, low tendency to use healthcare and high disease prevalence rates.
Joines, et al., 2003 North Carolina	Ecologic , cross-sectional N = 100 counties, 1990-92 discharge data County-level	Non-spatial and spatial OLS[s] regression models, spatial weights & lag models applied due to clustering & autocorrelation. [state hospital discharge data]	SES[l] & health resource: percent urban, employed in heavy lifting/ transportation, college graduates, non-whites, disabled; PCP[g] density, MRI/CT scanner availability, hospital bed density, discharge rates. *(Both – PCA[a] and SD[b])*	Surgical & medical hospitalization rates for low back problems (County)	Rates varied widely by county; both spatial effects and population SES[l] and health resource characteristics were determinants of variation in low back problem hospitalization rates.

Table 2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits (cont.)*

Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Liu & Pearlman, 2009 Rhode Island	Cross-sectional N=452 children Individual and census tract level	Cox proportional hazards model [state discharge database 2001-2005, census]	Individual: insurance, race, sex, age at 1st admit, length of stay, live in hospital zip code. Census tract: rates of crowded housing, racial minorities, neighborhood-level poverty *(Both –PCA[a] and SD[b])*	Repeat pediatric hospitalizations for asthma (Individual)	Higher readmission rates associated with Medicaid coverage; all three neighborhood inequality indices also associated with high readmission rates.
Pitkin Derose, 2008 Florida	Ecologic; cross-sectional N = 837 zip codes (Zip Code Tabulation Areas) Zip code level	Multivariate linear regression analyses [Multiple Florida state databases]	Primary care & social capital resources: hospital discharges & SES[l] factors (percent urban, uninsured, female, black, high school education, households with married couples, families below poverty; median age), diversity & voting indices, faith congregations, nonprofit organizations, mean commute times, distance to safety net provider, number of PCP[g]s, hospital beds *(Both – PCA[a] and SD[b])*	Preventable hospitalizations (PH[u]: asthma, congestive heart failure, chronic obstructive pulmonary disease, diabetes, hypertension) (Zip code tabulation area)	Longer mean commute times (lower bonding social capital) related to higher adult PH[u] rates; more racial/ethnic diversity (bridging social capital) related to lower nonelderly adult & higher pediatric rates; more faith-based organization (linking social capital) related to higher nonelderly adult rates. Safety net clinic within 20 miles related to lower adult rates; more pediatricians related to higher pediatric rates.
Zhan, C. et al., 2004 22 U.S. states	Cross-sectional N = 2,814 hospitals in 932 urban counties Individual and County/hospital level	Multiple logistic regression [HCUP[c] State In-Patient Databases (SID), AHA[j] annual survey, HRSA[p] ARF[e]s, 1998]	Individual Level: age, gender, race County Level: HMO[t] penetration, population characteristics (percent in poverty, unemployed, with college degree), healthcare capacity, mortality rates. *(Both – PCA[a] & SD[b])*	Preventable hospitalizations (PH[u]) for 14 ACSC[i]; county rates based on hospital site vs. patient residence. (County, hospital)	3.8% decrease in PH[u] related to 10% increase in HMO[t] penetration. Higher rates of PH[u] related to lower SES[l], advanced age, poor health, lower supply of PCP[g], higher supply of hospital beds.

Table 2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits (cont.)*

Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Murday & Corley, 2008 South Carolina	Mixed ecologic/case study – South Carolina N = 46 counties County	GIS[v] hot spot analysis: county to state ratio of ACSC[i] hospitalization rates, ACSC[i] as % of discharges. [statewide hospital database]	Access to primary care, regular PCP[g], SES[l] factors (race, income, insurance coverage). Described structural, financial & personal/cultural barriers to primary care access. *(Both – PCA[a] and SD[b]).*	Hospital/ED[f] visit rates for pediatric ACSC[i]: asthma; pneumonia; diabetes mellitus, dehydration; skin & ear, nose and throat infections; gastroenteritis; vaccine-preventable diseases (County)	Identified high visit rates for ACSC[i] by county; high rates significantly associated with no PCP[g], race, income, insurance coverage. New services resulted in lower rates in targeted counties.
Preventable Emergency Department Visits					
Dulin, et al., 2010a; Dulin, et al., 2010b Charlotte (Mecklenburg County), North Carolina	Ecologic N = 143 census tracts; vertically integrated health system (187,000 ED[f] visits; 50,000 primary care patients) Census tract	Geospatial model: CBPR[w]-developed, weighted index - Multiple Attribute Primary Care Targeting Strategy (MAPCATS); factor analysis to validate. [Carolinas Healthcare System, Claritas: U.S. census-data]	MAPCATS Index: SES[l] (median household income), population density, preventable ED[f] visits, insurance status (uninsured & Medicaid equally weighted); primary care safety net clinic use = protective factor. *(Both – PCA[a] and SD[b])*	Target areas identified by MAPCATS need increased primary care access to reduce preventable ED[f] use, for vulnerable and Hispanic populations. (Census tract)	Inappropriate ED[f] use related to population density & uninsured or Medicaid insurance. Individual & composite maps identified optimal places to increase primary care access for vulnerable populations, (Hispanics), and reduce primary care preventable ED[f] use.

Table 2.1: *Summary of studies of geographic variance in preventable hospitalizations and emergency department visits (cont.)*

Author (Year), Study Location	**Study Design, Sample, Unit(s) of Analysis**	**Model Methods: Spatial/Inferential Statistics [Data Sources]**	**Primary Care Access and/or Social Determinants (PCA[a]/SD[b])**	**Dependent Variable (Level)**	**Key Findings**
Lee, et al., 2007 Mississippi	Ecologic N = 89 hospital ED[6] service areas & 2148 census block groups Hospital service areas census block groups	Logistic regression [state ED[f] visit database, U.S. census data]	Census block group: Geographic travel distance and proportions of minority, elderly, female householders, high median house values, those with > 12 years education, unemployed, and poor populations. *(Both – PCA[a] and SD[b])*	ED[f] utilization; averaged travel distance to ED[f] (Census block group; Hospital service area)	Shorter distances were related to increased ED[6] use, even after controlling for SES[l] factors; travel distance > 5 miles reduced ED[f] use in disadvantaged block group areas.
Zlotnick, 2006 California	Cross-sectional; survey & medical record abstraction tool. N = 174 Medicaid-insured children & families. Individual surveys compared to community-level indictors (census tract, MUA[x]s)	Logistical regression; census tract characteristics matched to residence in MapInfo GIS[v] [Surveys, U.S. census data, HRSA[p] – MUA[x]s]	Individual level: income, biological parent vs. other. Community level: living in MUA[x], living in census tract with at least 10% of households reporting annual income < $12,000 *(SD[b]-Social determinants)*	Pediatric non-urgent ED[f] use, age-appropriate immunization levels (Individual)	Individual level: Low-income families (< $12,000) twice as likely to have non-urgent ED[f] use. Community-level: living in MUA[x] better predicted non-urgent ED[f] use than individual level indicators.

[a] PCA: primary care access, [b] SD: social determinants, [c] HCUP: Healthcare Cost & Utilization Project , [d] NIS: Nationwide In-patient Sample, [e] ARF: Area Resource File , [f] ED: emergency departments, [g] PCP: primary care physician , [h] PAH: potentially avoidable hospitalization, [i] ACSC: ambulatory care sensitive conditions, [j] AHA: American Heart Association, [k] ACSH: ambulatory care sensitive hospitalizations, [l] SES: socioeconomic status, [m] AHRQ: Agency for Healthcare Research & Quality, [n] FBI: Federal Bureau of Investigation, [o] CMS: Centers for Medicare and Medicaid Services, [p] HRSA: Health Resources and Services Administration, [q] EPA: Environmental Protection Agency, [r] FHH: Female-headed Households, [s] OLS: ordinary least squares, [t] HMO: Health maintenance organization, [u] PH: preventable hospitalization, [v] GIS: Geographic Information System , [w] CBPR: community-based participatory research, [x] MUA: medically underserved area

All 14 studies reviewed were descriptive in design: five were cross-sectional, seven were ecologic and two had both cross-sectional and ecologic components. Modeling and statistical analysis techniques used included geospatial modeling and hot spot analysis in two studies (Dulin, et al., 2010a and 2010b; Murday & Corley, 2008); factor analysis in two studies (Dulin, et al.; Hussain & Laditka, 2009); and regression analyses in 12 studies (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Finnegan, Gao, Pasquale & Campbell, 2003; Hossain & Laditka, 2009; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Laditka, Laditka & Probst, 2005; Laditka, Laditka & Probst, 2009; Lee, et al., 2007; Liu & Pearlman, 2009; Pitkin Derose,2008; Zhan, Miller, Wong & Meyer, 2004; and Zlotnick, 2006).

Units of geographic analysis varied between studies; some used multiple units, including census block groups, census tracts, "communities," zip codes, hospital service areas, medically underserved areas, states, and regions. All 14 studies examined PPAs and/or PPVs related to ACSC, but terms, definitions and conditions varied considerably. Terms used included potentially preventable hospitalizations, preventable hospitalizations, ambulatory care sensitive hospitalizations, hospitalizations and/or ED visits or visit rates for ACSC and ACSC-related charges, repeat hospitalizations, and total ED utilization. The ACSC definition and conditions included in each study varied widely, from single conditions (e.g., low back pain, asthma) in some studies, to 6-12 conditions in others, to the full list of ACSC as defined by AHRQ. Predictor variables also varied greatly in terms of both units of geographic analysis and potential predictors included. However, most predictor variables could be broadly classified into either aggregate primary care access "supply" measures (e.g., number of primary care physicians per population, number of hospital beds) or social determinant

"demand" measures (e.g., sociodemographic factors, such as census variables and measures of diversity). Of the 14 studies reviewed, 12 included predictive measures of social determinants and primary care access, one (Zlotnick, 2006) included only social determinant measures and one (Laditka, Laditka, & Probst, 2009) included only a primary care access measure.

2.3.1 Analytical methods

Geospatial modeling

Two studies in the Carolinas used spatial statistics or indices to analyze geographic variation in health resource utilization. Both studies sought to identify "hot spots" or areas of increased needs and fewer resources relative to other areas within a state or metropolitan area. Units of analysis used were counties within a specific state and census tracts within a metropolitan area studied. Dulin et al. (2010a & 2010b) conducted an ecologic analysis of 143 census tracts in and around Charlotte, North Carolina, in order to identify optimal places to increase primary care access for vulnerable populations, thereby reducing preventable ED use. They developed a weighted index of increased health needs, the Multiple Attribute Primary Care Targeting Strategy (MAPCATS). Factor analysis was used to validate the elements (median household income, population density, preventable ED visits, insurance status and primary care safety net clinic use) of the index at the census tract level, and then potential areas for future primary care clinics were identified. A mixed ecologic-case study conducted by Murday & Corley (2008) to analyze PPA and PPV rates identified counties with higher PPV rates for pediatric diagnoses and followed up with county representatives to develop proposals to improve primary care. A decrease in PPV rates was observed in the targeted

counties in the three years following program implementation, but state-level average PPV rates also declined during the same time period.

Both of these studies sought to identify areas of relative increased need for primary care by analyzing preventable ED visits as an important component. Health needs-based indices have not been widely used in the U.S., although such indices are commonly used in other countries, such as those historically belonging to the British Commonwealth, e.g., the United Kingdom, Canada, New Zealand, Australia (Bagheri, Holt & Benwell, 2009). However, it is difficult to ascertain the validity and reliability of such indices as tools to identify areas of increased primary care health needs. In the U.S., the methodology used to identify health professions shortage areas and MUAs is under review but has not changed in over 40 years.

Factor analysis

Two studies used factor analysis as part of their statistical analysis, to evaluate the validity of measures of increased health needs based on social determinants. Dulin, et al. (2010a & 2010b) used factor analysis to assess the validity of the MAPCATS index of increased primary care need. Hossain and Laditka (2009) used confirmatory factor analysis to attempt to identify any latent variables in the physician supply and social health determinant predictors assessed. Both these studies used factor analysis in conjunction with other statistical methods, e.g., Hossain and Laditka used spatial structural equation modeling and cluster analysis to identify predictors of areas with higher PPA rates for eleven identified ACSC.

Regression

Regression was used in 12 of the studies reviewed, including general estimating equation regression (Chen, Zhang, Sun & Mueller, 2009), a Cox proportion hazards model (Liu & Pearlman, 2009), and multivariate logistic regression (Chang, Mirvis & Waters, 2008; Zhan, Miller, Wong & Meyer, 2004; and Zlotnick, 2006), multivariate linear or ordinary least squares regression (Finnegan, Gao, Pasquale & Campbell, 2003; Lee, et al., 2007; Hossain & Laditka, 2009; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Laditka, Laditka & Probst, 2005; Laditka, Laditka & Probst, 2009; Pitkin Derose,2008). The most commonly used type of statistical analysis modeling was some form of multiple regression. Units analyzed included states, counties, zip codes, metropolitan statistical areas, hospital-level populations, census tracts and block groups, with counties being the unit level of analysis employed most frequently. None of the studies reviewed used geographically weighted regression, a regression technique which became widely available with the introduction of ArcGIS 9.3 by the Environmental Systems Research Institute, Inc. (ESRI) in 2008 (ESRI, 2008).

2.3.2 Predictors of PPAs

Potential predictors of PPA rates examined at aggregate community (census tract/ county/state levels) included aggregate demographic and socioeconomic (SES) variables (e.g., per capita income, proportion of people/families in poverty, education levels, median age, insurance and marital status, and urbanity-rurality); health resource variables (e.g., numbers of primary care physicians per capita, clinics or community clinics in an area, available hospital beds, travel distance to primary care); health/disease prevalence measures, and social capital measures (e.g., mean commute time to work, relative diversity, voting

indices, numbers of faith-based congregations and nonprofit organizations). In terms of demographic and SES variables, higher PPA rates were noted in community-level aggregate measures of lower SES (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Finnegan, Gao, Pasquale & Campbell, 2010; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Laditka, Laditka & Probst, 2005; Liu & Pearlman, 2009; Zhan, Miller, Wong & Meyer, 2004), lower education (Laditka et al., 2005), higher proportions of crowded housing (Liu & Pearlman) advanced age (Zhan, et al.), increased numbers of racial minorities (Liu & Pearlman), fewer Hispanics and Native Americans (Laditka, et al., 2005), and increased level of rurality for adults but not for children (Laditka, Laditka & Probst, 2009). Regarding health resource variables, higher PPA rates were found in areas with fewer primary care physicians (Chang, et al.; Chen, et al.; Laditka, et al., 2005; Zhan, et al.), more pediatricians (Pitkin Derose), less access to primary care (Hossain & Laditka, 2009), greater travel distance to primary care (Finnegan, et al.; Pitkin Derose, 2008), and increased access to hospital beds (Joines, et al., 2003; Laditka et al., 2005; Zhan, et al.). Higher PPA rates were also found in areas with poorer health or lifestyle factor measures and higher disease prevalence (Hossain & Laditka; Zhan, et al.).

Pitkin Derose (2008) conducted a regression analysis of the impact of multiple variables, including proxy measures for social capital, on PPA rates for 5 ACSC in Florida. This analysis used aggregate community characteristics at the Zip Code Tabulation Area (ZCTA) level and adjusted for multiple health resource, demographic and SES variables in addition to measures of social capital (neighborhood diversity index, relative diversity, voting indices, numbers of faith-based congregations and nonprofit organizations, percent uninsured) as potential predictors of increased PPA rates. Longer mean commute times and

more faith-based organizations were related to higher PPA rates in non-elderly adults but not in other age segments of the population; increased racial/ethnic diversity was associated with lower non-elderly adult but higher pediatric PPA rates (Pitkin Derose, 2008). This was the only study reviewed to examine measures of social capital as potential predictors of community-level PPA rates.

2.3.3 Predictors of PPVs

There are fewer studies examining potential community-level predictors of PPV rates than of PPA rates; only four studies seeking to explain the variance in PPV rates at community-levels were located using the designated inclusion and exclusion criteria (see Table 1). Dulin, et al. (2010a & 2010b) used factor analysis to develop and validate a weighted index of increased health needs which included preventable ED use, as well as four other elements (median household income, population density, and insurance status and primary care safety net clinic use) to identify optimal census tracts in which to increase primary care access for vulnerable populations, specifically Hispanics, in Charlotte, NC. Murday & Corley (2008) analyzed PPA and PPV rates for pediatric diagnoses and identified counties with increased rates in North Carolina; they then followed up with targeted county representatives to develop mutually agreeable proposals to improve primary care. In Mississippi, Lee, et al. (2007) noted increased ED utilization associated with shorter travel distances, even after controlling for other SES factors; travel distances of greater than 5 miles were associated with reduced ED use in disadvantaged block group areas. Zlotnick (2006) found that simply living in a Medically Underserved Area (MUA), a community-level indicator, was better at predicting non-urgent ED use in children than individual-level indicators, such as family income. Two of these four studies were conducted in pediatric populations.

2.4 Discussion

The results of these 14 studies of geographical variance in primary care access and preventable hospital and ED visits are somewhat mixed, and firm conclusions regarding the characteristics that may explain increased PPA and PPV rates remain as elusive at the aggregate community level as at the individual level. Several factors make comparing and contrasting the results of these 14 studies challenging, including differing levels of aggregation of data, differing definitions, and differing measures of both outcomes and explanatory variables across studies.

2.4.1 Multiple levels of data aggregation

Although data were most commonly aggregated to the county level, some studies aggregated data to the census block group or census tract, hospital, metropolitan statistical area, zip code, state, or even regional level. Different types of health and health-related data are more easily accessible at the levels at which they are most commonly collected. For example, data on numbers and kinds of primary care providers is collected by governing professional organizations such as state medical and nursing boards by address of practice and/or residence; thus, these data are relatively easy to aggregate to the zip code or state level. Health data and vital statistic data are generally collected and statistics disseminated at the county level, by city and county health departments, and thus are more easily obtained at this level. Hospital discharge data with identifiers, which is protected health information, may be aggregated by hospital or at the state level. Data with patient pseudo-identifiers can be obtained with special protections and firm data use agreements.

Census data were traditionally based on the decennial census long form sample, last used in the 2000 decennial census, which collected data for 20 percent of the U.S. population

(U.S. Census Bureau, 2008). Since 2000, census data has been collected through the American Community Survey (ACS), based on a much smaller sample of 2-3 million U.S. household interviews, or less than one percent of the enumerated population (U.S. Census Bureau, 2008). Due to small sample size, ACS data are therefore reported in multi-year estimates for geographic areas of less than 65,000 (U.S. Census Bureau, 2008). This makes consideration of all of the census tracts or metropolitan statistical areas (MSAs) within the country or a given state of interest difficult since every state has census designated places and census tracts with fewer than 65,000 population. Therefore, although census tracts and block groups most accurately reflect community or neighborhood characteristics – compared to counties or zip codes – they have often proved logistically difficult to work with or outdated when choosing a level of data aggregation. The studies that used census tracts or block groups in this review (Dulin, et al., 2010a & 2010b; Lee, et al., 2007; Liu and Pearlman, 2009; Zlotnick, 2006) were either working with smaller target areas (i.e., single metropolitan areas, small states or portions of a state) or using older data (2000 or older census data). Only one study used zip code or ZCTA-level aggregation of data. As described in the results section, Pitkin Derose (2008) conducted detailed analyses of PPA rates in Florida using multiple explanatory census and other variables. Zip codes allow easy aggregation of lists of addresses, such as those commonly used to collect data on primary care provider numbers, locations of care, and other health-related site-specific data. Zip codes have long been considered a less than ideal level of data aggregation due to their frequent realignments and reliance on postal delivery habits, but the newer ZCTA designations of the U.S. Census Bureau should prove somewhat more stable (2001).

Modifiable ariel unit problem (MAUP)

Spatial aggregations of data are subject to the Modifiable Ariel Unit Problem (MAUP), particularly for larger administrative units, such as states, counties, cities and zip codes. Thematic mapping assumes that incident data are normally or evenly distributed across space, which is generally not true and unlikely with variables examined in these types of analyses. MAUP arises when data on non-uniform spatial phenomena at multiple scales are aggregated into administrative units for spatial data analysis; the results are sensitive to the sizes and shapes used to define such administrative units (Jelinski & Wu, 1996). MAUP applies to two related spatial data analysis problems: 1) the scale problem, illustrated by differing results when incident or "point" data are aggregated to units of different size, and 2) the zoning problem, resulting from aerial units the same size but located differently, thus resulting in variation in data aggregated to each unit. Data aggregated into arbitrarily sized and shaped administrative boundaries can mask hot spots, resulting in drawing attention to larger areas than desired, and making true hot spot identification difficult. Such exploratory data methods, however, can be meaningful in identifying smaller areas for further analysis, and data aggregation to administrative units can be advantageous when it facilitates concurrent analysis of demographic data and other trends commonly collected with census units.

Public health researchers often are limited to use of aggregated secondary data, due to the protected and sensitive nature of health data and current surveillance mechanisms. Thus, such spatial analyses will always be subject to the distorting effects of MAUP. But as the utility of GIS applications in public health research is increasingly demonstrated to policy-

makers, more data aggregated at more appropriate units, with fewer distorting effects, such as census tracts and block groups, are becoming available to public health researchers.

2.4.2 Multiple definitions and measures of outcomes

Ten studies examined determinants of PPA rates, three studies examined PPV rates and one study investigated determinants of both. All 14 of the studies examined potentially preventable hospitalization or ED visits, and 12 of these defined such visits in terms of ACSC. The other two studies examined total and non-urgent ED utilization. Although the majority of studies used definitions of potentially preventable visits that employed the term ambulatory care sensitive conditions, terms and measures used varied, including hospitalization and /or ED visits or visit rates for various age groups, ACSC and ACSC-related charges, repeat hospitalizations, and total ED utilization. ACSC definitions and conditions included varied widely, from single conditions (e.g., low back pain, asthma) in some studies, to 6-12 of the "most common" conditions in others, to the full list of ACSC as defined by AHRQ.

2.4.3 Multiple explanatory variables

Most predictor variables could be broadly classified into either aggregate primary care access, or health resource, measures (such as number of primary care physicians per population, number of hospital beds), or social determinant/behavioral measures (e.g., demographic and SES factors, including census variables and measures of diversity). Of the 14 studies reviewed, 12 included predictive measures of both primary care access and social determinants, but the explanatory variables used varied considerably across studies.

Primary care access

On the "supply" side, numbers of primary care providers was negatively associated with PPA and PPV rates (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Dulin, et al., 2010; Laditka, Laditka & Probst, 2005; Hossain & Laditka, 2009; Joines, Hertz-Picciotto, Carey, Gesler & Suchindran, 2003; Murday & Corley, 2008; Pitkin Derose, 2008; Zhan, Miller, Wong & Meyer, 2004), with the exception that Pitkin Derose found more pediatricians per capita associated with higher pediatric PPA rates in Florida. Several studies indicated that increased PPA and PPV rates are more common in communities or counties lacking community or safety net clinics (Hossain & Laditka, 2009; Pitkin Derose, 2008), or where distances to primary care clinics is greater (Finnegan, Gao, Pasquale & Campbell, 2010; Pitkin Derose). Several studies also indicated that increased numbers of available hospital beds may result in higher PPA rates (Laditka, et al., 2005; Joines, et al., 2003; Zhan, et al., 2004), suggesting hospital-induced demand. Some studies concluded that risk for PPAs and PPVs is higher among those with public or no insurance (Chang, et al., 2008; Dulin, et al., 2010; Liu & Pearlman, 2009; Murday & Corley, 2008), but others found no association between PPA rates and insurance status (Chen, et al.; Pitkin Derose).

Per capita primary care physicians is a measure that is generally available and widely accepted as a primary care access measure in the U.S., and it has been used in needs assessments for geographical designation as a Health Professions Shortage Area or Medically Underserved Area for over 40 years. Data on the numbers of nurse practitioners and physician's assistants, which would increasingly help provide a more comprehensive picture of primary care resources available, have been more difficult to obtain than the data on physicians collected nationally by the American Medical Association and shared with the

Health Resources and Services Administration. Data on non-physician primary care providers can be requested from state Boards of Nursing and Medicine; however, none of the studies included in this review did so.

Social Determinants

On the "demand" or social determinants side, lower income, lower education, higher proportions of minority populations and lower social capital were associated by some studies with higher PPA or PPV rates. The strongest evidence supported an association between lower income and higher PPA/PPV rates; multiple studies with various aggregate income measures concluded that PPA and PPV rates were higher in areas of lower income (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Finnegan, Gao, Pasquale & Campbell, 2010; Liu & Pearlman, 2009, Murday & Corley, 2008;Zhan, Miller, Wong & Meyer, 2004; Zlotnick, 2004**).** This is consistent with studies conducted at the individual level (Davies, et al., 2001) and area-level studies conducted earlier in the 1990s (Billings, Anderson & Newman, 1996). Several studies also found higher PPA/PPV rates in areas with higher rates of people with less education (Laditka, Laditka & Probst, 2005; Zhan et al., 2004). Several studies found a relationship between higher PPA/PPV rates and higher proportions of minorities (Chang, et al., 2008; Liu & Pearlman, 2009; Murday & Corley, 2008), but one study found lower rates associated with minority (Hispanic and Native American) status, and another found increased racial/ethnic diversity associated with lower PPA rates in non-elderly adults but higher pediatric PPA rates (Pitkin Derose). In terms of social capital, Pitkin Derose found longer mean commute times and more faith-based congregations related to higher adult PPA rates; voting indices and numbers and nonprofit organizations were not significant predictors.

2.4.4 Summary of knowledge gaps identified

In spite of the differences in definitions and measures of outcomes and explanatory variables, common findings across studies indicated that PPA and PPV rates are higher in geographical areas of lower income, lower median education, and fewer physicians and community clinics. These rates may be higher in areas with less social capital. Some studies associated higher rates of no insurance or public insurance status with higher PPA or PPV rates, but others did not. Likewise, some studies indicated that areas with large proportions of minorities were at increased risk for higher PPA/PPV rates, but others found no such association, or negative associations between minority status and increased rates.

The inconsistency in explanatory variables noted may be due to MAUP or to differential risks for PPA/PPV rates across the life cycle, consistent with previous studies performed at the individual level for older adult (Laditka, 2003; Niefeld, et al., 2003; Menec, Sirski, Attawar, & Katz, 2006; Zeng, et al., 2006) and pediatric populations (Bindman, Chattopadhyay & Auerback, 2008; Cousineau, Stevens & Pickering, 2008; Flores, Abreu, Chaisson & Sun, 2003; Flores, Abreu, Tomany-Korman & Meurer, 2005; Pittard, Laditka & Laditka, 2008). In this review three studies (Liu & Pearlman, 2009; Murday & Corley, 2008; Zlotnick, 2006) looked exclusively at pediatric PPA/PPVs; three studies (Laditka, Laditka & Probst, 2005; Laditka, Laditka & Probst, 2009; Pitkin Derose, 2008) examined PPA/PPV rates for children and younger and older adults separately, and the remainder investigated PPA/PPV rates for adults or the total population.

Only four studies addressed preventable ED visits, and two of these examined total ED utilization and non-urgent ED use (versus ED use for ACSC). Far fewer studies examined PPV versus PPA rates, and none examined PPV rates for all ACSC or used

regression to examine relationships at administrative units smaller than counties. Only one study looked at the association between social capital and PPA (Pitkin DeRose, 2008); no studies examined relationships between social capital and PPV rates.

Implications for Practice

This review demonstrates the growing interest in modeling explanatory factors for public health problems such as high PPA and PPV rates. As over 30 million people obtain health insurance in the next 5-10 years, PPA and PPV rates are expected to increase, while ED resources decrease. Health centers, on the other hand, are expected to expand and increase in number, with over $11 billion over 5 years earmarked for such expansion (Draper, 2011). Well-situated health centers can minimize PPA and PPV rates by increasing primary care access and care coordination. Social determinants of health must be simultaneously addressed at both the individual and the population level.

Implications for research

This review highlights the current lack of consistency in definitions and measurement of PPAs and PPVs, as well as the great variety of potential predictors of these outcomes and geographic units of analysis used. Future studies of geographical variation in PPA/PPV rates should consider which geographical units most accurately capture the conceptual meaning of "neighborhood" or "community" and decrease the potential for MAUP, as well as how data are most easily accessible. Sometimes publicly collected data can be obtained at a finer level of granularity, and such opportunities should be explored. Standardization of the definition and measurement of PPA and PPV must occur in order for accurate comparison of results.

Use of multiple proxy measures for social capital facilitates analysis of this variable, due to public accessibility of these data, and inclusion of these measures in one study (Pitkin Derose, 2008) spurs contemplation of strategies to leverage existing community social capital as a potential future intervention to improve health outcomes at the community level. However, definitions and measures of social capital must also be standardized before researchers can use them successfully. Proxy variables and social capital measures without reliability and validity will likely continue to produce mixed results in research on associations between social capital and healthcare access, healthcare-seeking behaviors, and PPA/PPV rates. Using census data alone results in inadequate measures of the social determinants of health, and researchers must strive to develop better measures of social determinant concepts, rather than simply using census data due to its easy availability.

Implications for Policy

Increased funding for primary care services and coordination may exert a protective effect against increased PPAs and PPVs under publicly funded health programs. In the Medicaid patient population, for example, lower PPA and PPV rates have been associated with the use of public health clinics (Robbins, Valdmanis & Webb, 2008) or Federally Qualified Health Centers (Falik, Needleman, Wells & Korb, 2001), although it remains unclear if the lower rates are due to having a usual source of care or to enhanced services often found at such primary care sites. Medicaid managed care has also been associated with lower PPA and PPV rates compared to fee-for-service plans (Bindman, Chattopadhyay, Osmond, Huen & Bacchetti, 2005). And in California, higher funding of traditionally underfunded tribal health programs was linked to lower PPA rates among American Indian and Alaska Natives (Korenbrot, Kao & Crouch, 2009).

2.5 Summary

The 14 studies in this review used regression and spatial analyses of PPA and PPV rates at various levels of geographic aggregation to identify areas of increased primary care needs. In spite of the problems with consistency of outcomes, explanatory variables, measures, and units of analysis across studies, this review established social determinants and primary care measures as important determinants of PPA and PPV rates.

CHAPTER 3
Geographic Variance in Maryland's Preventable Emergency Department Visits: Comparison of Explanatory Models[1]

3.1 Introduction

Annual emergency department (ED) visits in the U.S. increased from 88.5 million in 1991 to 129.8 million in 2010 and are expected to continue to grow (American Hospital Association, 2009; Centers for Disease Control, 2011). More adults surveyed in 2011 listed "lack of access to other providers" (79.7%) than listed "seriousness of the medical problem" (66.0%) as a reason for their last ED visit (Gindi, Cohen & Kirzinger, 2012). And about 48.6 million Americans, or 15.7%, currently lack health insurance (DeNavas-Walt, Proctor & Smith, 2012), and concerns exist about the ability of primary care providers to meet increased demand as coverage expands. Maryland trends are comparable to those nationally. Maryland ED visits increased from 1.5 to 2.4 million from 1990 to 2007 and continue to grow by over 4% annually, leading to overcrowding, frustration and interest in strategies to reduce ED crowding (Gresenz, Ruder, & Lurie, 2009; Salamon, Cowdry, & Barclay, 2007; Barclay, 2007). About 20-30% of Maryland ED visits are consistently classified as non-emergent or potentially more appropriately treated in primary care, and about 20% of such visits are made by the uninsured (Gresenz, et al.; Salamon, et al.; Schur, Mohr & Zhao, 2003), who make up about 14% of the population (Maryland Health Care Commission, 2010). Barriers to primary care are implicated in increased rates of potentially preventable ED visits (PPVs) and may stem from factors intrinsic to healthcare delivery systems as well as the physical and social environments where people live and seek health care.

1. G. Rowe to be submitted to the *Western Journal of Nursing Research* in 2013.

3.2 Potentially Preventable Emergency Department Visits (PPVs)

Increased likelihood of inappropriate ED use has been associated with lack of a regular provider or usual source of care and inadequate access to primary care, as well as demographic and social variables such as income, age and female gender (Carret, Fassa, & Domingues, 2009; Falik, et al., 2006; Gresenz, Ruder, and Lurie, 2009; Laditka & Laditka, 2006; Shi, Samuels, Pease, Bailey & Corley, 1999). At the aggregate level, some researchers have found PPV rates higher among minorities, low-income groups and rural populations (Howard, Hakeem, Njue, Carey & Jallah, 2007; Laditka & Laditka; Shi, et al.), but others found no correlation between communities with high ED use and higher proportions of uninsured, low-income, minority or immigrant residents (Cunningham, Hadley, Kenny & Davidoff, 2007; Probst, Moore, Baxley & Lammie, 2003). Health inequities and barriers to primary care are implicated in higher PPV rates among minorities, low-income, and uninsured populations (Oster& Bindman, 2003). Little is known about factors that best explain aggregate community variation in PPV rates and whether these rates are different for uninsured populations compared to the general or total population.

Potentially preventable hospital admissions (PPAs) and ED visits (PPVs) are often used as proxy measures of lack of access to primary care, but they more accurately reflect increased health risks resulting from lack of access. The Agency for Healthcare Research and Quality (AHRQ) uses the number of visits for ambulatory care sensitive conditions (ACSC) - diagnoses such as asthma, diabetes, and acute conditions that should not require hospital or ED visits if properly managed in primary care - as a tool to monitor local safety net provider ability to meet the healthcare needs of low-income, vulnerable populations (AHRQ, 2003). This analysis used the AHRQ definition of PPVs, based on ED visits for ACSC, and

followed an initial spatial data analysis conducted for a Maryland mobile safety net provider to identify geographic hot spots of increased uninsured PPVs and decreased primary care access (Rowe, n.d.). Questions then arose about whether non-urgent ED visit behavior by the uninsured truly differs from that of the total population and what factors are associated with increased PPV rates at the community level.

3.3 Purpose

This study had two aims: 1) to compare and explain the distribution and geographic variance in Maryland PPV rates for total and uninsured populations; and 2) to compare and test the predictive value of regression models developed, using statistical analysis software with and without geographical mapping capability, to identify predictors of PPV rate variance. Potential explanatory variables tested included: number of primary care physicians/1,000 population, per capita income, percent of female-headed households, education level, owner-occupied housing rate, vacant housing rate, number of cars per population, disability rate and percent of households in linguistic isolation.

3.4 Methods

3.4.1 Conceptual Model

Flaskerud and Winslow's (1998) Vulnerable Populations Conceptual Model was used as the theoretical framework. The model explains health disparities in vulnerable populations through proposed relationships between (1) low socioeconomic and environmental resource availability (such as access to care) which lead to (2) increased relative risk, and (3) impaired health outcomes, such as morbidity and premature mortality. Empirical evidence supports the relationships described by the model (Flaskerud, et al., 2002; Flaskerud & Winslow), and its propositions have been tested (Bay, Kreulen, Shavers & Currier, 2006; Carr, 2006; Dyer,

2003; Flynn, Budd & Modelski, 2008; Rodehorst, Wilhelm, & Stepans, 2006) and blend well with what is known about health disparities, differential risks and differential resource availability in vulnerable populations (Flaskerud, 2002; Flaskerud, et al., 2002; Flaskerud & McQuiston, 2003; Kim, Flaskerud, Koniak-Griffin, & Dixon, 2005; Kim, Koniak-Griffin, Flaskerud, & Guarnero, 2004). Resource availability for residents of the ZCTAs was operationalized as aggregate social census and provider characteristics (per capita income and education levels reported by the U.S. Census Bureau and per capita primary care physician rates reported by the Health Resources Services Administration). Relative risk was operationalized as PPV rates.

3.4.2 Design

This ecologic case study analysis was conducted in three stages. First, regression models were built and results compared for model goodness-of-fit to the data and explanatory power using PPV rate data for FY 2008. Second, these models were applied to the FY 2009 data set to test the models' predictive ability. Third, statistical results indicating data goodness of fit and predictive utility were compared across the regression models tested in two types of statistical software, in order to determine the best model(s) and the best independent variables to explain geographic variance in PPV rates in Maryland. The best models will have the best fit to the data while explaining the most variance (adjusted R^2, pseudo-R^2) in the targeted outcome through provider, demographic and economic characteristics. Areas in Maryland where the uninsured and total populations visit the ED at higher rates for potentially preventable reasons are identified and may reflect a primary care access issue related to a healthcare system variable (e.g., number of primary care providers per capita) or a socioeconomic variable (e.g., low income) influencing health-seeking

behaviors. A good model balances goodness of fit of the data with parsimony of potential explanatory variables (Akaike information criterion).

3.4.3 Data Analysis

Data were analyzed using ArcGIS 10.0 (ESRI, Redlands, California, United States) and PASW SPSS 21.0 for Windows (SPSS Inc., Chicago, Illinois, United States). Spatial analysis was supplemented with GeoDa (Center for Geospatial Analysis and Computation at Arizona State University) (GeoDa, 2010). All independent and dependent variable data were aggregated and all analysis was done at the neighborhood (ZCTA) level. Regression models were built to explain geographic variance in FY 2008 PPV rates using ordinary least squares (OLS) and geographically weighted regression (GWR) in ArcGIS 10.0, and the generalized linear model (GLiM: Poisson and negative binomial) in SPSS 21.0. A model that best fit the FY 2008 data (i.e., had the lowest Akaike Information Criterion, AIC) was analyzed using each regression method (OLS, GWR, Poisson and negative binomial) and all four models were used to test the hypotheses that census and provider variables aggregated at the ZCTA level would explain variation in total and uninsured PPV rates. The models' goodness-of-fit and predictive utilities were then tested in the FY 2009 dataset and compared to determine which model(s) best explained geographic variation in PPV rates for the target populations.

3.4.4 Data sources

Three public data sources were used. Emergency department discharge data aggregated to the ZCTA level by patients' residence were requested through application to the Maryland Health Services Cost Review Commission and obtained for FY 2008 (July 1, 2007 to June 30, 2008) and 2009 (July 1, 2008 to June 30, 2009). These data were joined to shape files of the ZCTAs in Maryland obtained from the U.S. Census Bureau and rates were

calculated by dividing PPV by population for each ZCTA. The second dataset was downloaded from the HRSA GIS data storage website and included number of primary care doctors and population in Maryland in 2006 by ZCTA. Third, socioeconomic data from the 2000 census, including data on education, income, disabilities, housing, female-headed and linguistically isolated households, and cars per population was downloaded from the Census Bureau and joined to ZCTA shape files.

3.4.5 Joining Attribute Data to Geographic Feature Layers

The Census Bureau consolidates over 600 Maryland zip codes into 452 ZCTAs for more stable administrative units that can be mapped and are less likely to change over time than zip codes, used to facilitate mail delivery (Census Bureau, 2010). When attribute data were joined to ZCTA feature layers, 21 ZCTAs were not matched, and data in these ZCTAs were automatically reassigned to adjacent units. On review, these ZCTAs were small geographical areas totaling less than 5,600 people, or 0.001 of the state's total population. This left 431 ZCTAs, of which nine (2%) had no population and could be safely ignored. The model-building techniques used in ArcGIS and SPSS did exclude these from analyses, leaving N = 422 ZCTAs for analysis.

3.4.6 Independent Variables (IVs) and Determination of Adequate N for Regression

Independent or predictor variables entered and tested in these models were identified from the literature on PPV and conceptualization of factors potentially influencing PPV rates. Correlations of these IVs with the rates of total and uninsured PPV in FY 2008 and 2009 were also examined for significance prior to use. Using Stevens' criteria (1986) for determining the maximum number of predictors for this sample (N = 422), use of 15 ZCTAs

per predictor allows use of 28 predictors for simple regression, more than adequate for the nine predictors examined here.

3.4.7 Regression Methods - Computational Representations

Ordinary Least Squares. The classical or OLS regression equation establishes a global relationship among a dependent variable (DV) and a set of IVs and can be depicted:

$$Y_i = B_0 + B_1x_{1i} + B_2x_{2i} + \ldots + B_nx_{ni} + E_i, \text{ where:}$$

Y_i = the DV; x (from 1 to n) = the set of IVs; B = the regression coefficient; and E_i = the residual; all at location *l*. When applied to spatial data, OLS regression assumes uniform spatial processes such that a stimulus provokes the same response in all parts of the study area, which is highly unlikely. Patterns change across space, and OLS regression is difficult to apply to spatial data (due to spatial dependence, clustering, heteroscedasticity, and autocorrelation) and therefore by itself often not able to capture spatial effects. The OLS model was not expected to perform well in this analysis, but it was built to compare and test other models and to identify potential sources of multicollinearity. IVs with a variance inflation factor (VIF) > 7.5 may have high multicollinearity with another IV and thus may be considered for elimination.

Geographically Weighted Regression. In GWR models, relationships between DVs and IVs are allowed to vary over space, i.e., regression coefficients do not have to remain constant, so the spatial structure of the model changes from unit to unit of analysis across the study area. The GWR model can illustrate the locally changing influence of IVs on the DV. Thus, GWR functions as a local, versus global, spatial statistic. Outputs can be mapped and are location-specific. GWR models give much better fits to spatial data, even accounting for added model complexity and number of parameters (i.e., decreases in degrees of freedom).

GWR residuals are usually much less spatially dependent and can be mapped and analyzed for overall model performance and "goodness of fit" of the model to the local and global study area. The geographically weighted regression model equation is:

$Y_i = B_0 (u_i v_i)$ + the sum of $B_j(u_i v_i) X_{ij} + E_i$, where: Y_i = point estimate; $(u_i v_i)$ = coordinates; $B_0 (u_i v_i)$ = intercept; X_{ik} = set of observations; i = 1, …n cases and j = 1, …IVs; $B_j(u_i v_i)$ = the regression coefficient; and E_i = the error term, all for the *i*th point.

Generalized Linear Model: Poisson. DVs measured as counts or rates violate the assumptions of normality and homoscedasticity of OLS regression, but dichotomizing such data to perform logistic regression results in loss of much detail. Count and rate data are typically non-normally conditionally distributed, positively skewed, kurtotic, and have many low-count observations but none less than zero (Coxe, West & Aiken, 2009). Poisson regression is based on the Poisson distribution, a probability distribution that contains an exponential function and in which u = both the mean and the variance of the distribution. Poisson models use a log link, and there is no error term, skirting the issue of non-constant variance of errors in count data (Coxe, et al.). The model is depicted: $\ln (u\hat{}) = B_0 + B_1x_1 + B_2x_2 + \ldots + B_px_p$, where: u = predicted count on the outcome variable; X (from 1 to n) = set of IVs; and *B* = regression coefficient. There is no R^2 but a pseudo-R^2 can be calculated to estimate explanatory power by calculating "proportional reduction in deviance": $R^2_{deviance}$ = 1 – deviance (fitted model)/deviance (intercept only) (Coxe et al., p. 126).

Generalized Linear Model: Negative Binomial. Like Poisson regression, negative binomial models are a subset of the Generalized Linear Model (GLiM) and use a log link. In some cases the data being analyzed have too much variability for the Poisson

distribution to apply; such cases are over-dispersed and better models can be built using an over-dispersed Poisson or a negative binomial model. This model also allows for unexplained variability between units of analysis through assumption of a larger variability, an advantage comparable to the error term in OLS regression. Modeling still occurs with assumption of Poisson distribution with the same mean parameter, but the negative binomial model allows modeling of observed units with the same values on predictors on different Poisson distributions with different mean parameters (Coxe, et al.). The negative binomial model also uses an additional probability distribution, the gamma distribution, to represent distribution of the means, and so the error function results from the interaction of these two distributions (Coxe, et al.). This allows for model adjustment to the data in a way conceptually similar to the local adjustments made in GWR regression.

3.5 Results

3.5.1 Sample Characteristics

About 2 million ED visits not resulting in hospital admission occurred annually in FY 2008 and 2009 in Maryland. Of these, about 19 percent were for ACSC each year, and 24 and 23 percent of these were made by those without insurance in FY 2008 and 2009, respectively. This analysis was conducted at the administrative unit level of the ZCTA.

3.5.2 Exploratory Spatial Data Analysis

Maryland's population is most dense along the I-95 corridor between Baltimore and Washington, DC, with higher per capita incomes clustered in the suburbs of both cities. Using visual inspection and spatial statistics, similar patterns of concentration of high PPV rates were noted for total and uninsured populations. For the total population, rates were

highest in/around Baltimore City, in rural areas of western and southern Maryland, and on the Eastern Shore. For the uninsured, however, high rates were more highly concentrated in and around Baltimore City and on the lower Eastern Shore near Cambridge and Salisbury.

Screening Outcome Variables. Total and uninsured PPV rates were calculated by dividing the relevant number of ED visits per ZCTA by its population and multiplying by 100. In SPSS, these rates were rounded to whole integers. The distribution of rate data used as DVs at the ZCTA level was both positive (>= 0) and positively skewed for all four sub-samples (total and uninsured, FY 2008 and 2009). The mean visit rate for both years' uninsured data was 1.31; mean visit rates were 5.73 and 6.12 for FY 2008 and 2009 total data, respectively. Minimum and maximum rates varied from (0, 12) for FY 2008 uninsured to (0, 45) for FY 2009 total rates. Skews ranged from 2.43 for FY 2008 total PPV rates to 4.5 for FY 2009 uninsured PPV rates.

Based on the data distributions, it was hypothesized that the GLiM (Poisson and negative binomial) and GWR models would fit the PPV rate data better than the OLS models. Positive integer or count data, particularly that with a low mean (< 10), such as the rates calculated above, can produce biased results in OLS regression, because assumptions of linear regression (i.e., normal distribution, homogeneity of variance) are violated. Distributions like this call for consideration of the GLiM (log linear Poisson regression and its variants) to build a model with adequate explanatory power and data fit. GWR, which allows the regression coefficient to vary over space, is another alternative to build a model to fit the data when clustering is present.

Global and Local Spatial Patterns. Global and local spatial statistics were performed to evaluate for location-based confounding effects. Tobler's First Law of

Geography states that "everything is related to everything else, but near things are more related than distant things" (ESRI, 2006). Spatial statistics demonstrated the presence of clustering at both the global (Moran's I) and local (Getis-Ord Gi*, LISA) levels, indicating that GLiM and GWR models would likely produce better models than OLS regression.

Correlation. Correlations between IVs and total and uninsured PPV rates were examined. Correlations significant at the $p < 0.01$ level were found between the total PPV rate and all of the individual IVs, except disability rate and primary care physicians per 1,000 population, in both the FY 2008 and 2009 datasets; the correlation with the disability rate was significant at the $p < 0.05$ level in the FY 2008 data only, and no significant correlation was found between PPV rates and per capita primary care physicians. For the uninsured population, correlations significant at the $p < 0.01$ level were found between the uninsured PPV rate and all the individual IVs except disability rate, vacant housing rate and primary care physicians per capita, in both the FY 2008 and 2009 datasets; the correlations with disability rate and vacant housing rate were significant at the $p < 0.01$ level in the FY 2008 data but only at the $p < 0.05$ level in the FY 2009 data. Again, no significant correlation was found between PPV rates and per capita primary care physicians.

3.5.3 Regression Modeling Results

Results of the best OLS, GWR, Poisson and negative binomial regression models were individually summarized and compared. Models were developed using all of the IVs in the initial hypotheses and then making systematic adjustments subtracting non-significant or potentially redundant predictors and examining corresponding changes in model fit. Some interaction terms were initially included in the Poisson and negative binomial regression models but removed in the final reduced models, as they were not

significant. Multiple models and combinations of IVs were examined across all four modeling methods in order to determine the best model using each method and in comparison to one another. The same combinations of IVs consistently produced the best goodness of fit across all four modeling methodologies, although not all of the variables included were significant predictors in each model. All nine IVs for the models of total PPV rates were included and seven variables for the models of uninsured PPV rates: percent female-headed households, per capita income, education level, percent linguistically isolated households, owner-occupied housing rate, vacant housing rate, and disability rate. In a few cases further subtraction of one or more IVs decreased deviance by a very small amount, but then AIC increased as a result. Per capita primary care physicians was not a significant predictor in most models and was removed from models explaining uninsured PPV rate variance but kept in the models explaining total PPV rate variance because it contributed to goodness of fit in the GLiM models. Cars per population were also removed from the models of uninsured PPV rate variance due to potential multicollinearity concerns. Although the VIF of cars per population was only 3.4, it was the highest for any of the IVs in the OLS model and significantly correlated with other IVs; its removal from the models of uninsured rate data improved these models' performance.

SPSS Model Results. Results of Poisson and negative binomial regression models predicting FY 2009 total PPV rates are summarized in Table 3.1

Table 3.1: *Summary of Poisson and Negative Binomial Regression Models Predicting 2009 Total PPV Rate Variance*

	***Poisson*[1]**						***Negative Binomial*[2]**					
Parameter	*Unstandardized Coefficients*		*95% Wald Confidence Intervals for B*				*Unstandardized Coefficients*		*95% Wald Confidence Intervals for B*			
	B	Std. Error	Wald X^2	Sig.	Lower Bound	Upper Bound	B	Std. Error	Wald X^2	Sig.	Lower Bound	Upper Bound
Intercept	2.428	0.3297	54.241	<0.001**	1.782	3.074	2.189	0.9571	5.232	0.022*	0.313	4.065
Percent Female-headed Households	0.033	0.0035	91.211	<0.001**	0.040	91.211	0.040	0.0111	12.597	<0.001**	0.018	0.061
Percent High School Graduates(=> 25 y/o)	-0.009	0.0034	7.784	0.005**	-0.003	7.784	-0.010	0.0095	1.002	0.317	-0.028	0.009
Per capita Income	-2.691 E-005	3.7667E-006	51.020	<0.001**	-1.952 E-005	51.020	-2.586 E-005	8.9599 E-006	8.331	0.004**	-4.342 E-005	-8.300 E-006
Per capita Cars	0.006	0.0020	9.677	0.002**	0.010	9.677	0.009	0.0055	2.834	0.092	-0.002	0.020
Owner-occupied Housing Rate	-0.002	0.0016	1.768	0.184	0.001	1.768	-0.003	0.0046	0.529	0.467	-0.012	0.006
Vacant Housing Rate	0.004	0.0020	3.829	0.050*	0.008	3.829	0.005	0.0057	0.624	0.430	-0.007	0.016
Percent Linguistically Isolated Households	0.007	0.0044	2.172	0.141	0.015	2.172	0.005	0.0148	0.138	0.710	-0.023	0.034
Disability Rate	0.004	0.0019	4.714	0.030*	0.008	4.714	0.005	0.0061	0.757	0.384	-0.007	0.017
Primary Care Doctors/1000 Pop	0.025	0.0212	1.421	0.233	0.067	1.421	0.016	0.0641	0.059	0.808	-0.110	0.141

*Significant at the 0.05 level. **Significant at the 0.01 level.

[1]Poisson: Deviance = 556.747, Value/df = 1.355, AIC = 2052.106, BIC = 2092.533, Likelihood Ratio X^2 = 490.362, p < 0.001.

[2]Negative Binomial: Deviance = 76.173, Value/df = 0.185, AIC = 2401.288, BIC = 2441.715, Likelihood Ratio X^2 = 68.888, p < .001.

GLiM models of FY 2009 uninsured PPV rates performed similarly but contained fewer significant predictors than the models of total PPV rates. The Poisson regression models had better overall goodness of fit than the negative binomial models for all of the data sub-sets. Poisson models had lower AIC and BIC compared to negative binomial models, although deviance was also higher. But AIC and BIC, unlike deviance, take into account model complexity.

Indicators of model fit and explanatory power for model comparisons are summarized in Table 3.2.

Table 3.2: *Comparison of Explanatory Power and Indicators of Model Goodness of Fit for FY 2009 PPV Rate Data*

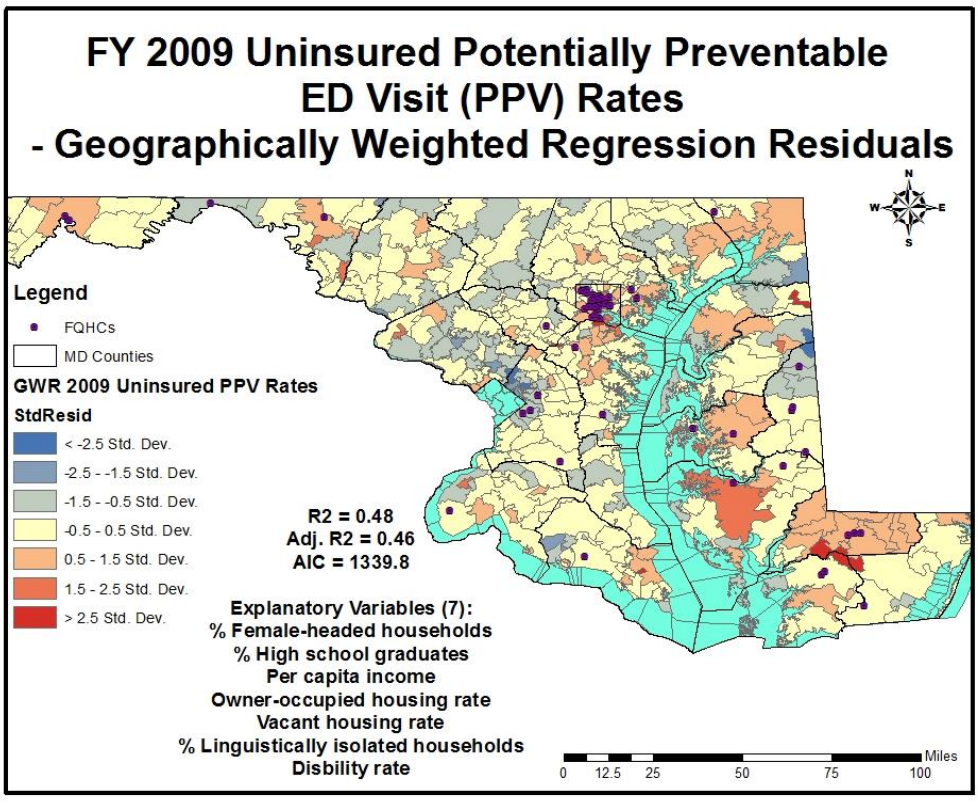
2009								
	Total				Uninsured			
	OLS	GWR	Poisson	Negative Binomial	OLS	GWR	Poisson	Negative Binomial
Intercept	1.433		2.428	2.189	0.623		2.210	2.041
St Error	1.083		0.33	0.957	0.359		0.683	1.136
Deviance			556.8	76.2			316.3	168.1
Deviance Value/df			1.355	0.185			0.766	0.407
R2 / Pseudo-R2	0.40	0.42	0.52	0.58	0.44	0.48	0.46	0.39
Effect Size (Adjusted R2)	0.39	0.40			0.43	0.46		
AIC	2306	2296	2052	2401	1356	1339.8	1069	1244
BIC			2093	2442			1101.4	1276
Wald Statistic[1]	229.5*				139.21*			
Omnibus Test Likelihood Ratio X^2			490.36*	68.89*			263.15*	105.44*
Koenker (BP) Statistic[2]	35.93*				155.6*			
Jarque-Bera Statistic[3]	7768*				1439*			

*Significant at the <.001 level.
[1]Significant p value indicates robust overall model significance.
[2]Significant p value indicates biased standard errors; use robust estimates.
[3]Significant p value indicates residuals deviate from a normal distribution.

Pseudo-R^2 was also highest in the Poisson model of all four models for the total (but not uninsured) rate data (see Table 3.2), indicating better explanatory power. In spite of a concern that models for total rates (up to 38 and 45 per 100 in 2008 and 2009, respectively) might become overly-dispersed, data for both years reflected a better fit with Poisson distribution and assumptions than with the negative binomial model.

ArcGIS Model Results. The four GWR models fit the data better than the OLS models (total and uninsured in FY 2008 and 2009), with lower AIC measures, and a higher adjusted R^2, in all cases (see Table 3.2). Figure 3.1 maps standardized residuals, indicating geographic goodness of fit, for the GWR model predicting FY 2009 uninsured PPV rate variance.

Figure 3.1: *Geographically weighted regression residuals in ArcGIS 10.0 - FY2009 per capita uninsured PPV rates*



Small standard deviation residuals (yellow) mark areas where the model fits the data well; large negative standard deviation residuals (red) mark areas where the model over-predicts the PPV rates; and large positive standard deviation residuals (blue) mark areas where the model under-predicts PPV rates. Inspection of GWR regression residuals for both the total and uninsured PPV rates illustrated a better model fit in suburban and near rural areas and a less good fit in urban and far rural areas of the state. Moderate adjusted R^2 values for total and uninsured PPV rate data (Table 3.2) indicated a moderate proportion of variance in PPV rates explained by these models. Proximity of adjusted R^2 to R^2 in all cases indicated use of an appropriate number of variables.

Comparison of Four Regression Methods (Table 3.2). The only goodness-of-fit test that can be compared across models is the AIC, which takes into account model complexity. AIC was consistently lowest for Poisson models, followed by GWR models for total and negative binomial models for uninsured rates for both years. The Poisson models also consistently produced lower BIC calculations compared to the negative binomial models (BIC is not calculated in ArcGIS). The Poisson model also had the highest explanatory power (pseudo-R2) across all four modeling methods in the total rate data sets and explanatory power comparable to that of the GWR model in the uninsured rate data sets. The GWR model had the highest explanatory power in the uninsured rate data sets.

Hypotheses Testing. It was originally hypothesized that there would be a relationship between the distribution of hot spots of increased PPV rates aggregated at the ZCTA level for total and uninsured populations. Visual inspection and spatial statistics confirmed similar patterns of higher PPV rates for both total and uninsured populations, but high PPV rates for the uninsured were more tightly concentrated in and around specific urban areas (Baltimore

City, Cambridge and Salisbury). Explanatory variables examined for relationships to PPV rates included number of primary care physicians/1,000 population, per capita income, percent of female-headed households, education level, owner-occupied housing rate, vacant housing rate, number of cars per population, disability rate and percent of households in linguistic isolation. Of these variables, per capita income and percent of female headed households were significant predictors of PPV rates in both populations and across all models capable of detecting this (GWR models do not specifically test for significance of predictors). Education level (percent of high school graduates) was also a significant predictor in the Poisson and negative binomial models for total PPV rates and in the Poisson model for FY 2009 uninsured rates. The vacant housing rate, disability rate and cars per population were also significant predictors of the total but not the uninsured PPV rates. Per capita primary care physicians, owner occupied housing rates, disability rates, and rates of people living in linguistically isolated households were not significant predictors in any of the FY 2009 models. All nine IVs were included in the models of total PPV rates because this produced models with the best goodness-of-fit. After excluding per capita primary care physicians and cars, the seven IVs remaining produced models with the best goodness-of-fit for the uninsured rates; deletion of any other IVs resulted in lower AIC values. The significant predictor variables for the FY 2009 total population were female-headed households, education level, per capita income, cars per population, disability rate and vacant housing rate. However, for the uninsured population, only per capita income and female-headed households were significant predictors of PPV rates.

Prediction. Using FY 2008 data for total PPV rates, OLS and GWR models built resulted in comparable R^2 and adjusted R^2 values when applied to the FY 2009 dataset, and

the Poisson and negative binomial models built resulted in higher pseudo-R^2 values. All of the models built using FY 2008 data for uninsured PPV rates resulted in higher adjusted or pseudo-R^2 values in the FY 2009 dataset. None of the increases in R^2 equaled more than a 9% increase in explanatory power, and all models performed similarly from FY 2008 to FY 2009. In the total rate data, the negative binomial model had the highest pseudo-R^2 (0.49 in FY 2008 and 0.58 in FY 2009) but AICs were lower in the comparable Poisson models, which also produced moderate pseudo-R^2 (0.47 in FY 2008 and 0.52 in FY 2009). The GWR and Poisson models performed equally well explaining the variance in uninsured rates (0.37 in FY 2008 and 0.46 in FY 2009, see Table 2).

3.6 Discussion

3.6.1 Spatial Analysis

In FY 2008 and 2009, less than a quarter of the 19% of Maryland's ED visits that were potentially preventable were made by the uninsured, indicating that factors other than insurance affect access to primary care and care seeking behavior at EDs statewide. High uninsured PPV rates were more concentrated around Baltimore City and on the lower Eastern Shore, while high total PPV rates were more widely distributed in these areas, in western and southern Maryland, and throughout the Eastern Shore. Lack of correlation between PPV rates and per capita primary care physicians was unexpected, since both are used as proxy measures of inadequate primary care access. Two caveats may explain these results: 1) per capita primary care physicians does not take into account the substantial and growing number of nurse practitioners and other providers, such as physician's assistants, serving as primary care providers; and 2) ZCTAs may not be the ideal units of aggregation

for per capita providers, i.e., people may seek care in a ZCTA other than the one in which they live.

3.6.2 Model Comparison

Overall, attempts to build the best model(s) to fit these data sets and explain geographic variation in total and uninsured PPV rates populations worked best using GIS and SPSS software simultaneously. Different types of exploratory data analysis can be done with each software type, leading to synergistic identification of the most appropriate variables to include in final models. For example, OLS regression offers the ability to review VIFs and test for multicollinearity but does not work well for outcomes that are non-normally distributed, positively skewed rates. The GiLM models, particularly the Poisson model, had the best fit for this type of outcome, but the GWR model, by allowing the regression coefficient to vary over space, addresses data clustering and also performed well at explaining variance. The ArcGIS models also utilize mapping capabilities and by mapping regression residuals can identify geographic areas where the model fits the data well and where it does not. All four models provided modest explanatory power which could be replicated or improved from one year to the next, but the Poisson models had the best goodness of fit, followed by the GWR models for total population and the negative binomial models for uninsured populations. Using analysis with all four models, the second hypothesis was accepted regarding explanatory power of the variables per capita income and percent of female headed households. Less convincing evidence was generated for accepting the explanatory power of educational level and rates of vacant housing, disability, cars, and linguistically isolated households. Poisson models supported the explanatory power of educational level and rates of disability, vacant housing, and cars in the total but not the

uninsured populations, but OLS and negative binomial models did not find these to be significant predictors. Rates of owner-occupied housing and primary care physicians failed to demonstrate explanatory power in any model. Also, the modest explanatory power of variables analyzed here indicates that some key variable(s) to explain high PPV rates are missing from this analysis. This may be due to a failure to include the best available socioeconomic or provider variables or to a lack of public health surveillance of key factors influencing primary care-seeking behavior.

3.6.3 Model Testing and Verification

Determining if models perform as intended can be partly done by examining goodness of fit and model performance on multiple years of data, as has been done here. But in order to truly verify model accuracy, models should be tested using other datasets to see if equally good results can be achieved. There are currently no clear rules for interpreting diagnostic statistics in GLiM, making evaluation of the Poisson and negative binomial models difficult (Coxe, West & Aiken, 2009). Model diagnostics in ArcGIS are also rudimentary, with more diagnostic capability for the OLS model (e.g., F-stat for model significance, Wald statistic for overall robust model significance) than the local GWR model. At this time, only OLS and GWR regression can be performed in ArcGIS. However, ArcGIS models offer the ability to illustrate results with mapping applications, and mapping standardized residuals gives some geographic indication of where OLS and GWR models fit the aggregated data well (in this case in suburban and near rural areas). This may indicate that a key variable measuring an aspect of population access or resources is missing from the models. Another potential implication is that explanatory variables act differently in rural and urban areas and so separate rural and urban models may be needed. However, models in this

analysis performed differently even between urban areas, with PPV rates consistently over-predicted near Baltimore but under-predicted near Washington, DC.

3.6.4 Limitations and Biases

Population-level analyses such as this are subject to ecologic bias due to aggregate data characteristics that differ from those analyzed at the individual-level (Abellan, Richardson & Best, 2008; Wakefield & Haneuse, 2008). This spatial analysis is also subject to the distorting influence of the modifiable ariel unit problem (MAUP), in which data aggregated into arbitrarily sized and shaped geographic units like ZCTAs can mask the boundaries of true hot spots and draw attention to areas larger than desired. Finally, neither ArcGIS nor the GLiM models have well-defined methods for model diagnostics.

3.6.5 Conclusions

This study provides an initial step in the ecologic analysis of Maryland communities with high PPV rates that may potentially lack access to primary care. The most compelling factors identified in this ZCTA-level analysis as potential contributors to increased PPV rates were 1) percent of female headed households, 2) per capita income and 3) education level, implying that people with fewer resources, whether economic or social, are more likely to seek care at an ED for primary care concerns. In this analysis, Poisson regression provided models that best fit the data considered, and the GWR model also performed well. The modest explanatory power of the models developed indicates that some key variable contributing to health-seeking behavior has not been captured here. Reasons for potentially preventable ED visits may also differ between rural and urban areas. As interest in behavioral and social determinants of health grows, so does the need to periodically review data collected through public health surveillance systems and its usefulness in assessing and

improving the health of modern populations. Due to the protected and sensitive nature of health data and current surveillance mechanisms, public health research will remain subject to the limitations of aggregated secondary data and the distorting effects of MAUP in spatial analyses. However, as policy-makers are increasingly exposed to the utility of GIS applications, more data aggregated at more appropriate units with fewer distorting effects (e.g., census tracts and block groups) may be made available to public health researchers.

CHAPTER 4
Social Capital, Neighborhood Disadvantage, and Potentially Preventable Emergency Department Visits in Metropolitan Baltimore[1]

4.1 Introduction

Interest in studying the effects of social capital on health outcomes has grown exponentially in recent years (Kawachi, Subramanian & Kim, 2008; Lee & Kim, 2012; Macintyre & Ellaway, 2000). This has coincided with growing recognition of the social determinants of health and health disparities (US Department of Health and Human Services (USDHHS), 2010) and new computerized modeling methodologies (Macintyre, Ellaway & Cummins, 2002), which are fueling renewed interest in studying the physical and social impact of the environment on health (Aboelata, et al., 2004; Dannenberg, et al., 2003; Lee & Rubin, 2007). Interest in studying social capital in public health is partly due to its potential to mediate the negative effects of living in a poor or disadvantaged neighborhood on health outcomes (Carpiano, 2008; Kruger, Reischl & Gee, 2007; Ross & Mirowsky, 2001; Sampson, 2003). This study aimed to quantify neighborhood-level social determinants of potentially preventable emergency department visits, based on previously developed measures of neighborhood disadvantage (Morenoff, Sampson & Raudenbush, 2001; Ross & Mirowsky), and to test a measure of social capital as a potential mediator of the negative impact of neighborhood disadvantage on these potentially preventable visits.

4.2 Background

4.2.1 Potentially preventable emergency department visits

Healthcare delivered in emergency departments (EDs) is more expensive than the same care delivered in out-patient primary care settings (Choudhry, et al., 2007; Institute of Medicine [IOM], 2006). Potentially preventable ED visits (PPVs) for ambulatory care

1. G. Rowe to be submitted to *Social Science and Medicine* in 2014.

sensitive conditions (ACSC) – diagnoses such as hypertension, diabetes, asthma and other conditions appropriately managed in primary care - place increased burden on these safety net providers of last resort. In the United States (U.S.), EDs are already struggling with issues of steadily increasing use, crowding and related negative impacts on safety and quality of care (Bernstein, et al., 2009; Institute of Medicine, 2007; Tang, Stein, Hsia, Maselli & Gonzales, 2010; Trzeciak & Rivers, 2003). At least 8% of all U.S. ED visits are for ACSC, meaning that they might have been prevented if patients had received better or higher quality primary care (Agency for Healthcare Research and Quality [AHRQ], 2001; Johnson, et al., 2012; Maslow & Ouslander, 2012; Steiner, 2010; Stranges and Stocks, 2010). Total U.S. PPV rates reflect health disparities and primary care barriers and vary by payer category: in 2007, 15% were made by those who were uninsured, 26% by those with private insurance, 22% by those with Medicaid, and 31% by those with Medicare (Tang, et al., 2010). Geographic variance in PPV rates may reflect neighborhood-level differences in the social determinants of health-seeking behaviors, such as income and education; higher rates are noted in poor communities and vulnerable populations (Johnson, et al., 2012; Magan, Alberquilla, Otero & Ribera, 2011).

Maryland ED visits have steadily increased over the past two decades and continue to grow, with higher numbers consistently noted in the Baltimore area (Gresenz, Ruder, & Lurie, 2009; Salamon, Cowdry, & Barclay, 2007; Barclay, 2007). About a third of Maryland ED visits are consistently classified as potentially preventable; across the state, about a fifth of such visits are made by the uninsured and another fifth by patients with Medicaid (Salamon, et al.; Schur, Mohr & Zhao, 2003). In Baltimore City, the proportion of ED visits

by the uninsured and those with Medicaid is higher than in the surrounding counties (Gresenz, et al., 2009).

4.2.2 Neighborhood Disadvantage

After decreasing during the 1990s, the number of Americans living in areas of concentrated poverty has increased during the 21st century, to 10.5% of those who are poor (Kneebone, Nadeau and Berube, 2011). Concentrated poverty is thought to contribute an environmental burden to health that is in addition to that associated with individual poverty (Sampson, Morenoff & Gannon-Rowley, 2002; Wilson, 1987). Income inequality (Wilkinson, 1996), neighborhood affluence (Wen, Browning & Cagney, 2003), and residential stability (Browning & Cagney, 2003) have also been associated with geographic variation in health. Morenoff, Sampson and Raudenbush described concentrated disadvantaged as "economic disadvantage in racially segregated urban neighborhoods" (2001, p. 7) and used a scale to measure neighborhood disadvantage (giving equal weight to percent of families below poverty, percent of families receiving public assistance, percent of unemployed in the civilian workforce, percent of female-headed households with children and percent of residents who are black). They found that areas of concentrated disadvantage and low social control/cohesion were associated with higher rates of homicide (Morenoff, et al.). Ross and Mirowsky (2001) also operationalized neighborhood disadvantage as a scale (with components of the prevalence of poverty, female-headed households with children, home ownership, and college educated residents). They found worse health among those living in disadvantaged neighborhoods; these effects were in addition to the effects of individual socioeconomic status on health (Ross & Mirowsky).

4.2.3 Social capital

Social capital is the aspects of social structure that individuals can access as resources for action, including social obligations and expectations, information channels and social norms (Coleman, 1988). It has also been defined as social networks and the associated norms of reciprocity and trustworthiness (Putnam, 2007). Social capital is thought to positively impact multiple measures of community well-being, including health, and to mediate health disparities (Carlson & Chamberlain, 2003; Kawachi, Kennedy & Wilkinson, 1999).

Social capital is rooted in social disorganization theory, which grew out of the early twentieth century ethnographic field work and ecological analysis of urban sociologists affiliated with the University of Chicago. Key assumptions are that social disorganization is caused by rapid social changes and breakdown of community social controls and is characterized by areas of economic disadvantage and high crime. Shaw and McKay found inverse relationships between areas of low socioeconomic status and social organization and high crime and disease rates in multiple US cities (1969/1942). Decades later, W.J. Wilson described concentrated economic and social disadvantage in poor, black urban areas resulting from larger societal processes of that time, i.e., segregation, job loss, income inequality, suburban flight, family disruption and increasing rates of female-headed households (1987). Sampson and colleagues extended social disorganization theory to consider social or collective efficacy, to explain why some poor neighborhoods are able to leverage informal social controls and neighborhood cohesion to reduce crime (Sampson & Groves, 1989; Sampson, Morenoff & Earls, 1999; Sampson, Raudenbush & Earls, 1997). Researchers in the 21st century are now applying social disorganization/social capital theory to study effects

of neighborhood social structure on health outcomes (Browning & Cagney, 2003; Kawachi & Berkman, 2010; Kawachi & Berkman, 2003).

4.2.4 Small Area Analysis Relating Social Capital to Primary Care Access

Several studies have investigated the role of social capital in explaining primary care access at the aggregate level, but neither social capital nor access to care have been consistently conceptually or operationally defined. Measures of social capital have included: 1) numbers of schools, non-profit organizations, and churches (Pitkin Derose, 2008; Youngblade, et al., 2006); 2) census (e.g., *commute time, relative diversity*) and other proxy variables (e.g., *voting indices*, *marital status*) to approximate social capital (Blankenau, Boye-Beaman, & Mueller, 2000; Pitkin Derose, 2008); and 3) survey questions/scales used to measure a dimension of social capital, such as *reciprocity, trust, civic engagement* (Ahern & Hendryx, 2003; Hendryx, Ahern, Lovrich & McCurdy, 2000; Prentice, 2006), *social support, inter-connectedness*, or *community participation* (Perry, Williams, Wallerstein & Waitzkin, 2008) and *social cohesion* and *informal social control* (Browning & Cagney, 2003). Measures of primary care access have included *use of healthcare* (Perry, et al.; Youngblade, et al., 2006); *trust in physician* (Ahern & Hendryx, 2003); *physician use in the last year when ill* (Blankenau, et al., 2000); *physical, Pap test or preventive check-up within a specified time* (Blankenau, et al., 2000; Prentice, 2006); *health status* (Blankenau, et al., 2000; Browning & Cagney, 2003); *regular source of care* (Prentice, 2006); *self-reported access to care problems* (Hendryx, et al., 2000); *barriers to care, satisfaction with care* and *quality of provider communication* (Perry, et al., 2008); *health care charges* (Youngblade, et al., 2006); and *preventable hospitalizations* (Pitkin Derose, 2008).

4.2.5 Knowledge Gaps Identified

Little is known about the impact of social capital on primary care access and potentially preventable hospital visits (PPAs) and PPVs, due to the limited number of studies to date, differing outcomes of interest, and differing conceptual and operational definitions of social capital. Hendryx et al. (2002) found that those in cities with more social capital reported fewer problems with access to care, but results were not controlled for other factors. Other studies of social capital and access to care, including those using proxy variables, had mixed results, with some - but not all - social capital measures positively associated with primary care access (Blankenau, et al.; Prentice; Perry, et al.). To date, the only study of the impact of community-level social capital on PPAs (Pitkin Derose, 2008) used multiple proxy measures for social capital and found mixed results. No published studies have examined the relationship between social capital and PPVs. Previous analysis of social determinants of PPV rates in Maryland found that significant predictors included percent of female-headed households, per capita income, and percent of high school graduates, indicating that social resources are key components in explaining variance in these PPV rates. (Rowe, n.d.).

This analysis sought to: 1) describe variation in neighborhood-level social determinants of health (e.g., poverty, diversity) across the Baltimore Metropolitan Statistical Area (MSA), 2) measure geographic variance in PPV rates explained by these determinants; and 3) examine whether neighborhood-level social capital could mediate the negative impact of living in a disadvantaged neighborhood on PPV rates.

4.3 Methods

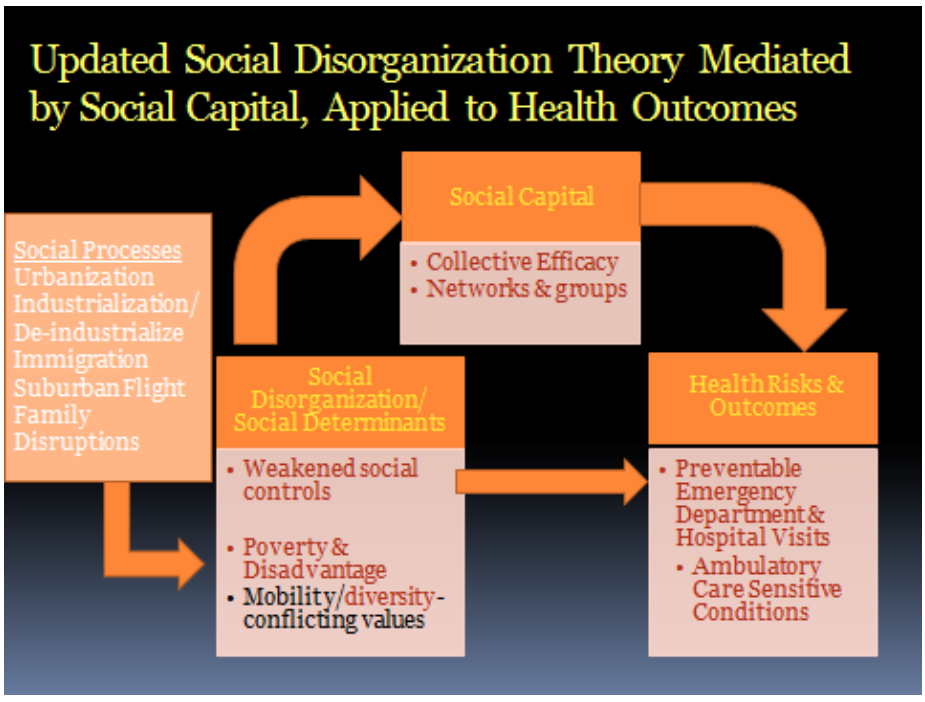
Regression models in SPSS 19 and ArcGIS 10.1 were built to explore the relationships between social determinants of health that indicate neighborhood disadvantage,

PPV rates, and social capital, all measured at the level of the zip code tabulation area (ZCTA). Social determinant data was obtained from the Census Bureau, PPV data was obtained from the Maryland Health Services Cost Review Commission (MHSCRC) and social capital data was obtained from the Baltimore Ecosystem Study (BES).

4.3.1 Theoretical Model: Social Capital

A modified version of social disorganization theory, mediated by social capital, was the theoretical framework for this study. Figure 4.1 depicts the impact of overall societal change processes on social disorganization, as envisioned by Shaw and McKay and updated by Wilson and Sampson, mediated by social capital, and applied to the targeted health outcomes.

Figure 4.1: *Updated social disorganization theory mediated by social capital, applied to health*



Two hypotheses were tested at the ZCTA level: 1) that aggregate census indicators of concentrated disadvantage, as described by Morenoff, Sampson and Raudenbush (2001),

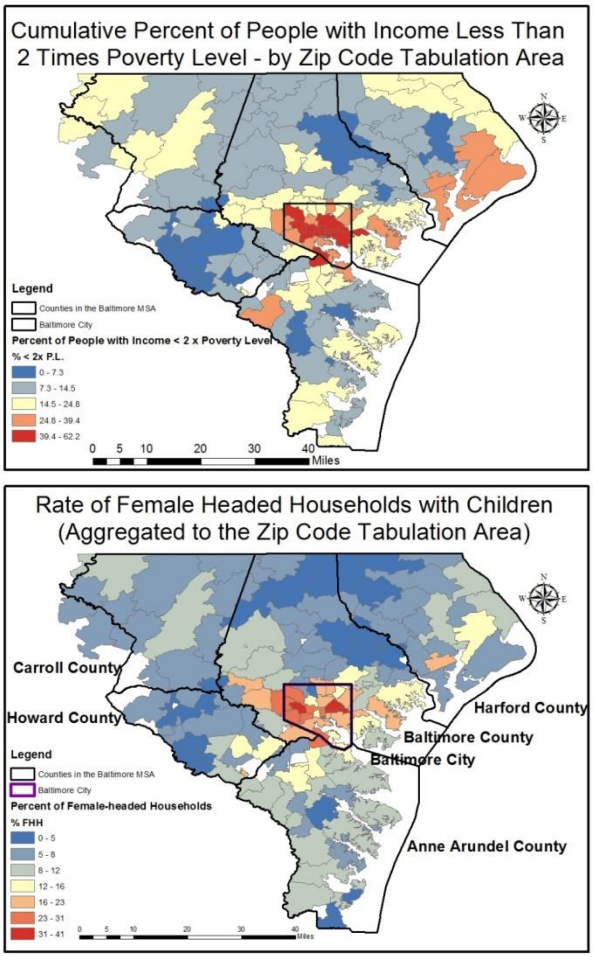
would explain a significant amount of the variance in PPV rates; and 2) that aggregate social capital would mediate the effect of concentrated disadvantage on PPV rates. Social capital was operationalized using the 2006 social capital survey administered by the BES (n.d.), described in section 4.3.4.

4.3.2 Study Design and Sample

The study was a cross-sectional ecological analysis of geographic variation in per capita PPV rates in the 132 ZCTAs of the Baltimore MSA (Baltimore City and County, Anne Arundel, Howard, Harford, and Carroll Counties). Geographically weighted regression (GWR) and generalized linear Poisson models were built using ArcGIS 10.0 and SPSS 19 to examine potential concentrated disadvantage explanatory variables (e.g., *percent of families in poverty*, *percent of households receiving public assistance*, *percent unemployed*, *percent of female-headed households with children,* and *percent minorities*) of these PPV rates, adapted from the methodology of Morenoff, Sampson and Raudenbush (2001). *Percent minorities* was used as a potential predictor rather than *percent black* and was calculated to include the total number of non-white and Hispanic residents in an area, divided by that area's total population. Other social determinant census indicators of concentrated disadvantage examined as potential explanatory variables included: *percent of people with income less than twice the poverty level*, *percent of those aged 0-64 years who were uninsured*, *percent of those aged 0-64 years with private (non-Medicaid, non-Medicare) insurance*, and *percent of those aged 25 years and older with a high school diploma or the equivalent*. *Primary care physicians per 1,000 population* was also examined as a potential explanatory variable for PPV rates.

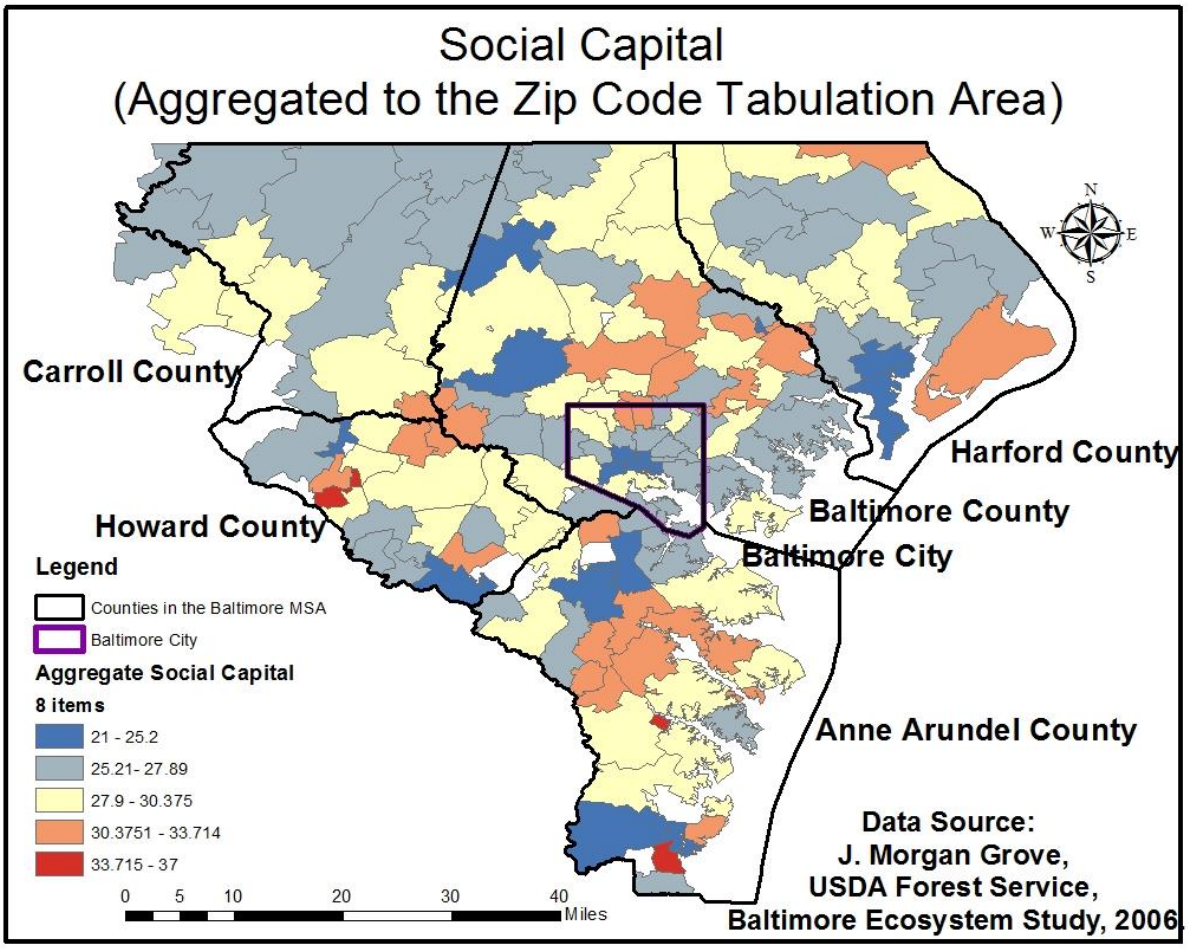
Generalized linear and GWR models are better able to handle data clustering than ordinary least squares (OLS) regression. Each variable was mapped in ArcGIS and examined using spatial statistics of Moran's I and Getis-Ord G* to determine if clustering was present. Some spatial clustering was present in PPV rates and most indices of neighborhood disadvantage, with more ZCTAs of higher neighborhood disadvantage in or near Baltimore City. This is illustrated by clustering of increased rates of relative poverty (cumulative percent of people with income less than twice the poverty level) and female-headed households in Figure 4.2.

Figure 4.2: *Distribution of important aggregate census variables that explain variance in potentially preventable emergency department visit rates*



Social capital had less spatial clustering (Figure 4.3).

Figure 4.3: *Distribution of social capital aggregated to the zip code tabulation area (ZCTA)*



A frequency distribution of each variable aggregated to the ZCTA level was also examined to determine if distribution was normal.

4.3.3 Data Sources

The study was a secondary analysis of data from three public databases: 1) enumerated data from the fiscal year 2008 (July 1, 2007-June 30, 2008) MHSCRC non-admitted ED data set for the Baltimore MSA for all ambulatory care sensitive conditions, as described above, aggregated to the ZCTA level as the dependent variable; 2) 2000 US census data from the U.S. Census Bureau for the 130 ZCTAs in the Baltimore MSA as the independent variables, and 3) ZCTA-level data measuring social capital from the BES for 2006 (Grove, 2006) as the potential mediating variable. Census data on 2006 insurance status

aggregated to the primary care service area (PCSA) by the Dartmouth Atlas of Healthcare (2013) was also used in the analyses of possible explanatory variables. Census data on total population per ZCTA drawn from the appropriate year was used in the denominator to calculate rates.

4.3.4 Social Capital Measurement Scale

Social capital is a multifactorial concept with multiple theoretical and operational definitions (Kawachi, Subramanian & Kim, 2008; Lee & Kim, 2012). The social capital scale used by the BES and in this analysis drew on questions from the Social Capital Community Benchmark Survey (Putnam, 2001) and previously validated collective efficacy or social cohesion measures (Sampson, Raudenbush & Earls, 1997) to capture data on multiple social capital dimensions (Walker, 2003). The earlier 2003 BES survey's 5-item social capital scale had good evidence of internal consistency reliability with an alpha reliability coefficient of 0.805 (Vemuri, Grove, Wilson, & Burch, 2011). In 2006 two additional items were added to the BES telephone survey's social capital scale, and the final 2006 scale asked respondents how strongly they agreed (on a 5-point scale) with seven statements about their neighborhood: a) *People in the neighborhood are willing to help one another,* b) *This is a close knit neighborhood,* c) *People in this neighborhood can be trusted,* d) *There are many opportunities to meet neighbors and work on solving community problems,* e) *There is an active neighborhood association,* f) *Municipal (local) government services (such as sanitation, police, fire, health & housing dept) are adequately provided and support the neighborhood's quality,* and g) *Churches or temples and other volunteer groups are actively supportive of the neighborhood* (BES, n.d.). The 2006 BES survey also added a "social networks" type question, "*About how many neighbors do you know by name….none, a few,*

about half, most of them, or all of them?" The social capital scale used in this analysis incorporated all eight of these items, thus addressing both cognitive and structural aspects of social capital. This 8-item scale demonstrated good internal consistency (Cronbach's alpha = 0.77). Factor analysis using principle components extraction and varimax rotation revealed a possible three components, but as one of these consisted of only a single factor (voluntary associations, question g above), items were forced to two factors: 1) social cohesion/trust (questions a, b, c, above and the question about neighbors known by name; and 2) collective action (questions d, e, f and g above).

4.3.5 Techniques of Data Analysis

Analysis proceeded using a four-step process for testing for mediation with regression analysis: 1) bivariate regression analysis of the indicators of concentrated disadvantage (independent variables) to predict PPV rates to test for a significant direct path between the independent and dependent variables; 2) bivariate regression of the independent variables to predict the mediating variable, social capital, to test for significance between these variables; 3) bivariate analysis of the mediator, social capital, to predict PPV rates, to test for a significant path between these two variables alone, and 4) multiple regression analysis with each independent variable combined with the mediator, social capital, followed by multivariate regression modeling with the significant predictors combined (Baron & Kenny, 1986; Fairchild & MacKinnon, 2009; Newsom, 2012). If the potential mediating variable remains significant, even if the independent variable is also still significant, the potential mediating variable is at least a partial mediator of the independent variable's effect on the dependent variable (Baron & Kenny, 1986; Fairchild & MacKinnon, 2009; Newsom, 2012). If the mediator variable is significant but the independent variable is no longer significant,

then the mediating variable is a full mediator. Interaction terms between significant predictor variables were also tested for significant moderating effects. Steps 1, 3 and 4 were conducted using generalized linear Poisson models, because PPV rate data was non-normally distributed, positively skewed, kurtotic, and with many low-count observations but none less than zero (Coxe, West & Aiken, 2009). GWR models were also used in Step 4, but GWR models with more than 3-4 explanatory variables became unstable. Step 2 was conducted using OLS regression, due to the normal distribution of the data for social capital.

4.4 Results

4.4.1 Bivariate Regression Analyses

The results of individual bivariate analyses to examine direct relationships of indicators of neighborhood disadvantage to PPVs are summarized in Table 4.1.

Table 4.1: *Summary of Bivariate Poisson Regression Analyses of Possible Explanatory Variables*[1] *of Potentially Preventable ED Visit (PPV) Rate*[2] *Variance*

Poisson Bivariate Regression Model Summaries								
Parameter	*Unstandardized Coefficients*				*95% Wald Confidence Intervals for B*			
	B	Std. Error	Wald X^2	Sig.	Lower Bound	Upper Bound	Deviance	Pseudo-R^2
Per capita income	-7.735 E-005	5.0116 E-006	238.224	< 0.001	-8.717 E-005	-6.753 E-005	126.845	0.675
Percent of families in poverty	0.052	0.0030	296.194	< 0.001	0.046	0.058	161.287	0.587
Percent of people with income less than 2 x the poverty level	0.034	0.0019	336.198	< 0.001	0.030	0.038	108.906	0.721
Percent female-headed households	0.061	0.0034	327.701	< 0.001	0.054	0.068	125.699	0.678
Percent minorities	1.865	0.1164	256.641	< 0.001	1.637	2.094	167.469	0.571
Percent households receiving public assistance	0.148	0.0085	303.959	< 0.001	0.132	0.165	152.770	0.609
Percent with private insurance	-0.088	0.0081	117.256	< 0.001	-0.103	-0.72	270.325	0.308
Percent uninsured	0.107	0.0351	9.268	0.003	0.038	0.176	378.225	0.032
Unemployment rate	0.016	0.0020	68.137	< 0.001	0.012	0.020	345.397	0.116
Percent high school graduates	-0.049	0.0029	287.457	< 0.001	-0.054	-0.043	136.858	0.650
Per capita primary care physicians[3]	0.105	0.0193	29.808	< 0.001	0.068	0.143	366.522	0.062
Social capital[4]	-0.126	0.0132	90.421	< 0.001	-0.151	-0.100	297.618	0.238
Social cohesion/trust[4]	-0.191	0.0220	74.860	< 0.001	-0.234	-0.147	308.628	0.210
Collective action[4]	0.008	0.0158	0.269	0.604	-0.023	0.039	390.490	< 0.001

[1]All data aggregated to Zip Code Tabulation Area, ZCTA, from U.S. Census 2000, U.S. Census Bureau, except 2006 data for *Percent with private insurance* and *Percent uninsured,* aggregated to Primary Care Service Area, PCSA, by the Dartmouth Atlas.
[2]FY 2008 emergency department data from the Maryland Health Service Cost Review Commission.
[3]2006 Data on physicians from the Health Resources and Services Administration Data Warehouse.
[4]2006 data from the Baltimore Ecosystem Study.

All the potential explanatory variables were significant, with the largest percent of variance explained (using pseudo-R^2 in the Poisson model) by the variables *percent of people with income less than twice the poverty level* (72%), followed by *percent of female-headed households* (68%) and *per capita income* (68%). All of the independent variables were positively associated with PPV rates, except *per capita income*, *percent with private insurance* and *percent high school graduates*.

All of the indicators of neighborhood disadvantage were also significant predictors of social capital, except *per capita primary care physicians* ($\beta = -0.149$, $p = 0.427$). *Per capita income* ($\beta < 0.001$, $p < 0.001$), *percent high school graduates* ($\beta = 0.119$, $p < 0.001$), and *percent with private insurance* ($\beta = 0.113$, $p = 0.045$) were positively associated with social capital. *Percent of families in poverty* ($\beta = -0.155$, $p < 0.001$), *percent of people with income less than twice the poverty level* ($\beta = -0.079$, $p < 0.001$), *percent female-headed households* ($\beta = -0.145$, $p < 0.001$), *percent minorities* ($\beta = -4.33$, $p < 0.001$), *percent of households receiving public assistance* ($\beta = -0.374$, $p < 0.001$), *percent uninsured* ($\beta = -0.627$, $p = 0.018$), and *unemployment rate* ($\beta = -0.055$, $p < 0.001$) were all negatively associated with social capital. None of the independent variables explained a large amount of the variance in social capital; *per capita income* explained the most (17.9%), followed by *percent high school graduates* (16.4%) and *percent of families in poverty* (16.3%).

Social capital was significantly negatively associated with PPV rates ($\beta = -0.126$, $p < 0.001$), explaining 23.8% of the PPV rate variance (Table 4.1). Social cohesion/trust, one of the two components of social capital identified through factor analysis, was also significantly negatively associated with PPV rates ($\beta = -0.191$, $p < 0.001$), independently explaining 21%

of the PPV rate variance. There was no significant association between collective action, the other component of social capital identified, and PPV rates ($\beta = 0.008$, $p = 0.604$).

4.4.2 Multiple Regression Analysis

Testing Mediation Effects. In this analysis, Poisson regression was used and social capital remained significant when paired with each independent variable, but each independent variable also remained significant, except *percent uninsured* (Table 4.2).

Table 4.2: *Poisson Regression Analyses: Summary of Possible Explanatory Variables[1]-plus Social Capital[2]-of PPV Rate[3] Variance*

Parameter	***Poisson Multivariate Regression Model Summaries***							
	Deviance	Pseudo-R2	Sig.	AIC	Deviance	Pseudo-R^2	Sig.	AIC
Per capita income	126.845	0.675	< 0.001	577.844			< 0.001	
With social capital					118.205	0.697	0.003	571.204
Percent of families in poverty	161.287	0.587	< 0.001	612.287			< 0.001	
With social capital					152.505	0.610	0.003	605.505
Percent of people with income less than 2 x the poverty level	108.906	0.721	< 0.001	559.906			< 0.001	
With social capital					102.648	0.737	0.012	555.647
Percent female-headed households	125.699	0.678	< 0.001	576.699			< 0.001	
With social capital					111.009	0.716	< 0.001	564.009
Percent minorities	167.469	0.571	< 0.001	618.468			< 0.001	
With social capital					147.658	0.622	< 0.001	600.658
Percent households receiving public assistance	152.770	0.609	< 0.001	603.770			< 0.001	
With social capital					137.561	0.648	< 0.001	590.561
Percent with private insurance	270.325	0.308	< 0.001	721.324			< 0.001	
With social capital					206.544	0.471	< 0.001	659.544
Percent uninsured	378.225	0.032	0.003	826.611			0.359	
With social capital					291.594	0.254	< 0.001	741.980
Unemployment rate	345.397	0.116	< 0.001	796.396			< 0.001	
With social capital					269.559	0.310	< 0.001	722.559
Percent high school graduates	136.858	0.650	< 0.001	587.857			< 0.001	
With social capital					127.534	0.674	<0.002	580.534
Per capita primary care physicians	366.522	0.062	< 0.001	817.521			< 0.001	
With social capital					281.838	0.279	< 0.001	734.837

[1]All data aggregated to Zip Code Tabulation Area, ZCTA, from U.S. Census 2000, U.S. Census Bureau, except 2006 data for *Percent with private insurance* and *Percent uninsured,* aggregated to Primary Care Service Area, PCSA, by the Dartmouth Atlas.
[2]2006 data from the Baltimore Ecosystem Study. [3]FY 2008 data from the Maryland Health Service Cost Review Commission.

The addition of social capital added only 1.6% to 5.1% to the explanation of PPV rate variance (pseudo-R^2) when paired with the variables that independently explained more than 50% of PPV rate variance (*per capita income, percent of families in poverty, percent of people with income less than twice the poverty level*, *percent of female-headed households, percent minorities, percent of households receiving public assistance*, or *percent high school graduates*).

Full and Reduced Poisson Multivariable Regression Models. Multiple multivariable regression analyses of all of the significant predictors of PPV rates, including social capital, were examined. Model 1 in Table 3 depicts the results of a regression model based on components of the Neighborhood Deprivation Index proposed by Morenoff, Sampson and Raudenbush (2001), with some modifications, plus social capital; this model explained 82% of the variance in PPV rates and had a relatively low Akaike Information Criterion (AIC). The modifications were 1) substitution of percent *of people with income less than twice the poverty level* for *percent of families in poverty*, and 2) *percent minorities* for *percent black. Unemployment rate* and *percent minorities* were not significant explanatory variables, but their inclusion in the model resulted in a lower AIC.

Model 2 in Table 4.3 shows the results of the best multivariable Poisson model, a reduced and adjusted model that included *percent of people with income less than twice the poverty level*, *percent of households receiving public assistance, percent female-headed households, percent uninsured, social capital* and an interaction term between *percent female-headed households* and *social capital*.

Table 4.3: *Full and Reduced Poisson Regression Explanatory[1] Models of Potentially Preventable ED Visit Rate[2] Variance*

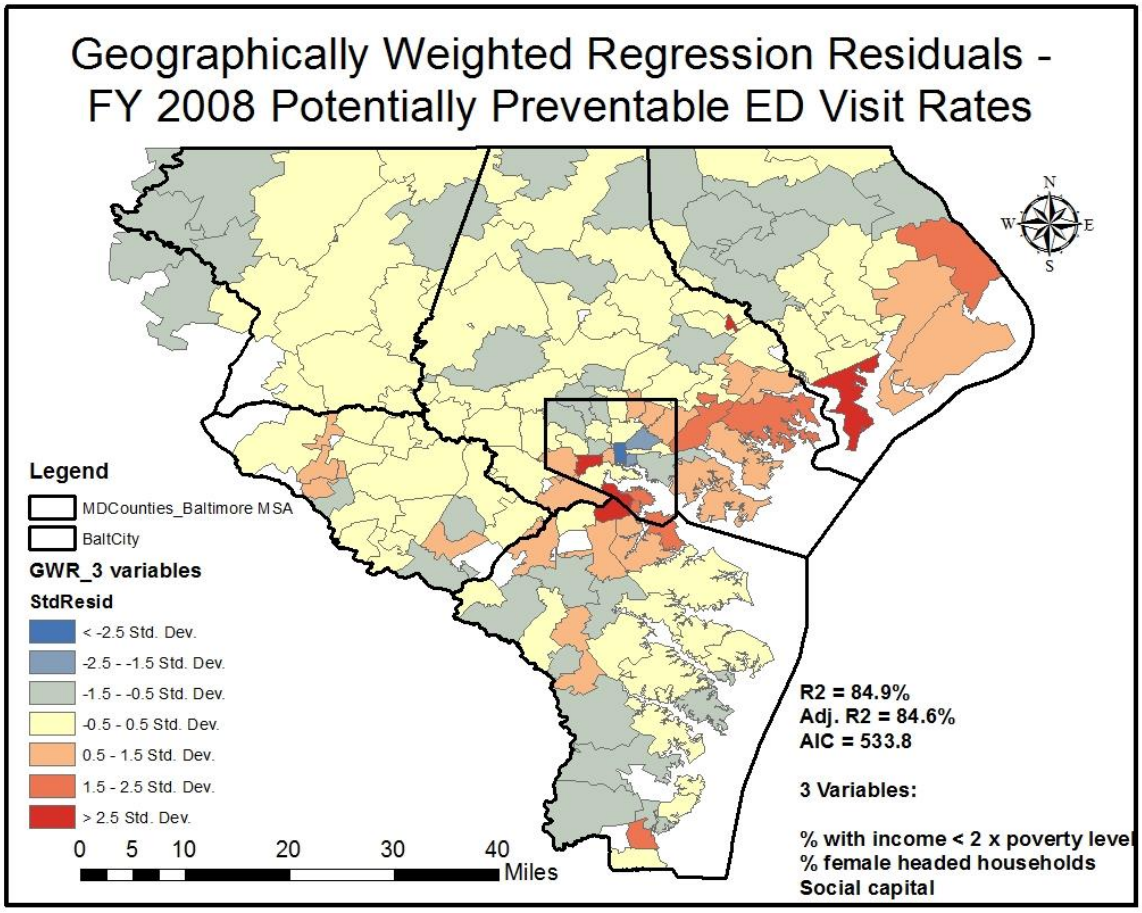
Poisson Regression Model Summaries									
Parameter	*Unstandardized Coefficients*		*95% Wald Confidence Intervals for B*						
	B	Std. Error	Wald X^2	Sig.	Lower Bound	Upper Bound	AIC	Deviance	Pseudo-R^2
Model 1: Adjusted Neighborhood Deprivation Index							531.060	70.061	0.821
Intercept	1.623	0.4742	11.721	0.001	0.694	2.553			
Percent of people with income less than 2 x the poverty level[3]	0.041	0.0066	38.504	< 0.001	0.028	0.054			
Percent households receiving public assistance	-0.153	0.0366	17.501	< 0.001	-0.225	-0.081			
Unemployment rate	-0.002	0.0036	0.399	0.528	-0.009	0.005			
Percent female-headed households	0.053	0.0109	23.889	< 0.001	0.032	0.075			
Percent minorities[4]	-0.153	0.2535	0.366	0.545	-0.650	0.343			
Social capital	-0.035	0.0155	5.009	0.025	-0.065	-0.004			
Model 2: Reduced Model, with Interaction Effects							515.361	54.976	0.859
Intercept	1.704	1.4313	1.417	0.234	-1.102	4.509			
Percent of people with income less than 2 x the poverty level[2]	0.152	0.0520	8.552	0.003	0.050	0.254			
Percent households receiving public assistance	-0.121	0.0375	10.414	0.001	-0.194	-0.47			
Percent female-headed households	-0.099	0.0628	2.466	0.116	-0.222	0.024			
Percent uninsured	0.132	0.0936	1.980	0.159	-0.052	0.315			
Social capital	-0.092	0.0288	10.267	0.001	-0.149	-0.036			
Interaction:Percent female-headed households & social capital	0.005	0.0022	6.058	0.014	0.001	0.010			

[1]Explanatory variable data aggregated to ZCTA from U.S. Census 2000, U.S. Census Bureau, except data on *social capital* from the 2006 Baltimore Ecosystem Study and *Percent uninsured, 2006,* aggregated to PCSA, by the Dartmouth Atlas.
[2]FY 2008 emergency department visit data from the Maryland Health Service Cost Review Commission.
[3]Original parameter was *Percent of families in poverty.* [4]Original parameter was *Percent Black.*

This model had the lowest AIC and the most variance (86%) explained. There was also a significant interaction term between *percent of people with income less than twice the poverty level* and *percent uninsured;* however, its inclusion in the model resulted in a higher AIC and no increase in variance explained. *Percent of female-headed households* and *percent uninsured* were not significant explanatory variables in this reduced and adjusted model, but deletion of these variables resulted in higher AICs, indicating models that fit the data less well.

Geographically Weighted Regression (GWR). The best GWR model tested explained 85% of the variance in PPV rates (AIC = 533.8) with three variables: *percent of people with income less than twice the poverty level*, *percent female-headed households*, and *social capital*. GWR regression residuals of this model demonstrated excellent model fit throughout the areas south, west and north of Baltimore City, with less good model fit in parts of Baltimore City and in the ZCTAs in the southern parts of Baltimore and Harford counties, and along the northwest shore of the Chesapeake Bay (Figure 4.4).

Figure 4.4: *Geographically weighted regression residuals for FY 2008 potentially preventable emergency department visit rates*



Areas with regression residuals with positive standard deviations (in red) indicate areas where the model is over-predicting PPV rates, while areas with regression residuals with negative standard deviations (in blue) indicate areas where the model is under-predicting PPV rates.

4.5 Discussion

This is the first study, to my knowledge, to examine the relationships between neighborhood disadvantage, social capital and PPV rates. All the indicators of neighborhood disadvantage reviewed were significant explanatory variables of PPV rates in bivariate analyses, and all were positively associated with PPV rates, except *per capita income,*

percent with private insurance and *percent high school graduates*. These findings are consistent with previous studies that have found higher PPA and PPV rates in poor communities and among vulnerable populations such as minorities, those with lower income or education, and the uninsured and Medicaid populations (Johnson, et al., 2012; Laditka, Laditka & Mastanduno, 2003; Magan, Alberquilla, Otero & Ribera, 2011; Oster and Bindman, 2003).

The analysis demonstrated that an adjusted neighborhood disadvantage index, including component variables of *percent of people with income less than twice the poverty level*, *percent of households receiving public assistance*, and *percent of female-headed households*, explained most of the variance in PPV rates in metropolitan Baltimore. *Percent of people with income less than twice the poverty level* by itself explained 72 percent of the variance in PPV rates, more than *per capita income* or *percent of families in poverty*. This may be due to this variable's ability to measure relative poverty, incorporating an element of relative income inequality into a measure of the magnitude of poverty, consistent with Wilkinson's theory that income inequality is detrimental to multiple health outcomes (1996).

This is also the first analysis, to my knowledge, to describe the mediating influence of social capital on the relationship between neighborhood disadvantage and PPV rates in the U.S. Following the four-step process outlined by Baron and Kenny (1986) to test for mediation with regression analysis, social capital was a significant partial mediator of all of the indicators of concentrated neighborhood disadvantage at the ZCTA level reviewed in this analysis, and a full mediator of *percent uninsured*. Mediation and confounding are conceptually quite different but statistically similar and so can be difficult to differentiate without theoretical basis. Mediation is believed to help delineate the causal pathway between

the independent and dependent variables, while confounding results from coincidental or spurious associations that can obscure true causal pathways (MacKinnon, Krull & Lockwood, 2000). The effect (β) of an independent variable is typically consistent in direction in mediation models but can change when confounding variables are controlled for through model inclusion (MacKinnon, et al., 2000). *Percent of people with income less than twice the poverty level* was consistently positively associated with PPV rates, and *social capital* was consistently negatively associated with PPV rates in all models. The mediating influence of social capital on neighborhood disadvantage and PPV rates is consistent with prior studies indicating that social capital mediates effects of neighborhood disadvantage on mental health (Haines, Beggs & Hurlbert, 2011; Kruger, Reischl, Gee, 2007) and general health (Browning & Cagney, 2003; Murayama, Fujiwara & Kawachi, 2012). However, additional evidence and differentiation of individual and neighborhood antecedents of PPV rates are needed.

In the final reduced model, the effects of *percent uninsured*, which was completely mediated by *social capital*, and *female-headed households*, which was completely mediated by the significant interaction term between *social capital* and *female-headed households*, both changed direction, indicating the possibility of inconsistent mediation or confounding effects. The former may indicate that social capital has the potential to convey some resource, perhaps knowledge of affordable primary care clinics, to mediate the relationship between lack of insurance and increased PPV rates. The latter may indicate that there is a clinically significant moderating relationship between *social capital* and *female-headed households* requiring further investigation. In the United States, over a fifth of all women (22.8%) lived in female-headed households with children in 2006-2008

(Kaiser Family Foundation, 2013). Wilson argues convincingly that higher rates of female-headed households among Blacks and in areas of concentrated urban poverty are inextricably linked to the loss of low-wage jobs for Black males in urban areas (2010). The interaction between neighborhood-level social capital and *percentage of female-headed households,* or other variables for which *female-headed households* may act as a proxy measure, needs to be more fully explored.

This analysis also adds to the knowledge regarding causal pathways on which social capital may operate as a mediating influence on neighborhood disadvantage and PPV rates. Factor analysis revealed two main components of social capital, social cohesion/trust and collective action. This is consistent with a growing body of research on social capital describing it as a multifactorial, community-level construct with both cognitive and structural dimensions (Kawachi, Subramanian & Kim, 2008). One of two components of social capital identified, social cohesion/trust, was also a significant mediator of indicators of neighborhood disadvantage on PPV rates, but the other component, collective action, was not. In this analysis, social capital and social cohesion/trust were significant partial mediators of the aggregate indicators of neighborhood disadvantage in explaining variance in neighborhood PPV rates, but collective action was not. An assumption that social cohesion/trust is generated through collective action is inherent in Putnam's approach to social capital (2000, 2003), but others posit that social cohesion/trust stems from greater economic equality (Uslaner, 2008) or institutions and policies (Beugelsdijk, 2006; Rothstein & Stolle, 2008) and may be a necessary antecedent to collective action or social participation (Giordano, Bjork & Lindstrom, 2012). The latter view is in keeping with Wilkinson's hypotheses regarding the negative effects of income inequality on health outcomes acting

through psychosocial mechanisms (1996) and with descriptions of the erosion of social cohesion/trust in areas of concentrated urban poverty, where disproportionate numbers of minorities live (Orr, 1999; Wilson, 2010; Wilson, 1987).

4.5.1 Research Implications

Health-seeking behaviors are influenced by demographic and population characteristics (e.g., income, insurance status). Community-level social capital may offer physical, cognitive and psychological resources to residents or it may simply bolster individual social supports and resources, thus counteracting poverty's negative impact. At the individual level, more social support may translate into more options for transportation, child care, health information, and social resources to facilitate timely primary care access, versus ignoring health needs until crisis states arise and emergent care is needed. Before we can differentiate the effects of individual-level social support and community-level social capital, one definition that is conceptually sound, measurable, reliable and valid must be chosen for social capital, a multifactorial concept with multiple theoretical and operational definitions. Many instruments to measure social capital have been developed in recent years. Several of these carefully constructed indices, as well as data collected, are made available to others online, including the Social Capital Community Benchmark Survey (Putnam, 2001), the Rupashinga scial capital index (Rupashinga and Goetz, 2008), and the Baltimore Ecosystem Survey social capital scale (BES, n.d.). The BES scale used in this analysis measured social capital as a community trait by aggregating survey data and included a cognitive dimension of social cohesion/trust and a structural dimension of collective action, consistent with other measures of social capital currently in use in public health (Kawachi, Subramanian & Kim,

2008; Lee & Kim, 2012). Further research on concise, reliable, and valid measures of social capital that can be incorporated into routinely administered surveys is needed.

More research is also needed in other settings before these findings can be generalized. The relationship between neighborhood disadvantage and PPVs, mediated by social capital, should also be further explored at alternative geographies, including census tracts and block groups, to determine the most appropriate aggregate level at which these neighborhood effects occur, followed by multi-level modeling to differentiate individual and neighborhood effects. More research is also needed to delineate how institutions and policies can promote growth in social cohesion/trust and social capital and thus counter the negative impact of relative poverty on health outcomes. In particular, the relationships or interaction between neighborhood-level social capital and insurance status and percentage of female-headed households with children need to be more fully explored.

4.5.2 Practice and Policy Implications

PPA and PPV rates are often used as a proxy measure for access to and utilization of primary care (Falik, et al., 2006; Gresenz, Ruder, and Lurie, 2009; Laditka & Laditka, 2006; Shi, Samuels, Pease, Bailey & Corley, 1999), but in this study PPV rates were used simply to quantify the healthcare seeking behavior that they actually represent. In fact, when controlled for by other variables, *per capita primary care physicians* and *rates of uninsured* were not found to be significant predictors of PPV rates at the ZCTA level. This is contrary to some previous findings of an inverse relationship between per capita primary care physicians and PPA or PPV rates (Chen, Zhang, Sun & Mueller, 2009; Laditka, Laditka & Probst, 2005; Hossain & Laditka, 2009; Murday & Corley, 2008; Zhan, Miller, Wong & Meyer, 2004). However, others have either found mixed results (Pitkin Derose, 2008) or

noted that primary care access barriers that lead to increased PPA/PPV rates may be more related to income, employment and other community factors influencing healthcare-seeking behavior than to the characteristics of health delivery systems (Chang, Mirvis & Waters, 2008; Liu & Pearlman, 2009; Ricketts, Randolph, Howard, Pathman & Carey, 2001; Zlotnick, 2006). Thus, having sufficient, well-situated clinics and primary care provider sites available and providing insurance coverage to a population may be necessary, but not sufficient, components of expanding access to primary care and decreasing PPV rates.

Primary care access expansion policies must also consider how to influence healthcare-seeking behaviors at the population level. Establishment of medical homes at community health centers (CHC) is one strategy that has proven effective at reducing PPAs and PPVs in vulnerable populations (Choudhry, et al., 2007; Rothkopf, Brookler, Wadhwa, and Sjovetz, 2011), through increased access to care and possibly greater social support. As medical homes become more common under healthcare reform, fostering community-level social capital is a potential strategy that CHCs should consider to facilitate better primary care access. Fostering growth in social capital requires time and commitment from multiple forces; CHCs may be able to leverage their efforts by partnering with other neighborhood entities in community organizing and capacity-building (Goodman, 2009; Michael, Farquhar, Wiggins & Green, 2008; Hawe & Shiell, 2000; Pavel, 2009; Payne & Williams, 2008; Semenza, March & Bontempo, 2006). State and local policies to reduce disparities and improve access to healthcare and other resources such as education, jobs, childcare, housing and safe neighborhoods may also promote the growth of social cohesion/trust in areas of concentrated disadvantage (Lee, Kiyu, Milman & Jimenez, 2007; Orr, 1999; Orr, 2007; Wilson, 1987). Policies aimed at reducing health disparities "should pay attention to the

characteristics of the areas in which people live as well as the characteristics of the people who live in these areas" (Smith, Hart, Watt, Hole & Hawthorne, 1998, p. 399).

4.5.3 Limitations

This study was a cross-sectional design, which can only identify associations, not establish chronology or causality. The level of operation of the constructs related to social capital is the neighborhood or population level, but application of analyses at this level to individuals is subject to the ecologic fallacy, in that individual behavior often differs from that analyzed in aggregate. Most interventions to reduce preventable ED use, however, currently occur at the individual, rather than aggregate, level. Ecologic biases also arise due to aggregation of data spatially and across time (Abellan, Richardson & Best, 2008) and because aggregate data cannot adequately characterize variability within the group as analyses of individual-level data would do (Wakefield & Haneuse, 2008). Also, multiple factors influence health seeking behaviors, and it is impossible to isolate and measure the precise impact of social capital on aggregate level behavior, even with regression analyses. Finally, the results of this analysis may not be generalizable to geographic datasets from other parts of Maryland or the United States.

4.5.4 Multi-year data

Use of multi-year data introduces potential for bias across time, but neighborhood-level ethnic, racial and economic succession typically proceed slowly in general (Shaw & McKay, 1969/1942) and specifically in Baltimore (Pietila, 2010; Johns Hopkins Medicine, n.d.). Demographic composition and poverty rates in Baltimore and the surrounding counties changed by less than 2-3 percent between 2000 and 2008/2010, except that the "white alone population" decreased by 5-10 percent in parts of Baltimore City and southern Howard

County from 2000 to 2010 (U.S. Census Bureau, 2013; Kneebone & Garr, 2010; National Center for Smart Growth Research and Education, 2012).

4.5.5 Levels of Data Aggregation

More public health research is examining neighborhood effects, but researchers must ensure that relevant geographic areas are defined and neighborhood characteristics appropriately identified (Roux, 2001). Data on social determinants, social capital, and PPV rates in this analysis were aggregated to the ZCTA level, smaller than the county/state levels most often used in similar previous analyses, but still potentially resulting in areas with boundaries that may or may not align with spatial phenomenon. Spatial data aggregations are subject to the modifiable ariel unit problem (MAUP); when data are aggregated into administrative boundaries of arbitrary size and shape, true hot spots may become indiscernible within the larger administrative units to which data are aggregated (Jelinski & Wu, 1996), introducing distorting influences into spatial statistical analyses. Data aggregation to the ZCTA level is a finer granulation than most analyses to date and corresponds with some larger communities and census designated places. Aggregation to the census tract level, however, might better reflect neighborhood characteristics, and public health researchers must work with policy-makers to find ways to make such data available while continuing to safeguard personal health data anonymity and confidentiality.

4.5.6 Conclusions

This is the first published analysis to examine the mediating influence of social capital on the relationship between neighborhood disadvantage and PPV rates in the U.S. The study examined all non-hospitalized PPVs in the study area for fiscal 2008 and used a valid, reliable measure of social capital, with data originally collected by the BES. Factor analysis

confirmed two major components of social capital, social cohesion/trust and collective action, previously identified in public health and other literature on social capital. Measures of neighborhood disadvantage were examined and statistical models built to explain a large amount (82-86%) of the variance in PPV rates at the aggregated ZCTA level. Social capital and social cohesion/trust, but not collective action, were significant mediators of neighborhood disadvantage in explaining PPV rates at the ZCTA level. More ecologic, individual and multi-level research is needed to delineate the causal path between neighborhood disadvantage and PPVs and how social capital mediates this relationship. In refining the definition of social capital, it is important to remember that social disorganization theory and the concept of social capital evolved from empiric observation of measurable outcomes occurring at the level of the urban neighborhood. Theoretical constructs must also be adapted to modern definitions of neighborhood.

CHAPTER 5
Summary and Discussion

5.1 Overview of Summary and Discussion

In developing my DNP capstone project, I realized the need for further research preparation to complement my clinical expertise and growing interest in social determinants of health. This dissertation illustrates my developing expertise as a scientist with expertise in measuring community level indices that reflect access to care, resources, and outcomes. This chapter summarizes how this research contributed to the knowledge of certain topic areas regarding neighborhood-level disadvantage, social determinants of health and social capital; what was learned about the state of Maryland in regard to social determinants of health; and implications for practice, research and policy.

I will first summarize what has been learned in the preceding three analyses about the geographic variance and social determinants of potentially preventable emergency department visits (PPV) in the United States and in Maryland, the impact of concentrated neighborhood disadvantage, and the potential mediating effect of social capital, within the context of current literature seeking theoretical and empirical understanding of social capital. The first manuscript was a literature review linking social determinants of health and potentially preventable hospital (PPA) and emergency department visit (PPV) rates. The second manuscript was a spatial investigation of socioeconomic predictors of variance in the PPV rates for the total and uninsured populations in Maryland, aggregated to the zip code tabulation area (ZCTA) level, using generalized linear and geographically weighted regression models. The third manuscript examined components of neighborhood disadvantage and the potentially mediating influence of social capital in explaining variance

in PPV rates in the greater Baltimore Metropolitan Statistical Area (MSA), also at the ZCTA level. Implications for practice, research and policy are also examined.

5.2 Contributions to Current Knowledge about Social Determinants of Health

This investigation sought to quantify the impact of social determinants of health-seeking behavior on PPVs at the community level, within the context of current understanding of how the social determinants of health operate. Social determinants include attributes such as housing, socioeconomic status, access to care, transportation, discrimination, and social or environmental stressors (Centers for Disease Control and Prevention, CDC, 2009). As our understanding of the impact of social determinants on health continues to grow, we find ourselves in the midst of an intellectual movement away from conceptualizing these determinants as resources for individuals to access, towards a framework of societal and economic structural determinants that impact health outcomes at the community level. Nationally and internationally, this paradigm shift is reflected in the changing language used to define the social determinants of health; we are moving from laundry list definitions of social and economic resources available to the individual, to definitions that acknowledge the interwoven, complex nature of social and economic structure encompassing environments of relative health potential available to populations (U.S., Department of Health & Human Services, 2013; World Health Organization, 2008). These changes represent an important shift in thinking about health and disease and their determinants. Conceptualization of disease etiology has previously evolved from a framework of biological risk factors to consideration of behavioral determinants of health, but this earlier shift still maintained – and perhaps magnified - a focus on individual risk and

responsibility for health status. Considering the social determinants of health requires us to reflect on the larger social, historical, political and economic organizations and policies that influence health at the population level. All three manuscripts in the preceding chapters focused on efforts to measure the social determinants of PPAs/PPVs at aggregate community levels, consistent with current conceptualizations of social determinants and population health.

5.2.1 Social Determinants of PPAs and PPVs

The 14 studies I reviewed in the first manuscript of geographic variation in PPA or PPV in the U.S. at the aggregate level were descriptive and used statistical analyses of geographic administration units; twelve used regression analyses. Geographic units of analysis, definitions of PPAs and PPVs and conditions included, and explanatory variables used, all varied considerably across studies. Although all of these studies sought to identify and explain areas of increased need for primary care demonstrated by geographical variance in PPA and PPV rates, firm conclusions about characteristics to explain this variation remained somewhat elusive. In spite of these differences in definitions and measures of outcomes and explanatory variables, across studies I found that PPA rates were higher in geographical areas of lower income, lower average education, and possibly less social capital. Some studies associated fewer primary care physicians and community clinics or higher rates of no insurance or public insurance status with higher PPA/PPV rates, but others did not. These findings were consistent with previous reviews at the individual and community level that found higher PPA rates in poor communities (Moy, Barrett & Ho, 2011; Stranges & Stocks, 2010; Wier, Merrill & Elixhauser, 2009) and related to reduced

access to primary care and inefficiencies in healthcare service delivery (Moy, Barrett & Ho, 2011; Russo, Jiang & Barrett, 2007).

In reviewing these studies it became clear that, as earlier stated by Ricketts, Randolph, Howard, Pathman & Carey (2001), PPA rates may more accurately reflect population-level - versus health system - access to care issues and influences on health-seeking behaviors such as income, employment, and insurance status. Likewise, some studies indicated that areas with large proportions of minorities were at increased risk for higher PPA/PPV rates, but others found no such association, or negative associations between minority status and increased rates. Only four studies examined PPV versus PPA rates and none examined PPV rates for all ACSC or examined relationships with PPVs at administrative units smaller than counties. Only one study looked at the association between social capital and PPA (Pitkin DeRose, 2008). No studies examined relationships between social capital and PPV rates.

Within the broader context of social determinants influencing population-level health outcomes, I reviewed the literature on community-level social determinants of health-seeking behavior for PPAs/PPVs and found that lack of primary care availability and/or insurance, two attributes commonly believed to contribute to increased preventable ED use, did not consistently or exclusively explain the variation in PPA/PPV rates in the U.S. Other social determinants, such as lower rates of income and education, and higher proportions of minority populations, were frequently associated with increased PPA/PPV rates at the community level. These associations supported the likelihood that socioeconomic and racial health disparities are reflected in place-based PPA rate variation, but they did not delineate a causal pathway to explain these relationships. Other gaps in knowledge identified included

which social determinants of health were most influential in affecting PPA/PPV rates and whether the social determinants identified to explain PPA rate variance would also explain PPV rate variance.

5.2.2 Geographic Variance in Total and Uninsured PPV Rates in Maryland

The second manuscript aimed to explain the geographic variation in PPV rates in Maryland at the ZCTA level and test the predictive value of regression models and explanatory socio-demographic census and provider variables in explaining this variance. Hot spots of increased PPV rates across the state were similar for total and uninsured populations, except that uninsured PPV rates were more clustered in urban areas. The Poisson and geographically weighted regression (GWR) models best fit the data and predicted 40-52% of variance in the total population and 46% of variance in the uninsured population. At the ZCTA level, significant predictors of increased PPV rates in both populations were *percent of female-headed households*, *per capita income* and *percent of people with a high school diploma*. *Primary care physicians per population* and housing, linguistic and disability characteristics were not significant predictors of PPV rates.

My analysis of PPV rates using census data at the ZCTA level in Maryland identified significant social determinant population-level predictors (per capita income and rates of high school education and female-headed households) similar to those previously identified for PPA rates (Chang, Mirvis & Waters, 2008; Chen, Zhang, Sun & Mueller, 2009; Finegan, Gao, Pasquale & Campbell, 2010; Laditka, Laditka & Probst, 2005; Liu & Pearlman, 2009; Pitkin Derose, 2008; Zhan, Miller, Wong and Meyer, 2004) and PPV rates (Murday & Corley, 2008; Zlotnick, 2006). This finding confirmed that social determinants and social resources are key components in understanding the health-seeking behaviors that

contribute to increased or decreased PPV rates. GWR models also indicated that a significant predictor was missing from the explanatory variables included, possibly a social determinant that could not be adequately represented by U.S. census data that is currently collected.

5.2.3 Social Capital as a Mediator of Neighborhood Disadvantage to Explain PPV Rate Variance

The third manuscript was an analysis of the mediating influence of social capital on the relationship between neighborhood disadvantage and PPV rates, which demonstrated that an adjusted neighborhood disadvantage index, including component variables of *percent of people with income less than twice the poverty level*, *percent of households receiving public assistance*, and *percent of female-headed households*, explained most (82-86%) of the variance in PPV rates in metropolitan Baltimore. *Percent of people with income less than twice the poverty level* by itself explained 72% of the variance in PPV rates, more than *per capita income* or *percent of families in poverty;* this may be due to this variable's ability to measure relative poverty, incorporating an element of relative income inequality into a measure of the magnitude of poverty. Social capital by itself explained 24% of the PPV rate variance. *Percent of households receiving public assistance* and *percent of female-headed households* also explained significant PPV rate variance. Social capital was a significant partial mediator of the impact of poverty and other measures of neighborhood disadvantage at the ZCTA level and a full mediator of *percent uninsured*. The interaction term between *social capital* and female-headed *households* was a full mediator of the effect of *female-headed households* on PPV rates.

This study will be the first published analysis, to my knowledge, of the mediating influence of social capital on the relationship between neighborhood disadvantage and PPV rates at any level, individual or aggregate, in the U.S. The mediating influence of social

capital on the relationship between neighborhood disadvantage and crime is well established (Sampson, 2003; Raudenbush, 2003; Morenoff, Sampson & Raudenbush, 2001). Several multi-level studies have also examined the influence of neighborhood-level social capital on health (Browning & Cagney, 2003; Murayama, Fujiwara & Kawachi, 2012); most have found that social capital exerts a positive influence on health outcomes, but additional evidence and differentiation of individual/family and neighborhood antecedents of health outcomes are still needed. Pitkin Derose (2008) did examine the relationship between social capital and PPA rates in Florida with mixed results, possibly due to use of census variables as proxy measures to represent social capital. The confirmation of social capital's mediating influence on the relationship between neighborhood disadvantage and PPV rates in my analysis adds to the knowledge on social determinants of health in several ways. First, social capital is a neighborhood-level characteristic, and with its inclusion in this analysis, we start to move away from explaining PPV rates only in terms of individual-level attributes (e.g., income, education, insurance status) towards consideration of community-level attributes that affect PPV rate variability and may offer a population-level intervention points. Second, social capital is a community asset, and community assets are strengths that can be leveraged to make health promotion and disease prevention interventions more effective.

In this analysis social capital was a significant partial mediator of all of the aggregate measures of concentrated neighborhood disadvantage reviewed at the ZCTA level, including rates of relative poverty and female-headed households, and a full mediator of the uninsured rate. The latter indicates that social capital has the potential to convey some resource, perhaps knowledge of affordable primary care clinics, to mediate the relationship between lack of insurance and increased PPV rates. Likewise, a statistically significant

interaction term between social capital and rates of female-headed households mediated the impact of female-headed households by itself in the models, indicating that there may be a clinically significant moderating relationship between these two variables requiring further investigation. In the United States, over a fifth of all women (22.8%) lived in female-headed households with children in 2006-2008 - although this varied widely across states, with the lowest percentage in Utah (13.9%) and the highest in the District of Columbia (43%) (Kaiser Family Foundation, 2013). The steady increase since the 1970s in numbers of children living in female-headed households, now 24%, has been linked to increased numbers of children living in poverty and increased risks of dropping out of school and the workforce and teen pregnancy (Mather, 2010). Wilson argues convincingly that higher rates of female-headed households among Blacks and in areas of concentrated urban poverty are inextricably linked to the loss of low-wage jobs for Black males in urban areas (2010). The interaction between neighborhood-level social capital and percentage of female-headed households with children, or other variables for which female-headed households with children may act as a proxy measure, needs to be more fully explored.

The third manuscript also adds to the knowledge regarding pathways of association on which social capital may operate as a mediating influence on neighborhood disadvantage and its impact on PPV rates. Factor analysis revealed two main components of social capital, social cohesion/trust and collective action, measured by the items of the BES social capital scale. This is consistent with a growing body of research on social capital describing it as a multifactorial, community-level construct with both cognitive and structural dimensions (Kawachi, Subramanian & Kim, 2008). One of two components of social capital identified, social cohesion/trust, was also a significant mediator of indicators of neighborhood

disadvantage on PPV rates, but the other component, collective action, was not. Social determinants of health have been previously linked to disparities in health outcomes (CDC, 2009; Koh, et al., 2010; Braveman, Cubbin, Egerter, Williams & Pamuk, 2010) and are believed to influence health outcomes by directly influencing risks and by indirectly influencing health-promoting behaviors and access to care (CDC). However, we know little about how social capital mediates the impact of neighborhood disadvantage on community-level health outcomes. It is believed that communities with high levels of social capital may offer health-protective benefits to their residents, perhaps through more rapid information dissemination and/or increased social pressure to conform to healthy norms and/or to avoid unhealthy behaviors (Kawachi, Kennedy & Glass, 1999). While Putnam would explain social cohesion/trust as a by-product of collective action or social participation (2000, 2003), my analysis implied that social cohesion/trust is either a community attribute that functions separately from collective action and/or social cohesion/trust is a necessary prerequisite to collective action. The latter interpretation is consistent with findings by others who posit that that social cohesion/trust stems from greater economic equality (Uslaner, 2008) or institutions and policies (Beugelsdijk, 2006; Rothstein & Stolle, 2008) and may be a necessary antecedent to collective action or social participation (Giordano, Bjork & Lindstrom, 2012). These hypotheses are in agreement with theories put forth by Wilkinson (1996) on the indirect psychosocial effects of income inequality on health and by Orr (1999) and Wilson (2010; 1987) on the erosion of social cohesion/trust in areas of concentrated urban poverty, where disproportionate numbers of minorities live. More research is needed to delineate how institutions and policies can promote growth in social cohesion/trust and social capital and thus counter the negative impact of income inequality on health outcomes.

5.3 Practice Implications

Potentially preventable hospital admissions (PPA) and PPV rates are often used as a proxy measure for access to and utilization of primary care (Falik, et al., 2006; Gresenz, Ruder, and Lurie, 2009; Laditka & Laditka, 2006; Shi, Samuels, Pease, Bailey & Corley, 1999), but in my analyses PPV rates were used simply to quantify the healthcare seeking behavior that they actually represent. In fact, when controlled for by other variables, *per capita primary care physicians* and *rates of uninsured* were not found to be significant predictors of PPV rates at the ZCTA level. This is contrary to some previous findings of an inverse relationship between per capita primary care physicians and PPA or PPV rates (Chen, Zhang, Sun & Mueller, 2009; Laditka, Laditka & Probst, 2005; Hossain & Laditka, 2009; Murday & Corley, 2008; Zhan, Miller, Wong & Meyer, 2004). However, others have either found mixed results (Pitkin Derose, 2008) or noted that primary care access barriers that lead to increased PPA/PPV rates may be more related to income, employment and other community factors influencing healthcare-seeking behavior than to the characteristics of health delivery systems (Chang, Mirvis & Waters, 2008; Liu & Pearlman, 2009; Ricketts, Randolph, Howard, Pathman & Carey, 2001; Zlotnick, 2006). Thus, having sufficient, well-situated clinics and primary care provider sites available and providing insurance coverage to a population are necessary, but not sufficient, components of expanding access to primary care and decreasing PPV rates.

Individual-level strategies to reduce PPVs have included discharge teaching, primary care referrals, post-visit telephone follow-up, and use of patient navigators, with limited results. Community-level strategies to build social capital and promote use of primary care may ultimately be more successful at decreasing PPV rates, but interventions at the

neighborhood level to date have been less common than those at the individual level, even though some social determinants largely exert their influence at the neighborhood level (Iton, 2006). Some evidence indicates that community-level interventions to foster social capital can result in enhanced community development efforts (Semenza, March, & Bontempo, 2006; Goodman, 2009; Payne & Williams, 2008; Snowden, 2005), but the paths between social capital, use of primary care and potentially preventable visits to the ED are not yet well elucidated.

Primary care access expansion policies must also consider how to influence healthcare-seeking behaviors at the population level. Establishment of medical homes at community health centers (CHC) is one strategy that has proven effective at reducing PPAs and PPVs in vulnerable populations (Choudhry, et al., 2007; Rothkopf, Brookler, Wadhwa, and Sjovetz, 2011), through increased access to care and possibly greater social support. As medical homes become more common under healthcare reform, fostering community-level social capital is a potential strategy that CHCs should consider to facilitate better primary care access. Fostering growth in social capital requires time and commitment from multiple forces; CHCs may be able to leverage their efforts by partnering with other neighborhood entities in community organizing and capacity-building (Goodman, 2009; Michael, Farquhar, Wiggins & Green, 2008; Hawe & Shiell, 2000; Pavel, 2009; Payne & Williams, 2008; Semenza, March & Bontempo, 2006).

Community and public health nurses often provide social support to clients (whether these are individuals, families or communities) and should be at the forefront of future investigations of community-level interventions to increase social capital. Some potential strategies include social marketing; community development and action, use of

community resource centers and asset mapping (Payne & Williams, 2008); use of community outreach workers or health educators (Chiu & West, 2007; Michael, Farquhar, Wiggins & Green, 2008; Farquhar, Michael & Wiggins, 2005), and use of case managers and patient navigators to improve primary care efficiency (Lee, Kiyu, Milman, and Jimenez, 2007). Some longitudinal studies indicate that it is possible to generate higher levels of social capital in communities with lower social capital at baseline (Onyx & Leonard, 2010; Pronyk, et al., 2008). Another strategy to improve the overall well-being of those in subsidized housing that has been trialed by the U.S. Department of Housing and Urban Development is to provide vouchers for people to move to less low-income neighborhoods. Any strategies that seek to reduce PPVs should consider ways to cultivate neighborhood-level social capital. Likewise, healthcare sector initiatives to improve population-level health outcomes should encourage clinicians to reach out to partner with those working towards comparable goals in other sectors, such as housing, education and business.

5.4 Research Implications

Health information systems (i.e., census data, vital statistics, surveillance and surveys) were envisioned and designed before interest arose in social determinants of health, and such systems are slow to change. Inherent in data already gathered, published and thus easily available is the temptation to use it as proxy measures in analyses of newer concepts, such as social capital, that lack widely available data. Some health researchers argue that "using existing data creatively" can result in valid measures of social capital (Lee & Kim, 2012; Putnam, 2000). Yet the body of research to date on social capital suggests that it is a multifactorial, community-level construct with both structural and cognitive dimensions, and thus, cannot be measured through proxy census variables. This may explain why Pitkin

Derose's exploration of associations between social capital and PPAs in Florida (2008), although very detailed, failed to show any association for numerous "social capital" variables tested. Mean commute times do not equate to bonding capital and racial and ethnic diversity is not the same thing as bridging capital. Likewise, voting rates may more accurately result from - rather than predict - social capital (Lee & Kim, 2012). Mean commute times, racial and ethnic diversity and voting rates can at best only measure one component of this multifactorial, community-level construct. At minimum, it might be possible to measure the *opposite* of social capital through data that has been shown to have a highly inverse relationship with social capital, such as crime rates or income inequality (Wilkinson, 1996; Lee & Kim, 2012). Given the number of recently developed instruments to measure social capital, it is far better to use one of these tools with proven reliability and validity to collect original data or risk continuing to produce mixed results in small area analysis of social capital and its effects. The BES social capital scale used in the third manuscript incorporated measures of two principle components: social cohesion/trust and collective action.

Research to replicate these or similar analyses in other states or MSAs is needed to determine if results obtained here regarding measurement of neighborhood disadvantage that explain PPV rate variance and the mediating effects of social capital are generalizable to other geographic populations. In particular, confirmation of social cohesion/trust as the more significant component of social capital in mediating the impact of neighborhood disadvantage on PPV rates is warranted. The relationship between neighborhood disadvantage and PPVs, mediated by social capital, should also be further explored at alternative geographies, including census tracts and block groups, to determine the most

appropriate aggregate level at which these neighborhood effects occur, followed by multi-level modeling to differentiate individual and neighborhood effects.

As mentioned in Chapters 3 and 4, those analyses were likely subject to the distorting influences of the modifiable areal unit problem. Social disorganization theory dictates that census tracts or block groups are the ideal level of aggregation for observation of social capital and neighborhood effects. Census tracts are locally determined, with about 2,500 to 8,000 people, to reflect socioeconomically homogeneous neighborhoods (Census Bureau, 2009). However, protected health data (individual's addresses) would need to be aggregated by researchers in order to calculate PPV rates at census tract levels. The MHSCRC is unlikely to approve this type of research unless benefits to their hospital constituents are perceived. Data aggregation to the ZCTA level is a finer granulation than most analyses to date and corresponds with some larger communities and census designated places, but census tracts would be preferable as the geographic units of analysis. In refining the definition of social capital, it is important to remember that social disorganization theory and the concept of social capital evolved from empiric observation of measurable outcomes occurring at the level of the urban neighborhood. Theoretical constructs must also be adapted to modern definitions of neighborhood.

Like other investigators, I have found that more research is still needed to: 1) refine the theoretical and operational definitions of neighborhood social characteristics such as neighborhood-level social capital and collective efficacy (Raudenbush, 2003; Sampson, 2003); 2) provide more evidence of social capital's mediating effects and to elucidate the pathways of how it works (Murayama, Fujiwara & Kawachi, 2012); and 3) differentiate individual and neighborhood-level effects with multi-level modeling. Nurse researchers

should work as members of inter-disciplinary research teams which may include other health care providers, social workers, sociologists, epidemiologists, and geographers, in addition to those working on coparable goals in other sectors such as education, housing and job creation. In addition, more research is needed that is longitudinal in nature and evaluates the effectiveness of interventions to build social capital (Egan, Tannahill, Petticrew & Thomas, 2008; Murayama, Fujiwara & Kawachi, 2012).

Interest in studying social capital continues to grow, due to its identification as a community asset and potential intervention point for improving health outcomes. Although collective efficacy, which is comparable to social cohesion/trust, has been conceptualized as task-specific (Sampson, Raudenbush, & Earls, 1997), social capital and social cohesion/trust should be explored as potential mediators of other health problems associated with areas of concentrated poverty, such as homicide, domestic violence, substance abuse, infant mortality, teen pregnancy, increased rates of sexually transmitted infections, and increased rates of chronic disease. Social capital may also prove to exert a mediating influence on neighborhood disadvantage in relation to these health outcomes.

5.5 Policy Implications

5.5.1 Informed New Social Surveillance Measures Needed

As the ACA is implemented and approximately 32-34 million more people obtain health insurance coverage by 2019, total hospital and ED visits and those for ACSC are expected to increase (Draper, 2011; Goodman, 2010; Katz, 2010). ED use and costs increased 7% and 17%, respectively, after health care reform in Massachusetts (DeLia & Cantor, 2009). Preventable hospitalizations also increased in Oregon after Medicaid coverage expansion (Saha, Solotaroff, Oster & Bindman, 2007). Under the ACA, health centers are to

expand access to vulnerable populations; about $11 billion in funds over 5 years is earmarked for health center operation, construction and expansion (Draper, 2011). Well-situated health centers have the potential to minimize PPA and PPV by increasing primary care access and care coordination (Draper; Felland, Hurley & Kemper, 2008). Health inequities and primary care barriers are implicated in higher PPA and PPV rates among minorities, low-income, and uninsured/Medicaid populations (Johnson, et al., 2012; Oster and Bindman, 2003; Laditka, Laditka & Mastanduno, 2003).

New measures of population-level social and behavioral determinants of health are needed to understand and address PPVs and other population-level health outcomes. The significant predictors identified in the second manuscript (*percent of female-headed households, per capita income, percent of high school graduates*) were census variables that indicated that social determinants and social resources are key components in understanding how to decrease PPV rates (Rowe, n.d.); however, they only explained 40-52% of variance in the PPV rates and at least one significant predictor was likely missing from the regression models. This led to consideration of other potential predictors, such as *percentage of families in poverty*, and *relative poverty*. Relative poverty measures, such *as income less than twice the poverty level*, measure those living in poverty plus the number of low-income working families (Urban Institute, 2013). In addition to consideration of aggregate income, such measures also incorporate some aspect of income inequality, which has also been implicated in poorer health outcomes (Wilkinson, 1996). This analysis also led to further consideration of *social capital* as a potential mediator of aggregate neighborhood disadvantage, which Morenoff, Sampson, and Raudenbush, defined using a 5-item scale: 1)

percentage of families in poverty, 2) *percentage of households receiving public assistance*, 3) *percent unemployed*, 4) *percent black* and 5) *percent of female-headed households* (2001).

Some socioeconomic indicators are more relevant to health at the population level than others, including concentrated disadvantage and affluence scales (Lantz & Pritchard, 2010). However, data needed to calculate such scales and data on social capital are not currently routinely collected and made publicly available to public health researchers in the U.S. Our vital statistics, reporting and surveillance systems for health data were designed to gather quality data on infectious disease and mortality rates. With the introduction of surveys such as the Behavioral Risk Factor Surveillance System, we have also developed the ability to gather data on some behavioral determinants of health. But development of data on measures relevant to the social determinants of health, such as social capital, are still in their infancy in the U.S. Both the United Kingdom (U.K.) and the World Bank have already developed tools to collect data on social capital (Harper, 2002; World Bank, 2010), and indices of area disadvantage are common in Commonwealth countries such as the U.K., Australia, and New Zealand. Public health researchers in the U.S. must make their evidence available to policy-makers, who may then choose to incorporate new measures in health surveillance. For example, in 2005 the Behavioral Risk Factor Surveillance Survey (BRFSS) added a question about social support, "How often do you get the social and emotional support you need?" which is included now every other year (Centers for Disease Control, 2010). The county health rankings developed by the Robert Wood Johnson Foundation and the University of Wisconsin use this question as a measure of family and social support (County Health Rankings, 2013). The body of research on social capital suggests that it is a multifactorial, community-level construct with both structural and cognitive dimensions, and

one that is well worth monitoring due to its potential to impact health outcomes. Several scales to measure social capital, including the one developed by the BES, are now available, have proven reliability and validity and could easily be adopted for use in public health surveillance.

5.5.2 Female-headed Households

A significant interaction term between *social capital* and female-headed households acted as a full mediator of *female-headed households*, indicating mediation of a moderator effect. In the U.S., over a fifth of all women (22.8%) live in female-headed households with children (Kaiser Family Foundation, 2013). The steady increase since the 1970s in numbers of children living in female-headed households, now 24%, has been linked to increased numbers of children living in poverty and increased risks of dropping out of school and the workforce and teen pregnancy (Mather, 2010). This interaction between neighborhood-level *social capital* and *percentage of female-headed households with children* needs to be more fully explored. However, there is sufficient evidence to warrant consideration of how social policies might be used to bolster health resource availability to this vulnerable sub-set of the population. Programs to extend insurance coverage to single mothers and children have been in existence in Maryland since the late 1990s, but little consideration has been given to the constraints on access to care placed on single, low-income women with children in terms of child care, transportation and missed time from work. Nurses should advocate for their clients among this vulnerable population in order to facilitate their access to appropriate social and economic supports. As medical homes become more common, fostering community-level social capital is a potential strategy that community clinics should consider to facilitate better primary care access. Case managers

should work with all patients, but particularly female heads of households with children, to ensure that they can access primary care in a timely fashion.

5.5.3 Concentrated Poverty and Neighborhood Disadvantage

My findings in chapter 4 supported the hypothesis that social cohesion/trust stems from greater economic equality (Uslaner, 2008) or institutions and policies (Beugelsdijk, 2006; Rothstein & Stolle, 2008) and may be a necessary antecedent to collective action or social participation (Giordano, Bjork & Lindstrom, 2012). If this is the case, then efforts to increase social capital or social cohesion/trust are unlikely to succeed without policies aimed at reversing the indirect psychosocial effects of income inequality on health in areas of concentrated poverty, where disproportionate numbers of minorities live.

As mentioned above, Wilson (1987; 1996; 2010) makes a convincing case to explain higher rates of female-headed households among Blacks and in areas of concentrated urban poverty as inextricably linked to the loss of low-wage jobs for Black males in urban areas and other larger societal processes such as suburban flight and deindustrialization that have concentrated poverty and disadvantage in urban neighborhoods. Wilson also argues that historical structural forces and policies in transportation (building of highways and freeways), housing (mortgage interest deductions and mortgages for veterans), and job creation (free trade agreements, transition to a service- and technology-based economy), while not necessarily intentionally racist, have had a disproportionately negative impact on those who have the fewest resources to cope – less educated, low-wage minority workers in urban areas, particularly in cities of the Midwest and Northeast such as Baltimore (2010). Although there are fewer people living in poverty in times of economic well-being, in general the gap between the rich and the poor in the United States has been steadily widening

for decades (Chokshi, 2013) and the number of Americans in the middle class, 51% in 2010, is down from 61% in 1970 (Sauter, Hess & Frolich, 2013). Without policies explicitly aimed at increasing the well-being of those living in the most disadvantaged areas, efforts to reduce health disparities are unlikely to succeed.

Healthcare reform to ensure insurance coverage and access to healthcare for all is an initial step towards improving the well-being of those living in disadvantaged neighborhoods and towards decreasing PPV rates. But long-term state and local policies to reduce health disparities and improve access to healthcare also will likely need to work in conjunction with comparative efforts in other sectors to improve public education, provide safe housing, control crime, create jobs and provide affordable child care. Placing primary care clinics within schools and public housing are some of the health-related policy initiatives being investigated as synergistic strategies to improve population-level health outcomes. Such efforts on the part of state and local government have the potential to promote the growth of social cohesion/trust in areas of concentrated disadvantage (Lee, Kiyu, Milman & Jimenez, 2007; Orr, 1999; Orr, 2007; Wilson, 1987; Wilson, 2010). Policies aimed at reducing health disparities "should pay attention to the characteristics of the areas in which people live as well as the characteristics of the people who live in these areas" (Smith, Hart, Watt, Hole & Hawthorne, 1998, p. 399). Neighborhood urban renewal and crime control strategies have direct effects on the health-seeking behaviors of people who live there.

In many parts of the country, including Maryland, economic pressures have forced the replacement of nurses in primary care with unlicensed personnel. Across the state of Maryland and the country nurses in public health have also faced budget cut-backs and downsizing in recent years. These changes in healthcare workforce leave fewer clinicians

with critical thinking skills working for vulnerable populations and who understand the importance of advocating for policy changes that would benefit the populations they serve, such as improving public schools, raising the minimum wage, less regressive taxation policies, or giving workers more input in their organizations. Those nurses who remain employed in primary care or public health must become increasingly adept at marketing the value that they add to healthcare delivered in these venues. As more nurse practitioners enter the primary care workforce, nursing schools must train these healthcare providers regarding effective advocacy strategies at the local and state levels and within their professional organizations in order to affect change on behalf of the populations that they serve. Again, such efforts have the potential to promote the growth of social cohesion/trust in areas of concentrated disadvantage.

5.6 Summary

These three studies have added to knowledge about PPVs and neighborhood-level social determinants associated with increased rates. The literature review found social determinants of health implicated in higher rates of PPVs, only one prior study that examined the relationship between preventable hospital admissions and social capital, and none that examined the relationship between social capital and preventable ED visits. The second manuscript identified the social determinants of health (e.g., income, education and single-parent households), of those available as census data, that were significant predictors of PPVs at the ZCTA level. Analyses also indicated that a significant explanatory factor was missing. The third manuscript turned to the literature on social capital which provided an established way of measuring neighborhood disadvantage from the literature on collective efficacy and crime prevention as well as a concept, social capital, which acted as a partial

mediator of neighborhood disadvantage on PPV rates. Regression analysis confirmed that components of neighborhood disadvantage explained most of the PPV rate variance between metropolitan ZCTAs and that social capital was a partial mediator of all of the significant socioeconomic measures of neighborhood disadvantage reviewed.

Nurses and nurse practitioners need to be aware of the role of the social determinants of health at work in the populations and communities that they serve. They must also develop skills to advocate for favorable policy change on behalf of these populations and monitor the literature on strategies to build community-level social capital and social cohesion/trust as such strategies are developed. Public health and nurse researchers must continue to investigate appropriate measures of social capital and other social determinants and appropriate levels of social determinant data aggregation and work with policy-makers to collect and disseminate these data. The role of social capital as a potential mediator of the effects of neighborhood disadvantage on other health outcomes, such as violence, substance abuse, teenage pregnancy and chronic disease, should also be explored.

Wilkinson advocated for increased awareness of the detrimental effects of income inequality on health by policy-makers and the public and recommended reassessment of policies on health, education, employment, business structure and regulation, and taxation (1996). Wilson has been praised for delineating the social processes that have led to areas of concentrated urban poverty in the U.S. but criticized for less detailed development of the policies and strategies that might be used to combat such concentrated disadvantage. Likewise, I have described the social determinants of PPVs but at this point I am less able to propose concrete strategies to bolster social capital and social cohesion/trust at the

community level and/or to reduce PPV rates. Strategies to increase social capital in communities are still being tested and developed (Murayama, Fujiwara & Kawachi, 2012). Fortunately, the policy solutions required to solve such daunting problems call for team approaches, which typically start with increased awareness and willingness to begin a dialogue about the issue(s). Publication of these three manuscripts should, at minimum, raise awareness and start that necessary dialogue about social capital as a potential mediator of PPV rates and other health outcomes.

APPENDIX 1
IRB APPROVAL

University of Maryland, Baltimore
Institutional Review Board
Phone: (410) 706-5037
Fax: (410) 706-4189
Email: hrpo@som.umaryland.edu

NOT HUMAN RESEARCH
DETERMINATION

Date: October 9, 2013

To: Gina Rowe
RE: HP-00057454

This letter is to acknowledge that the UMB IRB reviewed the information provided and has determined that the submission does not require IRB review. This determination has been made with the understanding that the proposed project does not involve a systematic investigation designed to develop or contribute to generalizable knowledge **OR** a human participant (see definitions below).

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are human subject research in which the organization is engaged, please submit a new request to the IRB for a determination.

Definitions –

Human Research: Any activity that either:
- Is "Research" as defined by DHHS and involves "Human Subjects" as defined by DHHS ("DHHS Human Research"); or
- Is "Research" as defined by FDA and involves "Human Subjects" as defined by FDA ("FDA Human Research").

Research as Defined by DHHS: A systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge.

Research as Defined by FDA: Any experiment that involves a test article and one or more human subjects, and that meets any one of the following:
- Must meet the requirements for prior submission to the Food and Drug Administration under section 505(i) of the Federal Food, Drug, and Cosmetic Act meaning any use of a drug other than the use of an approved drug in the course of medical practice;
- Must meet the requirements for prior submission to the Food and Drug Administration under section 520(g) of the Federal Food, Drug, and Cosmetic Act meaning any activity that evaluates the safety or effectiveness of a device; OR
- Any activity the results of which are intended to be later submitted to, or held for inspection by, the Food and Drug Administration as part of an application for a research or marketing permit.

Human Subject as Defined by DHHS: A living individual about whom an investigator (whether professional or student) conducting research obtains (1) data through Intervention or Interaction with the

individual, or (2) information that is both Private Information and Identifiable Information. For the purpose of this definition:

- Intervention means physical procedures by which data are gathered (for example, venipuncture) and manipulations of the subject or the subject's environment that are performed for research purposes.
- Interaction means communication or interpersonal contact between investigator and subject.
- Private Information means information about behavior that occurs in a context in which an individual can reasonably expect that no observation or recording is taking place, and information which has been provided for specific purposes by an individual and which the individual can reasonably expect will not be made public (for example, a medical record).
- Identifiable Information means information that is individually identifiable (i.e., the identity of the subject is or may readily be ascertained by the investigator or associated with the information).

Human Subject as Defined by FDA: An individual who is or becomes a subject in research, either as a recipient of the test article or as a control. A subject may be either a healthy human or a patient. A human subject includes an individual on whose specimen (identified or unidentified) a medical device is used.

Please keep a copy of this letter for future reference. If you have any questions, please do not hesitate to contact the Human Research Protections Office (HRPO) at (410) 706-5037 or HRPO@som.umaryland.edu.

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