THE LANDSCAPE ACROSS THE CONTINUUM OF INVASIVE CERVICAL CANCER PREVENTION: A GEOSPATIAL APPROACH

A Dissertation

by

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ABSTRACT

In the United States (U.S.) over the past decade, approximately 40,000 women have died from a disease that is mostly preventable, invasive cervical cancer (ICC). Since the 1950's, with the introduction of the Papanicolaou (Pap) screening test, there has been a ≥ 60% decline in the incidence rate. Screening is highly effective in reducing the incidence of ICC, but it is only one component of the multi-step process of the "continuum of care" (i.e. screening, diagnosis, and treatment). There is increasing concern about why women in the U.S. are still dying from ICC and why minority women are disproportionately burdened with higher mortality rates.

To address these concerns, a multidisciplinary approach informed by theoretical frameworks and methods in GISHealth, health geography, epidemiology, and sociology were used to examine three aims: (1) characterize the effort to manually geocode healthcare facilities that provided invasive cervical cancer preventive services; (2) examine if geographic accessibility, defined as travel time and travel distance, differs for women who live in rural areas as opposed to women who live in non-rural areas; and (3) determine if socioeconomic status, acculturation, race/ethnicity, and geography are associated with ICC through the examination of main effects and interactions using a case-control research design.

I found that there was a 90% improvement in geocode quality type and a corresponding spatial shift that ranged from 0.02 to 151,368 meters after manual intervention of geocoding of healthcare facilities, which took 42 hours of processing

time. The Mann-Whitney test confirmed that there was a significant ($P < 0.001$) difference in travel time for all services across the ICC continuum of care comparing women who resided in rural areas to women who resided in non-rural areas. Multivariable conditional logistic regression results showed that female-headed households, not having health insurance, being a Hispanic woman, being a non-Hispanic white woman, travel time to a cervical cancer screening facility, living in a rural area as opposed to a non-rural area, and low educational attainment had increased odds while living in poverty and "speaking Spanish but not speaking English well" had decreased odds with ICC (statistically significant at $P < 0.050$).

DEDICATION

I dedicate this dissertation to my brother Nick. There are no words to express my gratitude to him. His selflessness enabled me to continue my graduate training, but most importantly, he saved our family!

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For Chapter II, Yolanda J. McDonald was responsible for the research design, data processing, data analyses, tables, references search, manuscript writing, reviewing, and editing, and first author correspondence; Michael Schwind (undergraduate student) contributed to the research design, data processing, tables, figures, manuscript writing, and references search; Dr. Daniel W. Goldberg reviewed the research design and the manuscript; Amanda Lampley (undergraduate student) contributed to manuscript writing and references search; and Dr. Cosette M. Wheeler, as the representative of the New Mexico HPV Pap Registry Steering Committee, provided data and reviewed the manuscript.

For Chapter III, Yolanda J. McDonald was responsible for the research design, data processing, data analyses, tables, references search, manuscript writing, reviewing, and editing, and first author correspondence; Dr. Daniel W. Goldberg reviewed the research design and manuscript; Dr. Isabel C. Scarinci reviewed the manuscript; Dr.

Philip E. Castle reviewed the statistical analyses and the manuscript; Dr. Jack Cuzick contributed to the research design and reviewed the statistical analyses and the manuscript; Michael Robertson contributed to the data processing; and Dr. Cosette M. Wheeler, as the representative of the New Mexico HPV Pap Registry Steering Committee, provided data, and was responsible for final approval of research design and manuscript review.

For Chapter IV, Yolanda J. McDonald was responsible for the research design, data processing, data analyses, tables, figures, references search, and manuscript writing, reviewing, and editing; Billy Hales authored Python™ coding procedure for the census tract population-based derived census variables; Dr. Swetha Peteru was lead author for coding to produce case control matching routine conducted in R; Dr. Daniel W. Goldberg reviewed the research design and reviewed the chapter; Dr. Daikwon Han reviewed the data analyses strategy and manuscript; Dr. Philip E. Castle reviewed the research design and statistical analyses strategy; Dr. Jack Cuzick contributed to the research design and the statistical analyses strategy; and Dr. Cosette M. Wheeler, as the representative of the New Mexico HPV Pap Registry Steering Committee, provided data, contributed to the research design, and reviewed the chapter.

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NOMENCLATURE

ACA-DEC	Affordable Care Act Dependent Coverage Expansion
AMC	American Community Survey
AOR	Adjusted Odds Ratio
CLR	Conditional Logistic Regression
CTC	Census-tract Value
CTP	Census-tract Population-based Value
EXC	Exceptions
ICC	Invasive Cervical Cancer
HPV	Human Papillomavirus
NCI	National Cancer Institute
NIH	National Institutes of Health
NM	New Mexico
NMHPVPR	New Mexico HPV Pap Registry
NMTR	New Mexico Tumor Registry
OR	Odds Ratio
Pap	Papanicolaou (Pap) screening test
RUCA	Rural-Urban Commuting Area
SEER	Surveillance, Epidemiology, and End Results
SES	Socioeconomic Status
U.S.	United States

USPS	United States Postal Service
VIF	Variance Inflation Factor
ZCTA	ZIP Code Tabulation Areas

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CHAPTER I

INTRODUCTION

Invasive cervical cancer (ICC) is mostly preventable because precancerous lesions (i.e. cervical intraepithelial neoplasia [CIN]) can be detected through cervical cytology (Papanicolaou [Pap] test) and treated prior to becoming invasive (Papanicolaou and Traut 1943, Ayre 1964). Since the introduction of the pap smear in the 1950's, there has been a ≥ 60% decline in the ICC incidence rate in the U.S. (Chasan and Manrow 2010). Despite the scientific knowledge and healthcare resources in the U.S., it is estimated that there will be 12,820 new cases and 4,210 deaths from ICC in the U.S. during 2017 (American Cancer Society 2017).

Another significant aspect of ICC is that it remains a cancer health disparity (Lisovicz et al. 2008). Health disparity is defined as a health difference that is closely linked to social, economic, and/or environmental disadvantage (U.S. Deparment of Health & Human Services 2017). The most recent (2009-2013) National Cancer Institute (NCI) Surveillance, Epidemiology, and End Results Program (SEER) data reports that minority sub-groups are more likely to develop ICC compared to white non-Hispanic women (Surveillance 2017). Hispanic women have the highest age-adjusted per 100,000 population (direct age adjusted using the 2000 US Standard Population) incidence rate of ICC (9.4), followed by Blacks (8.9), American Indian/Native Alaskan (7.7), non-Hispanics whites (7.5), Asian/Pacific Islander (6.2), and the overall rate is 7.5 (Surveillance 2017).

Extensive research has shown that race/ethnicity is attributed to differences in the incidence rate of ICC among minority groups (Akers, Newmann and Smith 2007, Coughlin et al. 2003, Garner 2003, Hicks et al. 2006, Horner et al. 2011a, Saslow et al. 2012, Shi et al. 2012). However, disparities in cervical cancer screening, diagnosis, excisional treatment therapies, and mortality include a complex web of covariates and confounders, such as age (Downs et al. 2008, Akers et al. 2007, Hicks et al. 2006, Saraiya et al. 2007, Yabroff et al. 2005, McCarthy et al. 2010, Niccolai et al. 2013); socioeconomic status, including low educational attainment (Lin, Schootman and Zhan 2015, Niccolai et al. 2013, McCarthy et al. 2010, Coughlin et al. 2003); immigration and acculturation (Akers et al. 2007, Garces-Palacio and Scarinci 2012, Horner et al. 2011b), behavioral/lifestyle (Au et al. 2007, Tomita et al. 2011); access to healthcare (Horner et al. 2011b, Akers et al. 2007); healthcare provider characteristics (Akers et al. 2007); deficiencies in the healthcare system (Akers et al. 2007, Hicks et al. 2006); and geography-based factors, including regional differences and rural versus non-rural residence (Akers et al. 2007, Coughlin et al. 2003, Downs et al. 2008, Shi et al. 2012, Saslow et al. 2012, Yabroff et al. 2005) that contribute to differences in ICC outcomes. For example, rural women have a greater likelihood of being older, having low educational attainment, and living below the federal poverty-level, which are risk factors associated with ICC (Akers et al. 2007, Yabroff et al. 2005, Bazargan et al. 2004).

There is a need for an evidence-based geospatial approach to examine not only socioeconomic status, acculturation, and race/ethnicity but also the influence of geography (i.e. as defined as rural versus non-rural residence and travel time and travel

distance to the nearest healthcare facility that provided ICC preventive services) with ICC health disparities. ICC preventive care, referred to as the "invasive cervical cancer continuum of care", consists of a multi-step process moving across screening (Pap and/or HPV testing), diagnostic testing (colposcopy), and excisional treatment procedures (loop electrosurgical excision procedure or cone biopsy) (Schiffman and Castle 2005). Prior research has considered the effects of non-spatial risk factors for cervical precancer and ICC outcomes (e.g. early age of sexual intercourse, HPV infection, socioeconomic position, low educational attainment, health insurance status, race/ethnicity, and being an immigrant) (Downs et al. 2010, Saraiya et al. 2007, Newmann and Garner 2005) but few studies have examined the effect of spatial factors (e.g. accessibility to preventive services) across the cervical cancer continuum of care nor the interactions of non-spatial and spatial factors.

Access to healthcare is often perceived as a simplistic concept. Five dimensions of access have been identified that embody the broad term 'access' to healthcare: availability, accessibility, accommodation, affordability, and acceptability (Penchansky and Thomas 1981). Geographic accessibility, for the purpose of this study is defined as (1) rural versus non-rural access to healthcare facilities that have the necessary equipment and trained personnel to perform all of the services across the ICC continuum of care and (2) travel time and travel distance, which represent the spatial dimensions of access (Zhan and Lin 2014, Boscoe et al. 2011, Henry et al. 2011) to healthcare services and is frequently characterized in health studies (Continelli, McGinnis and Holmes 2010, Henry et al. 2011). Previous research has established that in rural areas there are limited

medical infrastructures, including inadequate coverage of medical providers ranging from primary care physicians to medical oncologists who treat patients with ICC, as compared to non-rural areas (Hawkins and Curtiss 1997, Hart et al. 2002). Thus geographic accessibility have the potential to become a barrier to health outcomes (Obrist et al. 2007, Penchansky and Thomas 1981, Newmann and Garner 2005), in particular as at-risk women move through the continuum of specialty care. Furthermore, challenges in access can be exacerbated by the necessity to travel to three different healthcare facility locations to receive preventive services. This dissertation contributes to the broader understanding of the main effects and interactions of socioeconomic status, acculturation, race/ethnicity, and geography (e.g. rural versus non-rural residence and travel time and travel distance) in the context of ICC health disparities.

The Population-based Research Optimizing Screening through Personalized Regimens (PROSPR) U54 RFA demonstrates the National Cancer Institute's (NCI) recognition of the critical need to consider screening, diagnosis, and treatment surveillance/documentation linked to existing successful cancer registries. To meet this need, the NM HPV Outcomes and Practice Effectiveness PROSPR Research Center (NM-HOPES-PROSPR) have partnered with the New Mexico Tumor Registry (NMTR) and the New Mexico HPV Pap Registry (NMHPVPR). The NMTR is a founding member of the National Cancer Institute's (NCI) Surveillance, Epidemiology, and End Results (SEER) Program, and has continuously participated in that program since 1973. The NMTR is the data source for de-identified address-level cases diagnosed with ICC from 2006 – 2014. In anticipation of the critical need for population-based, woman-

based surveillance of U.S. cervical cancer screening, the New Mexico Notifiable Diseases and Conditions administrative code (NMAC 7.4.3.12) incorporated mandatory state-wide reporting of all cervical screening (Pap and HPV) and all diagnostic and treatment procedures (cervical, vulvar and vaginal pathology), whether positive or negative or abnormal or normal, respectively. The innovative surveillance system of the NMHPVPR is the data source for (1) address-level healthcare facilities locations that provided services across the ICC continuum of care in New Mexico during the years 2010 - 2012 and for (2) de-identified address-level events of ICC preventive services in New Mexico during the years 2000 - 2014. Currently, New Mexico is the only state with the capacity to fully monitor population-based, woman-based preventive ICC procedures. New Mexico offers a rich research opportunity because the ICC surveillance is being conducted amongst a diverse population. For example, (1) the cervical cancer target screening population is 45% Hispanic, 44% white non-Hispanic, 9% American Indian/Native American, < 2% African American, and <1% all other (U.S. Census Bureau 2011); (2) twenty percent of the female population is below federal poverty level (U.S. Census Bureau 2011); and (3) twenty-three percent of the population lives in rural area (U.S. Census Bureau Center for Economic Studies 2012). Worldwide, cervical cancer is the third most common cancer in women and the second most common cause of death from cancer among women aged 14 to 44 years. The Centers for Disease Control and Prevention 2013 report ranked NM in the second tier ICC incidence rate group (direct age-adjusted ICC incidence rate, using a 95% CI, of 7.2 – 7.7 per 100,000

population). New Mexico is at the bottom of this second tier group at 7.2, and is ranked 22nd in the U.S. for incidence of ICC.

The purpose of this dissertation is to address the need for evidence-based geospatial approaches to examine not only socioeconomic status, acculturation, and race/ethnicity but also the influence of geography (i.e. as defined as rural versus non-rural residence and travel time and travel distance to the nearest healthcare facility that provided ICC preventive services) with ICC through three different interdependent chapters. The initial step (i.e. Chapter II) of this dissertation quantified the effort (i.e. time) required to manually correct the geocodes of the healthcare facilities in New Mexico that provided services across the ICC continuum of care, documented the match rate improvement between the original geocoded and the corrected geocode, and measured the corresponding spatial shift by geocode quality type resulting from the corrections. Next, Chapter III of this dissertation measured and quantified geographic accessibility (i.e. defined as travel time and travel distance to health care facilities that provided service across the ICC continuum of care) in New Mexico, during the years 2010 - 2012, stratified by rural and non-rural census tracts. In chapter IV, I demonstrated how a population-based statewide cervical cancer screening registry (i.e. NMHPVPR), along with a state-wide cancer registry (i.e. NMTR), can be utilized as sources for controls and cases to contribute to the growing area of research on ICC health disparities. The purpose of this chapter was to investigate if there were statistically significant differences in socioeconomic status (e.g. educational attainment, female headed-household, health insurance status, and poverty), acculturation (e.g. English

language proficiency and foreign born status), race/ethnicity (e.g. American Indian, Hispanic, and non-Hispanic white), and geography (e.g. rural-urban residence type and travel time to preventive ICC services) associated with ICC. In the context of this chapter, ICC health disparities were measured as socioeconomic status, acculturation, race/ethnicity, and/or geography variables having an increased odds ratio associated with ICC.

Specific Aims

Aim 1 will characterize the effort to manually geocode healthcare facilities that provided ICC preventive services in New Mexico during the years 2010 - 2012. New Mexico is representative of state with a notable rural landscape. The quantification of the effort required to manually geocode addresses and the corresponding spatial shift pre and post manual geocoding will inform distance and time calculation measurements, which are commonly used in healthcare accessibility, healthcare services, and health disparities research.

Aim 2 will examine if geographic accessibility (i.e. defined as travel time and travel distance) differs among women who live in rural areas, as opposed to women who live in non-rural areas. Results from Aim 1 will allow for the calculation of potential access to healthcare facilities that provided services across the ICC continuum of care in New Mexico for the years 2010 - 2012. The characterization, quantification, and statistical analysis of geographic accessibility to the three different types of services

required to prevent ICC, stratified by rural and non-rural areas will contribute to healthcare accessibility, healthcare services, rural health, and health disparities research.

Aim 3 will determine if socioeconomic status, acculturation, race/ethnicity, and geography are associated with ICC through the examination of main effects and interactions. Results from Aim 2 will be included as covariates (e.g. travel time to health care facility that provided cervical cancer screening). To the best of my knowledge, this aim is novel and will contribute to ICC health disparities literature because it is the first U.S.-based study to conduct population-based, case-control research designed to examine covariates associated with ICC as well as the inclusion of geography, which is often omitted from case-control studies.

Dissertation Chapter Outline

This dissertation is organized around three interdependent chapters (Chapters II – IV). The results and findings from each chapter provided the necessary data and findings that informed the next chapter. Chapter II was published July 2016 in *The Journal of Rural Health*. Chapter III was published May 2017 in *Geospatial Health*. Chapter IV will serve as the research foundation for an additional publication to be submitted during summer 2017 and two more publications within the next year. Additionally, Chapter IV will serve as preliminary research for the NSF Faculty Early Career Development (CAREER) Program proposal that I will submit July 20, 2018. The following chapter outlines are based on the abstracts of the published chapters and Chapter IV abstract.

Chapter II

Geocoding is the science and process of assigning geographical coordinates (i.e. latitude, longitude) to a postal address. The quality of the geocode can vary dramatically depending on several variables, including incorrect input address data, missing address components, and spelling mistakes. A dataset with a considerable number of geocoding inaccuracies can potentially result in an imprecise analysis and invalid conclusions. There has been little quantitative analysis of the amount of effort (i.e. time) to perform geocoding correction, and how such correction could improve geocode quality type. This study used a low-cost and easy to implement method to improve geocode quality type of an input database (i.e. addresses to be matched) through the processes of manual geocode intervention, and it assessed the amount of effort to manually correct inaccurate geocodes, reported the resulting match rate improvement between the original and the corrected geocodes, and documented the corresponding spatial shift by geocode quality type resulting from the corrections. Findings demonstrated that manual intervention of geocoding resulted in a 90% improvement of geocode quality type, took 42 hours to process, and the spatial shift ranged from 0.02 to 151,368 meters. This study provides evidence to inform research teams considering the application of manual geocoding intervention that it is a low-cost and relatively easy process to execute. (McDonald et al. 2017)

Chapter III

Multiple intrapersonal and structural barriers, including geography, may prevent women from engaging in cervical cancer preventive care - screening, diagnostic colposcopy, and excisional pre-cancer treatment procedures. Geographic accessibility, stratified by rural and non-rural areas, to necessary services across the cervical cancer continuum of preventive care is largely unknown. Healthcare facility data for New Mexico (2010 – 2012) was provided by the New Mexico Human Papillomavirus Pap Registry (NMPHPVR), the first population-based statewide cervical cancer screening registry in the United States. Travel distance and time between the population-weighted census tract centroid to the nearest facility providing screening, diagnostic, and excisional treatment services were examined using proximity analysis by rural and non-rural census tracts. Mann-Whitney Test ($P < .05$) was used to determine if differences were significant and Cohen's *r* to measure effect. Across all cervical cancer preventive healthcare services and years, women who resided in rural areas had a significantly greater geographic accessibility burden when compared to non-rural areas (4.4 vs 2.5 km and 4.9.4 vs 3.0 minutes for screening; 9.9 vs 4.2 km and 10.4 and 4.9 minutes for colposcopy; and 14.83 vs 6.6 km and 14.42 and 7.4 minutes for precancer treatment services, all $P < .001$). Improvements in cervical cancer prevention should address the potential benefits of providing the full spectrum of screening, diagnostic and precancer treatment services within individual facilities. Accessibility assessments distinguishing

rural and non-rural areas are essential when monitoring and recommending changes to service infrastructures (e.g. mobile versus brick and mortar). (McDonald et al. 2016)

Chapter IV

Invasive cervical cancer is mostly a preventable disease. Despite a 50% decrease in deaths in the U.S. since the 1950's, the mortality rate has stagnated. During the past decade, approximately 40,000 deaths are attributed to invasive cervical cancer (ICC) and minority women are disproportionately burdened with the disease. The purpose of this study was to investigate if there were statistically significant ($P \leq .050$) differences for socioeconomic status, acculturation, race/ethnicity, and geography variables with ICC using a case-control research design. ICC cases were obtained from the New Mexico Tumor Registry (2006 - 2014) and controls from the New Mexico HPV Pap Registry (2000 - 2014), the only population-based statewide cervical cancer screening registry in the U.S. Univariable and multivariable conditional logistic regression were used to calculate odds ratios as well as intersectionality research methods to inform the interconnected relationship of these variables in producing increased odds of ICC in New Mexico. Multivariable conditional logistic results indicated that living in poverty, and "speaking Spanish but not speaking English well" covariates were statistically significant and had a decreased odds ratio with ICC. Female-headed households, not having health insurance, being a Hispanic woman, being a non-Hispanic white woman, travel time to a cervical cancer screening facility, living in a rural area as opposed to a

non-rural area, and low educational attainment were significant and had an increased odds ratio with ICC. Regression and interaction results suggest evidence of the Hispanic Paradox. ICC prevention efforts should consider socioeconomic status, acculturation, race/ethnicity, and geography variables separately and jointly.

Chapter V

Chapter V concludes and summarizes dissertation findings as well as suggests further research. This dissertation was designed so that chapters build on each other and inform future research. Taken together, these analyses and findings elucidate the important role of geography in health studies, ranging from improving the precision of calculating travel time, understanding how travel time is experienced differently for women who live in a rural area compared to a non-rural area, and understanding how travel time and rural and non-rural residence can increase a woman's odds ratio with ICC. This is the first-time that a population-based, state-wide cervical cancer screening registry has been used in the U.S. for a case-control study. Notwithstanding the limitations of opportunistic screening practices in the U.S., this study aligns with previous research that health is complex and interconnected, as demonstrated by the conditional logistic regression analyses and intersectionality study approach methods.

Chapters II, III, and IV were reviewed and approved by the University of New Mexico Human Research Review Committee and by the Texas A&M University Institutional Review Board.

CHAPTER II

AN ANALYSIS OF THE PROCESS AND RESULTS OF MANUAL GEOCODE CORRECTION[*]

Introduction

Geocoding is the process of matching postal addresses to their corresponding geographical coordinates (i.e. latitude, longitude) (Rushton et al. 2006). Sophisticated science, data sets, and algorithms underlie this complex process (Boscoe 2008, Zandbergen 2008). There are a large number of published studies (Goldberg et al. 2008a, Ratcliffe 2001) that describe the numerous algorithms that are used during the geocoding process to attempt to match an input address to an address stored in a reference database. The variability in algorithms, addresses, and databases can lead to a variety of errors in the geocoded results (Ratcliffe 2001, Gilboa et al. 2006, Zandbergen 2008, Goldberg et al. 2013, Schootman et al. 2007, Zandbergen 2011). There is no such thing as a "one size fits all" type of geocoding system that works perfectly in every situation and for every user. The accuracy of this complex process can range from the centroid of a rooftop to the centroid of a state (Jacquez and Rommel 2009).

[*] Reprinted with permission from McDonald, Y. J., M. Schwind, D. W. Goldberg, A. Lampley & C. M. Wheeler (2017) An analysis of the process and results of manual geocode correction. *Geospatial Health*, 12, 84-89. Copyright 2017 by the authors.

This leads to the following questions: Should inaccuracies be incorporated into research or should they be omitted entirely? Should inaccuracies be corrected? Is there a threshold that inaccuracies should not exceed?

Previous studies have indicated that researchers should attempt to correct inaccurate data so that real world variances can be incorporated into analysis (Krieger 2003, Zandbergen 2007, Goldberg et al. 2008a, Zandbergen et al. 2012, Goldberg and Cockburn 2012, Murray et al. 2011). The practical application of reducing geocode inaccuracies is to improve the source data (i.e. geocoded data) used for spatial analysis (Strickland et al. 2007). However, despite calls to pay heed to geocode quality by type and to employ manual geocode correction methods, there are few documented case studies that evaluate the cost effectiveness of this practice, or the improvements that can be expected by undertaking such an effort (Goldberg et al. 2008a). The purpose of this study was to quantify the effort (i.e. time) required to manually correct the geocodes in a health related dataset, as well as the match rate improvement between the original geocoded and the corrected geocode, and the corresponding spatial shift by geocode quality type resulting from the corrections. The results of this study can be used to help guide researchers as they decide whether or not to undertake manual geocoding correction to improve the geocode quality type of a dataset.

Methods

Web based geocoding and interactive geocoding correction procedures were performed using the Texas A&M University (TAMU) Geoservices Online Geocoding service, version 4.01, which was developed by the study authors (Goldberg 2008). The corrections were performed by the study authors, a Ph.D. student and an honors undergraduate student. This web-based system allows for rapid manual intervention of previously geocoded data by drawing from online satellite imagery, street maps, and additional geocoding engines to determine an improved geocode for each record (Goldberg 2008).

This system allows a user to upload a dataset and analyze each record one at a time. It compares the current location of each geocode to that of another location provided by an alternate geocoder (i.e. Google Maps) within the TAMU online geocoding platform, and allows the user the flexibility to execute a manual intervention process to determine a more accurate geocode. The user can select which geocoder produced a more accurate location and the dataset can be updated with the corrected coordinates. In the event that neither geocoder provides an accurate location, the user can utilize online sources to refine an address (e.g. misspelling of an address) as well as aerial imagery and street views to attempt to find the location intuitively, and visually verify a location using Google Maps. The TAMU Geoservices Online Geocoding service utilizes publicly accessible data so person-hours are the only cost associated with the geocode correction processes. It is free to all researchers, and the source code can be

made available upon request to researchers and/or organizations that wish to use it https://geoservices.tamu.edu/.

To analyze the impact of the geocode correction process, a health related dataset was used. This dataset contained 784 addresses of health service facilities located within the state of New Mexico that offered cervical screening (Pap and/or Human Papillomavirus testing), diagnostic testing (colposcopy), and excisional pre-cancer treatment (loop electrosurgical excision procedure or cone biopsy). Although this data is publically available, it is not practical to obtain information on specific tests offered by individual clinics or providers. This unique health service facilities dataset was provided by the New Mexico HPV Pap Registry (NMHPVPR). The NMHPVPR is the first population-based statewide cervical screening registry in the United States; it includes address-level data on healthcare facilities providing aforementioned services in rural and urban areas. Due to the uniqueness of this data set, the authors invested the effort to have the most accurate geocoding possible.

The first step of processing was to geocode the entire set of addresses using the TAMU Geoservices Online Geocoding service. The version of the geocoding service used for this research included the 2015 Navteq Address Points database, the 2010 USPS ZIP+4 reference files, the 2010 Boundary Solutions National Parcel Data Layer, and the 2010 US Census TIGER/Lines the reference, and the US Census Bureau 2010 Cartographic Boundary files for Minor Civil Divisions, Zip Code Tabulation Areas, Counties, and States. Once the results were obtained, the geocoded file was uploaded to the TAMU Geoservices Online Geocoding Correction Service; Figure 1 displays the

geocode correction tool interface. This service provides a user interface that displays a map which shows the point obtained from the TAMU geocoding system and the point obtained from the alternate geocoder, i.e. Google Maps. If the alternate geocoder is able to find a match that is more accurate than the original match, a button can be pressed that updates the original geocode with the more accurate geocode. As previously noted, in the case that both geocodes appear to be inaccurate, the next step would be to attempt manual interactive geocoding. Online resources can be used to refine the address contained within the input file and often photo(s) of the building to be geocoded are available online. In addition, the user can study aerial imagery and street views of the location and attempt to manually locate the site; Figure 2 displays the correction prompt. If the site is located, the user marks that spot on the map and the geocode will be updated. These processes were used to update and correct the health service facility dataset analyzed for this study. The final file contained information about the original geocodes and the corrected geocodes, which were used for comparative analysis.

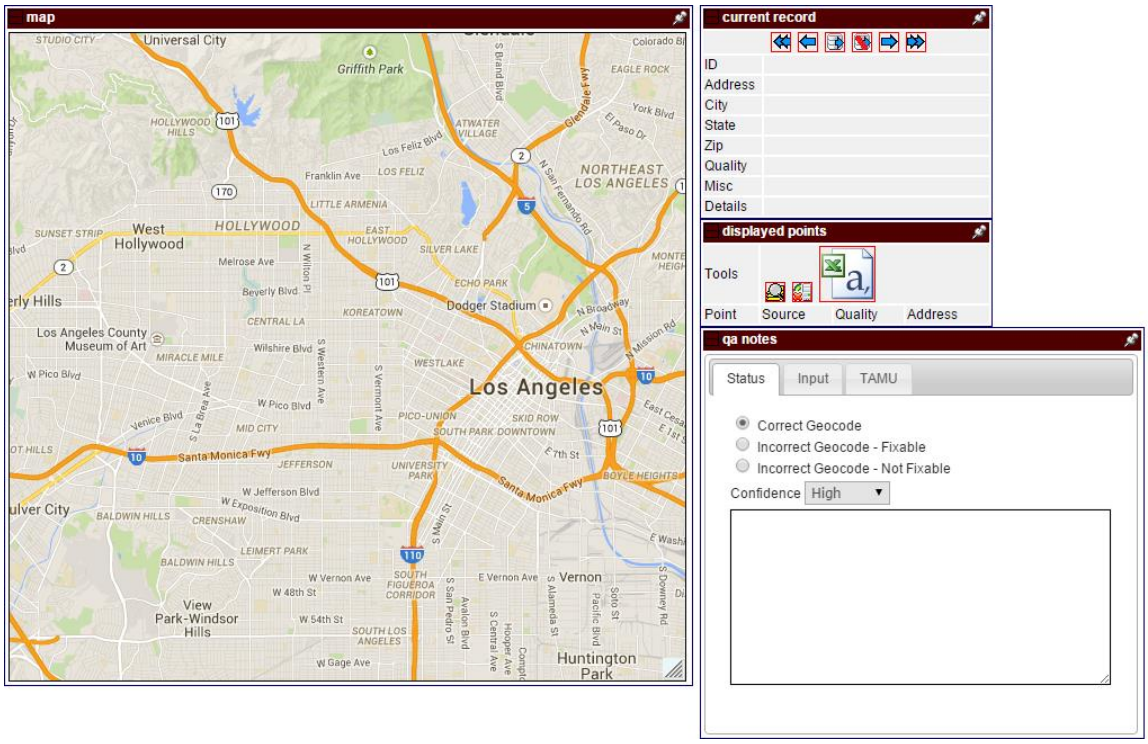

Figure 1. Manual geocode correction tool interface**.**

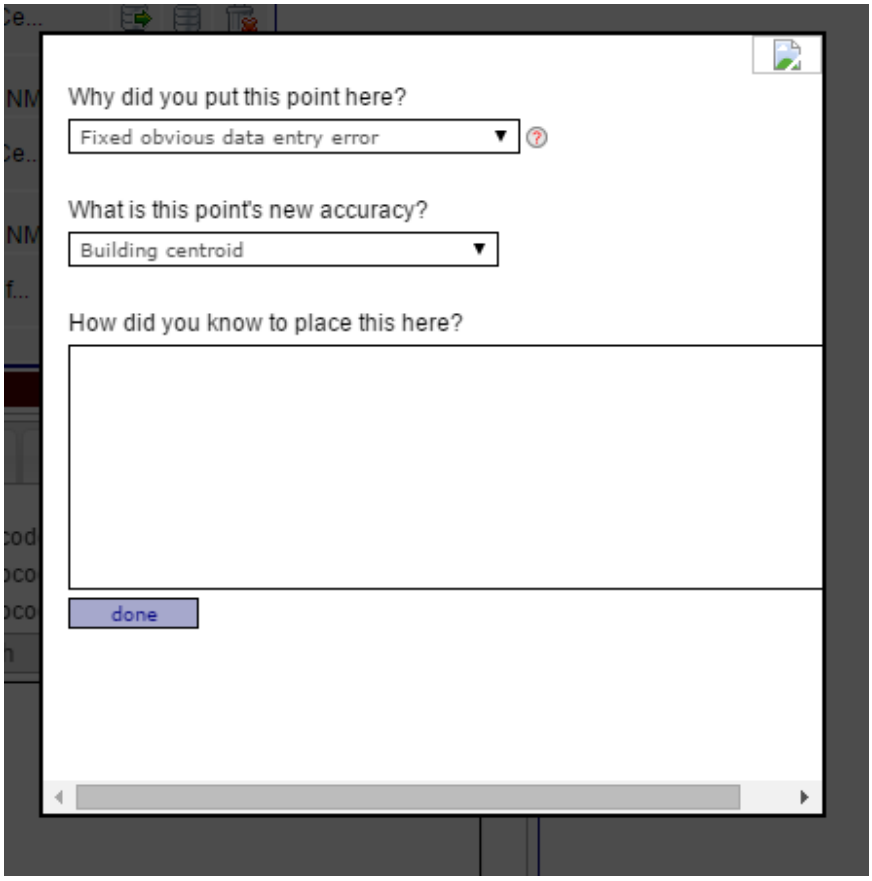

Figure 2. Prompt for new accuracy description.

Results

This section provides a description of the results that were obtained from manually correcting the 784 geocodes. The same method used in prior research (Goldberg et al. 2008a) was used to classify an improved record as one of two criteria (Rushton et al. 2006). A record that was originally non-geocodable and a geocode was obtained after processing was categorized as criteria one. A record that was previously

geocodable and the accuracy of the geocode was improved after processing was categorized as criteria two (Boscoe 2008). It should be noted that we considered a record that has a lower North American Association of Central Cancer Registries (NAACCR) GIS Coordinate Quality Code (Goldberg 2008) after it has been processed, to be an improvement in accuracy according to criteria 2. We acknowledge that without direct field observation, it is not possible to assess with 100% accuracy that the original geocode was improved. All of the records in the dataset were geocodeable in the original file, therefore no records met criteria one. For measuring improvement, we followed the geocode output type hierarchy of the NAACCR GIS Coordinate Quality Code.

Of the 784 records, 709 met criteria two. Ninety percent of the original addresses were corrected to a higher accuracy after the manual correction processes and 10% did not change. Of the 75 records that did not change, 21 were of the Exact Parcel Centroid quality, 50 were of Address Range Interpolation, and four records were of the USPS Zip Centroid quality. Table 1 shows that of the 71 addresses that matched to either Exact Parcel Centroid or Address Range Interpolation these records were already either the second or the third highest ranked geocode quality types (Goldberg 2008).

Table 2 contains the original and corrected geocode quality type for the dataset. The original dataset contained zero records that were geocoded to the Building Centroid quality type. The corrected dataset contains 638 (81.38%) geocodes of this quality. It is notable that the original geocoded dataset contained 204 (26%) geocodes that matched to the USPS Zip Centroid quality type and after manual geocoding correction there were only four (< 1%) records.

Table 1. Geocode quality types and descriptions ranked from most to least accurate and geocode quality types of the original and corrected dataset.

Quality Type	Description	Original Quality Type Total (*N* = 784)	%	Corrected Quality Type Total (*N* = 784)	%
Building centroid	Matched to the centroid of the building	0	0.00	638	81.38
Exact parcel centroid point	Matched to the centroid of the parcel	194	24.75	44	5.61
Address range interpolation	Uses information about the address number ranges to estimate the position of a numbered address	386	49.23	79	10.08
Street centroid	Matched to the centroid of the street	0	0.00	18	2.29
USPS zip centroid	Matched to the zip code area centroid	204	26.02	4	0.51
City centroid	Matched to the centroid of the city	0	0.00	1	0.13
State centroid	Matched to the centroid of the state	0	0.00	0	0.00

USPS, United States Postal Service.

Discussion

Processing Time

The correction process of the entire dataset consisting of 784 records was completed in 42.21 hours. The average processing time was 194 seconds per record. In the following sections, we will discuss the quality improvement of the dataset. The purpose of analyzing both the time taken and the geocode quality improvement is to illustrate the effort that is involved versus the improvement in geocode accuracy gained.

Spatial Shift

Of the 784 geocodes, 709 were assigned a new set of coordinates during the correction process. In this section we will review the spatial shift that the majority of the geocodes underwent. This distance was measured in meters (m) using the XY to Line tool within ArcGIS 10.1. Of the addresses that met criteria 2, the spatial shift improvements ranged from the smallest (0.018851 m) to the largest (151,368 m), the mean was 1,963 m, and the median was 114 m (Table 2).

Table 2. Geocode quality types of the original and corrected dataset and spatial shift improvement by each geocode quality type correction.

Old Geocode Quality Type	New Geocode Quality Type[a]	Total (*N*=703)		Spatial Shift (m)				
		N	%	Mean	Median	IQR (Q1, Q3)[b]	Minimum	Maximum
Address range interpolation	Building centroid	323	45.95	355.22	105.88	(54.21, 221.96)	3.49	33936.56
Address range interpolation	Exact parcel centroid	10	1.42	253.77	72.32	(42.75, 130.22)	7.04	1904.97
Exact parcel centroid	Building centroid	171	24.32	116.62	11.66	(2.29, 27.25)	0.02	8260.35
USPS zip centroid	Building centroid	143	20.34	5070.82	3094.47	(1446.09, 5455.60)	191.04	54717.53
USPS zip centroid	Exact parcel centroid	14	1.99	9903.80	5669.26	(3036.69, 11614.65)	871.14	41691.95
USPS zip centroid	Address range interpolation	29	4.13	6581.60	3405.08	(858.99, 12227.95)	114.31	23920.18
USPS zip centroid	Street centroid	13	1.85	22956.72	11708.03	(3959.76, 20884.24)	1734.06	151367.94
All corrections		703		1963.18	113.81	(24.64, 940.39)	0.02	151367.94

USPS, United States Postal Service.

[a] Geocode quality Type Change of $N \geq 5$

[b] IQR, Interquartile Range

For the smallest spatial shift improvement category, i.e. Exact Parcel Centroid to Building Centroid, we found that these geocode quality types were closely aligned and required minimal processing time (in seconds), mean 100 seconds and the median 52. In the event that the original geocode location of an Exact Parcel Centroid quality type was already accurate but needed to be updated to Building Centroid, the building was selected to reflect its true level of accuracy. The newly selected point was located proximate to the original point, resulting in the small difference between the original and corrected geocodes. For the largest spatial shift the geocode quality improved from USPS Zip Centroid to Street Centroid and the processing time was 1,276 seconds (21.2 minutes). Figure 3 illustrates an example of the spatial shift between the original and corrected geocoded points. In the bottom left of the diagram, it can be seen that many corrected geocoded points were derived from the same original point. In this case, many addresses were originally geocoded to a zip code centroid and then corrected to more accurate single location-based geocode.

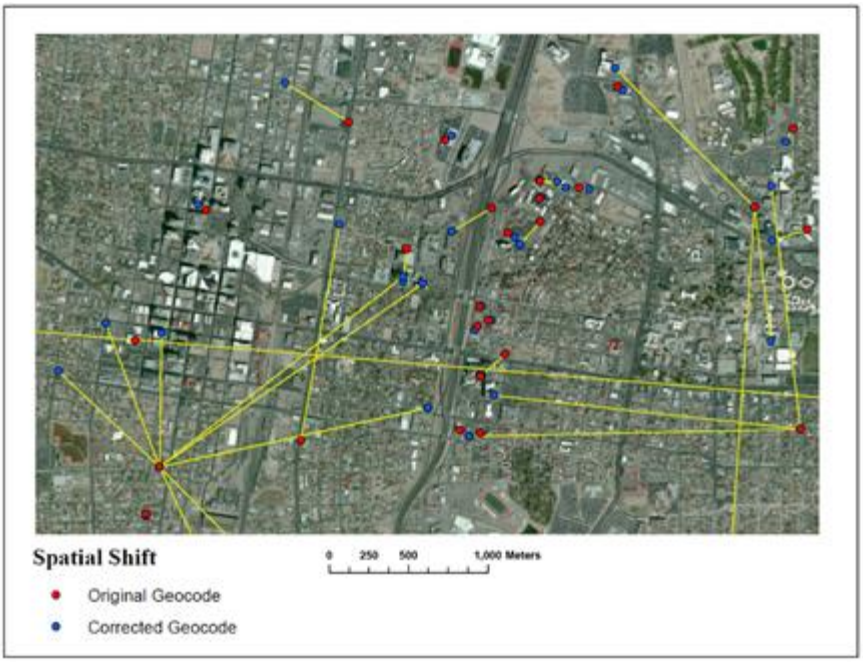

Figure 3. Spatial shift from original geocode to corrected geocode.

Geocoding a list of addresses is often just the first step to a more extensive project (Rushton et al. 2006, Goldberg, Wilson and Knoblock 2007). This first step, however, is very important because it can ultimately dictate the accuracy and direction of the final result (Oliver et al. 2005, Zandbergen 2009, Wey et al. 2009). Prior research has demonstrated that geocoded datasets should be evaluated not only for match rate but also by geocode quality type (Goldberg et al. 2008a, Rushton et al. 2006). Based on the level of accuracy of geocodes and the research purpose, it is our recommendation that researchers pause and evaluate if it is necessary to invest time to improve the accuracy of the geocodes (Krieger et al. 2001, Bonner et al. 2003, Nuckols, Ward and Jarup 2004, Oliver et al. 2005, Schootman et al. 2007, Zandbergen 2007, Zandbergen 2009, Grubesic

and Matisziw 2006). This study illustrates that a dataset of lower geocode quality types can be improved to a higher level of quality with very little investment of time, effort, or finances. The original dataset contained zero geocodes that matched to a building centroid. After 42 hours (≈ one week of work), 638 (81%) of the geocodes matched to a building centroid. Our spatial shift findings support previous studies demonstrating that inaccurate geocoding produces positional errors (Cayo and Talbot 2003, Ward et al. 2005). These errors have the potential to impact health analysis ranging from inaccurate local disease rates to imprecise accessibility measures; these health analysis studies are frequently used to inform health policy decisions (Jacquez 2012). The manual intervention geocoded dataset that was produced as part of this study is now more suitable to be used for analysis because it will yield more reliable results.

This study was reviewed and approved by the University of New Mexico Human Research Review Committee and by the Texas A&M University Institutional Review Board.

Conclusion

The current study provides additional motivation and evidence-based findings for the purpose of demonstrating that manual geocoding correction is both a feasible and economical method for improving the quality of geocoded data. And, we demonstrated that the manual intervention geocoded processes resulted in increased match rates, higher confidence in geocode quality, and improved geocode match types. Finally, this

study supports prior research that has been conducted in the geocoding accuracy and analysis field, and supports that prior findings are transferable from one geographic region to another as well as across domains of health services (Goldberg et al. 2008a). As demonstrated by this study, the TAMU Geoservices geocoder and the geocode correction tool, which is integrated in the online web service, is a low to no cost, easy to use option to improve geocode accuracy.

CHAPTER III

HEALTH SERVICE ACCESSIBILITY AND RISK IN CERVICAL CANCER PREVENTION: COMPARING RURAL VERSUS NONRURAL RESIDENCE IN NEW MEXICO[*]

Introduction

Despite our knowledge on how to prevent invasive cervical cancer, the American Cancer Society estimates that in the United States during 2015, there will be 12,900 cases of invasive cervical cancer and 4,100 deaths (American Cancer Society 2015). Invasive cervical cancer (ICC) is mostly preventable because precancer can be detected through cervical cancer screening (Papanicolaou [Pap] and/or human papillomavirus [HPV] testing) and treatment can excise precancerous lesions prior to invasion (Dürst et al. 1983). Screening is highly effective in reducing the incidence of invasive cervical cancer (Cuzick et al. 2014, Leyden et al. 2005, Saslow et al. 2012) but it is just one component of the full spectrum of cervical cancer preventive care. ICC preventive care, herein the continuum of preventive care, consists of a multi-step process moving across screening, diagnostic colposcopy, and excisional pre-cancer treatment procedures (Schiffman and Castle 2005).

[*]Reprinted with permission from McDonald, Y. J., D. W. Goldberg, I. C. Scarinci, P. E. Castle, J. Cuzick, M. Robertson & C. M. Wheeler (2016) Health Service Accessibility and Risk in Cervical Cancer Prevention: Comparing Rural Versus Non-rural Residence in New Mexico. *The Journal of Rural Health*.

While there has been considerable research on non-spatial risk factors for cervical pre-cancer and cancer outcomes (e.g., sociodemographics and behavioral variables) (Downs et al. 2010, Newmann and Garner 2005, Vamos et al. 2015), few studies have examined the association of spatial factors (e.g., access to services) and the continuum of preventive care. Moreover, despite declines in cervical cancer incidence, rural and non-rural disparities persist (Singh 2012). Previous studies comparing the rural versus metropolitan cervical cancer incidence rate during 1998-2001 found a 14% higher rate in rural areas (Benard et al. 2007) and a study of the 2000-2008 period reported a 15% higher rate in in rural areas (Singh 2012). Although access to care is a complicated matrix of interacting variables (Daley et al. 2011), there is consensus that access to screening and follow-up services is a potential driver for cervical cancer incidence (Singh 2012, Downs et al. 2008, Horner et al. 2011a, Benard et al. 2007).

Geographic accessibility (generally characterized as travel distance or travel time) frequently represents the spatial dimensions of access (Zhan and Lin 2014, Boscoe et al. 2011, Henry et al. 2011) to healthcare services and it is commonly used as a predictor variable for health outcomes (Continelli et al. 2010, Henry et al. 2011, Guidry et al. 1997). The prevention of cervical cancer could require travel to different healthcare facilities because not all providers and not all facilities can perform the services across the full continuum of preventive care (Schiffman and Castle 2005). For example, once a positive cervical screening test is detected, a diagnostic colposcopy would often be performed, and in some instances, an excisional treatment must be sought if precancer is detected - this could require travel to different healthcare facilities. Thus geographic

accessibility has the potential to become a barrier to optimal health outcomes (Penchansky and Thomas 1981, Newmann and Garner 2005), in particular as women with increasing risks for cervical precancer (e.g., abnormal screening or diagnostic results) move through the continuum of preventive care (Hawkins and Curtiss 1997, Guidry et al. 1997).

Even though clinical care delivery for cervical cancer screening, diagnostic, and pre-cancer treatment is similar for all women, access to various specialty services may differ based upon rural and non-rural residence (Barry and Breen 2005, Yabroff et al. 2005) but has not been specifically analyzed by service type across the continuum of preventive care. In rural areas limited medical infrastructures, including inadequate supply of providers ranging from primary care physicians and mid-level practitioners who most frequently recommend Pap tests, to gynecologic oncologists and medical oncologists who treat patients with cervical cancer (Hart et al. 2002, Hawkins and Curtiss 1997), and fewer on-site oncology services including radiation and chemotherapy are additional barriers that rural residents must navigate (Yabroff et al. 2005). Population characteristics that place women at greater risk for incidence and mortality from cervical cancer, such as poverty, being elderly, and lack of or inadequate health insurance coverage are disproportionally concentrated in the less populated, rural areas of the United States (Yabroff et al. 2005, Harris and Leininger 1993, Newmann and Garner 2005).

There is extant literature on geographic accessibility for preventive services to breast and colorectal cancer treatment facilities, and some studies have stratified

differences by rural and non-rural residence. While findings have been inconsistent, studies have examined the association between geographic accessibility and breast cancer outcomes (Hahn et al. 2007, Jones et al. 2005, Henry et al. 2011, Boscoe et al. 2011). Using a multistate dataset, Henry et al (2011) found that longer travel time was not associated with a higher risk of late-stage breast cancer diagnosis and that accessibility to screening services was not correlated with rural/urban residence type. A study using the Surveillance, Epidemiology, and End Results (SEER) Program registry supported previous findings that women residing in rural areas, compared to women living in urban areas, had an increased likelihood of mastectomy (Jacobs et al. 2008). Regardless of where one lives, studies have found that increased travel distance was a statistically significant predictor of mastectomy (Boscoe et al. 2011, Schroen et al. 2005). Colorectal cancer research has found that spatial access to an oncologist had a statistically significant association with survival amongst rural residents while the finding did not exist for those living in urban areas(Wan et al. 2012). In contrast, geographic accessibility to preventive services across the continuum of cervical cancer preventive care is understudied; previous studies have examined one component of the continuum rather than access to all of the necessary multi-step preventive processes(Gunderson et al. 2013).

This study aimed to describe geographic accessibility, defined as travel distance and travel time to healthcare facilities that performed cervical cancer screening (Pap and/or HPV testing), diagnostic testing (colposcopy), and excisional pre-cancer treatment services (loop electrosurgical excision procedure or cone biopsy) in New

Mexico, during the years 2010 to 2012. Results were stratified by rural and non-rural census tract to examine geographic accessibility by these dimensions, as Guidry et al. (1997) has identified this level of analysis as a gap in the literature. Drawing upon the call for the standardization of what constitutes rural and non-rural geography, we utilized definitions proposed by Meilleur et al. (2013). To our knowledge, this is the first study to measure geographic accessibility to healthcare facilities that performed actual services across the continuum of preventive care for cervical cancer prevention.

Methods

Study Area and Screening Population

The study area was New Mexico, a state with a female population of 1,042,716 (U.S. Census Bureau 2011). The most recent cervical cancer screening guidelines recommend initiating screening at age 21 years and stopping screening at age 65 years (Cuzick et al. 2014, Moyer 2012, Saslow et al. 2012). Approximately 57% of the New Mexico female population are within the age eligibility for this screening guideline (U.S. Census Bureau 2011). Twenty-three percent of the overall female population lives in a rural area (U.S. Census Bureau Center for Economic Studies 2012), 20% are below the federal poverty level, and 16% have less than a high school education (U.S. Census Bureau 2011).

Data Sources

The Office of Rural Health Policy, U.S. Department of Health and Human Services, (Hirsch 2007) provided Rural–Urban Commuting Area (RUCA) codes at the census-tract level. Socio-demographic data (e.g., population, education, and poverty status) were obtained from the American Community Survey (ACS), 5-year estimates (2007-2011) (U.S. Census Bureau 2011). The New Mexico HPV Pap Registry (NMHPVPR) was the source for healthcare facility data for the years 2010-2012. Established in 2006, the NMHPVPR is the first population-based statewide cervical screening registry in the United States. The NMHPVPR includes address-level data on healthcare facilities that provided cervical screening (Pap and/or HPV testing), diagnostic testing (colposcopy), and excisional pre-cancer treatment (loop electrosurgical excision procedure or cone biopsy). NMHPVPR acts as a designee of the New Mexico Department of Health that operates under NMAC 7.4.3, which specifies the list of Notifiable Diseases and Conditions for the state of New Mexico. The NMAC 7.4.3 specified that laboratories must report to the NMHPVPR all results for Pap and HPV tests, and cervical, vulvar and vaginal pathology performed on women residing in New Mexico.

Geographic Units

The geographic unit of analysis was the census tract (N = 499). To compute the mean population-weighted census tract centroid, we used census tract (U.S. Census Bureau 2011) and block group-level (U.S. Census Bureau 2013) population data retrieved from the ACS 5-year estimates (2007-2011 & 2009-2013). Census tracts are small, relatively permanent statistical subdivisions of counties, are relatively homogenous in population characteristics and organized to maintain an optimum population size of 4,000 (range between 1,200 - 8,000) (United States Census Bureau 2012b). Block groups are statistical divisions of census tracts and range in population between 600 – 3,000 (United States Census Bureau 2012a). We used ACS 5-year estimates (2007-2011) for the female age group most closely aligned with the cervical cancer screening guidelines (21-64 years old). The population-weighted centroid method used 498 census tracts; tract 9403 deleted due to zero population count (located within the Los Alamos Laboratory area).

Rural and Non-Rural Geography

There is not a single established definition for "rural" in U.S. research or policy studies. Most recently, the Office of Rural Health Policy (ORHP) definition was proposed as a standard, in order for cancer researchers to adopt one standard that can be used to define rural, and thereby utilize a common analytical approach (Meilleur et al.

2013). The multiple definitions for rural and non-rural reflect the multidimensional nature of these concepts, often leading to confusion and unwanted mismatches in program eligibility (United States Department of Agriculture 2017). Cancer research studies evaluating outcomes and patterns of care have used various definitions of rural, resulting in difficulty to compare studies and generalizability (Meilleur et al. 2013). Because the purpose of our study was to determine if there was a significant difference in access to health services across the continuum of preventive care comparing rural to non-rural census tracts, we opted to utilize the ORHP definition as discussed in Meilleur et al. (2013). The ORHP defines rural as Rural-Urban Commuting Area Codes (RUCA) 4 through 10 as well as secondary RUCA codes 2 or 3 that are at least 400 square miles in area with a population density of no more than 35 people. The RUCA taxonomy is based on the size of cities and towns and their functional relationships as measured by work commuting flows (Hirsch 2007). Moreover, while the ORHP does not require agencies to adopt its definition of rural, and recognizes that alternate definitions may be better suited for the purpose of specific program requirements, the ORHP definition is used to determine geographic eligibility to apply for rural health grants (Hirsch 2007).

Geographic Spatial Analytical Approaches

Two types of locations were used in this analysis: (1) the origin (i.e., population-weighted centroid of the census tracts for the state of New Mexico) and (2) the destination (i.e., geographic coordinates [latitude and longitude] of the facilities). We

used two measures of geographic accessibility to conduct proximity analysis to the nearest destination from the point of origin by year for each type of service provided across the continuum of preventive care. First, travel distance (hereafter referred to as distance) via roads *from* the road nearest to the population-weighted census tract centroid *to* the nearest facility providing specific service within the continuum of preventive care was measured. Second, shortest travel time (hereafter referred to as time) *from* the road nearest to the population-weighted census tract centroid *to* the nearest facility providing specific service within the continuum of preventive care was measured.

The Texas A&M University Geoservices Online Geocoding service, version 4.01 was used to geocode the New Mexico healthcare facility data by type of service provided across the continuum of preventive care (Texas A&M University Geocoder). All healthcare facilities could be geocoded, however, to improve quality we used the Geocode Correction tool within the Texas A&M University Geocoder as described by Goldberg et al. (2008b) (Texas A&M University Geocoder). The mean population-weighted centroid function within ArcGIS 10.1 was used to compute the centroids of the census tracts (Environmental Systems Research Institute). The population-weighted centroid is a summary single reference point, which represents how the population is spatially distributed and grouped at the census tract-level (Office for National Statistics 2015). Due to the common data limitation of not having patient-level addresses, geographic accessibility studies address this limitation by assigning a single point location to represent the location of a population. The travel time computation based

upon this single point is assumed representative of the travel time realized by population members (Delamater et al. 2012). This assumption can mask significant variability, which is revealed in the range, but is necessary because of the uncertainty of potential factors that influence travel when conducting population-based studies (Witlox 2007). Census tracts were weighted based upon screen eligible population to remove effects based upon varying population. The ACS 5-year estimates (2007-2011) of the female population (21-64 years old) were used to represent the screen eligible population, as this age group is most closely aligned with current cervical cancer screening guidelines of women aged 21-65 years old. As a first step in data processing, we used Python™ programming language (version 2.7.5) (Python Software Foundation) to automate the enumeration of census tracts by their screen eligible population. This allowed for the calculation of a weight of each census tract to be based upon the screen eligible population. We then used these weights to adjust for effects based upon varying population; the source code is available from the authors by request.

Distances and times were calculated using the Shortest Path calculator developed for the North American Association of Central Cancer Registries, which is maintained at the Texas A&M University GeoInnovation Service Center. The shortest path and fastest route methodology was computed as described by Henry et al. (2011).

Distance was grouped into seven categories (in kilometers): <15; 15-< 30; 30-< 45; 45-< 60; 60-<75; 75-<100; and 100+. These categories were established based on breast cancer research of geographic proximity analysis of surgical and treatment facilities (Boscoe et al. 2011). Time was grouped into seven categories (in minutes):

<10; 10-< 20; 20-< 30; 30-< 40; 40-< 50; 50-<60; and ≥60. Similarly, these categories were established based on breast cancer treatment geographic proximity to diagnosing facility and nearest mammography facility research (Henry et al. 2011).

The Mann-Whitney Test (2 independent samples, $P < .05$, 2-tailed) was used to determine if differences in distance and time were statistically significant for rural census tracts versus non-rural census tracts. Cohen's *r* was calculated to determine effect size (Fritz, Morris and Richler 2012). A small effect is 0.1, a medium effect is 0.3, and a large effect is 0.5 (Cohen 1988, Fritz et al. 2012).

Travel time by aforementioned categories were mapped by rural and non-rural areas to display spatial representation of geographic accessibility, which aided in visually identifying gaps in the location of services (Foley and Platzer 2007). To map density of cervical screening, diagnostic, and excisional pre-cancer treatment facilities by screening population, we used the screen eligible population by census tract.

This study was reviewed and approved by the University of New Mexico Human Research Review Committee and by the Texas A&M University Institutional Review Board.

Results

All healthcare facilities were successfully geocoded. Based upon geocode quality codes (Goldberg et al. 2008b) approximately 81% of healthcare facilities were geocoded at the building centroid, 6% at the exact parcel centroid, 10% address range

interpolation, 2% street centroid, and less than 1% US Postal Service Zip Code area centroid and city centroid level. Table 3 shows the address-level healthcare facilities that provided services across the continuum of preventive care in New Mexico for the years 2010 through 2012. In terms of the percentage of services across the study years, facilities in rural areas provided the majority of total services in the form of screening (75 – 79%) compared to 68-69% of facilities in non-rural areas.

The percentage of screening and diagnostic services was consistently higher in non-rural areas compared to rural areas; there was a slight increase for both areas during 2011. However, rural areas in 2012 dropped back to 2010 levels while non-rural areas retained the majority of the increase. The percent of facilities that provided all services (screening, diagnostic and precancer treatment) in non-rural areas was consistently higher compared to facilities in rural areas year-to-year but the differential was reduced from 45% in 2010 to 37% in 2012.

Table 3. Healthcare facilities performing various cervical cancer preventive services by year by rural and non-rural census tracts in New Mexico, 2010 - 2012.

	2010				2011				2012			
	Non-Rural		Rural		Non-Rural		Rural		Non-Rural		Rural	
Services Provided[a]	*N*	%	*N*	%	*N*	%	*N*	%	*N*	%	*N*	%
Screening Only[b]	228	69.3%	241	78.8%	240	67.8%	230	75.7%	234	68.0%	232	79.2%
Diagnostic Only[c]	3	0.8%	2	0.7%	3	0.9%	2	0.6%	4	1.2%	1	0.3%
Excisional Treatment Only[d]	0	0.0%	1	0.3%	0	0.0%	0	0.0%	1	0.3%	0	0.0%
Screening and Diagnostic Only	51	15.6%	38	12.4%	67	18.9%	49	16.1%	60	17.4%	36	12.3%
All Services[e]	47	14.3%	24	7.8%	44	12.4%	23	7.6%	45	13.1%	24	8.2%

[a]No facilities were identified that only provided screening and excisional treatment services or diagnostic and exicisional treatment services

[b]Screening services include Pap smear and/or HPV testing

[c]Diagnostic service is colposcopy

[d]Excisional treatment services includes cone and loop electrosurgical excision procedure

[e]Screening, Diagnostic, and excisional treatment

Across all cervical cancer preventive healthcare services and years, women who resided in rural areas had a significantly greater geographic accessibility burden when compared to non-rural areas (4.4 vs 2.5 km and 4.9 vs 3.0 minutes for screening; 9.9 vs 4.2 km and 10.4 and 4.9 minutes for colposcopy; and 14.8 vs 6.6 km and 14.4 and 7.4 minutes for precancer treatment services, all P < .001). Distance and time increase as one must seek advanced care to prevent cervical cancer, however, the finding was less pronounced for non-rural census tracts. Appendix A and B, show 2010 - 2012 time and distance measurements from the population-weighted census tract centroid to the nearest healthcare facility that provided a cervical cancer preventive service care by non-rural and rural census tracts.

The Mann-Whitney's U test was used to evaluate the distance and time differences from the population-weighted centroid to the nearest facility providing cervical screening services by non-rural and rural census tracts (Table 4). Reporting results from 2012, which is representative of the findings during the study period, we found a significant small effect for time (Median (*Mdn*) unit of measurement expressed as minutes) to screening services comparing rural *(Mdn* = 5.40) and non-rural (*Mdn* = 3.00) census tract groups, $P < .001$, and $r = .198$. For time to diagnostic services, we found a significant medium effect comparing rural (*Mdn* = 10.20) and non-rural census (*Mdn* = 5.40) tract groups, $P < .001$, and $r = .327$.

Similarly, there was a medium effect for travel time to nearest healthcare facility that provided excisional service comparing rural (*Mdn* = 16.20) and non-rural (*Mdn* = 7.80) census tract groups, $P < .001$, and $r = .300$. We found a significant small effect for distance to screening services comparing rural *(Mdn* = 4.41) and non-rural (*Mdn* = 2.57) census tract groups, $P < .001$, and $r = .210$. For distance to diagnostic services, we found a significant medium effect comparing rural (*Mdn* = 9.72) and non-rural census (*Mdn* = 4.39) tract groups, $P < .001$, and $r = .309$. Similarly, there was a small effect for time to nearest healthcare facility that provided excisional service comparing rural (*Mdn* = 17.25) and non-rural (*Mdn* = 6.63) census tract groups, $P < .001$, and $r = .284$.

Table 4. Differences in travel distance (kilometers) and travel time (minutes) by non-rural census tracts versus rural census tracts[a].

Distance (km)	Mdn Diff.[b]	IQR[c]	U[d]	*P*[e]	*r*[f]	Time (minutes)	Mdn Diff.[b]	IQR[c]	U[d]	*P*[e]	*r*[f]
Screening[g]											
2010	2.060	1.288-7.081	$2.9* 10^9$	<.001	.210*	2010	1.800	1.800-7.800	$2.9* 10^9$	<.001	.210*
2011	1.770	1.304-7.339	$2.9* 10^9$	<.001	.205*	2011	1.800	1.800-8.400	$3.0* 10^9$	<.001	.198*
2012	1.835	1.304-7.483	$2.9* 10^9$	<.001	.210*	2012	2.400	1.800-9.000	$3.0* 10^9$	<.001	.198*
Diagnostic[h]											
2010	5.601	2.478-14.307	$2.5* 10^9$	<.001	.303**	2010	5.400	3.000-12.000	$2.4* 10^9$	<.001	.320**
2011	6.164	2.768-14.774	$2.5* 10^9$	<.001	.311**	2011	6.000	3.600-12.600	$2.4* 10^9$	<.001	.326**
2012	5.327	2.800-14.500	$2.5* 10^9$	<.001	.309**	2012	4.800	3.600-13.200	$2.4* 10^9$	<.001	.327**
Excisional Treatment[i]											
2010	7.821	3.734-19.441	$2.6* 10^9$	<.001	.273*	2010	7.200	4.200-18.000	$2.5* 10^9$	<.001	.292*
2011	6.180	3.862-23.529	$2.8* 10^9$	<.001	.243*	2011	5.400	4.800-19.800	$2.7* 10^9$	<.001	.264*
2012	10.622	4.136-25.476	$2.6* 10^9$	<.001	.284*	2012	8.400	4.800-19.800	$2.5* 10^9$	<.001	.300**

[a]Analysis included non-rural (n=301) and rural (n=197) census tracts weighted by target screening population

[b]Difference in Medians (Rural - Non-Rural)

[c]IQR indicates Interquartlie Range (Q1 - Q3)

[d]Indicates Mann Whitney *U* score

[e]Mann Whitney Test (2 Independent Samples, $P < .05$, 2-tailed)

[f]Cohen's *r* indicates effect size of Mann-Whitney *U* test, .1 is a small effect(*), .3 is a medium effect(**), and .5 is a large effect (***)

[g]Screening services include Pap smear and/or HPV testing

[h]Diagnostic service is colposcopy

[i]Excisional treatment services includes cone and loop electrosurgical excision procedure

Visual representation of female (21-64 years old) population density in New Mexico revealed vast areas that have extremely low population density dominating the state. Differences in female population density range from .033 to 1231 (mean 225 and standard deviation of 268). There was an observed relationship with densely population areas and the presence of healthcare facilities that provided services across the continuum of preventive care. As posited, densely populated areas, i.e. non-rural census tracts, had a large number of facilities that provided services across all components of the continuum of preventive care. Travel time and travel distance from the population-weighted census tract centroid to the nearest healthcare facility comparing rural to non-rural census tracts varied significantly. The disparity is most pronounced in the northwestern portion of the state, which is rural and the female population density is low. In this area, travel time to cervical cancer diagnostic colposcopy and excisional pre-cancer treatment services is predominantly 60+minutes. In the southeastern portion of the state, which has low population density and is mainly rural, a cluster of non-rural census tracts is present and has similar travel times and distances to diagnostic and treatment services, as compared to the rural census tracts in this area.

Discussion

This study set out with the aim of describing geographic accessibility to healthcare facilities providing services across the continuum of cervical cancer preventive care stratified by rural and non-rural census tracts in New Mexico during the years 2010 to 2012. Our findings confirm that women in rural areas, as opposed to those

residing in non-rural areas, are significantly burdened with longer travel distances and times to obtain preventive cervical cancer health care services. Women living in rural areas may be less inclined or delayed to seek follow-up care, which could result in treatment of invasive cervical cancer rather than of pre-invasive cancer. There are fewer facilities providing all services across the continuum of preventive care in rural census tracts, as compared to non-rural census tracts. Visual inspection of spatial maps illustrates that predominant clusters of facilities, regardless of type of service provided are located in the most densely populated, non-rural areas of the state. These finding support previous research that rural areas have limited medical infrastructure (Hart et al. 2002, Hawkins and Curtiss 1997). While rural census tracts have a comparable percentage of facilities that provided only cervical screening services, as compared to non-rural census tracts, this finding does not preclude a contribution to failures in the continuum of cervical cancer preventive care at this level. Previous studies have reported that physicians in rural clinics are less likely to recommend and/or perform cervical cancer screening (Barry and Breen 2005, Yabroff et al. 2005, Gulitz, Bustillo-Hernandez and Kent 1998). Thus, the service that is most accessible to women in rural areas (i.e., cervical screening) may not be adequately recommended.

Since our study is the first to describe distance and time to all services across the continuum of cervical cancer preventive care, we do not have comparative measures. The most similar cervical cancer research study to our work examined travel distance and travel time to the nearest general practitioner (GP) and the nearest cancer center (Brewer et al. 2012). Our data are in agreement with Brewer et al. (2012) who reported a

median distance to the nearest cancer center facility, which would be equipped to perform diagnostic and excisional pre-cancer treatment services for cervical cancer prevention, as 21 kilometers compared to less than one kilometer for a general practice facility that would predominantly provide cervical screening services. We found that the median distance to excisional pre-cancer treatment services (14.77 kilometers for rural versus 6.56 kilometers for non-rural census tracts) was farther than to cervical screening services (4.37 kilometers for rural versus 2.48 kilometers for non-rural census tracts); our travel time findings also align.

There were fewer healthcare facilities that provided diagnostic and excisional pre-cancer treatment services, as compared to cervical screening services, which is to be expected. All women aged 21-64 years need to access a facility that provides cervical cancer screening services, whereas the need for diagnostic or excisional pre-cancer treatment procedures during 2010 through 2012 was approximately 10 and 100 fold less, respectively, when compared to cervical screening (NMHPVPR 2015).

This study was limited by the absence of individual-level usage of services; it measures population-based access rather than realized individual access. Being limited to address-level healthcare facilities that provided services across the continuum of preventive care for New Mexico only, we did not integrate geographic accessibility for areas adjacent to state boundaries. However, state-level data records report that less than 3% of services across the continuum of preventive care were provided outside of New Mexico (NMHPVPR 2015). Due to data limitations, these findings do not consider that distance to care could be longer for individual women who participate in systems of care

that would then require bypassing the nearest facility (Boscoe et al. 2011) to receive care as a system member. Furthermore, distances and travel time to care for individual women who do not have health insurance might be longer still, potentially exacerbating poor health outcomes associated with lack of health insurance (Institute of Medicine Committee on the Consequences of Uninsurance 2002, Baker et al. 2001).

The geographical accessibility findings in this study were strengthened by the use of actual healthcare facility locations that provided services across the continuum of preventive care. The use of actual healthcare facilities locations rather than a default of a primary care physician location is a more accurate measure of geographic accessibility (Hart et al. 2002). Stratification by rural and non-rural census tracts extends our knowledge of differences in geographical accessibility. Our use of the ORHP rural definition supports the call for it to be a research standard; we further this initiative by highlighting its use for determining geographic eligibility to apply for health grants. Findings based upon the use of the ORPH rural definition can be used in public policy settings to support the need for resources. Finally, we used the Shortest Path method to compute distance and time because mountainous areas of the Western United States, such as our study area, it is recommended for improved accuracy versus Euclidean distance measurement (Boscoe, Henry and Zdeb 2012).

Conclusion

This study has demonstrated that those at greatest risk for cervical cancer (i.e., those who require excisional treatment for cervical pre-cancer) are burdened with the greatest distance and longest time to obtain required specialty health care, as compared to those accessing cervical screening and diagnostic services, irrespective of where one resides. Women who live in rural census tracts are disproportionality burdened, as compared to those living in non-rural census tract. Recent research found that universal compliance to the recommended screening guideline for all screen-eligible women (i.e., 3-year cytology) along with 100% compliance to colposcopy/biopsy referrals resulted in the greatest reduction in lifetime cervical cancer incidence (72.2%), as compared to current screening practice (48.5%) (Kim et al. 2015). We found that healthcare facilities providing both screening and colposcopy/biopsy services or the full spectrum of screening, colposcopy/biopsy and excisional precancer treatment services were limited at 12% and 17% for rural, and 8% and 13% for non-rural census tracts respectively. These findings illustrate the challenges that women with cytologic or histologic abnormalities will often be referred for follow-up at different facilities simply because few facilities offer colposcopy and excisional services. Furthermore, the need to access multiple different facilities as the risk of invasive cervical cancer increases presents additional barriers for at-risk women.

Future research should examine the relationship between geographic accessibility (stratified by rural and non-rural areas) to healthcare services by race/ethnicity groups

given the documented cervical cancer disparities among racial/ethnic minorities. Further, efforts to investigate how geographic accessibility to healthcare facilities may influence failures of 3-year interval cervical screening and failures in recommended follow-up for diagnosis and treatment of cervical abnormalities should be undertaken. Our use of the proposed ORHP definition (Meilleur et al. 2013) to define rural and non-rural census tracts has a practical application. If unequal access is found and the ORHP definition is used, health practitioners would have met the geographic eligibility requirement to apply for a rural health grant and have evidence-based findings to support the need for resources. Other factors related to geographic accessibility, including direct costs (e.g., cost for gas), indirect costs (e.g., ability to take time off work), and availability of public transportation (Marcus et al. 1992, Block and Branham 1998) should also be considered in future studies. Continued efforts are needed to ensure that all women have comparable access to services across the continuum of cervical cancer preventive care.

CHAPTER IV

THE ROLE OF SOCIOECONOMIC STATUS, ACCULTURATION, RACE/ETHNICITY, AND GEOGRAPHY WITH INVASIVE CERVICAL CANCERS: A CASE–CONTROL STUDY IN NEW MEXICO

Introduction

Invasive cervical cancer is mostly a preventable disease because cervical cytology (Papanicolaou [Pap] test) can detect precancerous lesions and treatment can avert the onset of the invasive stage (Ayre 1964, Papanicolaou and Traut 1943). In 1964, it was posited that, given the existing rate of cervical cytology and screening coverage, invasive cervical cancer (ICC) would most likely be eliminated by 1970 (Ayre 1964). Over the past 35 years, ICC has decreased by 54% in the U.S. (Adegoke, Kulasingam and Virnig 2012). However, in the U.S., it is estimated in 2017 that 12,820 new cases of ICC will be diagnosed, 4,210 deaths will result, (American Cancer Society 2017) and minority women will continue to be disproportionately burdened with the disease (Watson et al. 2008).

There is a directional relationship between socioeconomic status (SES) and ICC health outcomes (Evans, Wolfe and Adler 2012). A world-wide meta-analysis of case-control studies found that that being in a low class social group, as opposed to a high class group, increased the risk for ICC among study populations from North America, South America, Asia, and Africa (Parikh, Brennan and Boffetta 2003). Of these U.S.

based studies, the focus was on sexual and hormonal factors (Ursin et al. 1996), contraceptive and reproductive risk factors (Schiff et al. 2000), and dietary and serum carotenoids (Van Eenwyk, Davis and Bowen 1991). Previous non-case-control studies in the U.S. found that lower SES (Boscoe et al. 2014, Clegg et al. 2009) and rural residency are associated with increased ICC incidence rates (Benard et al. 2008) as well as higher mortality from ICC (Singh et al. 2011).

A case-control study is an appropriate research design to investigate ICC because it is a disease with a low incidence rate and has a long latency period (Hennekens and Buring 1987). A major obstacle to execute a case-control study in the U.S. is the availability of an appropriate population-based control source to examine the association of SES, acculturation, race/ethnicity, and geography with ICC. Due to opportunistic screening practices (i.e. patient initiated) in the U.S., prior ICC case-control studies have primarily relied on hospital (Wylie-Rosett et al. 1984), integrated health care delivery systems (Kamineni et al. 2013), and clinics (Schiff et al. 2000, Becker et al. 1994) as sources for controls. The present study overcomes the obstacle of a U.S.-based, population-based case-control study to investigate ICC due to lack of an appropriate source for controls through a unique collaboration with The New Mexico HPV Pap Registry (NMHPVPR). The NMHPVPR is the first and only population-based, statewide cervical cancer screening registry in the U.S., which was established in 2006.

Much of the previous research has operationalized SES as a composite variable (Eggleston et al. 2006) and/or used factor analysis to reduce the dimensions of SES (Zhan and Lin 2014). “Intersectionality,” a term first used by Crenshaw (1991) to

explain how the intersection of gender and race results in different lived experiences of domestic violence for women of color as opposed to white women, has enabled researchers to examine differences between and within groups (Hankivsky et al. 2010). Rather than examine variables as separate factors that do not inform, influence, and overlap to create a complex web of health, public health researchers and social scientists have applied intersectionality research methods to understand the interconnectedness and interplay of variables associated with health outcomes (Williams et al. 2012, Weber and Parra-Medina 2003). Previous research found that race/ethnicity and gradients of poverty associated with cervical cancer precursor rates (i.e. cervical intraepithelial neoplasia grade 2 or higher and adenocarcinoma in situ [CIN2+/AIS]) were analyzed, which revealed that areas with a higher percentage of Black women and residents with higher proportions of poverty had increased rates of CIN2+/AIS, as compared to other areas (Niccolai et al. 2013). A prior study that used non-Hispanic white women as a referent category to examine race/ethnicity and neighborhood poverty interaction with ICC mortality found that irrespective of neighborhood poverty level, Puerto Rican women who resided in low and moderate poverty neighborhoods had an increased risk of death and Black women living in high poverty neighborhoods had a 50% more likely risk of dying (McCarthy et al. 2010). A comparison of non-Hispanic whites' and Hispanics' cancer risk from air toxics found that ethnic status interacts significantly and differs directionally with class, gender, and age; interactions among these variables resulted in disproportionately greater risk for Hispanics (Collins et al. 2011).

This study utilized a case-control research design to investigate if there were statistically significant differences for the following variables: SES (e.g. poverty), acculturation (e.g. language proficiency skills), race/ethnicity (e.g. American Indian), and geography (i.e. rural versus non-rural residence type) with ICC resulting in health disparities in New Mexico. SES, acculturation, race/ethnicity (e.g. Hispanic, non-Hispanic white, and American Indian woman), and geography were unpacked as separate explanatory variables of interest (i.e. covariates) using univariable and multivariable conditional logistic regression (Pourhoseingholi, Baghestani, & Vahedi, 2012) and employed intersectionality research methods (McCall, 2005) to illuminate the interwoven relationship of these dimensions in producing unequal risk of ICC. The potential of geographic accessibility being a potential barrier to care (Newmann and Garner 2005, Penchansky and Thomas 1981) is exacerbated by the multi-step ICC preventive care process of screening, diagnostic colposcopy, and excisional precancer treatment procedures (Schiffman and Castle 2005), which could potentially require travel to three different healthcare facilities (McDonald et al. 2016). In the context of this study, ICC health disparities were measured as SES, acculturation, race/ethnicity, and/or geography having a statistically significant increased odds ratio associated with ICC.

The null hypothesis is:

H_0: All women in New Mexico = the same odds ratio among cases and controls for ICC irrespective of SES, acculturation, race/ethnicity, and geography.

The alternative hypothesis is:

H_1: All women in New Mexico ≠ the same odds ratio among cases and controls for ICC irrespective of SES, acculturation, race/ethnicity, and geography and differences are statistically significant at a *P* value < .050, 95% CI.

Although extensive research has been carried out on SES and race/ethnicity as variables that influence ICC incidence rate and mortality (Newmann and Garner 2005), no single study exists, to the knowledge of the authors, which utilizes a case-control research design, includes geography (i.e. rural versus non-rural type and travel time to preventive ICC services), and employs an intersectionality methods approach. This study aimed to demonstrate how a cancer registry, along with a population-based cervical screening registry, can be utilized as sources for cases and controls to contribute to the burgeoning and multifaceted area of research on ICC health disparities. The present study fills a gap in the literature by (1) recognizing that while geography is a probable confounder, inherent in ecologic studies (Gomez et al. 2011), it is also a variable of interest that can be adjusted for by using multivariable regression analysis; thereby, including geography as an explanatory variable rather than controlling for it by matching on it, and (2) by heeding the call that geography needs to be a component of the intersectionality matrix (Hankivsky et al. 2010, Valentine 2007, Chen et al. 2008).

Methods

Data Sources

This study was conducted as part of the New Mexico HPV Outcomes and Practice Effectiveness PROSPR Research Center that includes the partnership of the New Mexico HPV Population Registry (NMHPVPR) and the New Mexico Tumor Registry (NMTR). The Population-based Research Optimizing Screening through Personalized Regimens (PROSPR), administered by the University of New Mexico Health Sciences Center (U54 RFA), demonstrates the National Cancer Institute's (NCI) recognition of the critical need to consider screening, diagnosis, and treatment surveillance linked to existing successful cancer registries. The NMHPVPR acts as a designee of the New Mexico Department of Health that operates under NMAC 7.4.3; it specifies the list of Notifiable Diseases and Conditions for the state of New Mexico. The NMAC 7.4.3 specified that laboratories must report to the NMHPVPR all results for Pap and HPV tests, and cervical, vulvar and vaginal pathology performed on women residing in New Mexico. The NMTR is a state-wide population-based cancer registry and a founding member of the NCI's Surveillance, Epidemiology, and End Results (SEER) Program and has continuously participated in that program since 1973.

Case-Control Design

A retrospective case-control design (Figure 4) was used because the aim of this research is to examine the main effects and interactions of SES, acculturation, race/ethnicity, and geography with ICC (Breslow and Day 1980, Schlesselman 1982). Due to the limited number of cases, a matched case-control design was used to improve comparability between cases and controls. To adjust for age, a known confounder (Franceschi et al. 2009), cases and controls were matched on age. To detect confounding, all explanatory variables (herein covariates) unadjusted odds ratio were compared to adjusted odds ratio to determine if there was a change of $\geq$ or $\leq 10\%$ in the odds ratio (Szklo and Nieto 2014). Multivariable conditional logistic regression was used to adjust for confounding (Pourhoseingholi, Baghestani and Vahedi 2012).

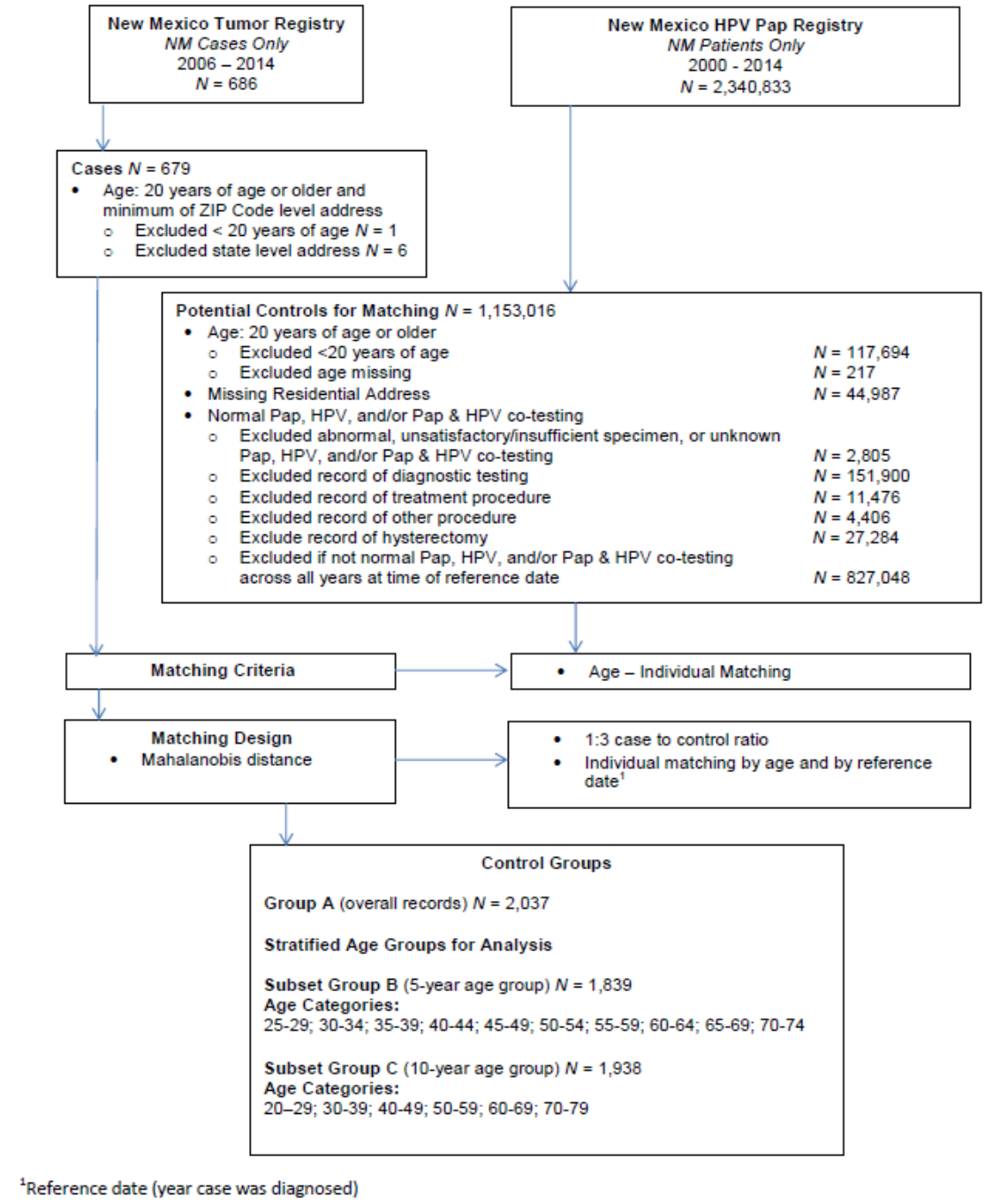

Figure 4. Case-Control study design

An individual matched design requires the use of conditional logistic regression (CLR), which reduces the bias in odds ratio, as compared to unconditional logistic regression (Breslow and Day 1980). CLR is similar to logistic regression, with the exception that the intercept and regression coefficients are estimated by factoring the pairing of cases and controls (i.e. conditioned on) with regard to the variable(s) that was used for matching (Szklo and Nieto 2014, Breslow and Day 1980). The difference in interpretation between CLR and logistic regression is similar with the exception that CLR coefficients are adjusted for not only the covariates in the model but also for the variable that was matched on (Szklo and Nieto 2014).

Cases were ascertained from de-identified, individual-level women diagnosed with malignant, primary site ICC data (N = 686) obtained from the NMTR. Primary site ICC data were coded to the International Classification of Disease for Oncology, third edition (ICD-O-3) per SEER site codes C530-C531 and C538-C539. Eligible cases included women diagnosed with ICC from January 1, 2006 through December 31, 2014, 20 years of age and older, and had a residential address that could be geo-coded at the US Postal Service ZIP Code (USPS ZIP Code) level or lower level of geography (N = 679). Seven cases were excluded from the study (one case < 20 years of age and six cases had state-level residential address assignment). The reference date for controls was the year of diagnosis of a case. To facilitate a backward look for controls from the NMHPVPR, ascertainment of controls was from the period January 1, 2000 through December 31, 2014. The NMHPVPR (N = 2,340,833) originates from the same reference population as the cases, i.e. women in New Mexico. Selection criteria for

eligible controls were women 20 years of age or older with a normal screening (i.e. Pap test, HPV test, and/or Pap/HPV co-testing) history. Controls were excluded if age was missing; no residential address; a record of an abnormal, unsatisfactory/insufficient specimen, or unknown Pap test, HPV test, or Pap/HPV co-testing; a record of diagnostic testing (i.e. biopsy, NOS of cervix, endometrium, vagina, vulva, or labium); a record of treatment procedure for precancerous lesions (i.e. loop electrosurgical excision procedure or other excisions); a record of other procedure; a record of a hysterectomy during the study period, and if any of the aforementioned exclusion criteria occurred during any of the years prior to the reference date. SPSS (version 23.0) was used to select records of women 20 years of age and older and to create separate datasets based on reference date (IBM Corp. Released 2014. IBM SPSS Statistics for Windows. Version 23.0). The reference date is defined as the year the case was diagnosed. A total of 18 datasets were created: nine for cases (i.e. 2006 through 2014) and nine for controls (i.e. 2006 through 2014). A procedure was implemented using SQL Server 2012 (Microsoft SQL Server 2012) programming language to select controls that met the selection and exclusion criteria of "potential controls." The procedure included a routine that conducted a backward look for controls. For example, to select potential controls for 2014, all events (i.e. screening, diagnostic testing, treatment, other procedures, and hysterectomy) in the NMHPVPR database were reviewed from 2000 through 2014. Individual matching of controls was executed using the 'optmatch' R package (version 3.0.1), which utilizes the Mahalanobis distance matrix (Kleyman and Hansen 2006). To reduce potential confounding of age, cases and controls were matched by exact age.

Individual matching was done using a 1:3 case to control ratio and by the reference date (i.e. 2014 cases dataset to 2014 potential controls dataset were matched). A procedure in R was used to remove a control once it was selected for a specific dataset to prevent duplication of controls. The 18 separate datasets were merged into one masterfile using a procedure in Python™ (version 3.5.2) (Python Software Foundation), and a stratum field for each case and its assigned controls was added to the file.

Geocoding

All of the cases and controls were successfully geocoded using the Texas A&M University Geoservices Online Geocoding service, version 4.01 (Texas A&M University Geocoder). Records were reviewed and manually geocoded to improve quality. Based on geocode quality codes (Goldberg et al. 2008b) 506 (74%) cases were geocoded at the building centroid, 60 (9%) by address range interpolation, 112 (16%) by the USPS ZIP Code area centroid, and less than 1% by city centroid level and state centroid. Of the controls, 811 (39%) were geocoded at the building centroid, 772 (38%) by address range interpolation, and 454 (22%) by USPS ZIP Code area centroid. Table 5 shows the address-level cases and controls geocoding results pre and post manual geocoding.

Table 5. Geocode quality type for cases and control pre and post manual geocoding.

Geocode Quality Type	Cases (*N* = 686) Pre (#/%)	Cases (*N* = 686) Post (#/%)	Controls (*N* = 2,037) Pre (#/%)	Controls (*N* = 2,037) Post (#/%)
Building Centroid	459 (66.91)	507 (73.91)	751 (36.87)	811 (39.81)
Address Range Interpolation	73 (10.64)	60 (8.75)	700 (34.36)	772 (37.90)
USPS ZIP Code Area	147 (21.43)	112 (16.33)	586 (28.77)	454 (22.29)
City Centroid	1 (0.15)	1 (0.15)	0 (0)	0 (0)
State Centroid	6 (0.87)	6 (0.87)	0 (0)	0 (0)

Census-tract Assignment for Geocoded Addresses with a US Postal Service ZIP Code Centroid

Residential addresses were geocoded using 2010 US Census TIGER, 2013 NAVTEQ, and National Parcel Geometries data files. The linkage from residential addresses to SES, acculturation, race/ethnicity, and geography variables was performed at the census tract level. Census tracts are small, relatively permanent statistical subdivisions of counties, are relatively homogenous in population characteristics and organized to maintain an optimum population size of 4,000 (range between 1,200 and 8,000) (United States Census Bureau 2012b). The census tract is an appropriate geographic level for examining health disparities in the U.S. (Krieger et al. 2002). A census-tract designation, based on the centroid of a USPS ZIP Code, was assigned to 112 (16%) of the cases and 454 (22%) of the controls – these addresses were predominantly Post Office boxes. One case had a city centroid; it was identified as

Cañones (population of 118 as per the 2010 Decennial Census). The census tract of 35039000400 covers the entire geographic area of Cañones. Therefore, this case was assigned to said census tract.

Post Office boxes are a challenge for disease registry and surveillance data. An often debated question is whether to include or exclude address level data that are associated with Post Office boxes, which have been geocoded based on the centroid of a USPS ZIP Code (Hurley et al. 2003, Oliver et al. 2005, Gregorio et al. 1999, Zandbergen 2009, McElroy et al. 2003, Rushton et al. 2006, Kravets and Hadden 2007). Previous studies have reported a subject loss between 5 and 16% of cases due to unmatched cases, which includes Post Office boxes (Gregorio et al. 1999). Oliver et al. (2005) found that 26% of unmatched addresses in the Virginia Cancer Registry were predominantly due to rural routes and Post Office boxes. Based on the rurality of our study area, our Post Office boxes findings align with previous studies.

It is common practice to assign a latitude and longitude to a Post Office box based on the centroid of a USPS ZIP code, however, this method can introduce potential bias (Gregorio et al. 1999, Hurley et al. 2003, Rushton et al. 2006). It has been demonstrated that while it is possible to obtain street addresses for Post Office box holders from the US Postal Service, there is not substantial improvement in geocoding accuracy to warrant the labor intensive work; additionally tracing identification methods are often required because of box holder turnover (Hurley et al. 2003).

Exclusion, i.e. subject loss, of ZIP Code based geocoded addresses can potentially result in selection bias (Gregorio et al. 1999, Hurley et al. 2003, Oliver et al.

2005). On the other hand, several studies have reported that inclusion of these addresses can result in potential misclassification when linking SES data (Hurley et al. 2003, Bonner et al. 2003, Kravets and Hadden 2007). These issues are problematic in terms of bias and there is no guideline or threshold on how much variance is tolerable comparing the assignment of SES variables linked to the centroid of a census tract based on a Zip Code versus the centroid based on a census tract. To compound this issue, the proportion of rural population in the study can potentially contribute to increased misclassification (Hurley et al. 2003, Kravets and Hadden 2007).

Overall, there is consensus that Post Office boxes, which are geocoded at the USPS ZIP Code level, are more likely to be in rural areas and may not be representative of the overall study population (Kravets and Hadden 2007, Hurley et al. 2003). Based on the Office of Rural Health Policy definition for rural (Hirsch 2007), of the addresses in our study that had a designated Post Office residential address, 83 (74%) cases and 286 (63%) controls were in rural areas. The exclusion of cases and controls in our study that are located in rural areas and are associated with Post Office Boxes would potentially mask differences between rural and non-rural SES, acculturation, race/ethnicity, and geography covariates. In New Mexico, at a state-wide level, 23% of women live in a rural area (U.S. Census Bureau Center for Economic Studies 2012). The decision to either include or exclude these cases and controls would introduce bias. For the purpose of our study, we included the cases and controls because the exclusion would directly influence the interpretation of geographic health disparities due to loss of rural areas,

which are reflective of the population dynamics of New Mexico (Kravets and Hadden 2007, Rushton et al. 2006).

To reduce misclassification basis by inclusion of addresses with a Post Office Box, we used the 2010 ZIP Code Tabulation Areas (ZCTA) Relationship File obtained from the US Census Bureau (U.S. Census Bureau 2016). The ZCTA Reference File is a cross-walk file that contains ZCTAs and corresponding census tract(s). For addresses that were geocoded at the centroid of a USPS ZIP Code (e.g. Post Office Box address), the ZCTA Reference File provided us with a tool to create a census tract population-based value (CTP) to measure SES, acculturation, race/ethnicity, and travel time (i.e. driving time to the nearest preventive ICC healthcare provider) variables. Applying the principle of Tobler's Law *(Tobler 1970),* near things are more related than distant things, and that one single point is not representative of the entire ZIP Code area, we derived population-based SES values based on the census tract(s) data within the ZCTA rather than a value derived from one single point of a census tract within the entirety of the assigned zip code generated by the geocoder.

A five-step process was used to derive a CTP value. The first step was to download a ZCTA Relationship File, which was obtained from the U.S. Census Bureau (http://www.census.gov/geo/reference/zctas.html). The downloaded file includes ZCTA and census-tract fields. A ZCTA may have one or multiple assigned census tracts. Of the study records that were geocoded at the US Postal Service ZIP Code level, 88 (79%) of the cases and 369 (81%) of the controls had more than one census tract within the ZCTA. Second, SPSS was used to validate if each ZCTA had a corresponding ZIP Code,

which is typically the outcome (U.S. Census Bureau 2015). There were 7 (6%) cases and 46 (10%) controls that did not have a USPS ZIP Code assigned to a ZCTA. The unmatched records are due to administrative ZIP Codes, i.e. a zip code that exists for a specific location, such as a Post Office building. These records were classified as exceptions (herein EXC). For the EXC records, the latitude and longitude of the Post Office building address was obtained from NM HomeTownLocator® (HomeTownLocator 2017). ArcGIS 10.3 (Environmental Systems Research Institute) was used to identify the census tract of the Post Office building using the latitude and longitude obtained from HomeTownLocator® as well as the contiguous census tracts of the identified census tract. The EXC records consisted of the identified census tract of the Post Office and the contiguous census tracts. The third step, a procedure implemented with the Python™ programming language was used to create a file that linked each ZCTA to its corresponding census tract(s). As a quality check, we verified that the census tract assigned by the TAMU Geocoder was contained within the census tract(s) of the ZCTA Relationship File. Fourth, using another procedure implemented with Python™, we applied a heuristic for cases and controls whereby records that had a geocode quality type of USPS ZIP Code were flagged as either CTP (i.e. designating a record that was contained with the ZCTA Reference File) or EXC (i.e. designating a record that was an administrative USPS ZIP Code). All other records, which had a geocode quality type of building centroid or address interpolation, were flagged as CTC (i.e. designating a record that was geocoded at the centroid of a census tract). The fifth step, an automated procedure also implemented with Python™, was developed to create

population-based SES, acculturation, race/ethnicity, and geography variables for CTP and EXC records using Python™. A CTP value was derived by adding the census tract value(s) of a given variable of interest (e.g. below federal poverty level) within a ZCTA and dividing by the population-based denominator of the variable (Figure 5). For EXC, the same procedure was followed by using the identified census tract(s) surrounding the physical Post Office building. CTC records were linked directly to census tract values from the U.S. Census Bureau and from travel time computed by the authors (McDonald et al. 2016). The study contains three distinct SES, acculturation, race/ethnicity, and travel time values: (1) a census-tract derived from a building centroid or address interpolation geocode quality type (herein CTC), (2) a census-tract population-based value derived from a USPS ZIP Code geocode quality type within the ZCTA Reference File (herein CTP), and (3) a census-tract population-based value derived from a USPS ZIP Code geocode quality type that is an administrative ZIP Code (herein EXC). The source code is available from the authors by request. Of the 112 cases, 105 (94%) were CTP and 7 (6%) were EXC. Of the 454 controls, 408 (90%) were CTP and 46 (10%) were EXC.

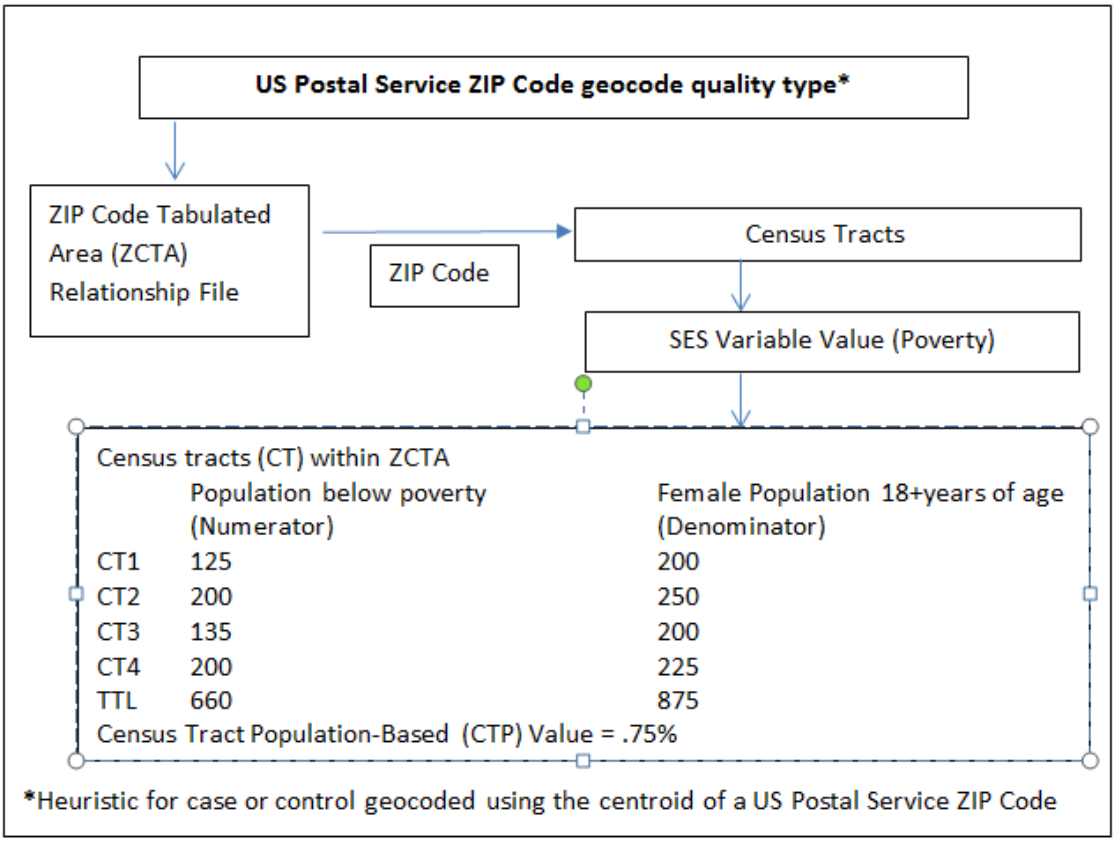

Figure 5. Example of census-tract population-based derived below federal poverty level variable

Explanatory Factors

There is a paucity of individual-level SES data within U.S. cancer surveillance data because it is rarely collected by public health data systems (Boscoe et al. 2014, Gomez et al. 2011). Analysis is based on the scale of available data (Kirby, Delmelle and Eberth 2016), such as area-based measures (Krieger et al. 2003). In the absence of SES, acculturation, and race/ethnicity data in medical records, the Public Use Decennial

Census and the American Community Survey (ACS) datasets are routinely used for U.S.-based health disparities research (Krieger 1992, Henry et al. 2013). These datasets are adequate secondary sources but do not allow for individual-level analysis to be conducted. The use of ecological analysis (e.g. census tract level and county level data) is a well-established approach of cancer disparities research due to the restrictions of public-use availability of individual-level SES, acculturation, and race/ethnicity data (Singh et al. 2003, Eggleston et al. 2006, Benard et al. 2008, Swegal et al. 2016, Niccolai et al. 2013, Lupo et al. 2015). The NMHPVPR is an apt data source because it is a population-based state-wide resource of potential controls for a case-control study design. Refer to Figure 4 for inclusion and exclusion criteria available in the NMHPVPR. The NMHPVPR steering committee provided the following data points based on female gender: de-identified address of patient seeking preventive cervical cancer service (e.g. Pap test) as well as hysterectomy; outcome of service (i.e. normal or abnormal); age of patient on date of service; year of service; and address of healthcare facility that provided service. Age was calculated by subtracting year of service minus age of patient on date of service. In addition, the NMHPVPR captures race/ethnicity (obtained directly or through linkage to health plan data), social security number, and occupation. The steering committee oversight representative of the NMHPVPR, Dr. Cosette Wheeler, did not have confidence in the quality of the race/ethnicity data point and would not release it. The other data points were out of the scope of this study. For the purpose of this study, age was the only demographic data point available for analysis in the NMHPVPR, which was used as the matching variable. For parsimony, SES,

acculturation, race/ethnicity, and geography covariates for cases and controls were at the census tract level and data sources were the 2010 U.S. Decennial Census, American Community Survey (2010-2014, 5-year estimates), Rural-Urban Commuting Area Codes, and calculated travel distances per McDonald et al. 2016.

Outcome Variable

The outcome variable is a dichotomous variable, operationalized as 0 = absence of ICC (i.e. control) and 1 = presence of ICC (i.e. case).

Covariates

For parsimony, SES, acculturation, race/ethnicity, and geography-based variables were constructed and analyzed at the census tract level. SES, acculturation, and race/ethnicity data were obtained from the 2010 U.S. Decennial Census and the ACS (2010 - 2014, 5-year estimates). This particular dataset was selected because it is the first 5-year estimates file (data collected from 2010 through 2014) of insurance status. Of note, the time period aligns with "The Patient Protection and Affordable Care Act" (PPACA), commonly referred to as the Affordable Care Act, which was enacted on March 23, 2010. Travel time data was computed as described by McDonald and colleagues (McDonald et al. 2016). The measurement is based on the travel time (in minutes) from the population weighted centroid of a census tract to the nearest specified

cervical cancer preventive healthcare facility. A recent study found that the nearest facility was as an adequate proxy for utilization (Alford-Teaster et al. 2016). The health care facility data were obtained from the NMHPVPR. The rural versus non-rural residence type (i.e. designated by RUCA classification) was based on the area definition of the Office of Rural Health Policy (U.S. Deparment of Health & Human Services 2015). Population-based values for the state of New Mexico were derived at the census tract level (N = 498). One census tract was deleted from the study because it does not have population data; it is located within the Los Alamos Laboratory area.

SES and race/ethnicity variables are well-established covariates used in health disparities studies (Krieger et al. 2003, Newmann and Garner 2005, Williams et al. 2012, Hiatt et al. 2001, Cowburn et al. 2013, Messer et al. 2006, Kamineni et al. 2013, Seeff and McKenna 2003, Guidry et al. 1997). Several studies have examined acculturation (e.g. English language proficiency) as a covariate to understand health disparities (Collins et al. 2011, Jimenez, Collins and Grineski 2013). While there is no standard for measuring community-level SES (Robert et al. 2004), there is agreement that to avoid potential loss and error of statistical information, continuous variables are the preferred method for analyzing and reporting results in epidemiologic research (Bennette and Vickers 2012). There were 20 covariates used in this study that were categorized as SES, acculturation, race/ethnicity, or geography. The SES covariates were: (1) percent of female population 18+ years of age living below the federal poverty level (living below poverty level), (2) percent of female population 18+ years of age without health insurance (without health insurance), (3) low educational attainment defined as percent

of female population 18+ years of age non-high school graduate or equivalent (low educational attainment), (4) medium educational attainment defined as percent of female population 18+ years of age with high school diploma, some college, or associate degree (medium educational attainment), (5) high educational attainment defined as percent of female population 18+ years of age with bachelor degree or higher (high educational attainment), (6) percent of households with no vehicle (no vehicle), (7) percent of family households that are female-headed households [no husband present] (female-headed household), (8) percent of female population 20+ years of age never married (never married), (9) percent of female population 20+ years of age married (married), and (10) percent of female population 20+ years of age separated, divorced, or widowed (separated, divorced, or widowed). The acculturation covariates were: (11) percent of total population foreign born (foreign born), (12) percent of foreign born population that are a U.S. citizen (foreign born that are a U.S. citizen), and (13) percent of population 5+ years of age that speak Spanish but speak English not very well ("speak Spanish but speak English not very well"). The race/ethnicity covariates were: (14) percent of female population 20+ years of age American Indian (American Indian women), (15) percent of female population 20+ years of age Hispanic (Hispanic women), and (16) percent of female population 20+ years of age non-Hispanic white (non-Hispanic white women). The geography covariates were: (17) travel time to cervical cancer screening facility (in minutes), (18) travel time to cervical cancer diagnostic facility (in minutes), (19) travel time to cervical cancer treatment facility (in minutes), and (20) rural versus non-rural residence type as designated by RUCA classification (Appendix C). Herein, covariates

referred to as an abbreviated version. For example, percent of female population 20+ years of age Hispanic referred to as "Hispanic women."

For the purpose of data analyses, all covariates, with the exception of rural versus non-rural residence (i.e. RUCA), were operationalized as continuous variables. RUCA does not have a continuous data structure, so it was operationalized as dichotomous covariate (0 = non-rural and 1= rural). As recommended by Bennette and Vickers (2012), preliminary assessment (i.e. descriptive statistics and univariable analysis) of SES, acculturation, and race/ethnicity covariates were categorized as quartiles based on the data distribution of controls (Hsieh et al. 1991). Descriptive statistics and univariable analysis were run for continuous, categorical, and dichotomous covariates (See Table 6, Table 7, and Appendix 4). It has become routine in health disparities literature to use the area-based socioeconomic measure for poverty, which is categorized as: <5%; 5% to <10%; 10% to< 20%; ≤ 20%; and unknown at the census tract level (Boscoe et al. 2014, Krieger et al. 2002). The uppermost quartile is informative because it reflects the federal definition of a poverty area, defined any census tract with a poverty rate of ≤ 20% (Bernstein 1995, Bishaw 2014). For the purpose of comparative study, poverty was categorized per the established area-based categories. However, the first quartile had less than 30 counts, so the area-based poverty covariate was not suitable for analysis (Kish 1965, Niccolai et al. 2013). To further investigate poverty, considering the poverty area definition, a dichotomous covariate was operationalized as 0 = < 20% and 1 = ≥ 20% of percent of population living below the federal poverty level. Based on a prior study of travel distance to mammography facilities, travel time was operationalized as high (<15

minutes), medium (15-30 minutes), and low (> 30) minutes to healthcare facilities that provided specified preventive ICC care (Alford-Teaster et al. 2016).

Data Analysis Strategy

After running descriptive statistics and univariable analysis, all further data analyses were conducted using the continuous covariates and the dichotomous RUCA variable. To assess normal distribution of data, histograms and absolute values of skewness and kurtosis were measured (Kim 2013). Four covariates (American Indian women, travel time to cervical cancer screening facility, travel time to cervical cancer diagnostic facility, and travel time to cervical cancer treatment facility) exceeded an absolute skew value of > 2 and an absolute kurtosis value of > 7 (West, Finch and Curran 1995). Therefore, parametric and nonparametric statistical methods were used to examine correlations between the 20 covariates and ICC (Appendix E and F). Pearson's Product-Moment Correlation Coefficient does not require the assumption of normal distribution but is sensitive to outliers and highly skewed data (Kowalski 1972), and Spearman's rank order correlation coefficient a distribution free statistical measures of correlation, (Newson 2002) were run to measure the magnitude and direction of association.

Next, CLR, using the conditional method of maximum likelihood estimation, was used to analyze the data (Hosmer and Lemeshow 1989, Schlesselman 1982). The conditional maximum likelihood estimation is the preferred approach to estimating

parameters of the logistic model as compared to discriminant analysis (Schlesselman 1982), and it avoids estimation of a large number of nuisance parameters (Schlesselman 1982, Kleinbaum 1994). A CLR model has three specific data requirements: (1) the binary outcome variable (i.e. dependent variable) was measured on a dichotomous scale (0 = control and 1 = case), (2) the data is prepared case by case (e.g. one subject/observation per row), and (3) each case and its corresponding controls (i.e. the study design 1:3 case to control ratio) form one stratum (Hosmer and Lemeshow 1989). The study dataset satisfied these requirements. Based on results from univariable analysis, multivariable analysis was conducted. Multivariable analysis was not conducted for categorical covariates as these were examined for the purpose of preliminary assessment (Bennette and Vickers 2012). The Variance Inflation (VIF) diagnostic was used to detect multicollinearity in the multivariable, interactions, and stratification analyses. Three CLR multivariable models were used in our analyses (Table 7). Model 1 was considered to be the baseline and included all statistically significant covariates from the univariable analysis. Covariates that had a likelihood ratio *P* value of <0.050 (two-tailed) and an odds ratio that did not cross 1.0000 were considered to be statistically significant in the univariable and multivariable analyses. Model 1 excluded separated, divorced, or widowed (*P* =.212) and percent of foreign born (*P* =.089). The second model (Model 2) excluded American Indian women and medium educational attainment because the covariates VIF for all race/ethnicity sub-groups and education sub-groups were ≥ 10. Hispanic women (*P* = .0498 [odds ratio crossed 1.0000]) and non-Hispanic white women (*P* = .0638) were near statistical

significance (*P* values were ≤ .100), so these covariates were included in Model 2. A review of the correlation matrix revealed a statistically significant and strong strength of relationship between medium and high educational attainment, $r(2714) = -.713$, $P < .001$. Low and high educational attainment are more prevalent in the literature as covariates for ICC (Hiatt et al. 2001, Parikh et al. 2003), so medium educational attainment was excluded from Model 2 to assess the VIF impact. Initially, percent American Indian and medium educational attainment were excluded separately (i.e. Model 2 and Model 3); however, the results were similar in terms of odds ratios and VIF, so both covariates were excluded simultaneously, hence Model 2. To simplify the model, low educational attainment, which was statistically significant ($P = .006$), was included in Model 3 and non-significant high educational attainment covariate was excluded ($P = .399$). Married versus never married was included in the model, as being married is associated with an increased risk of ICC (Kvikstad and Vatten 1996) as well as an earlier diagnosis of ICC (El Ibrahimi and Pinheiro 2016).

A logistic regression model does not assume a linear relationship between the covariates and the outcome variable or that covariates are normally distributed or homoscedasticity. Logistic regression requires that observations are independent, which was satisfied through the research design because cases were only measured once (Hussain 2008, Collett 2003). The Box-Tidwell transformation was used to test the assumption of linearity in the logit (Sands et al. 1994); there were no violations observed of this assumption, so Model 3 was not further adjusted.

Stratified analyses were performed by 5-year age groups (Group B, e.g. 25-29, 30-34…70-74, cases (N = 613), controls (N = 1,839) and 10-year age groups (Group C, e.g. 20-29, 30-39…70-79, cases (N = 646, controls (N = 1,938) for covariates in Model 3 (Table 7). Groups B and C were selected based on at least 30 cases per grouping for meaningful analysis (Kish 1965, Niccolai et al. 2013).

To facilitate the examination of 3rd and 2nd order interactions of SES, acculturation, race/ethnicity, and geography covariates with ICC an intersectionality matrix was developed (Appendix G). Covariates were centered, and then cross product terms (i.e. interaction terms) were centered. Multiplicative interaction terms (de Mutsert et al. 2009) were considered statistically significant if the P value < .050 (two-tailed), 95% confidence interval (CI), and odds ratio did not cross 1.0000 (Vandenbroucke et al. 2007). Statistically significant interaction terms, along with corresponding centered covariates were loaded into a CLR model.

SPSS was used to construct descriptive statistics, tests for normality and linearity, and perform univariable analysis. CLR modeling and analysis, and VIF test were performed using R as well as SPSS. Initially, the data analysis plan was to conduct CLR, VIF, and interactions analysis in SPSS. However, a bug in SPSS prevented interaction terms analysis to conducted using SPSS, therefore R was used. SPSS and R results for CLR and VIF were the same based on four decimal digit comparisons. Stratification analyses were conducted in R. All analyses were considered statistically significant if P value was ≤ .050 (two-tailed). In addition to aforementioned P value, for

univariable analysis, multivariable analysis, stratification, and interaction terms, the odds ratio value could not cross the threshold of 1.0000 using a 95% confidence intervals.

Results

Descriptive Statistics

Descriptive statistics for continuous covariates and the RUCA (i.e. rural versus non-rural indicator) covariate are presented in Table 6. The table has three columns of values, the first are population-based, the second are cases, and the third are controls. The controls were representative of the general population of New Mexico (Table 6). Observable differences were noted for cases compared to the controls and the population-based sub-groups for Hispanic women, non-Hispanic white women, “speak Spanish but speak English not very well”, and low educational attainment. High educational attainment varied across the population-based, cases, and controls groups.

Overall, based on histograms, the data had normal distribution with the exception of four covariates, which were detected measuring skew and kurtosis. The following variables exceeded the absolute values threshold for skew (> 2) and kurtosis (> 7): American Indian women (4.589/21.893), travel time to cervical cancer screening facility (4.493/32.548), travel time to cervical cancer diagnostic facility (3.163/12.708), and travel time to cervical cancer treatment facility (2.548/7.642), skew and kurtosis respectively.

Table 6. Socioeconomic status, acculturation, race/ethnicity, and geography characteristics of census-tract level population and invasive cervical cancer cases (2006 -2014) and controls (2000 - 2014), New Mexico

	Population-level[§] Mean, Median (inter-quartile range)[*]	**Cases (*n* = 679) Mean, Median (inter-quartile range)[*]**	**Controls (*n* = 2,037) Mean, Median (inter-quartile range)[*]**
Socioeconomic Status (SES)			
Percent living below the federal poverty level[a]	19.83, 17.56 (11.54, 26.40)	20.62, 18.88 (13.06, 27.41)	18.56, 16.65 (11.00, 24.52)
Percent without health insurance[a]	79.26, 81.05 (73.12, 88.22)	78.21, 79.94 (72.26, 86.52)	81.37, 83.18 (75.85, 88.89)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	16.00, 13.61 (7.60, 22.42)	17.61, 15.76 (9.51, 23.96)	14.53, 12.17 (6.33, 20.97)
Medium Educational Attainment (Percent HS graduate or equivalent, some college, or Associate's degree)[a]	60.34, 61.43 (54.05, 67.93)	60.48, 61.31 (54.91, 67.15)	58.99, 60.53 (52.42, 66.69)
High Educational Attainment (Percent Bachelor's degree or higher)[a]	23.62, 20.29 (11.99, 32.81)	21.88, 19.08 (11.96, 31.12)	26.45, 23.58 (14.60, 35.77)
Percent Married[a]	47.95, 47.28 (38.61, 56.90)	47.57, 46.90 (39.53, 55.17)	49.01, 49.32 (40.43, 57.27)
Percent Never Married[a]	24.28, 22.55 (16.16, 30.63)	24.16, 22.78 (17.21, 30.60)	23.15, 22.18 (16.36, 28.17)
Percent Separated, Divorced, or Widowed[a]	27.75, 27.40 (22.18, 32.71)	28.24, 27.64 (22.79, 32.71)	27.82, 27.40 (22.42, 32.04)
Percent no vehicle available for household members[a]	6.00, 4.59 (1.98, 8.66)	5.84, 4.68 (2.53, 8.38)	5.38, 4.27 (1.93, 7.34)
Percent Female-headed household[b]	21.85, 21.38 (15.31, 27.99)	22.47, 22.27 (16.80, 27.40)	20.83, 20.70 (15.25, 26.04)

Table 6. Continued.

	Population-level[§] Mean, Median (inter-quartile range)[*]	**Cases (*n* = 679) Mean, Median (inter-quartile range)[*]**	**Controls (*n* = 2,037) Mean, Median (inter-quartile range)[*]**
Acculturation			
Percent foreign born[a]	9.29, 6.82 (4.03, 12.60)	10.37, 7.38 (4.59, 14.53)	9.79, 7.30 (4.59, 13.06)
Percent foreign born & U.S. Citizen[a]	42.95, 39.83 (23.84, 60.14)	39.78, 37.02 (23.41, 52.21)	43.63, 36.62 (25.67, 60.40)
Percent speak Spanish but speak English not very well[a]	7.44, 4.67 (1.97, 10.37)	8.93, 6.29 (2.69, 13.38)	7.65, 4.72 (2.09, 10.37)
Race/Ethnicity			
Percent American Indian[b]	9.81, 2.21 (1.32, 4.92)	7.59, 2.21 (1.31, 4.14)	5.95, 2.20 (1.33, 4.12)
Percent Hispanic[b]	40.68, 37.73 (22.90, 55.75)	46.21, 46.06 (26.83, 64.05)	42.02, 38.03 (24.86, 58.45)
Percent non-Hispanic White[b]	46.46, 48.77 (31.38, 64.89)	43.63, 45.13 (27.46, 60.95)	48.64, 50.29 (33.69, 65.10)
Geography			
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	8.73, 3.60 (1.80, 9.60)	9.66, 4.20 (1.80, 10.80)	7.53, 3.60 (1.80, 9.00)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	14.74, 6.00 (3.60, 17.40)	15.80, 7.20 (3.60, 17.40)	12.36, 6.00 (3.60, 13.30)
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	19.88, 9.60 (4.80, 24.15)	20.95, 10.20 (5.40, 27.26)	16.63, 9.00 (4.80, 19.20)
	N (%)	*N (%)*	*N (%)*
Residence Type[d]			
Non-Rural	301 (60.44)	400 (58.91)	1401 (68.78)
Rural	198 (39.56)	279 (41.09)	636 (31.22)

[a]American Community Survey (2010 -2014), [b]US 2010 Decennial Census, [c]Based on travel time from population weighted centroid to the nearest specified invasive cervical cancer preventive healthcare facility, and [d]Office of Rural Health Policy

[§] Population-level data derived from New Mexico census tracts (*N* = 498)

Descriptive statistics (Appendix D) for categorical covariates, in particular at the uppermost quartile, revealed observable differences between controls compared to cases and population-based values for the following covariates: living below the federal poverty level, without health insurance, never married, separated, divorced, or widowed, female-headed households, travel time to cervical cancer screening facility, travel time to cervical cancer diagnostic facility, travel time to cervical cancer treatment facility, and RUCA (i.e. rural versus non-rural indicator). A similar pattern of upper quartile differences was observed between cases compared to controls and population-based values for: all race/ethnicity sub-groups; foreign born, foreign born that are a U.S. citizen, "speak Spanish but speak English not very well", low educational attainment, high educational attainment, and married. Households with no vehicle varied across the population-based, cases, and controls groups.

Correlations

Pearson's results demonstrated that 18 out of 20 correlations were statistically significant ($p < .050$, two-tailed). Of the significant correlations, 14 were positive in direction and 4 were negative in direction. The correlations of ICC with marital status of separated, divorced, or widowed and foreign born were non-significant. Sixteen out of 20 correlations were statistically significant ($P < .050$, two-tailed) based on Spearman's results. In general, Spearman's results were similar to Pearson's in terms of magnitude and direction, with the exception of two additional non-significant covariates (American

Indian women and travel time to cervical cancer screening facility). Of the significant correlations, 12 were positive in direction and 4 were negative in direction. Pearson's and Spearman's results indicated a small effect size (i.e. $r < .10$) for statistically significant covariates. The results from both correlation matrices suggested a protective relationship (i.e. statistically significant negative correlation coefficient) with ICC and high educational attainment, married, non-Hispanic white women, and foreign born that are a U.S. citizen (Appendix E and F).

Univariable Analyses

Table 7 displays univariable results (i.e. unadjusted odds ratio) of CLR analysis whereby the continuous covariates and RUCA (i.e. rural versus non-rural indicator) covariate associated with ICC were measured at the census tract level. The covariates were predominantly statistically significant with ICC, with the exception of marital status of separated, divorced, or widowed and foreign born. Being married, non-Hispanic white women, and foreign born that are a U.S. citizen were significantly negatively associated with ICC. The remaining covariates were significantly positively associated with ICC. Living in a rural area as opposed to a non-rural area emerged as the most significant positive association with ICC (OR = 1.5435; 95% CI, 1.2883-1.84922). The most significant negative association with ICC was high educational attainment (OR = 0.9773; 95% CI, 0.9709-0.9837).

Table 7. Socioeconomic status, acculturation, race/ethnicity, and geography unadjusted and adjusted odds ratios with invasive cervical cancer cases (2006 -2014) and controls (2000 - 2014), New Mexico.

	Univariable		Multivariable					
			Model 1		Model 2		Model 3	
	OR	95% CI	AR	95% CI	AR	95% CI	AR	95% CI
Socioeconomic Status (SES)								
Percent living below the federal poverty level[a]	1.0185***	(1.0102,1.0269)	0.9799*	(0.9642, 0.9959)	0.9811*	(0.9655, 0.9969)	0.9814*	(0.9659, 0.9971)
Percent without health insurance[a]	1.0264***	(1.0184, 1.0345)	1.0227**	(1.0064, 1.0394)	1.0241**	(1.0079, 1.0405)	1.0249**	(1.0088, 1.0412)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	1.0276***	(1.0193, 1.0360)	1.5743	(0.4503, 5.5044)	1.0276**	(1.0079, 1.0478)	1.0309***	(1.0125, 1.0496)
Medium Educational Attainment (Percent HS graduate or equivalent, some college, or Associate's degree)[a]	1.0150**	(1.0061, 1.0240)	1.5333	(0.4392, 5.3526)				
High Educational Attainment (Percent Bachelor's degree or higher)[a]	0.9773***	(0.9709, 0.9837)	1.5263	(0.4367, 5.3342)	0.9952	(0.9843, 1.0063)		
Percent Married[a]	0.9892**	(0.9817, 0.9968)	1.0039	(0.9874, 1.0207)	1.0020	(0.9858, 1.0185)	1.0022	(0.9884, 1.0162)
Percent Never Married[a]	1.0119*	(1.0025, 1.0214)	1.0021	(0.9832, 1.0214)	1.0004	(0.9816, 1.0195)		
Percent Separated, Divorced, or Widowed[a]	1.0073‡	(0.9958, 1.0189)						
Percent no vehicle available for household members[a]	1.0208*	(1.0024, 1.0394)	0.9951	(0.9663, 1.0248)	0.9919	(0.9637, 1.0210)	0.9910	(0.9629, 1.0200)
Percent Female-headed household[b]	1.0276***	(1.0161, 1.0392)	1.0450**	(1.0171, 1.0736)	1.0416**	(1.0144, 1.0696)	1.0435**	(1.0164, 1.0712)

Table 7. Continued.

	Univariable		Multivariable					
			Model 1		Model 2		Model 3	
	OR	95% CI	AR	95% CI	AR	95% CI	AR	95% CI
Acculturation								
Percent foreign born[a]	1.0096‡	(0.9986, 1.0207)						
Percent foreign born & U.S. Citizen[a]	0.9923***	(0.9883, 0.9962)	0.9987	(0.9963, 1.0038)	0.9989	(0.9938, 1.0040)	0.9986	(0.9936, 1.0036)
Percent speak Spanish but speak English not very well[a]	1.0195***	(1.0089, 1.0302)	0.9589**	(0.9340, 0.9845)	0.9576**	(0.9329, 0.9831)	0.9556***	(0.9313, 0.9805)
Race/Ethnicity								
Percent American Indian[b]	1.0068*	(1.0014, 1.0122)	1.0214	(0.9845, 1.0597)				
Percent Hispanic[b]	1.0091***	(1.0050, 1.0131)	1.0373*	(1.0000, 1.0759)	1.0164**	(1.0064, 1.0264)	1.0168***	(1.0072, 1.0264)
Percent Non-Hispanic White[b]	0.9878***	(0.9835, 0.9920)	1.0386	(0.9977, 1.0811)	1.0156**	(1.0044, 1.0269)	1.0152**	(1.0048, 1.0258)
Geography								
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	1.0124***	(1.0059, 1.0190)	1.0124*	(1.0013, 1.0236)	1.0125*	(1.0014, 1.0237)	1.0123*	(1.0013, 1.0235)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	1.0091***	(1.0048, 1.0135)	0.9969	(0.9865, 1.0075)	0.9970	(0.9866, 1.0075)	0.9968	(0.9864, 1.0073)
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	1.0081***	(1.0044, 1.0118)	1.0049	(0.9970, 1.0129)	1.0053	(0.9975, 1.0131)	1.0057	(0.9980, 1.0135)
Residence Type[d]	1.5435***	(1.2883, 1.8492)	1.2175	(0.9662, 1.5342)	1.2282	(0.9748, 1.5475)	1.2568*	(1.0067, 1.5692)

[a]American Community Survey (2010 -2014), [b]US 2010 Decennial Census, [c]Based on travel time from population weighted centroid to the nearest specified invasive cervical cancer preventive healthcare facility, and [d]Office of Rural Health Policy

*P < .050, two-tailed, ** P < .010, two-tailed, *** P < .001, two-tailed, ‡Non-significant in univariate model, not included in multivariable model

Appendix D shows univariable results of CLR analyses in which the categorical covariates and RUCA (i.e. rural versus non-rural indicator) covariate associated with ICC were measured at the census tract level. The last two columns are the odds ratio with the designated reference category and the 95% CI. This analysis was conducted to explore the potential variability within covariates and inform the results of interaction terms analysis. The majority of covariates had at least one statistically significant quartile level except for American Indian women and separated, divorced, or widowed. Most uppermost quartiles were statistically significant, with the exception of foreign born, whereby only the third quartile was statistically significant and protective (OR = 0.7427; 95% CI, 0.5723-0.9637). Thirteen of the 20 covariates predicted an increase in the odds associated with ICC. Of these 13 covariates, the following four covariates showed an increase in the odds of having ICC at every quartile level: without health insurance, low educational attainment, medium educational attainment, and female-headed households. The strongest and the most significant positive association was the uppermost quartile for low educational attainment (OR = 2.5075; 95% CI, 1.9226-3.2704). The following five covariates revealed a decrease in the odds associated with ICC: the third and fourth quartile of non-Hispanic white women, the third quartile of foreign born, the uppermost quartile for foreign born that are a U.S. citizen, the third and fourth quartile of high educational attainment, and the uppermost quartile for being married. The strongest and most significant negative association was the uppermost quartile for high educational attainment (OR = 0.4219; 95% CI, 0.3244-0.5487). Of

these five protective covariates, none revealed a decrease in the odds of having ICC at every quartile level.

Multivariable Analyses

Table 7 displays multivariable results (i.e. adjusted odds ratio) for a series of CLR models in which the continuous covariates and RUCA (i.e. rural versus non-rural indicator) covariate associated with ICC were measured at the census tract level. Of the 20 study covariates, the marital status of separated, divorced, or widowed (P = .037) and foreign born (P =.089) were excluded from Model 1 because the covariates were non-significant in the univariable analysis. Model 1 demonstrated that after controlling for other covariates, without health insurance (OR = 1.0227; 95% CI, 1.0064-1.0394), travel time to cervical cancer screening facility (OR = 1.0124; 95% CI, 1.0013-1.0236), and female-headed households (OR = 1.0450, 95% CI, 1.0170-1.0736) were statistically significant and had an increased odds of having ICC. In terms of decreased odds of having ICC, Model 1 showed that after controlling for other covariates, living below the federal poverty level (OR = 0.9799; 95% CI, 0.9642-0.9959) and "speak Spanish but speak English not very well" (OR = 0.9589; 95% CI, 0.9340-0.9845) were statistically significant.

Model 2 excluded American Indian women and medium educational attainment level because the VIF was ≥ 10. In terms of race/ethnicity sub-groups, all VIF values were ≥ 10. However, Hispanic women and non-Hispanic white women P values were

near statistical significance (P = .050 and P = .064, respectively), while American Indian women (P = .258) well exceed the statistical significance threshold. Similarly, all education sub-groups VIF were ≥ 10. The decision to exclude the medium education covariate was based on a statistically significant and strong strength of relationship between medium and high educational attainment observed in the correlation matrices (i.e. Pearson's and Spearman's) as well as low and high educational attainment are more prevalent in the literature as covariates for ICC. Model 2 revealed that after controlling for other covariates, the following covariates in Model 1 remained statistically significant and had an increased odds of ICC: without health insurance remained (OR = 1.0241; 95% CI, 1.0079-1.0405), travel time to cervical cancer screening facility (OR = 1.0125; 95% CI, 1.0014-1.0237), and female-headed households (OR = 1.0416; 95% CI, 1.0144-1.0696). Additionally, Hispanic women (OR = 1.0164; 95% CI, 1.0064-1.0264), non-Hispanic white women (OR = 1.0156; 95% CI, 1.0044-1.0269), and low education attainment (OR = 1.0276; 95% CI, 1.0079-1.0478) emerged as statistically significant and had increased odds of having ICC. In terms of decreased odds of having ICC, Model 2 aligned with Model 1 results after controlling for other covariates, living below the federal poverty level (OR = 0.9811, 95% *CI* = 0.9655-0.9969) and "speak Spanish but speak English not very well" (OR = 0.9576, 95% *CI* = 0.9329-0.9831) were statistically significant.

To simplify Model 3, one educational and one marital status covariate were input in the model. High educational attainment was excluded because it was non-significant in Model 2 (P = .399) compared to the statistically significant low educational

attainment covariate (*P* = .006). Applying a similar rationale, being married (*P* = .812) versus being never married (*P* = .969) was included in Model 3 because being married had a slightly lower *P* value. However, both of these *P* values were non-significant and a review of the literature found being married is a more relevant covariate with ICC in the literature (El Ibrahimi and Pinheiro 2016, Kvikstad and Vatten 1996). Model 3 showed that after controlling for other covariates, the following covariates in Model 2 remained statistically significant and had an increased odds of ICC: without health insurance remained (OR = 1.0249; 95% CI, 1.0088-1.0412), Hispanic women (OR = 1.0168; 95% CI, 1.0072-1.0264), non-Hispanic white women (OR = 1.0152; 95% CI, 1.0048-1.0258), travel time to cervical cancer screening facility (OR = 1.0123; 95% CI, 1.0013-1.0235), low education attainment (OR = 1.0309, 95% CI, 1.0125-1.0496), and female-headed households (OR = 1.0435, 95% CI, 1.0164-1.0712). In addition, living in a rural area as opposed to a non-rural area (OR = 1.2568; 95% CI, 1.0067-1.5692) emerged as statistically significant covariate and had an increased odds of having ICC. After controlling for other covariates, Model 3 results were similar to Model 2 for statistically significant covariates that had decreased odds of having ICC, which were living below the federal poverty level (OR = 0.9814; 95% CI, 0.9659-0.9971) and "speak Spanish but speak English not very well" (OR = 0.9556; 95% CI, 0.9313-0.9805). A model with only the statistically significant covariates from Model 3 was run (results not shown). The results showed no change in terms of covariates that were statistically significant or direction of odds ratios. Box-Tidwell transformations confirmed the linearity of the relationship between all of the covariates and the logit of the outcome variable (i.e. ICC)

for Model 3. Confounding was observed for medium educational attainment in Model 1, high educational attainment in Model 1 and 2, and for RUCA (i.e. rural versus non-rural indicator) covariate for all three models, which was adjusted for by using multivariable conditional logistic regression.

Stratified Analyses

Table 8 displays stratification analyses for Group B (5-year age categories). Group B revealed after controlling for other covariates, a statistically significant increased adjusted odds of having ICC for the following covariates and age groups: Hispanic women for age group of 30–34 (OR = 1.0460; 95% CI, 1.0015-1.0930) and age group of 50-54 (OR = 1.0408; 95% CI, 1.0054-1.0770); low educational attainment for group 35-39 (OR = 1.0644; 95% CI, 1.0072-1.1249) and age group 55-59 (OR = 1.1212; 95% CI, 1.0323-1.2177); and without health insurance for age group 50-54 (OR = 1.0510; 95% CI, 1.0031-1.1010). The following covariates and age groups after controlling for other covariates, demonstrated a statistically significant decreased adjusted odds of having ICC for Group B: living below the federal poverty level for age group 25–29 (OR = 0.9140; 95% CI, 0.8395-0.9951) and age group 35-39 (OR = 0.9458; 95% CI, 0.8979-0.9963), “speak Spanish but speak English not very well” for age group 45-49 (OR = 0.8800; 95% CI, 0.8056-0.9613), age group 50-54 (OR = 0.9084; 95% CI, 0.8420-0.9800), and age group 55-59 (OR = 0.8817; 95% CI, 0.7890-0.9852).

Table 8. Stratification (5-years of age) socioeconomic status, acculturation, race/ethnicity, and geography odds ratios with invasive cervical cancer cases (2006 - 2014) and controls (2000 - 2014), New Mexico.

	25-29		30-34		35-39		40-44		45-49	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Socioeconomic Status (SES)										
Percent living below the federal poverty level[a]	0.9140*	(0.8395, 0.9951)	1.0161	(0.9504, 1.0860)	0.9458*	(0.8979, 0.9963)	0.9858	(0.9372, 1.0370)	1.0454	(0.9921, 1.1015)
Percent without health insurance[a]	0.9603	(0.8812, 1.0465)	1.0104	(0.9530, 1.0710)	1.0073	(0.9563, 1.0611)	0.9981	(0.9514, 1.0470)	1.0461	(0.9944, 1.1004)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	0.9753	(0.8852, 1.0746)	1.0239	(0.9578, 1.0950)	1.0644*	(1.0072, 1.1249)	1.0201	(0.9666, 1.0770)	1.0324	(0.9737, 1.0947)
Percent Married[a]	1.0156	(0.9439, 1.0927)	1.0130	(0.9534, 1.0760)	0.9795	(0.9427, 1.0178)	0.9948	(0.9555, 1.0360)	1.0174	(0.9732, 1.0635)
Percent no vehicle available for household members[a]	0.9483	(0.7891, 1.1396)	1.0288	(0.9271, 1.1420)	1.0557	(0.9629, 1.1575)	1.0020	(0.9221, 1.0890)	0.9687	(0.8792, 1.0675)
Percent Female-headed household[b]	1.1031	(0.9466, 1.2854)	1.0066	(0.9105, 1.1130)	1.0083	(0.9282, 1.0953)	1.0536	(0.9779, 1.1350)	0.9969	(0.9164, 1.0844)
Acculturation										
Percent foreign born & U.S. Citizen[a]	1.0073	(0.9838, 1.0313)	1.0126	(0.9903, 1.0350)	0.9882	(0.9730, 1.0036)	0.9998	(0.9844, 1.0160)	0.9992	(0.9848, 1.0138)
Percent speak Spanish but speak English not very well[a]	1.1360	(0.9461, 1.3642)	0.9046	(0.8061, 1.0150)	0.9326	(0.8640, 1.0067)	1.0154	(0.9388, 1.0980)	0.8800**	(0.8056, 0.9613)
Race/Ethnicity										
Percent Hispanic[b]	0.9614	(0.9105, 1.0152)	1.0460*	(1.0015, 1.0930)	1.0211	(0.9914, 1.0517)	0.9912	(0.9618, 1.0220)	1.0197	(0.9908, 1.0494)
Percent Non-Hispanic White[b]	0.9764	(0.9203, 1.0359)	1.0138	(0.9647, 1.0650)	1.0122	(0.9820, 1.0434)	1.0104	(0.9775, 1.0440)	1.0033	(0.9714, 1.0363)
Geography										
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	0.951	(0.8697, 1.0399)	0.9990	(0.9455, 1.0550)	1.0160	(0.9780, 1.0554)	1.0121	(0.9742, 1.0510)	0.9779	(0.9340, 1.0239)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	1.0154	(0.9506, 1.0846)	0.9969	(0.9449, 1.0420)	0.9925	(0.9616, 1.0244)	1.0293	(0.9850, 1.0760)	0.9922	(0.9551, 1.0307)
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	1.0465	(0.9957, 1.0998)	1.0082	(0.9797, 1.0370)	1.0157	(0.9932, 1.0386)	0.9897	(0.9582, 1.0220)	0.9917	(0.9645, 1.0197)
Residence Type[d]	1.0074	(0.2783, 3.6470)	1.7141	(0.6667, 4.4070)	1.4314	(0.7166, 2.8592)	1.0897	(0.5101, 2.3280)	0.7684	(0.3874, 1.5238)

Table 8. Continued.

	50-54		55-59		60-64		65-69		70-74	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Socioeconomic Status (SES)										
Percent living below the federal poverty level[a]	1.0084	(0.9636, 1.0550)	0.9950	(0.9300, 1.0646)	0.9824	(0.9325, 1.0350)	0.9771	(0.9164, 1.0420)	0.9762	(0.8840, 1.0780)
Percent without health insurance[a]	1.0510*	(1.0031, 1.1010)	1.0315	(0.9763, 1.0898)	1.0369	(0.9832, 1.0940)	1.0442	(0.9734, 1.1200)	1.067	(0.9595, 1.1870)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	1.0248	(0.9748, 1.0770)	1.1212**	(1.0323, 1.2177)	0.9967	(0.9369, 1.0600)	0.9995	(0.9197, 1.0860)	0.9846	(0.8835, 1.0970)
Percent Married[a]	0.9844	(0.9438, 1.0270)	1.0290	(0.9689, 1.0927)	0.9929	(0.9459, 1.0420)	0.9869	(0.9229, 1.0550)	1.0293	(0.9560, 1.1080)
Percent no vehicle available for household members[a]	1.0057	(0.9174, 1.1030)	0.9647	(0.8680, 1.0723)	0.9950	(0.9103, 1.0880)	0.8763	(0.7589, 1.0120)	0.9786	(0.8272, 1.1580)
Percent Female-headed household[b]	1.0078	(0.9278, 1.0950)	1.0524	(0.9514, 1.1641)	1.0662	(0.9738, 1.1670)	1.0844	(0.9678, 1.2150)	1.0724	(0.9446, 1.2170)
Acculturation										
Percent foreign born & U.S. Citizen[a]	0.9921	(0.9758, 1.0090)	1.0038	(0.9820, 1.0261)	1.0015	(0.9852, 1.0180)	0.9831	(0.9619, 1.0050)	0.9946	(0.9672, 1.0230)
Percent speak Spanish but speak English not very well[a]	0.9084*	(0.8420, 0.9800)	0.8817*	(0.7890, 0.9852)	1.0227	(0.9356, 1.1180)	0.9568	(0.8490, 1.0780)	0.9502	(0.8049, 1.1220)
Race/Ethnicity										
Percent Hispanic[b]	1.0408*	(1.0054, 1.0770)	1.0329	(0.9941, 1.0733)	1.0041	(0.9715, 1.0380)	1.0414	(0.9955, 1.0890)	1.0120	(0.9470, 1.0810)
Percent Non-Hispanic White[b]	1.0321	(0.9952, 1.0700)	1.0402	(0.9948, 1.0876)	1.0265	(0.9912, 1.0630)	1.0158	(0.9653, 1.0690)	0.9702	(0.9045, 1.0410)

Table 8. Continued.

	50-54		55-59		60-64		65-69		70-74	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Geography										
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	1.0199	(0.9854, 1.0560)	1.0152	(0.9493, 1.0856)	1.0279	(0.9933, 1.0640)	0.9953	(0.9395, 1.0540)	1.0608	(0.9568, 1.1760)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	1.0046	(0.9740, 1.0360)	1.0129	(0.9612, 1.0674)	0.9937	(0.9614, 1.0270)	0.9836	(0.9411, 1.0280)	0.9705	(0.8947, 1.0530)
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	0.9883	(0.9664, 1.0110)	0.9859	(0.9412, 1.0328)	1.0015	(0.9752, 1.0280)	1.0230	(0.9929, 1.0540)	0.9903	(0.9516, 1.0130)
Residence Type[d]	1.0754	(0.5398, 2.1420)	0.7791	(0.3118, 1.9466)	1.7436	(0.8741, 3.4780)	1.1565	(0.4607, 2.9030)	2.9084	(0.8341, 10.1410)

[a]American Community Survey (2010 -2014), [b]US 2010 Decennial Census, [c]Based on travel time from population weighted centroid to the nearest specified invasive cervical cancer preventive healthcare facility, and [d]Office of Rural Health Policy

*P < .050, ** P < .010, *** P < .001, two-tailed

Note: OR represent adjusted odds ratio

Table 9 displays stratification analyses for Group C (10-year age categories). Group C revealed after controlling for other covariates, a statistically significant increased adjusted odds of having ICC for the following covariates and age groups: travel time to cervical cancer treatment facility for age group 20-29 (OR = 1.0453; 95% CI, 1.0001-1.0926); Hispanic women for age group of 30-39 (OR = 1.0274; 95% CI, 1.0046-1.0507) and age group of 50-59 (OR = 1.0330; 95% CI, 1.0083-1.0583); non-Hispanic white women for age group 50-59 (OR = 1.0316; 95% CI, 1.0046-1.0594) and age group 60-69 (OR = 1.0285; 95% CI, 1.0005-1.0570); low educational attainment for group 30-39 (OR = 1.0483; 95% CI, 1.0064-1.0919) and age group 50-59 (OR = 1.0515; 95% CI, 1.0085-1.0964); without health insurance for age group 50-59 (OR = 1.0415; 95% CI, 1.0063-1.0779); and living in a rural area as opposed to a non-rural area for age group 70-79 (OR = 2.4097; 95% CI, 1.0590-5.4830). The following covariates and age groups after controlling for other covariates demonstrated a statistically significant decreased adjusted odds of having ICC for Group C: living below the federal poverty level for age group 20–29 (OR = 0.86920; 95% CI, 0.8042-0.9395); "speak Spanish but speak English not very well" for age group 30-39 (OR = 0.9298; 95% CI, 0.8747-0.9885) and age group 50-59 (OR = 0.9055; 95% CI, 0.8530-0.9613). For all covariates and by age groups the VIF values were ≤ 10.

Table 9. Stratification (10-years of age) socioeconomic status, acculturation, race/ethnicity, and geography odds ratio with invasive cervical cancer cases (2006 - 2014) and controls (2000 - 2014), New Mexico.

	20-29		30-39		40-49		50-59		60-69		70-79	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Socioeconomic Status (SES)												
Percent living below the federal poverty level[a]	0.8692***	(0.8042, 0.9395)	0.9709	(0.9340, 1.0092)	1.0111	(0.9776, 1.0460)	1.0090	(0.9738, 1.0455)	0.9879	(0.9495, 1.0280)	0.9719	(0.9092, 1.0390)
Percent without health insurance[a]	0.9801	(0.8812, 1.0465)	1.0067	(0.9710, 1.0437)	1.0245	(0.9913, 1.0590)	1.0415*	(1.0063, 1.0779)	1.0336	(0.9933, 1.0760)	1.0229	(0.952, 1.0990)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	0.9851	(0.9080, 1.0688)	1.0483*	(1.0064, 1.0919)	1.0210	(0.9837, 1.0600)	1.0515*	(1.0085, 1.0964)	1.0076	(0.9618, 1.0560)	1.0320	(0.9524, 1.1180)
Percent Married[a]	1.0362	(0.9710, 1.1057)	0.9894	(0.9586, 1.0213)	1.0022	(0.9744, 1.0310)	0.9995	(0.9663, 1.0338)	0.9943	(0.9575, 1.0330)	1.0083	(0.9572, 1.0620)
Percent no vehicle available for household members[a]	1.0270	(0.8922, 1.1820)	1.0324	(0.9674, 1.1018)	0.9832	(0.9255, 1.0440)	0.9830	(0.9193, 1.0510)	0.9623	(0.8944, 1.0350)	0.9699	(0.8548, 1.1000)
Percent Female-headed household[b]	1.1355	(0.9952, 1.2955)	1.0048	(0.9438, 1.0696)	1.0380	(0.9845, 1.0950)	1.0261	(0.9652, 1.0909)	1.0741	(1.0035, 1.1500)	1.0596	(0.9579, 1.1720)
Acculturation												
Percent foreign born & U.S. Citizen[a]	1.0047	(0.9841, 1.0258)	0.9973	(0.9853, 1.0095)	1.0007	(0.9908, 1.0110)	0.9964	(0.9842, 1.0089)	0.9978	(0.9853, 1.0100)	0.9986	(0.9782, 1.0190)
Percent speak Spanish but speak English not very well[a]	1.1379	(0.9840, 1.3025)	0.9298*	(0.8747, 0.9885)	0.9607	(0.9123, 1.0120)	0.9055**	(0.8530, 0.9613)	0.9901	(0.9275, 1.0570)	1.0131	(0.9133, 1.1240)

Table 9. Continued.

	20-29		30-39		40-49		50-59		60-69		70-79	
	OR	**95% CI**	**AR**	**95% CI**	**AR**	**95% CI**	**AR**	**95% CI**	**AR**	**95% CI**	**AR**	**95% CI**
Race/Ethnicity												
Percent Hispanic[b]	0.9763	(0.9328, 1.0220)	1.0274*	(1.0046, 1.0507)	1.0073	(0.9881, 1.0270)	1.0330**	(1.0083, 1.0583)	1.0177	(0.9929, 1.0430)	0.9983	(0.9624, 1.0360)
Percent Non-Hispanic White[b]	0.9800	(0.9309, 1.0317)	1.0114	(0.9867, 1.0368)	1.0169	(0.9957, 1.0390)	1.0316*	(1.0046, 1.0594)	1.0285*	(1.0005, 1.0570)	0.9949	(0.9551, 1.0360)
Geography												
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	0.9352	(0.8704, 1.0048)	1.0134	(0.9837, 1.0440)	1.0087	(0.9887, 1.0290)	1.0209	(0.9921, 1.0505)	1.0187	(0.9919, 1.0460)	1.0400	(0.9769, 1.1070)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	1.0342	(0.9742, 1.0978)	0.9921	(0.9672, 1.0177)	1.0119	(0.9864, 1.0380)	1.0071	(0.9816, 1.0333)	0.9893	(0.9656, 1.0140)	0.9865	(0.9393, 1.0360)
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	1.0453*	(1.0001, 1.0926)	1.0121	(0.9951, 1.0293)	0.992	(0.9725, 1.0120)	0.9883	(0.9689, 1.0082)	1.0098	(0.9912, 1.0290)	0.9954	(0.9684, 1.0230)
Residence Type[d]	0.9607	(0.3119, 2.9588)	1.5309	(0.8971, 2.6125)	0.9562	(0.5945, 1.5380)	0.9373	(0.5466, 1.6073)	1.3982	(0.8334, 2.346)	2.4097*	(1.0590, 5.4830)

[a]American Community Survey (2010 -2014), [b]US 2010 Decennial Census, [c]Based on travel time from population weighted centroid to the nearest specified invasive cervical cancer preventive healthcare facility, and [d]Office of Rural Health Policy

*P < .050, ** P < .010, *** P < .001, two-tailed

Note: OR represent adjusted odds ratio

Table 10 displays 3rd order and 2nd order interaction term results. Of the 177, 3rd order interaction terms examined, nine (5%) were statistically significant. Of those, seven showed a decrease in the odds of having ICC. The most increased odds ratio interaction term for ICC was associated with high educational attainment*living in a rural area as opposed to a non-rural area*Hispanic women (OR = 1.0011; 95% CI, 1.0005-1.0017). The most protective interaction term associated with ICC was "speak Spanish but speak English not very well"*lives in a rural area as opposed to a non-rural area* living below the federal poverty (OR = 0.9976; 95% CI, 0.9961-0.9991).

Table 10 displays 2nd order interaction terms results. Thirty percent (23) of the 87, 2nd order interactions terms were statistically significant. Of those, 19 revealed a decrease in the odds of having ICC. The most increased interaction term odds ratio for having ICC was associated with non-Hispanic white women*living in a rural area as opposed to a non-rural area (OR = 1.0129; 95% CI, 1.0041-1.0219). The most protective interaction term associated with ICC was "speak Spanish but speak English not very well"*lives in a rural area as opposed to a non-rural area (OR = 0.9650; 95% CI, 0.9429-0.9877). There were no violations of VIF factor for significant interaction term models for 3rd or 2nd order interaction terms.

Table 10. Interaction terms results (3rd and 2nd order)

Interaction Terms	coef	Odds Ratio	95% CI	*P* value
3rd order				
H_EDU*RUCA*H_W	0.0011	1.0011**	(1.0005, 1.0017)	0.0003
L_EDU*RUCA*NHW_W	0.0008	1.0008*	(1.0001, 1.0015)	0.0306
No_Ins*H_W*RUCA	-0.0006	0.9994*	(0.9989, 0.9998)	0.0063
H_EDU*RUCA*AI_W	-0.0008	0.9992*	(0.9984, 0.9999)	0.0283
POV_Pers*H_W*RUCA	-0.0012	0.9988**	(0.9982, 0.9994)	0.0001
L_EDU*RUCA*H_W	-0.0012	0.9988**	(0.9982, 0.9995)	0.0003
SP_ENW*RUCA*No_Ins	-0.0015	0.9985*	(0.9973, 0.9997)	0.0184
L_EDU*RUCA*POV_Pers	-0.0016	0.9984*	(0.9972, 0.9995)	0.0056
SP_ENW*RUCA*POV_Pers	-0.0024	0.9976*	(0.9961, 0.9991)	0.0013
2nd order				
NHW_W*RUCA	0.0129	1.0129*	(1.0041, 1.0219)	0.0042
No_Ins*NHW_W	0.0006	1.0060**	(1.0002, 1.0010)	0.0038
SP_ENW*NHW_W	0.0008	1.0010*	(1.0002, 1.0015)	0.0145
L_EDU*NHW_W	0.0008	1.0008**	(1.0004, 1.0010)	0.0006
MAR*POV_Pers	0.0008	1.0008*	(1.0001, 1.0010)	0.0158
H_EDU*No_Ins	0.0007	1.0007*	(1.0001, 1.0014)	0.0341
H_EDU*H_W	0.0005	1.0004*	(1.0001, 1.0008)	0.0085
H_W*TT_Diag	-0.0003	0.9997*	(0.9995, 0.9999)	0.0046
H_W*TT_Trt	-0.0003	0.9997*	(0.9996, 0.9999)	0.0031
SP_ENW*TT_Trt	-0.0004	0.9996*	(0.9992, 0.9999)	0.0177
No_Ins*H_W	-0.0006	0.9994**	(0.9991, 0.9997)	0.0002
POV_Pers*H_W	-0.0008	0.9992**	(0.9988, 0.9996)	0.0001
H_W*FHH	-0.0008	0.9992*	(0.9987, 0.9998)	0.0059
L_EDU*H_W	-0.0009	0.9991**	(0.9988, 0.9995)	0.0001
L_EDU*No_Ins	-0.0012	0.9988*	(0.9981, 0.9996)	0.0016
POV_Pers*No_Ins	-0.0013	0.9987**	(0.9979, 0.9994)	0.0005
No_Ins*FHH	-0.0013	0.9987*	(0.9977, 0.9996)	0.0070
L_EDU*POV_Pers	-0.0014	0.9986*	(0.9978, 0.9994)	0.0003
POV_Pers*FHH	-0.0015	0.9985*	(0.9975, 0.9995)	0.0026
SP_ENW*No_Ins	-0.0016	0.9984**	(0.9975, 0.9993)	0.0008
SP_ENW*POV_Pers	-0.0021	0.9979**	(0.9969, 0.9989)	0.0001
SP_ENW*FHH	-0.0023	0.9977*	(0.9961, 0.9993)	0.0044
FHH*L_EDU	-0.0015	0.9958*	(0.9973, 0.9996)	0.0089
H_W*RUCA	-0.0165	0.9837*	(0.9572, 0.9922)	0.0002
SP_ENW*RUCA	-0.0356	0.9650*	(0.9429, 0.9877)	0.0026

*$P < .050$, ** $P < .001$, two-tailed

KEY: Living Below Poverty (POV_Pers), W/out Health Insurance (No_Ins), Low Education (L_EDU), High Education (H_EDU), Married (MAR), Female-headed Household (FHH), Speaks Spanish, English not well (SP_ENW), American Indian Women (AI_W), Hispanic Women (H_W), Non-Hispanic White Women (NHW_W), Travel Time Diagnosis (TT_Diag), Travel Time Treatment (TT_Trt), and RUCA

Statistically significant interactions were loaded into three separate models: (1) all terms, (2) 3rd order only, and (3) 2nd order only (results not shown). All model results were non-significant and VIF threshold was not satisfied.

Discussion

This study aimed to investigate the alternative hypothesis if there were ICC health disparities in New Mexico as a result of SES, acculturation, race/ethnicity, and geography covariates associated with ICC using a case-control study design. In general, univariable analysis aligned with previous results from qualitative and quantitative ICC health disparities ICC research (Boscoe et al. 2014, Newmann and Garner 2005). Race/ethnicity covariates are commonly examined in health disparities studies, univariable analysis showed that American Indian and Hispanic women had a significant increased odds ratio with ICC and non-Hispanic white women had a significant decreased odds ratio with ICC. In the multivariable analysis, American Indian women were no longer significant and the presence of an increased odds ratio remained for Hispanic women. Surprisingly, the non-Hispanic white women covariate changed direction from protective in the univariable model to an increased odds in the multivariate analysis; it remained significant. The non-significant multivariable result of American Indian women with ICC may be partly explained by the University of New Mexico Cancer Center Native American Education & Outreach Program, which has been diligently working with American Indian communities to increase cervical cancer

screening awareness and services by working with community health representatives and the Indian Health Service (New Mexico Department of Health Comprehensive Cancer Program 2012). Stratification results demonstrated that Hispanic women had significant increased odds for younger and middle age groups (30-34 and 50-54 for the 5-year age groups and 30-39 and 50-59 for the 10-year age groups) while increased odds for non-Hispanic white women was among older age grouping (none for 5-year age group and 50-59 and 60-69 for 10-year age group).

Poverty, another traditional health disparity variable, which has been associated with ICC (Boscoe et al. 2014), was found to have a significant increased odds ratio in the univariable model but protective in the multivariable model. Stratification results showed that living below the poverty level was significant and protective with ICC for the following 5 and 10 years of age groups: 25-29, 35-39 and 20-29. A possible explanation for this might be the concerted efforts by the New Mexico Department of Health Breast and Cervical Cancer Early Detection Program (NMBCC), which includes bilingual services (New Mexico Department of Health 2012). The NMBCC, established in 1991, administers free to low-cost cervical cancer screening to low income, uninsured, and underserved women as part of the National Breast and Cervical Early Detection Program mandated by the Breast and Cervical Mortality Prevention Act of 1990 (Centers for Disease Control and Prevention 2017). The younger age group findings revealed in the stratification analyses warrants further analysis. A potential explanation is contraceptive usage which requires annual contact with a physician who may suggest adherence to the recommended Pap test guidelines. It has been found that long term oral

contraceptive use could contribute to the risk for ICC (Moreno et al. 2002) but a recent study found contradictory evidence (Chih et al. 2014). Another possible explanation is that our study operationalized poverty as a continuous variable as opposed to the common area-based categorical measure (Krieger et al. 2002). The data structure did not allow for the use of the area-based poverty measure (i.e. less than 30 cells in the first quartile). Additionally, the inclusion of the dichotomous poverty covariate (i.e. 0 = < 20% and 1 = ≥ 20% of percent of population living below the federal poverty level) yielded non-significant findings (results not shown).

Contrary to expectations, not having health insurance univariable, multivariate, and stratification findings were incongruent with the poverty results; the covariates typically operate in the same direction (UC Davis Center for Poverty Research 2015). An examination of stratification results showed that significant increased odds was at the 50-54 for the 5-year age group for those without insurance, which overlapped with the 10-year age group at 50-59. A potential explanation is that the Affordable Care Act Dependent Coverage Expansion (ACA-DCE) allowed young adults to remain on their parents' health insurance plans until age 26 years, therefore it might elucidate why living at the poverty level was protective for the 20-29 age group. However, a recent study found that within one year of the ACA-DEC there was an increase in early stage diagnosis for women between 21-25 years old (Robbins et al. 2015). Our study did not contain enough counts to examine the age strata of 20-24 years old women, which could have potentially supported Robbins et al. (2015) findings. Future research should continue to include age stratification to examine the effects of the ACA-DCE.

With respect to examining geography as a variable of interest rather than excluding it for analysis (i.e. using it as a matching variable) was informative. Travel times to all types of ICC preventive healthcare services were statistically significant for univariable analysis. However, in the multivariable analysis, only travel time to screening facility remained significant as an increased odds with ICC. This raises concern because screening is the first step in ICC preventive care. In New Mexico, during the years 2008 – 2011, screening rates among women 21 to 65 years of age was 71.1% but notably decreases after age 40 (Cuzick et al. 2014). Stratification analyses for travel time to screening facilities was not significant for either Group B or C. Meanwhile, living in a rural area versus a non-rural area was significant and had increased odds ratio with ICC in the univariable and multivariate analyses. Furthermore, elderly women (i.e. age group 70-79) had a significant increased odds ratio of living in a rural area as opposed to a non-rural area with ICC, which aligns with direction of findings from prior studies using primarily qualitative methods (Newmann and Garner 2005, Yabroff et al. 2005). This reinforces the responsibility and role of primary care physicians to communicate the importance of cervical cancer screening, in particular in rural areas.

One unanticipated finding was the acculturation language covariate, "speaks Spanish and English not well", flipped from an increased odds ratio in the univariable model to a decreased odds ratio in multivariable analysis. Stratification results for 5-year age groups (45-49, 50-54, and 55-59) and 10-year age groups (30-39 and 50-59) revealed that "speaks Spanish but English not well, was protective with ICC. The

inclusion of this covariate in cross-product terms (i.e. interactions) resulted in the most predominant (24%) significant 2nd order interaction terms results. These results seem to be consistent with other research that found that if access to screening is available, language is not a major barrier (Zambrana et al. 1999). In support of our finding, in New Mexico between 2009 and 2011, an educational intervention program was led by community health workers who were attuned to Hispanic culture in New Mexico (i.e. messaging was culturally appropriate and in Spanish and English), which resulted in 76.5% of previously noncompliant participants (i.e. had not had a pap test in the 3 years) receiving a Pap test after the intervention (Thompson et al. 2014). In contrast to our findings, it has been suggested that low English language acculturation among Mexican origin woman may contribute to lower awareness of cervical cancer risk factors and beliefs (Luque et al. 2010). Although being foreign born and a U.S. citizen was significant in the univariable model, the non-significant findings in all other analyses of being foreign born does not support previous research (Tsui et al. 2007).

The present study was designed to explore the use of an intersectionality methods approach. With respect to this aim, another unexpected finding emerged from the 3rd and 2nd order interaction terms. The interaction results, along with the "speak Spanish but English not well", suggests the presence of the Hispanic Paradox. The Hispanic Paradox, refers to a contradiction whereby Hispanics in the U.S., despite their relatively low socioeconomic status, experience better health outcomes compared to other minorities as well as lower mortality rates compared to other race/ethnicity sub-groups, including non-Hispanic whites (Markides and Eschbach 2011, Markides and Coreil 1986). The

interaction results (e.g. covariate*covariate) demonstrated how language can bound other covariates that are typically found to be risk factors and create a community context whereby the interaction results are protective with ICC. For example, "speak Spanish but English not well" joint results with each of the following covariates was significant and protective despite multivariate main effect result for covariates showed a significant and increased odds with ICC: not having health insurance, female-headed household, and living in a rural area as opposed to a non-rural area. Additionally, the Hispanic and the low education covariates each demonstrated a significant increased odds ratio with ICC in the univariable, multivariate, and stratification results. However, low educational attainment*Hispanic women was significant and protective with ICC while high educational attainment*Hispanic women as well as low educational attainment*non-Hispanic white women were significant and had an increased odds ratio with ICC. Our results are in accord with a recent study that found that the mortality rate of female genital cancers are positively and significantly associated with Blacks and non-Hispanic whites who have a high degree of socioeconomic deprivation but paradoxically negatively and significantly associated with Hispanics (Philips et al. 2013). The inclusion of RUCA (i.e. rural versus non-rural indicator) as a cross-product term was significant and protective for Hispanic women but had an increased odds ratio for non-Hispanic white women with ICC. This interaction result revealed how rural residence type is not experienced the same by race/ethnicity sub-groups. Similarly, ICC with American Indian women*high educational attainment*RUCA compared to

Hispanic women*high educational attainment*RUCA were juxtaposed; again demonstrating how race/ethnicity can alter odds with ICC.

It is notable that during our study period, the age for diagnosed ICC was 49 (median) and 51 (mean), and the 50-54 age group had the most numerous amount of significant covariates. The covariates in this age group were Hispanic women and not having health insurance, which had an increased odds ratio and "speak Spanish but English not well" had a decreased odds ratio with ICC. Similarly, the 50-59 age group reflected the same trends with the addition of increased odds ratio for non-Hispanic white women and low education risk with ICC. These results draw our attention to nuances of these variables as well as reinforce that being Hispanic and language skills are not one dimensional.

The univariable, multivariable, stratification, and interaction results are important findings because to the best of the study authors' knowledge, this is the first U.S.-based study to conduct a population-based, case-control study design examining SES, acculturation, race/ethnicity, and geography covariates association with ICC. A note of caution is due here because odds ratios were interpreted using a four decimal digit number and the majority of the significant findings were approaching 1.000. However, the most notable finding, "speaks Spanish but English not well", was protective with ICC and adequately out of range of the odds ratio threshold for multivariate and stratification results (OR = 0.9556; 95% CI, 0.9313-0.9805).

For parsimonious interpretation, the unit of analysis was the census tract, which may cause concern for ecological fallacy. The principal contribution of this study is that

it is the first U.S.-based, population-based, case-control study to investigate covariates associated with ICC. The decision to use census-tract measures is supported by previous research that has demonstrated that this scale is representative of a homogenous population and in terms of policy, reflects administrative boundaries used by local, state, and federal governments for resource allocation (Krieger et al. 2003)The study authors acknowledge the bias of an ecologic study design as well as the associated bias of the use of census-level covariates. The hypothesis of this study is population-based, i.e. women residing in New Mexico. The use of the NMTR and the NMHPVPR allows for the examination of ICC with contextual SES, acculturation, race/ethnicity, and geography based covariates. Future research should include individual level covariates, including the calculation of travel time based on de-identified household to the nearest healthcare facility providing preventive cervical cancer services as well as the location that was utilized by the study participants. Individual level data, such as SES and race/ethnicity will require field collection, which was outside the scope of this study, and multilevel model analysis, which will elucidate the association of ICC with covariates at an aggregate level compared to an individual level.

A strength of this study was the use of ICC cases obtained from a well-established state-wide cancer registry (i.e. NMTR) and controls from the only U.S. population-based cervical cancer preventive registry (i.e. NMHPVPR). However, it is important to bear in mind the possible selection bias among controls because the NMHPVPR reflects approximately 71% screening participation in the New Mexico due to opportunistic screening practices in the U.S. The women who opted to screen may

have overall better health practices since they are engaged in preventive healthcare, further biasing the study results. The current findings add to a growing body of literature on the role of geography in health disparities research. The inclusion of travel time to preventive services as well as the use of healthcare facilities that provided actual services as opposed to the more commonly used proxy of a primary care physician location is more representative of the experience of travel time (McDonald et al. 2016). In case-control studies, geography (e.g. residential address or USPS ZIP Code) is frequently a matching variable, thereby eliminating the potential to examine it as a covariate of interest. It is suggested that the association of geography-based covariates, as utilized in this study, with ICC are investigated in future research.

Conclusion

Our findings suggest that language is not always a barrier to preventive ICC services and associated with an increased odds ratio with ICC. We posit that language is central to one's culture and to a sense of community as well as maintaining social capital networks. While language may not be the specific cultural mechanism (Markides and Eschbach 2011) that accounts for the Hispanic Paradox, further investigation is strongly recommended. As demonstrated by the culturally appropriated ICC intervention program in New Mexico, the barrier to language can be mediated. The findings support intervention programs targeted to American Indians, through efforts such as the joint partnership between the University of New Mexico, the Native American community

and the Indian Health Service, which can potentially reduce ICC. Prevention of ICC is critical among American Indian women because even though their incidence rate is comparable to non-Hispanic white women, they are disproportionately burdened with a higher mortality rate from ICC (Centers for Disease Control and Prevention 2016). Interaction results may partly be explained by the Hispanic Paradox but non-significant findings of interaction terms in the fully loaded CLR model and high multicollinearity (i.e. VIF > 10) suggests that new quantitative research techniques should be developed to improve intersectionality analyses. Overall, this study strengthens the hypothesis that SES as well as interactions with acculturation, race/ethnicity, and geography can influence health outcomes and should be examined jointly and separately (Braveman et al. 2010). Geography, whether location-based (e.g. the latitude and longitude of a healthcare facility) to place-based (e.g. contextual effects, including cultural, structural and institutional factors) should be included in health studies to more accurately represent how health is traversed and experienced. More research is needed to collect individual-level data not only for the covariates used in this study but also for behavioral covariates for cases and controls. The additional data would allow for further research to be undertaken in the following areas: (1) compare odds ratio results based on the ecological-level study (current study) to odds ratios results from individual-level data, (2) conduct multilevel analysis at the individual and census tract level, and (3) construct "realized access" measures for travel time to healthcare facilities that provided preventive ICC services and compare results to "potential access" to services.

CHAPTER V

CONCLUSION

The results of this research support the idea that geography matters. This dissertation has demonstrated that the term geography is broadly used in health research, but its epistemology is often overlooked. This study set out to examine the following three aims: (1) to characterize the effort to manually geocode healthcare facilities that provided invasive cervical cancer preventive services (Chapter II), (2) to examine if geographic accessibility, defined as travel time and travel distance, differs for women who live in rural areas, as opposed to women who live in non-rural areas (Chapter III), and (3) to determine if socioeconomic status, acculturation, race/ethnicity, and geography are associated with ICC through the examination of main effects and interactions using a case-control research design (Chapter IV) in New Mexico.

Taken together, these findings posit that geography should be examined as an explanatory variable rather than it being controlled for as a nuisance variable (Mariotti et al. 1986). Chapter II demonstrated that *a priori* knowledge of the study area (e.g. high percentage of rural addresses) can inform the study design to determine whether manual geocoding, a relative low cost procedure that markedly improves the quality of geocoded addresses, is appropriate. The findings in Chapter III revealed that women who live in rural areas, as opposed to those that live in non-rural areas were disproportionately burdened with statistically significant longer travel times and travel distances. Because prevention of ICC can require up to three clinical visits to three different healthcare

facilities (Schiffman and Castle 2005), this study provides evidence that as severity of illness increases, so does travel distance to a healthcare facility that can provide precancerous excisional treatment services. This finding aligns with prior studies that distance to healthcare service could serve as a proxy for severity-of-illness (Obrist et al. 2007). The use of healthcare facilities that provided services across the ICC continuum of care, rather than using a primary care physician location as a proxy for health services location, can serve as a comparative data point for future studies that measure travel time and travel distance to preventive ICC services. The study findings suggests several courses of action for preventing ICC, including the use of the recently developed mobile colposcopy technology as well as the need to provide the full spectrum of services across the ICC continuum of care at the same facility location rather than potentially requiring a woman to travel to as many as three different locations to seek services. A natural progression of this research is to analyze the role of travel time, stratified by rural and non-rural residence, as a factor for women failing to seek or delay follow-up care. Chapter IV demonstrated that comparing univariable and multivariable CLR results shows that socioeconomic status, acculturation, race/ethnicity, and geography are not one dimensional and vary in statistical significance and direction. Multivariable CLR, while controlling for other variables, revealed one unanticipated finding, which was living below poverty, and "speaking Spanish well but English not well" covariates were statistically significant and protective with ICC. These results could be explained in part by the efforts of the New Mexico Department of Health Breast and Cervical Cancer Early Detection Program use of bilingual intervention efforts. There are, however, other

possible explanations for these regression results as well as the interaction terms findings, such as the presence of the Hispanic Paradox. It is suggested that the Hispanic Paradox may contribute to lower female genital cancer mortality rates among Hispanic women with a high degree of socioeconomic deprivation as compared to Black and non-Hispanic white women within the same deprivation index (Philips et al. 2013). There are still many unanswered questions about the Hispanic Paradox but evidence from this research suggests that language as a cultural mechanism should be further examined. The challenge now is to develop statistical methods to address multicollinearity and contextual effects beyond multilevel analysis to measure the interwoven and interconnected covariates that represent "place" in terms of health outcomes. The non-significant finding among American Indian women with ICC suggests that the efforts of the University of New Mexico Cancer Center Native American Education & Outreach Program have improved ICC outcomes among this race/ethnicity sub-group.

This dissertation would not be possible without the use of the de-identified address-level data provided by the innovative NMHPVPR, the first and only population-based statewide cervical cancer screening registry in the U.S., and the de-identified address-level case data from the NMTR. The use of these data allowed this research to extend our knowledge of the influence geographic accessibility in relation to preventive ICC services as well as geographic accessibility to be examined as an explanatory variable (i.e. covariate) using inferential statistics. To address ecological fallacy, future research should be undertaken to include field collection of individual level data, which was outside the scope of this dissertation, which would then allow for the utilization of

multilevel model analysis. The present study should prove to be particularly valuable to the efforts of NM-HOPES-PROSPR effort to better understand ICC health disparities in New Mexico, and NIH/NCI initiatives for using geospatial approaches to cancer control and population sciences and improving cancer control in rural communities (Schootman et al. 2017). This research contributes to health geography literature by utilizing a case-control research design, an epidemiological method of analysis, as described in Meade and Emch (2010). The study demonstrated how secondary data can be used for a case-control research design to investigate health disparities that include geographic accessibility to services and residence type (i.e. rural versus non-rural residence). Additionally, the use of intersectionality theory as a lens to examine health disparities, coupled with interaction terms as a method to measure intersectionality, responds to the call by Valentine (2007) to develop geographic thinking of variability within and between groups, i.e. apply the concept of intersectionality. To the best of my knowledge, this dissertation is novel and will inform ICC health disparities research because it is the first U.S.-based study to conduct a population-based, case-control study examining covariates associated with ICC along with the inclusion of geography as an explanatory variable, which is often omitted from case-control studies.

REFERENCES

Adegoke, O., S. Kulasingam & B. Virnig (2012) Cervical cancer trends in the United States: a 35-year population-based analysis. *Journal of Women's Health,* 21**,** 1031-7.

Akers, A. Y., S. J. Newmann & J. S. Smith (2007) Factors underlying disparities in cervical cancer incidence, screening, and treatment in the United States. *Current Problems in Cancer,* 31**,** 157-181.

Alford-Teaster, J., J. M. Lange, R. A. Hubbard, C. I. Lee, J. S. Haas, X. Shi, H. A. Carlos, L. Henderson, D. Hill, A. N. Tosteson & T. Onega (2016) Is the closest facility the one actually used? An assessment of travel time estimation based on mammography facilities. *Int J Health Geogr,* 15**,** 8.

American Cancer Society. 2015. What are the key statistics about cervical cancer?

---. 2017. What are the key statistics about cervical cancer?

Au, W. W., S. Abdou-Salama, C. H. Sierra-Torres & A. Al-Hendy (2007) Environmental risk factors for prevention and molecular intervention of cervical cancer. *International Journal of Hygiene and Environmental Health,* 210**,** 671-678.

Ayre, J. E. (1964) Impact of cytology and cytogenectics upon gynecology and obstetrics *Obstetrical and Gynecological Survey,* 19**,** 799-837.

Baker, D. W., J. J. Sudano, J. Albert, M., E. A. Borawski & A. Dor (2001) Lack of health insurance and decline in overall health in late middle age. *New England Journal of Medicine,* 345**,** 1106-1112.

Barry, J. & N. Breen (2005) The importance of place of residence in predicting late-stage diagnosis of breast or cervical cancer. *Health & Place,* 11**,** 15-29.

Bazargan, M., S. H. Bazargan, M. Farooq & R. S. Baker (2004) Correlates of cervical cancer screening among underserved Hispanic and African-American women. *Preventive Medicine,* 39**,** 465-73.

Becker, T. M., C. M. Wheeler, N. S. McGough, C. A. Parmenter, S. W. Jordan, C. A. Stidley, R. S. McPherson & M. H. Dorin (1994) Sexually transmitted diseases and other risk factors for cervical dysplasia among southwestern hispanic and non-hispanic white women. *Journal of the American Medical Association,* 271**,** 1181-1188.

Benard, V. B., S. S. Coughlin, T. Thompson & L. C. Richardson (2007) Cervical cancer incidence in the United States by area of residence, 1998 –2001. *Obstetrics & Gynecology,* 110**,** 681-686.

Benard, V. B., C. J. Johnson, T. D. Thompson, K. B. Roland, S. M. Lai, V. Cokkinides, F. Tangka, N. A. Hawkins, H. Lawson & H. K. Weir (2008) Examining the association between socioeconomic status and potential human papillomavirus-associated cancers. *Cancer,* 113**,** 2910-8.

Bennette, C. & A. Vickers (2012) Against quantiles: categorization of continuous variables in epidemiologic research, and its discontents. *BMC Medical Research Methodology,* 12**,** 1-5.

Bernstein, R. 1995. Statistical Brief: Poverty areas. U.S. Census Burea.

Bishaw, A. 2014. Changes in areas with concentrated poverty: 2000 to 2010. U.S. Census Bureau.

Block, B. & R. A. Branham (1998) Efforts to improve the follow-up of patients with abnormal Papanicolaou test results. *The Journal of the American Board of Family Practice,* 11**,** 1-11.

Bonner, M. R., D. Han, J. Nie, P. Rogerson, J. E. Vena & J. L. Freudenheim (2003) Positional accuracy of geocoded addresses in epidemiologic research. *Epidemiology,* 14**,** 408-412.

Boscoe, F. P. 2008. The science and art of geocoding: Tips for improving match rates and handling unmatched cases in analysis. In *Geocoding health data: The use of geographic codes in cancer prevention and control, research, and practice,* eds. G. Rushton, M. P. Armstrong, J. Gittler, B. R. Greene, C. E. Pavlik, M. M. West & D. L. Zimmerman, 95-109. Boca Raton, FL: CRC Press.

Boscoe, F. P., K. A. Henry & M. S. Zdeb (2012) A nationwide comparison of driving distance versus straight-line distance to hospitals. *The Professional Geographer,* 64**,** 188-196.

Boscoe, F. P., C. J. Johnson, K. A. Henry, D. W. Goldberg, K. Shahabi, E. B. Elkin, L. K. Ballas & M. Cockburn (2011) Geographic proximity to treatment for early stage breast cancer and likelihood of mastectomy. *Breast,* 20**,** 324-328.

Boscoe, F. P., C. J. Johnson, R. L. Sherman, D. G. Stinchcomb, G. Lin & K. A. Henry (2014) The relationship between area poverty rate and site-specific cancer incidence in the United States. *Cancer*.

Braveman, P. A., C. Cubbin, S. Egerter, D. R. Williams & E. Pamuk (2010) Socioeconomic disparities in health in the united states: what the patterns tell us. *American Journal of Public Health,* 101**,** S186-189.

Breslow, N. E. & N. E. Day. 1980. *Statistical methods in cancer research. Volume 1 - The analysis of case-control studies*. Lyon, France: International Agency for Research on Cancer.

Brewer, N., N. Pearce, P. Day & B. Borman (2012) Travel time and distance to health care only partially account for the ethnic inequalities in cervical cancer stage at diagnosis and mortality in New Zealand. *Australian and New Zealand Journal of Public Health,* 36**,** 335-342.

Cayo, M. R. & T. O. Talbot (2003) Positional error in automated geocoding of residential addresses. *International Journal of Health Geographics,* 2**,** 10.

Centers for Disease Control and Prevention. 2016. Cancer Among American Indians and Alaska Natives.

---. 2017. National Breast and Cervical Cancer Early Detection Program

Chasan, R. & R. Manrow. 2010. FACT SHEET - Cervical Cancer. 1-2. National Institutes of Health.

Chen, J., R. E. Roth, A. T. Naito, E. J. Lengerich & A. M. Maceachren (2008) Geovisual analytics to enhance spatial scan statistic interpretation: an analysis of U.S. cervical cancer mortality. *International Journal of Health Geographics,* 7**,** 57.

Chih, H. J., A. H. Lee, L. Colville, D. Xu & C. W. Binns (2014) Condom and oral contraceptive use and risk of cervical intraepithelial neoplasia in Australian women. *Journal of Gynecologic Oncology,* 25**,** 183-187.

Clegg, L. X., M. E. Reichman, B. A. Miller, B. F. Hankey, G. K. Singh, Y. D. Lin, M. T. Goodman, C. F. Lynch, S. M. Schwartz, V. W. Chen, L. Bernstein, S. L. Gomez, J. J. Graff, C. C. Lin, N. J. Johnson & B. K. Edwards (2009) Impact of socioeconomic status on cancer incidence and stage at diagnosis: selected findings from the surveillance, epidemiology, and end results: National Longitudinal Mortality Study. *Cancer Causes & Control,* 20**,** 417-435.

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences* Hillsdale, N.J: L. Erlbaum Associates.

Collett, D. 2003. *Modeling binary data*. Boca Raton, FL: Chapman& Hall/CRC.

Collins, T. W., S. E. Grineski, J. Chakraborty & Y. J. McDonald (2011) Understanding environmental health inequalities through comparative intracategorical analysis: racial/ethnic disparities in cancer risks from air toxics in El Paso County, Texas. *Health & Place,* 17**,** 335-44.

Continelli, T., S. McGinnis & T. Holmes (2010) The effect of local primary care physician supply on the utilization of preventive health services in the United States. *Health & Place,* 16**,** 942-951.

Coughlin, S. S., R. J. Uhler, T. Richards & K. M. Wilson (2003) Breast and cervical cancer screening practices among Hispanic and Non-Hispanic women residing near the United States-Mexico border, 1999-2000. *Family & Community Health,* 26**,** 130-139.

Cowburn, S., M. J. Carlson, J. A. Lapidus & J. E. DeVoe (2013) The association between insurance status and cervical cancer screening in community health centers: exploring the potential of electronic health records for population-level surveillance, 2008-2010. *Preventing Chronic Disease,* 10**,** E173.

Crenshaw, K. (1991) Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stanford Law Review,* 43**,** 1241-1299.

Cuzick, J., O. Myers, W. C. Hunt, M. Robertson, N. E. Joste, P. E. Castle, V. B. Benard, C. M. Wheeler & New Mexico HPV Pap Registry Steering Committee (2014) A population-based evaluation of cervical screening in the United States: 2008-2011. *Cancer Epidemiology, Biomarkers & Prevention,* 23**,** 765-73.

Daley, E., A. Alio, E. H. Anstey, R. Chandler, K. Dyer & H. Helmy (2011) Examining barriers to cervical cancer screening and treatment in Florida through a socio-ecological lens. *Journal of Community Health,* 36**,** 121-31.

de Mutsert, R., K. J. Jager, C. Zoccali & F. W. Dekker (2009) The effect of joint exposures: examining the presence of interaction. *Kidney International,* 75**,** 677-81.

Delamater, P. L., J. P. Messina, A. M. Shortridge & S. C. Grady (2012) Measuring geographic access to health care: Raster and network-based methods. *International Journal of Health Geographics,* 11**,** 1-18.

Downs, I. Scarinci, M. H. Einstein, Y. Collins & L. Flowers (2010) Overcoming the barriers to HPV vaccination in high-risk populations in the US. *Gynecologic Oncology,* 117**,** 486-490.

Downs, J. S. Smith, I. Scarinci, L. Flowers & G. Parham (2008) The disparity of cervical cancer in diverse populations. *Gynecologic Oncology,* 109**,** S22-30.

Dürst, M., L. Gissmann, H. Ikenberg & H. zur Hausen (1983) A papillomavirus, DNA from a cervical carcinoma and its prevalence in cancer biopsy samples from different geographic regions. *Proceedings of the National Academy of Sciences,* 80**,** 3812-3815.

Eggleston, K. S., A. L. Coker, M. Williams, G. Tortolero-Luna, J. B. Martin & S. R. Tortolero (2006) Cervical cancer survival by socioeconomic status, race/ethnicity, and place of residence in Texas, 1995–2001. *Journal of Women's Health,* 15**,** 941-951.

El Ibrahimi, S. & P. S. Pinheiro (2016) The effect of marriage on stage at diagnosis and survival in women with cervical cancer. *Psych-Oncology*.

Environmental Systems Research Institute.

Evans, W., B. Wolfe & N. Adler. 2012. The SES and health gradient: A brief review of the literature In *The biological consequences of socioeconomic inequalities,* eds. B. Wolfe, W. Evans & T. E. Seeman, 1-37. New York: Russel Sage Foundation.

Foley, R. & H. Platzer (2007) Place and provision: mapping mental health advocacy services in London. *Social Science & Medicine,* 64**,** 617-32.

Franceschi, S., M. Plummer, G. Clifford, S. de Sanjose, X. Bosch, R. Herrero, N. Munoz, S. Vaccarella, G. International Agency for Research on Cancer Multicentric Cervical Cancer Study & G. International Agency for Research on Cancer Human Papillomavirus Prevalence Surveys Study (2009) Differences in the risk of cervical cancer and human papillomavirus infection by education level. *British Journal of Cancer,* 101**,** 865-870.

Fritz, C. O., P. E. Morris & J. J. Richler (2012) Effect size estimates: current use, calculations, and interpretation. *Journal Of Experimental Psychology: General,* 141**,** 2-18.

Garces-Palacio, I. C. & I. C. Scarinci (2012) Factors associated with perceived susceptibility to cervical cancer among Latina immigrants in Alabama. *Maternal and Child Health Journal,* 16**,** 242-248.

Garner, E. O. (2003) Cervical cancer: Disparities in screening, treatment, and survival. *Cancer Epidemiology, Biomarkers & Prevention,* 12**,** 242s-247s.

Gilboa, S. M., P. Mendola, A. F. Olshan, C. Harness, D. Loomis, P. H. Langlois, D. A. Savitz & A. H. Herring (2006) Comparison of residential geocoding methods in population-based study of air quality and birth defects. *Environmental Research* 101**,** 256-262.

Goldberg, D., J. Wilson, C. Knoblock, B. Ritz & M. Cockburn (2008a) An effective and efficient approach for manually improving geocoded data. *International Journal of Health Geographics,* 7.

Goldberg, D. W. 2008. A geocoding best practices guide. In *North American Association of Central Cancer Registries, Inc.* Springfield, IL.

Goldberg, D. W., M. Ballard, J. H. Boyd, N. Mullan, C. Garfield, D. Rosman, A. M. Ferrante & J. B. Semmens (2013) An evaluation framework for comparing geocoding systems. *International Journal of Health Geographics,* 12**,** 50.

Goldberg, D. W. & M. G. Cockburn (2012) The effect of administrative boundaries and geocoding error on cancer rates in California. *Spatial and Spatio-Temporal Epidemiology,* 3**,** 39-54.

Goldberg, D. W., J. P. Wilson & C. A. Knoblock (2007) From text to geographic coordinates: The current state of geocoding. *Urisa Journal,* 19**,** 33-47.

Goldberg, D. W., J. P. Wilson, C. A. Knoblock, B. Ritz & M. G. Cockburn (2008b) An effective and efficient approach for manually improving geocoded data. *International Journal of Health Geographics,* 7**,** 60.

Gomez, S. L., S. L. Glaser, L. A. McClure, S. J. Shema, M. Kealey, T. H. Keegan & W. A. Satariano (2011) The California Neighborhoods Data System: a new resource for examining the impact of neighborhood characteristics on cancer incidence and outcomes in populations. *Cancer Causes Control,* 22**,** 631-47.

Gregorio, D. I., E. Cromley, R. Mrozinski & S. J. Walsh (1999) Subject loss in spatial analysis of breast cancer. *Health & Place,* 5**,** 173-177.

Grubesic, T. H. & T. C. Matisziw (2006) On the use of ZIP codes and ZIP code tabulation areas (ZCTAs) for the spatial analysis of epidemiological data. *International Journal of Health Geographics,* 5**,** 58.

Guidry, J. J., L. A. Aday, D. Zhang & R. J. Winn (1997) Transportation as a barrier to cancer treatment. *Cancer Practice,* 5**,** 361-366.

Gulitz, E., M. Bustillo-Hernandez & E. B. Kent (1998) A provider survey. *Cancer Practice,* 6**,** 325-332.

Gunderson, C. C., E. K. Nugent, D. S. McMeekin & K. N. Moore (2013) Distance traveled for treatment of cervical cancer: who travels the farthest, and does it impact outcome? *International Journal of Gynecological Cancer,* 23**,** 1099-103.

Hahn, K. M. E., M. L. Bondy, M. Selvan, M. J. Lund, J. M. Liff, E. W. Flagg, L. A. Brinton, P. Porter, J. W. Eley & R. J. Coates (2007) Factors associated with advanced disease stage at diagnosis in a population-based study of patients with newly diagnosed breast cancer. *American Journal of Epidemiology,* 166**,** 1035-1044.

Hankivsky, O., C. Reid, R. Cormier, C. Varcoe, N. Clark, C. Benoit & S. Brotman (2010) Exploring the promises of intersectionality for advancing women's health research. *International Journal for Equity in Health,* 9**,** 5.

Harris, R. & L. Leininger (1993) Preventive care in rural primary care practice. *Cancer,* 72**,** 1113-1118.

Hart, L. G., E. Salsberg, D. M. Phillips & D. M. Lishner (2002) Rural health care providers in the United States. *The Journal of Rural Health,* 18**,** 211-231.

Hawkins, R. & C. Curtiss (1997) Cancer resources for providers in the rural community. *Cancer Practice,* 5**,** 383-386.

Hennekens, C. H. & J. E. Buring. 1987. Case-control studies. In *Epidemiology in Medicine,* ed. S. L. Mayrent, 132-152. Philadelphia: Lippincott Williams & Wilkins.

Henry, K. A., F. P. Boscoe, C. J. Johnson, D. W. Goldberg, R. Sherman & M. Cockburn (2011) Breast cancer stage at diagnosis: is travel time important? *Journal of Community Health,* 36**,** 933-42.

Henry, K. A., R. Sherman, S. Farber, M. Cockburn, D. W. Goldberg & A. M. Stroup (2013) The joint effects of census tract poverty and geographic access on late-stage breast cancer diagnosis in 10 US States. *Health & Place,* 21**,** 110-121.

Hiatt, R. A., R. J. Pasick, S. Stewart, J. Bloom, P. Davis, P. Gardiner, M. Johnston, J. Luce, K. Schorr, W. Brunner & F. Stroud (2001) Community-based cancer screening for underserved women: design and baseline findings from the Breast and Cervical Cancer Intervention Study. *Preventive Medicine,* 33**,** 190-203.

Hicks, M. L., O. W. S. Yap, R. Matthews & G. Parham (2006) Disparities in cervical cancer screening, treatment and outcomes. *Ethnicity & Disease,* 16**,** S3-63-S3-66.

Hirsch, S. 2007. Request for public comment on use of Rural Urban Commuting Areas (RUCAs). ed. National Archives and Records Administration, 24589-24591. Washington, D.C.: Federal Register.

HomeTownLocator, N. 2017. Profile.

Horner, M. J., S. F. Altekruse, Z. Zou, L. Wideroff, H. A. Katki & D. G. Stinchcomb (2011a) U.S. geographic distribution of prevaccine era cervical cancer screening, incidence, stage, and mortality. *Cancer Epidemiology, Biomarkers, & Prevention,* 20**,** 591-599.

--- (2011b) U.S. geographic distribution of prevaccine era cervical cancer screening, incidence, stage, and mortality. *Cancer Epidemiology, Biomarkers & Prevention* 20**,** 591-599.

Hosmer, D. W. & S. Lemeshow. 1989. *Applied Logistic Regression*. New York: Wiley & Sons.

Hsieh, C.-c., P. Maisommeuve, P. Boyle, G. J. Macfarlane & C. Roberston (1991) Analysis of quantitative data by quantiles in epidemiologic studies: Classification according to cases, noncases, or all subjects? *Epidemiology,* 2**,** 137-140.

Hurley, S. E., T. M. Saunders, R. Nivas, A. Hertz & P. Reynolds (2003) Post office box addresses: A challenge for geographic information system-based studies. *Epidemiology,* 14**,** 386-391.

Hussain, J. N. (2008) Sensitivity analysis to select the most influential risk factors in a logistic regression model. *International Journal of Quality, Statistics, and Reliability,* 2008**,** 1-10.

IBM Corp. Released 2014. IBM SPSS Statistics for Windows. Version 23.0. Armonk, NY.

Institute of Medicine Committee on the Consequences of Uninsurance (2002) Care Without Coverage: Too Little, Too Late. http://www.ncbi.nlm.nih.gov/pubmed/25057604 (last accessed.

Jacobs, L. K., K. A. Kelley, G. D. Rosson, M. E. Detrani & D. C. Chang (2008) Disparities in urban and rural mastectomy populations : the effects of patient- and county-level factors on likelihood of receipt of mastectomy. *Annals of Surgical Oncology,* 15**,** 2644-52.

Jacquez, G. M. (2012) A research agenda: does geocoding positional error matter in health GIS studies? *Spatial and Spatio-Temporal Epidemiology,* 3**,** 7-16.

Jacquez, G. M. & R. Rommel (2009) Local indicators of geocoding accuracy (LIGA): theory and application. *International Journal of Health Geographics,* 8**,** 60.

Jimenez, A. M., T. W. Collins & S. E. Grineski (2013) Intra-ethnic disparities in respiratory health problems among Hispanic residents impacted by a flood. *The Journal of Asthma,* 50**,** 463-471.

Jones, B. A., A. Dailey, L. Calvocoressi, K. Reams, S. V. Kasl, C. Lee & H. Hsu (2005) Inadequate follow-up of abnormal screening mammograms: Findings from the race differences in screening mammography process study (United States). *Cancer Causes & Control,* 16**,** 809-821.

Kamineni, A., S. Weinmann, K. K. Shy, A. G. Glass & N. S. Weiss (2013) Efficacy of screening in preventing cervical cancer among older women. *Cancer Causes & Control,* 24**,** 1653-1660.

Kim, H. Y. (2013) Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Eendodontics,* 38**,** 52-54.

Kim, J. J., N. G. Campos, S. Sy, E. A. Burger, J. Cuzick, P. E. Castle, W. C. Hunt, A. Waxman, C. M. Wheeler & H. P. V. P. R. S. C. New Mexico (2015) Inefficiencies and High-Value Improvements in U.S. Cervical Cancer Screening Practice: A Cost-Effectiveness Analysis. *Annals of Internal Medicine,* 163**,** 589-597.

Kirby, R. S., E. Delmelle & J. M. Eberth (2016) Advances in spatial epidemiology and geographic information systems. *Annals of Epidemiology***,** 1-9.

Kish, L. 1965. *Survey Sampling*. New York: John Wiley & Sons, Inc.

Kleinbaum, D. G. 1994. *Logistic regression. A self-learning text.* New York, New York: Springer.

Kleyman, Y. & B. Hansen (2006) Basic uses of the optmatch package. *CRAN. R-project,* R package version 3.2.2.

Kowalski, C., J. (1972) On the effects of non-normality on the distribution of the sample product-moment correlation coefficient. *Journal of the Royal Statistical Society. Series C (Applied Statistics),* 21**,** 1-12.

Kravets, N. & W. C. Hadden (2007) The accuracy of address coding and the effects of coding errors. *Health & Place,* 13**,** 293-298.

Krieger, N. (1992) Overcoming the absence of socioeconomic data in medical records: validation and application of a census-based methodology. *American Journal of Public Health,* 82**,** 703-710.

Krieger, N. (2003) Place, space, and health: GIS and epidemiology. *Epidemiology,* 14**,** 384-385.

Krieger, N., J. T. Chen, P. D. Waterman, D. H. Rehkopf & S. V. Subramanian (2003) Race/Ethnicity, gender, and monitoring socioeconomic gradients in health: A comparison of area-based socioeconomic measures—The Public Health Disparities Geocoding Project. *American Journal of Public Health,* 93**,** 1655-1671.

Krieger, N., J. T. Chen, P. D. Waterman, M. J. Soobader & R. Carson (2002) Geocoding and monitoring of US socioeconomic inequalities in mortality and cancer incidence: Does the choice of area-based measure and geographic level matter?: The public health disparities geocoding project. *American Journal of Epidemiology,* 156**,** 471-482.

Krieger, N., P. Waterman, K. Lemieux, S. Zierler & J. W. Hogan (2001) On the wrong side of the tracts? Evaluating the accuracy of geocoding in public health research. *American Journal of Public Health,* 91**,** 1114-1116.

Kvikstad, A. & L. J. Vatten (1996) Cancer risk and prognosis in Norway: comparing women in their first marriage with women who have never married. *Journal of Epidemiology and Community Health,* 50**,** 51-55.

Leyden, W. A., M. M. Manos, A. M. Geiger, S. Weinmann, J. Mouchawar, K. Bischoff, M. U. Yood, J. Gilbert & S. H. Taplin (2005) Cervical cancer in women with comprehensive health care access: attributable factors in the screening process. *Journal of the National Cancer Institute,* 97**,** 675-83.

Lin, Y., M. Schootman & F. B. Zhan (2015) Racial/ethnic, area socioeconomic, and geographic disparities of cervical cancer survival in Texas. *Applied Geography,* 56**,** 21-28.

Lisovicz, N., T. Wynn, M. Fouad & E. E. Partridge (2008) Cancer health disparities: What we have done. *The American Journal of the Medical Sciences,* 335**,** 254-259.

Lupo, P. J., H. E. Danysh, E. Symanski, P. H. Langlois, Y. Cai & M. D. Swartz (2015) Neighborhood-Based Socioeconomic Position and Risk of Oral Clefts Among Offspring. *American Journal of Public Health,* 105**,** 2518-2525.

Luque, J. S., H. Castaneda, D. M. Tyson, N. Vargas, S. Proctor & C. D. Meade (2010) HPV awareness among Latina Immigrants and Anglo American women in the Southern U.S.: Cultural models of cervical cancer risk Factors and beliefs. *NAPA Bull,* 34**,** 84-104.

Marcus, A. C., L. A. Crane, C. P. Kaplan, A. E. Reading, E. Savage, J. Gunning, G. Bernstein & J. S. Berek (1992) Improving adherence to screening follow-up among women with abnormal pap smears:results from a large clinic-based trial of three intervention strategies. *Medical Care,* 30**,** 216-230.

Mariotti, S., R. Capocaccia, G. Farchi, A. Menotti, A. Verdecchia & A. Keys (1986) Age, period, cohort and geographical area effects on the relationship between risk factors and coronary heart disease mortality *Journal of Chronic Diseases,* 39**,** 229-242.

Markides, K. S. & J. Coreil (1986) The health of Hispanics in the southwestern United States: An epidemiologic paradox. *Public Health Reports,* 101**,** 253-265.

Markides, K. S. & K. Eschbach. 2011. Hispanic paradox in adult mortality in the United States. In *International Handbook of Adult Mortality,* eds. R. G. Rogers & E. M. Crimmins, 227-240. Springer Science+Business Media B.V.

McCarthy, A. M., T. Dumanovsky, K. Visvanathan, A. R. Kahn & M. J. Schymura (2010) Racial/ethnic and socioeconomic disparities in mortality among women diagnosed with cervical cancer in New York City, 1995-2006. *Cancer Causes & Control,* 21**,** 1645-1655.

McDonald, Y. J., D. W. Goldberg, I. C. Scarinci, P. E. Castle, J. Cuzick, M. Robertson & C. M. Wheeler (2016) Health Service Accessibility and Risk in Cervical Cancer Prevention: Comparing Rural Versus Nonrural Residence in New Mexico. *The Journal of Rural Health*.

McDonald, Y. J., M. Schwind, D. W. Goldberg, A. Lampley & C. M. Wheeler (2017) An analysis of the process and results of manual geocode correction. *Geospatial Health,* 12**,** 84-89.

McElroy, J. A., P. L. Remington, A. Trentham-Dietz, S. A. Robert & P. A. Newcomb (2003) Geocoding addresses from a large population-based study: lessons learned. *Epidemiology,* 14**,** 399-407.

Meade, M. S. & M. Emch. 2010. *Medical Geography*. New York, NY: The Guilford Press.

Meilleur, A., S. V. Subramanian, J. J. Plascak, J. L. Fisher, E. D. Paskett & E. B. Lamont (2013) Rural residence and cancer outcomes in the United States: issues and challenges. *Cancer Epidemiology, Biomarkers & Prevention,* 22**,** 1657-67.

Messer, L. C., B. A. Laraia, J. S. Kaufman, J. Eyster, C. Holzman, J. Culhane, I. Elo, J. G. Burke & P. O'Campo (2006) The development of a standardized neighborhood deprivation index. *Journal of Urban Health,* 83**,** 1041-62.

Microsoft SQL Server 2012. Redmond, WA: Microsoft.

Moreno, V., F. X. Bosch, N. Muñoz, C. J. L. M. Meijer, K. V. Shah, J. M. M. Walboomers, R. Herrero & S. Franceschi (2002) Effect of oral contraceptives on risk of cervical cancer in women with human papillomavirus infection: the IARC multicentric case-control study. *The Lancet,* 359**,** 1085-1092.

Moyer, V. A. (2012) Screening for cervical cancer: U.S. Preventive Services Task Force recommendation statement. *Annals of Internal Medicine,* 156**,** 880-892.

Murray, A. T., T. H. Grubesic, R. Wei & E. A. Mack (2011) A hybrid geocoding methodology for spatio-temporal data. *Transactions in GIS,* 15**,** 795-809.

New Mexico Department of Health. 2012. Breast & Cervical Cancer Early Detection Program.

New Mexico Department of Health Comprehensive Cancer Program. 2012. New Mexico Cancer Plan, 2012-2017. 1-58. Albuquerque, New Mexico.

Newmann, S. J. & E. O. Garner (2005) Social inequities along the cervical continuum: A structured review. *Cancer Causes & Control,* 16**,** 63-70.

Newson, R. (2002) Parameters behind "nonparametric" statistics: Kendall's tau, Somers' D and mediandifferences. *The Stata Journal,* 2**,** 45-64.

Niccolai, L. M., P. J. Julian, A. Bilinski, N. R. Mehta, J. I. Meek, D. Zelterman, J. L. Hadler & L. Sosa (2013) Geographic poverty and racial/ethnic disparities in cervical cancer precursor rates in Connecticut, 2008-2009. *American Journal of Public Health,* 103**,** 156-63.

New Mexico HPV Pap Registry. 2015. *Unpublished Report*.

Nuckols, J. R., M. H. Ward & L. Jarup (2004) Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environmental Health Perspectives,* 112**,** 1007-1015.

Obrist, B., N. Iteba, C. Lengeler, A. Makemba, C. Mshana, R. Nathan, S. Alba, M. W. Hetzel, I. Mayumana, A. Schulze & H. Mshinda (2007) Access to health care in contexts of livelihood insecurity: A framework for analysis and action. *Plos Medicine,* 4**,** e308-1588.

Office for National Statistics. 2015. Population-weighted centroids.

Oliver, M. N., K. A. Matthews, M. Siadaty, F. R. Hauck & L. W. Pickle (2005) Geographic bias related to geocoding in epidemiologic studies. *International Journal Of Health Geographics,* 4**,** 29.

Papanicolaou, G. N. & H. F. Traut. 1943. *Diagnosis of uterine cancer of the vaginal smear*. New York: Commonwealth Fund.

Parikh, S., P. Brennan & P. Boffetta (2003) Meta-analysis of social inequality and the risk of cervical cancer. *International Journal of Cancer,* 105**,** 687-691.

Penchansky, R. & J. W. Thomas (1981) The concept of access: Definition to consumer satisfaction. *Medical Care,* XIX**,** 127-140.

Philips, B. U., E. Belasco, K. S. Markides & G. Gong (2013) Socioeconomic deprivation as a determinant of cancer mortality and the Hispanic paradox in Texas, USA. *International Journal for Equity in Health,* 12.

Pourhoseingholi, M. A., A. Baghestani, Reza & M. Vahedi (2012) How to control confounding effects by statistical analysis. *Gastroenterology and Hepatology From Bed to Bench,* 5**,** 79-83.

Python Programming Language. Python Software Foundation. Wilmington, DE.

Ratcliffe, J. H. (2001) On the accuracy of TIGER-type geocoded address data in relation to cadastral and census areal units. *International Journal of Geographical Information Science,* 15**,** 473-485.

Robbins, A. S., X. Han, E. M. Ward, E. P. Simard, Z. Zheng & A. Jemal (2015) Association between the affordable care act dependent coverage expansion and cervical cancer stage and treatment in young women. *Journal of American Medical Association,* 314 2107-2202.

Robert, S. A., I. Strombom, A. Trentham-Dietz, J. M. Hampton, J. A. McElroy, P. A. Newcomb & P. L. Remington (2004) Socioeconomic Risk Factors for Breast Cancer. *Epidemiology,* 15**,** 442-450.

Rushton, G., M. P. Armstrong, J. Gittler, B. R. Greene, C. E. Pavlik, M. M. West & D. L. Zimmerman (2006) Geocoding in cancer research. *American Journal of Preventive Medicine,* 30**,** S16-24.

Sands, M. E., G. K. Zagars, A. Pollack & A. C. von Eschenbach (1994) Serum prostate-specific antigen, clinical stage, pathologic grade, and the incidence of nodal metastases in prostate cancer. *Urology,* 44**,** 215-220.

Saraiya, M., F. Ahmed, S. Krishnan, T. B. Richards, E. R. Unger & H. W. Lawson (2007) Cervical cancer incidence in a prevaccine era in the United States, 1998-2002. *Obstetrics & Gynecology,* 109**,** 360-370.

Saslow, D., D. Solomon, H. W. Lawson, M. Killackey, S. L. Kulasingam, J. Cain, F. A. Garcia, A. T. Moriarty, A. G. Waxman, D. C. Wilbur, N. Wentzensen, L. S. Downs, Jr., M. Spitzer, A. B. Moscicki, E. L. Franco, M. H. Stoler, M. Schiffman, P. E. Castle, E. R. Myers & ACS-ASCCP-ASCP Cervical Cancer Guideline Committee (2012) American Cancer Society, American Society for Colposcopy and Cervical Pathology, and American Society for Clinical Pathology screening guidelines for the prevention and early detection of cervical cancer. *CA: A Cancer Journal For Clinicians,* 62**,** 147-72.

Schiff, M., J. Miller, M. Masuk, L. van Asselt King, K. K. Altobelli, C. M. Wheeler & T. M. Becker (2000) Contraceptive and reproductive risk factors for cervical intraepithelial neoplasia in American Indian women. *International Journal of Epidemiology,* 29**,** 983-998.

Schiffman, M. & P. Castle (2005) The promise of global cervical-cancer prevention. *The New England Journal of Medicine,* 353**,** 2101-2104.

Schlesselman, J. J. 1982. *Case-control studies: Design, conduct, analysis*. New York, NY: Oxford University Press, Inc.

Schootman, M., S. L. Gomez, K. A. Henry, E. D. Paskett, G. L. Ellison, A. Oh, S. H. Taplin, Z. Tatalovich & D. A. Berrigan (2017) Geospatial approaches to cancer control and population sciences. *Cancer Epidemiology, Biomarkers & Prevention,* 26**,** 472-475.

Schootman, M., D. A. Sterling, J. Struthers, Y. Yan, T. Laboube, B. Emo & G. Higgs (2007) Positional accuracy and geographic bias of four methods of geocoding in epidemiologic research. *Annals of Epidemiology,* 17**,** 464-70.

Schroen, A. T., D. R. Brenin, M. D. Kelly, W. A. Knaus & C. L. Slingluff, Jr. (2005) Impact of patient distance to radiation therapy on mastectomy use in early-stage breast cancer patients. *Journal of Clinical Oncology* 23**,** 7074-7080.

Seeff, L. C. & M. T. McKenna (2003) Cervical cancer mortality among foreign-born women living in the United States, 1985 to 1996. *Cancer Detection and Prevention,* 27**,** 203-208.

Shi, X., J. Alford-Teaster, T. Onega & D. Wang (2012) Spatial access and local demand for major cancer care facilities in the United States. *Annals of the Association of American Geographers,* 102**,** 1125-1134.

Singh, G. K. (2012) Rural-urban trends and patterns in cervical cancer mortality, incidence, stage, and survival in the United States, 1950-2008. *Journal of Community Health,* 37**,** 217-223.

Singh, G. K., B. A. Miller, B. F. Hankey & B. K. Edwards. 2003. Area socioeconomic variations in U.S. cancer incidence, mortality, stage, treatment, and survival, 1975-1999., ed. National Cancer Institute. Bethesda, MD.: National Institutes for Health.

Singh, G. K., S. D. Williams, M. Siahpush & A. Mulhollen (2011) Socioeconomic, rural-urban, and racial inequalities in us cancer mortality: Part I-all cancers and lung cancer and part ii-colorectal, prostate, breast, and cervical cancers. *Journal of Cancer Epidemiology,* 2011**,** 107497.

Strickland, M. J., C. Siffel, B. R. Gardner, A. K. Berzen & A. Correa (2007) Quantifying geocode location error using GIS methods. *Environmental Health,* 6**,** 10.

Surveillance, E., and End Results Program. 2017. SEER Stat Fact Sheets: Cervix Uteri Cancer In *Turning Cancer Data Into Discovery*, ed. N. C. Institute, Cervical cancer facts.

Swegal, W. C., M. Singer, E. Peterson, H. S. Feigelson, S. A. Kono, S. Snyder, T. A. Melvin, G. Calzada, N. R. Ghai, D. M. Saman & S. S. Chang (2016) Socioeconomic Factors Affect Outcomes in Well-Differentiated Thyroid Cancer. *Otolaryngol Head Neck Surg,* 154**,** 440-445.

Szklo, M. & F. J. Nieto. 2014. *Epidemiology: Beyong the basics*. Burlington, MA: Jones & Bartlett Learning.

Texas A&M University Geocoder. College Station, TX.

Texas A&M University GeoInnovation Service Center Shortest Path. College Station, TX.

Thompson, B., H. Vilchis, C. Moran, W. Copeland, S. Holte & C. Duggan (2014) Increasing cervical cancer screening in the United States-Mexico border region. *The Journal of Rural Health,* 30**,** 196-205.

Tobler, W. R. (1970) A computer movie simulating urban growth in the Detroit region. *Economic Geography,* 46**,** 234-240.

Tomita, L. Y., C. M. Roteli-Martins, L. L. Villa, E. L. Franco & M. A. Cardoso (2011) Associations of dietary dark-green and deep-yellow vegetables and fruits with cervical intraepithelial neoplasia: modification by smoking. *The British Journal of Nutrition,* 105**,** 928-937.

Tsui, J., M. Saraiya, T. Thompson, A. Dey & L. Richardson (2007) Cervical cancer screening among foreign-born women by birthplace and duration in the United States. *Journal of Women's Health,* 16**,** 1447-1457.

U.S. Census Bureau. 2011. American Community Survey, 5-year estimates (2007-2011). U.S. Census Bureau.

---. 2013. American Community Survey, 5-year estimates (2009-2013).

---. 2015. ZIP Code™ Tabulation Areas (ZCTAs™).

---. 2016. Download 2010 ZIP Code Tabulation Area (ZCTA) Relationship Files.

U.S. Census Bureau Center for Economic Studies. 2012. U.S. Census Bureau, 2010 census of population and housing, population and housing unit counts, CPH-2-33, New Mexico. ed. E. a. S. A. U.S. Deparment of Commerce. Washington, DC: U.S. Government Printing Office.

U.S. Deparment of Health & Human Services. 2015. Federal Office of Rural Health Policy: Defining rural population. Health Resources and Services Administration.

---. 2017. Healthy People 2020: Health Disparities Data.

UC Davis Center for Poverty Research. 2015. How does poverty relate to health insurance coverage?

United States Census Bureau. 2012a. Geography: geographic terms and concepts - block group.

---. 2012b. Geography: geographic terms and concepts - census tract.

United States Department of Agriculture. 2017. Rural Classifications. Economic Research Service.

Ursin, G., C. Pike, S. Preston-Martin & G. III d'Ablaing (1996) Sexual, reproductive, and other risk factors for adenocarcinoma of the cervix: results from a population-based case-control study (California, United States). *Cancer Causes & Control,* 7**,** 391-401.

Valentine, G. (2007) Theorizing and researching intersectionality: A challenge for feminist geography. *The Professional Geographer,* 59**,** 10-21.

Vamos, C. A., A. E. Calvo, E. M. Daley, A. R. Giuliano & H. Lopez Castillo (2015) Knowledge, Behavioral, and Sociocultural Factors Related to Human Papillomavirus Infection and Cervical Cancer Screening Among Inner-City Women in Panama. *Journal of Community Health,* 40**,** 1047-1056.

Van Eenwyk, J., F. G. Davis & E. Bowen (1991) Dietary and serum carotenoids and cervical intraepithelial neoplasia. *International Journal of Cancer,* 48**,** 34-38.

Vandenbroucke, J. P., E. von Elm, D. G. Altman, P. C. Gotzsche, C. D. Mulrow, S. J. Pocock, C. Poole, J. J. Schlesselman, M. Egger & for the STROBE Initiative (2007) Strengthening the reporting of observational studies in epidemiology (STROBE): Explanation and elaboration. *PLOS Medicine,* 4**,** e297.

Wan, N., F. B. Zhan, Y. Lu & J. P. Tiefenbacher (2012) Access to healthcare and disparities in colorectal cancer survival in Texas. *Health & Place,* 18**,** 321-9.

Ward, M. H., J. R. Nuckols, J. Giglierano, M. R. Bonner, C. Wolter, M. Airola, W. Mix, J. S. Colt & P. Hartge (2005) Positional Accuracy of Two Methods of Geocoding. *Epidemiology,* 16**,** 542-547.

Watson, M., M. Saraiya, V. Benard, S. S. Coughlin, L. Flowers, V. Cokkinides, M. Schwenn, Y. Huang & A. Giuliano (2008) Burden of cervical cancer in the United States, 1998-2003. *Cancer,* 113**,** 2855-2864.

Weber, L. & D. Parra-Medina (2003) Intersectionality and Women's Health: Charting a Path to Eliminating Health Disparities. 7**,** 181-230.

West, S. G., J. F. Finch & P. J. Curran. 1995. Structural equation models with nonnormal variables: problems and remedies. In *Structural equation modeling: Concepts, issues and applications.* , ed. R. H. Hoyle, 56-75. Newbery Park, CA: Sage.

Wey, C. L., J. Griesse, L. Kightlinger & M. C. Wimberly (2009) Geographic variability in geocoding success for West Nile virus cases in South Dakota. *Health & Place,* 15**,** 1108-1114.

Williams, D. R., E. Z. Kontos, K. Viswanath, J. S. Haas, C. S. Lathan, L. E. MacConaill, J. Chen & J. Z. Ayanian (2012) Integrating multiple social statuses in health disparities research: the case of lung cancer. *Health Services Research,* 47**,** 1255-77.

Witlox, F. (2007) Evaluating the reliability of reported distance data in urban travel behaviour analysis. *Journal of Transport Geography,* 15**,** 172-183.

Wylie-Rosett, J., S. L. Romney, N. S. Slagle, S. Wassertheil-Smoller, G. L. Miller, P. R. Palan, D. J. Lucido & C. Duttagupta (1984) Influence of vitamin A on cervical dysplasia and carcinoma in situ. *Nutrition and Cancer,* 6**,** 49-57.

Yabroff, K. R., W. F. Lawrence, J. C. King, P. Mangan, K. S. Washington, B. Yi, J. F. Kerner & J. S. Mandelblatt (2005) Geographic disparities in cervical cancer mortality: What are the roles of risk factor prevalence, screening, and use of recommended treatment? *The Journal of Rural Health,* 21**,** 149-157.

Zambrana, R. E., N. Breen, S. A. Fox & M. L. Gutierrez-Mohamed (1999) Use of cancer screening practices by Hispanic women: Analyses by subgroup. *Preventive Medicine,* 29**,** 466-477.

Zandbergen, P. A. (2007) Influence of geocoding quality on environmental exposure assessment of children living near high traffic roads. *BMC Public Health,* 7**,** 37.

Zandbergen, P. A. (2008) A comparison of address point, parcel and street geocoding techniques. *Computers, Environment and Urban Systems,* 32**,** 214-232.

--- (2009) Geocoding quality and implications for spatial analysis. *Geography Compass,* 3**,** 647-680.

--- (2011) Influence of street reference data on geocoding quality. *Geocarto International,* 26**,** 35-47.

Zandbergen, P. A., T. C. Hart, K. E. Lenzer & M. E. Camponovo (2012) Error propagation models to examine the effects of geocoding quality on spatial analysis of individual-level datasets. *Spatial and Spatio-Temporal Epidemiology,* 3**,** 69-82.

Zhan, F. B. & Y. Lin (2014) Racial/Ethnic, socioeconomic, and geographic disparities of cervical cancer advanced-stage diagnosis in Texas. *Women's Health Issues,* 24**,** 519-527.

Appendix A. Travel time (minutes) from population-weighted census tract centroid to nearest healthcare facility that provided cervical cancer screening, diagnostic, and excisional treatment services for non-rural census tracts and rural census tracts in New Mexico, 2010-2012.

Non-Rural (301) Time (minutes)										
Screening[a]	**2010**	**2011**	**2012**	**Diagnostic[b]**	**2010**	**2011**	**2012**	**Treatment[c]**	**2010**	**2011**	**2012**
<10	89.82%	88.03%	87.18%	<10	77.16%	77.96%	76.02%	<10	66.86%	65.58%	64.42%
10-< 20	6.84%	8.62%	9.48%	10-< 20	16.57%	15.88%	16.99%	10-< 20	22.86%	19.39%	20.72%
20-< 30	0.92%	1.03%	1.03%	20-< 30	3.02%	2.90%	2.85%	20-< 30	3.75%	5.33%	5.16%
30-< 40	1.07%	1.07%	1.07%	30-< 40	1.47%	1.47%	2.35%	30-< 40	3.89%	6.76%	6.71%
40-< 50	0.73%	0.63%	0.63%	40-< 50	1.17%	1.17%	1.17%	40-< 50	2.03%	2.03%	2.08%
50-< 60	0.00%	0.00%	0.00%	50-< 60	0.00%	0.00%	0.00%	50-< 60	0.00%	0.29%	0.29%
60+	0.62%	0.62%	0.62%	60+	0.62%	0.62%	0.62%	60+	0.62%	0.62%	0.62%
Mean	5.28	5.50	5.59	Mean	7.63	7.69	8.11	Mean	10.26	11.29	11.41
Median	3.00	3.00	3.00	Median	4.80	4.80	5.40	Median	7.20	7.20	7.80
IQR[d]	1.80-6.00	1.80-6.30	1.80-6.30	IQR[d]	2.40-9.60	3.00-9.60	3.00-10.50	IQR[d]	4.20-12.60	4.20-13.80	4.20-13.80
Min	0.01	0.01	0.01	Min	0.60	0.60	0.60	Min	0.60	0.60	0.60
Max	76.80	76.80	111.00	Max	84.60	84.60	84.60	Max	96.00	96.00	96.00
Rural (197)											
<10	68.89%	67.64%	68.06%	<10	49.12%	47.19%	47.70%	<10	41.43%	42.01%	37.51%
10-< 20	12.92%	14.43%	14.01%	10-< 20	18.60%	18.81%	19.06%	10-< 20	15.84%	16.31%	19.49%
20-< 30	8.75%	9.07%	9.07%	20-< 30	9.54%	10.35%	9.68%	20-< 30	7.71%	7.71%	9.56%
30-< 40	3.27%	2.29%	2.29%	30-< 40	6.05%	7.95%	7.67%	30-< 40	7.62%	7.62%	7.23%
40-< 50	1.29%	1.29%	1.29%	40-< 50	4.81%	5.20%	2.66%	40-< 50	6.06%	5.77%	5.94%
50-< 60	0.50%	1.48%	1.48%	50-< 60	1.66%	1.98%	1.77%	50-< 60	4.70%	4.70%	5.87%
60+	4.38%	3.80%	3.80%	60+	10.20%	8.51%	11.46%	60+	16.64%	15.88%	14.41%
Median	11.79	11.84	11.89	Median	20.97	21.02	21.81	Median	29.19	27.86	28.53
IQR[d]	4.80	4.80	5.40	IQR[d]	10.20	10.80	10.20	IQR[d]	14.40	12.60	16.20
IQR	1.80-16.50	2.10-16.80	2.10-17.10	IQR	5.10-31.50	4.80-32.70	5.40-33.30	IQR	5.70-48.00	5.70-46.80	6.30-48.30
Min	0.01	0.01	0.01	Min	0.60	0.60	0.60	Min	0.60	0.60	0.60
Max	188.40	188.40	186.00	Max	194.40	194.40	194.40	Max	195.60	195.60	195.60

[a]Screening services include Pap smear and/or HPV testing; [b]Diagnostic service is colposcopy; [c]Excisional treatment services includes cone and loop electrosurgical excision procedure; [d]IQR indicates Interquartile Range (Q1-Q3)

Note: Census tracts weighted based upon screen eligible population.

Appendix B. Travel distance (kilometers) from population-weighted census tract centroid to nearest healthcare facility that provided cervical cancer screening, diagnostic, and excisional treatment services for non-rural census tracts and rural census tracts in New Mexico, 2010-2012.

Non-Rural (301) Distance (kilometers)											
Screening[a]	**2010**	**2011**	**2012**	**Diagnostic[b]**	**2010**	**2011**	**2012**	**Treatment[c]**	**2010**	**2011**	**2012**
<15	94.93%	94.84%	94.09%	<15	85.40%	85.70%	84.47%	<15	80.03%	76.59%	76.24%
15-< 30	3.72%	3.91%	4.49%	15-< 30	11.94%	11.30%	12.00%	15-< 30	12.01%	10.61%	10.96%
30-< 45	0.86%	0.75%	0.93%	30-< 45	1.73%	2.08%	1.72%	30-< 45	3.91%	6.73%	6.73%
45-< 60	0.50%	0.50%	0.50%	45-< 60	0.92%	0.92%	1.81%	45-< 60	2.26%	3.67%	3.67%
60-< 75	0.00%	0.00%	0.00%	60-< 75	0.00%	0.00%	0.00%	60-< 75	1.17%	1.68%	1.68%
75-< 100	0.00%	0.00%	0.00%	75-< 100	0.00%	0.00%	0.00%	75-< 100	0.11%	0.22%	0.22%
100+	0.00%	0.00%	0.00%	100+	0.00%	0.00%	0.00%	100+	0.50%	0.50%	0.50%
Mean	4.49	4.67	4.76	Mean	7.27	7.30	7.87	Mean	10.91	12.66	12.88
Median	2.29	2.57	2.57	Median	4.12	4.18	4.39	Median	6.50	6.55	6.63
IQR[d]	1.80-6.00	1.80-6.30	1.80-6.30	IQR[d]	2.40-9.60	3.00-9.60	3.00-10.50	IQR[d]	4.20-12.60	4.20-13.80	4.20-13.80
Min	0.03	0.03	0.03	Min	0.21	0.21	0.21	Min	0.21	0.45	0.45
Max	52.69	55.68	55.65	Max	56.71	56.71	56.71	Max	110.58	110.58	110.58
Rural (197)											
<15	75.68%	75.68%	76.10%	<15	60.42%	57.46%	58.47%	<15	51.21%	52.26%	47.12%
15-< 30	14.15%	13.99%	13.57%	15-< 30	13.60%	15.22%	13.04%	15-< 30	10.27%	10.27%	15.20%
30-< 45	4.78%	4.14%	4.14%	30-< 45	7.39%	6.37%	9.76%	30-< 45	5.36%	5.36%	6.25%
45-< 60	2.65%	3.51%	3.51%	45-< 60	7.83%	11.32%	5.85%	45-< 60	10.16%	9.12%	10.69%
60-< 75	2.74%	2.67%	2.67%	60-< 75	2.74%	4.12%	4.29%	60-< 75	5.26%	5.67%	3.67%
75-< 100	0.00%	0.00%	0.00%	75-< 100	4.44%	2.78%	4.38%	75-< 100	6.65%	7.81%	6.18%
100+	0.00%	0.00%	0.00%	100+	3.57%	2.72%	4.21%	100+	11.09%	9.50%	10.88%
Mean	10.87	11.08	11.13	Mean	23.36	23.33	24.65	Mean	37.28	34.91	36.35
Median	4.35	4.35	4.41	Median	9.72	10.35	9.72	Median	14.32	12.73	17.25
IQR[d]	1.80-16.50	2.10-16.80	2.10-17.10	IQR[d]	5.10-31.50	4.80-32.70	5.40-33.30	IQR[d]	5.70-48.00	5.70-46.80	6.30-48.30
Min	0.03	0.03	0.03	Min	0.32	0.32	0.43	Min	0.32	0.76	0.76
Max	74.85	73.50	73.85	Max	199.75	193.51	161.30	Max	252.73	215.30	214.04

[a]Screening services include Pap smear and/or HPV testing; [b]Diagnostic service is colposcopy; [c]Excisional treatment services includes cone and loop electrosurgical excision procedure; [d]IQR indicates Interquartile Range (Q1-Q3)

Note: Census tracts weighted based upon screen eligible population.

Appendix C. Operationalized socioeconomic, acculturation, race/ethnicity, and geography variables at the census-tract level.

Explanatory Variables	Data Source	ACS[a] or DC[b] Table	Numerator	Denominator	Supporting Literature
Socioeconomic Status (SES)					
Percent living below the federal poverty level	ACS (2010 -2014)[a]	B17001	Income in the past 12 months below the poverty level for females 18 yrs. of age & over	Female population 18 yrs. of age & over below the poverty level + Female population 18 yrs. of age & over at & above the poverty level	Boscoe, F., et al., (2014); Krieger, N., et al. (2003)
Percent without health insurance	ACS (2010 -2014)[a]	B27001	Female population 18 yrs. of age no health insurance coverage	Female population 18 yrs. of age & over	Cowburn, S., et al., (2013); Hiatt, R.A., et al., (2001)
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)	ACS (2010 -2014)[a]	Table S1501	Female Population 18 -24 yrs. of age less than high school + Female population 25 yrs. of age & over less than 9th grade + Female population 25 yrs. of age & over 9th to 12th grade & no diploma	Female population 18 -24 yrs. of age + Female population 25 yrs. of age & over	Hiatt, R.A., et al., (2001); Krieger, N., et al. (2003)
Medium Educational Attainment (Percent HS graduate or equivalent, some college, or associate degree)	ACS (2010 -2014)[a]	Table S1501	Female Population 18 -24 yrs. of age high school graduate or equivalent + Female Population 18-24 yrs. of age some college or associate degree + Female population 25 yrs. of age & over high school graduate or equivalent + Female population 25 yrs. of age & over some college, no degree + Female population 25 yrs. of age & over Associate's degree	Female population 18 -24 yrs. of age + Female population 25 yrs. of age & over	Modified definition used by Coughlin, S.S., et al., (2008) & Williams, D.R., et al., (2012) to create a middle category reflective of an individual who has graduated from HS but does not have a bachelor's degree)
High Educational Attainment (Percent Bachelor's degree or higher)	ACS (2010 -2014)[a]	Table S1501	Female Population 18 -24 yrs. of age Bachelor's degree or higher + Female population 25 yrs. of age & over Bachelor's degree + Female population 25 yrs. of age & over graduate or professional degree	Female population 18 -24 yrs. of age + Female population 25 yrs. of age & over	Modified definition used by Coughlin, S.S., et al., (2008); Hiatt, R.A., et al., (2001) by adding graduate or professional degree
Percent Married	ACS (2010 -2014)[a]	S1201	Female population 20 yrs. of age & over now married	Female population 20 yrs. of age & over	Coughlin, S.S., et al., (2008); Kamineni, A., et al., (2013)
Percent Never Married	ACS (2010 -2014)[a]	S1201	Female population 20 yrs. of age & over never married	Female population 20 yrs. of age & over	Coughlin, S.S., et al., (2008); Kamineni, A., et al., (2013)
Percent Separated, Divorced, or Widowed	ACS (2010 -2014)[a]	S1201	Female population 20 yrs. of age & over separated + Female population 20 yrs. of age & over divorced + Female population 20 yrs. of age & over widowed	Female population 20 yrs. of age & over	Kamineni, A., et al., (2013)
Percent no vehicle available for household members	ACS (2010 -2014)[a]	B08201	No vehicle available in the household	Total households	Coughlin, S.S. & J. King, (2010); Scarinci, I.C., et al., (2010) provided qualitiative evidence to support transportation as a barrier to access
Percent Female-headed household	US 2010 Decennial Census[b]	P19	Female householder, no husband & present	Total family households (2 or more person households)	Collins, T.W., et al., (2011); Messer, L.C., et al., (2006)

Appendix C. Continued.

Explanatory Variables	Data Source	ACS[a] or DC[b] Table	Numerator	Denominator	Supporting Literature
Acculturation					
Percent foreign born	ACS (2010 -2014)[a]	B05001	Total population U.S. citizen by naturalization + Total population Not a U.S. citizen	Total population	Hiatt, R.A., et al., (2001); Seeff, L.C. & M.T. McKenna, (2003)
Percent foreign born & U.S. Citizen	ACS (2010 -2014)[a]	B05001	Total population U.S. citizen by naturalization	Total population U.S. citizen by naturalization + Total population Not a U.S. citizen	This variable not used but could be derived from Collins, T.W., et al., (2011)
Percent speak Spanish but speak English not very well	ACS (2010 -2014)[a]	B16001	Total population 5 yrs. of age & over speak Spanish & speak English less than very well	Total population 5 yrs. of age & over	Collins, T.W., et al., (2011) the variable was Speak Spanish, speak English not very well or not at all;
Race/Ethnicity					
Percent American Indian	US 2010 Decennial Census[b]	P12C	Female Native American population 20 yrs. of age & over	Female population 20 yrs. of age & over	Chao, A., et al., (1996); Coughlin, S.S., et al., (2008)
Percent Hispanic	US 2010 Decennial Census[b]	P12H	Female Hispanic population 20 yrs. of age & over	Female population 20 yrs. of age & over	Becker, T.M., et al., (1994); Eggleston, K.S., et al., (2006)
Percent White Non-Hispanic	US 2010 Decennial Census[b]	P12I	FemaleWhite Non-Hispanic population 20 yrs. of age & over	Female population 20 yrs. of age & over	Becker, T.M., et al., (1994); Eggleston, K.S., et al., (2006)
Geography					
Travel Time to cervical cancer screening healthcare facility (in minutes)	Computed Measure[c]		Categorical variable <15, 15-29, & ≥30 minutes travel time		Alford-Teaster, J., et al., (2016) travel time to mammography facility; McDonald, Y.J., et al., (2016)
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)	Computed Measure[c]		Categorical variable <15, 15-29, & ≥30 minutes travel time		Henry, K.A., et al., (2011) travel time to breast cancer diagnosis facility; McDonald, Y.J., et al., (2016)
Travel Time to cervical cancer treatment healthcare facility (in minutes)	Computed Measure[c]		Categorical variable <15, 15-29, & ≥30 minutes travel time		Guidry, J.J., et al., (1997); McDonald, Y.J., et al., (2016)
Residence Type	ORPH[d]		Dichotomous variable (0 = non-rural, 1 = rural)		Coughlin, S.S., et al., (2008) used the 2003 Rural/Urban Continuum codes;Eggleston, K.S., et al., (2006) used the U.S. Census 2000 definition of rural

[a]American Community Survey (2010 -2014), [b]U.S. 2010 Decennial Census, [c]Based on travel time from population weighted centroid to nearest specified invasive cervical cancer preventive healthcare facility, & [d]Office of Rural Health Policy

Appendix D. Socioeconomic status, acculturation race/ethnicity, and geography characteristics of census-tract level population invasive cervical cancer cases (2006 -2014) and controls (2000-2014), New Mexico.

		Population-level[§]		**Cases (*n* = 679)**		**Controls (*n* = 2,037)**		**OR**	**95% CI**
Socioeconomic Status (SES)	Category	*N*	%	*N*	%	*N*	%		
Percent living below the federal poverty level[a]	<20	284	57.03	365	53.76	1275	62.59	1.0000 (Ref)	
	≥20	214	42.97	314	46.24	762	37.41	1.4298***	(1.2012, 1.7018)
	Fisher's Exact test (two-tailed) = .001								
Percent without health insurance[a]	<11.11	111	22.29	94	13.84	509	24.98	1.0000 (Ref)	
	11.12-16.82	104	20.88	156	22.97	510	25.04	1.6468**	(1.2414, 2.1844)
	16.83-24.15	131	26.31	207	30.49	510	25.04	2.1626***	(1.6491, 2.8359)
	≥24.16	152	30.52	222	32.70	508	24.94	2.3414***	(1.7860, 3.0695)
	$\chi^{2e} < .001$								
Low Educational Attainment (Percent non-high school (HS) graduate or equivalent)[a]	<6.33	106	21.29	98	14.43	520	25.53	1.0000 (Ref)	
	6.34-12.17	112	22.49	146	21.50	505	24.79	1.5341**	(1.1554, 2.0370)
	12.18-20.97	131	26.31	193	28.42	503	24.69	2.0309***	(1.5453, 2.6693)
	≥20.98	149	29.91	242	35.65	509	24.99	2.5075***	(1.9226, 3.2704)
	$\chi^{2e} < .001$								
Medium Educational Attainment (Percent HS graduate or equivalent, some college, or Associate's degree)[a]	<52.42	106	21.28	121	17.82	516	25.33	1.0000 (Ref)	
	52.43-60.53	122	24.50	187	27.54	511	25.09	1.5584**	(1.2024, 2.0197)
	60.54-66.69	122	24.50	189	27.84	504	24.74	1.5991***	(1.2329, 2.0741)
	≥66.70	148	29.72	182	26.80	506	24.84	1.5255**	(1.1774, 1.9766)
	$\chi^{2e} = .001$								
High Educational Attainment (Percent Bachelor's degree or higher)[a]	<14.60	174	34.94	244	35.94	509	24.98	1.0000 (Ref)	
	14.61-23.58	120	24.10	197	29.01	512	25.14	0.8001	(0.6394, 1.0013)
	23.59-35.77	102	20.48	135	19.88	507	24.89	0.5586***	(0.4372, 0.7136)
	≥35.78	102	20.48	103	15.17	509	24.99	0.4219***	(0.3244, 0.5487)
	$\chi^{2e} < .001$								

Appendix D. Continued.

		Population-level[§]		Cases (*n* = 679)		Controls (*n* = 2,037)		OR	95% CI
	Category	*N*	%	*N*	%	*N*	%		
Percent Married[a]	<40.43	147	29.52	185	27.25	511	25.09	1.0000 (Ref)	
	40.44-49.32	130	26.10	196	28.87	511	25.09	1.0492	(0.8266, 1.3318)
	49.33-57.27	99	19.88	159	23.42	506	24.84	0.8654	(0.6746, 1.1100)
	≥57.28	122	24.50	139	20.46	509	24.98	0.7523*	(0.5829, .09709)
	χ^{2e} = .037								
Percent Never Married[a]	<16.36	127	25.50	144	21.21	510	24.99	1.0000 (Ref)	
	16.37-22.18	112	22.49	167	24.59	509	25.04	1.1541	(0.8930, 1.4915)
	22.19-28.17	110	22.09	163	24.01	515	24.98	1.1248	(0.8719, 1.4510)
	≥28.17	149	29.92	205	30.19	503	24.99	1.4575**	(1.1360, 1.8699)
	χ^{2e} = .025								
Percent Separated, Divorced, or Widowed[a]	<22.42	129	25.90	158	23.27	509	23.52	1.0000 (Ref)	
	22.43-27.40	120	24.10	173	25.48	510	26.51	1.0949	(0.8535, 1.4047)
	27.41-32.05	110	22.09	164	24.15	509	27.93	1.0392	(0.8098, 1.3337)
	≥32.06	139	27.91	184	27.10	509	22.04	1.1676	(0.9117, 1.4955)
	χ^{2e} = .640								
Percent no vehicle available for household members[a]	<1.93	121	24.30	132	19.44	511	25.08	1.0000 (Ref)	
	1.94-4.27	115	23.09	165	24.30	508	24.94	1.2618	(0.9721, 1.6378)
	4.28-7.35	108	21.69	186	27.39	510	25.04	1.4113**	(1.0928, 1.8230)
	≥7.36	154	30.92	196	28.87	508	24.94	1.4966**	(1.1606, 1.9300)
	χ^{2e} = .011								
Percent Female-headed household[b]	<15.25	123	24.70	105	15.46	510	25.03	1.0000 (Ref)	
	15.26-20.70	105	21.08	185	27.25	512	25.14	1.7484***	(1.3338, 2.2920)
	20.71-26.04	116	23.29	186	27.39	506	24.84	1.7738***	(1.3557, 2.3208)
	≥26.05	154	30.93	203	29.90	509	24.99	1.9300***	(1.4790, 2.5186)
	χ^{2e} < .001								

Appendix D. Continued.

Acculturation	Category	**Population-level[§]** *N*	%	**Cases (*n* = 679)** *N*	%	**Controls (*n* = 2,037)** *N*	%	**OR**	**95% CI**
Percent foreign born[a]	<4.59	155	31.12	176	25.92	514	25.23	1.0000 (Ref)	
	4.60-7.30	109	21.89	160	23.56	505	24.79	0.9291	(0.7267, 1.1877)
	7.31-13.58	116	23.29	131	19.29	512	25.14	0.7427*	(0.5723, 0.9637)
	≥13.59	118	23.70	212	31.23	506	24.84	1.2212	(0.9651, 1.5452)
	χ^{2e} < .001								
Percent foreign born & U.S. Citizen[a,1 & 2]	<26.67	138	27.71	191	28.13	509	24.98	1.0000 (Ref)	
	25.68-39.62	107	21.49	175	25.77	510	25.04	0.9204	(0.7263, 1.1664)
	39.63-60.40	130	26.10	193	28.42	512	25.14	1.0125	(0.8009, 1.2799)
	≥60.41	123	24.70	120	17.68	506	24.84	0.634**	(0.4897, 0.8207)
	χ^{2e} = .001								
Percent speak Spanish but speak English not very well[a]	<2.09	135	27.11	134	19.73	513	25.18	1.0000 (Ref)	
	2.10-4.72	118	23.69	141	20.77	507	24.89	1.0794	(0.8257, 1.4110)
	4.73-10.37	121	24.30	189	27.84	508	24.94	1.4375**	(1.1109, 1.8601)
	≥10.38	124	24.90	215	31.66	509	24.99	1.6270***	(1.2659, 2.0911)
	χ^{2e} < .001								

Appendix D. Continued.

		Population-level[§]		Cases (*n* = 679)		Controls (*n* = 2,037)		OR	95% CI
	Category	*N*	%	*N*	%	*N*	%		
Race/Ethnicity									
Percent American Indianb	<1.33	126	25.30	538	79.23	515	25.28	1.0000 (Ref)	
	1.34-2.21	118	23.69	65	9.57	505	24.79	0.9041	(0.7059, 1.1578)
	2.22-4.12	110	22.09	24	3.53	512	25.14	1.0072	(0.7906, 1.2832)
	≥4.13	144	28.92	52	7.66	505	24.79	0.9929	(0.7763, 1.2699)
	$\chi^{2e} = .819$								
Percent Hispanicb	<24.86	145	29.12	134	19.73	509	24.99	1.0000 (Ref)	
	24.87-38.03	107	21.49	142	20.91	515	25.28	1.0474	(0.8015, 1.3688)
	38.04-58.45	128	25.70	191	28.13	505	24.79	1.4427**	(1.1167, 1.8638)
	≥58.46	118	23.69	212	31.23	508	24.94	1.5919***	(1.2392, 2.0448)
	$\chi^{2e} < .001$								
Percent non-Hispanic Whiteb	<33.69	142	28.51	229	33.73	514	25.23	1.0000 (Ref)	
	33.70-50.29	124	24.90	187	27.54	506	24.84	0.8331	(0.6618, 1.0486)
	50.30-65.10	109	21.89	132	19.44	512	25.14	0.5695***	(0.4434, 0.7315)
	≥65.11	123	24.70	131	19.29	505	24.79	0.5805***	(0.4534, 0.7434)
	$\chi^{2e} < .001$								

Appendix D. Continued.

		Population-level[§]		Cases (*n* = 679)		Controls (*n* = 2,037)		OR	95% CI
	Category	*N*	%	*N*	%	*N*	%		
Geography									
Travel Time to cervical cancer screening healthcare facility (in minutes)[c]	<15	415	83.33	561	82.62	1770	86.89	1.0000 (Ref)	
	15-29	54	10.84	67	9.87	188	9.23	1.1218	(0.8375, 1.5025)
	≥30	29	5.82	51	7.51	79	3.88	1.9923***	(1.3918, 2.8519)
	$\chi^{2e} < .001$								
Travel Time to cervical cancer diagnostic healthcare facility (in minutes)[c]	<15	357	71.69	477	70.25	1550	76.09	1.0000 (Ref)	
	15-29	71	14.26	99	14.58	293	14.38	1.1000	(0.8586, 1.4093)
	≥30	70	14.06	103	15.17	194	9.52	1.7002***	(1.3152, 2.1979)
	$\chi^{2e} < .001$								
Travel Time to cervical cancer treatment healthcare facility (in minutes)[c]	<15	308	61.85	414	60.97	1364	66.96	1.0000 (Ref)	
	15-29	80	16.06	108	15.91	354	17.38	0.9986	(0.7840, 1.2720)
	≥30	110	22.09	157	23.12	319	15.66	1.6095***	(1.6095, 1.2928)
	$\chi^{2e} < .001$								
Residence Type[d]	Non-Rural	301	60.44	400	58.91	1401	68.78	1.0000 (Ref)	
	Rural	198	39.56	279	41.09	636	31.22	1.5435***	(1.2883, 1.8492)
	Fisher's Exact test (two-tailed) = .001								

[a]American Community Survey (2010 -2014), [b]US 2010 Decennial Census, [c]Based on travel time from population weighted centroid to the nearest specified invasive cervical cancer cervical cancer preventive healthcare facility, and [d]Office of Rural Health Policy

[§] Population-level data derived from New Mexico census tracts (*N* = 498), [e]Pearson Chi-Square crosstab result, *$P < .050$, two-tailed, ** $P < .010$, two-tailed, *** $P < .001$, two-tailed

Appendix E. Pearson's product-moment correlation coefficient.

	No_Ins	L_EDU	M_EDU	H_EDU	MAR	NMAR	SDW	NOCAR	FHH	FB	FB_US	SP_ENW	AI_W	H_W	NHW_W	TT_Scr	TT_Diag	TT_Trt	RUCA	ICC
Living Below Poverty	.683**	.662**	.193**	-.595**	-.490**	.539**	.087**	.551**	.648**	.457**	-.471**	.578**	.227**	.480**	-.631**	.128**	.121**	.185**	.147**	.085**
W/out Health Insurance (No_Ins)		.739**	.174**	-.638**	-.313**	.446**	-.071**	.319**	.507**	.539**	-.507**	.626**	.410**	.396**	-.660**	.203**	.180**	.184**	.183**	.127**
Low Education (L_EDU)			.047*	-.734**	-.192**	.252**	-.016	.242**	.429**	.652**	-.481**	.789**	.136**	.628**	-.695**	.112**	.136**	.201**	.237**	.129**
Medium Education (M_EDU)				-.713**	-.172**	.130**	.106**	.101**	.263**	-.179**	-.194**	-.042*	.190**	.109**	-.244**	.043*	.114**	.160**	.233**	.064**
High Education (H_EDU)					.252**	-.265**	-.060**	-.239**	-.480**	-.336**	.470**	-.525**	-.225**	-.515**	.654**	-.108**	-.173**	-.250**	-.325**	-.134**
Married (MAR)						-.766**	-.595**	-.640**	-.770**	-.047*	.293**	-.116**	-.244**	-.232**	.414**	.180**	.180**	.181**	.067**	-.053**
Never Married (NMAR)							-.060**	.519**	.730**	.155**	-.343**	.187**	.412**	.234**	-.545**	-.054**	-.124**	-.148**	-.136**	.047*
Separated, Divorced, Widowed (SDW)								.347**	.283**	-.121**	-.027	-.055**	-.135**	.068**	.038*	-.212**	-.124**	-.096**	.066**	.024
No Vehicle (NOCAR)									.604**	.086**	-.233**	.097**	.255**	.060**	-.259**	-.086**	-.072**	-.050**	.075**	.043*
Female-headed Household (FHH)										.251**	-.379**	.324**	.318**	.433**	-.679**	-.166**	-.191**	-.179**	-.046*	.092**
Foreign Born (FB)											-.425**	.887**	-.232**	.628**	-.470**	.038*	-.025	-.016	-.137**	.033
Foreign Born, U.S. Citizen (FB_US)												-.509**	-.072**	-.434**	.476**	-.039*	-.058**	-.089**	-.148**	-.074**
Speaks Spanish, English not well (SP_ENW)													-.183**	.768**	-.617**	.113**	.089**	.154**	.015	.070**
American Indian Women (AI_W)														-.325**	-.359**	.209**	.138**	.096**	.168**	.048*
Hispanic Women (H_W)															-.756**	.006	.028	.100**	-.088**	.084**
Non-Hispanic White Women (NHW_W)																-.118**	-.084**	-.121**	-.005	-.108**
Travel Time Screenig (TT_Scr)																	.767**	.667**	.237**	.076**
Travel Time Diagnosis (TT_Diag)																		.857**	.374**	.081**
Travel Time Treatment (TT_Trt)																			.385**	.086**
RUCA																				.090**

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

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

Appendix F. Spearman's rank order correlation coefficient.

	No_Ins	L_EDU	M_EDU	H_EDU	MAR	NMAR	SDW	NOCAR	FHH	FB	FB_US	SP_ENW	AI_W	H_W	NHW_W	TT_Scr	TT_Diag	TT_Trt	RUCA	ICC
Living Below Poverty	.688**	.687**	.172**	-.640**	-.501**	.502**	.162**	.558**	.643**	.349**	-.493**	.574**	.146**	.515**	-.649**	-.021	.054**	.111**	.167**	.092**
W/out Health Insurance (No_Ins)		.735**	.166**	-.678**	-.338**	.421**	.005	.356**	.518**	.412**	-.561**	.588**	.170**	.443**	-.632**	.107**	.176**	.177**	.196**	.133**
Low Education (L_EDU)			.097**	-.803**	-.234**	.283**	.042*	.319**	.459**	.456**	-.522**	.740**	.019	.609**	-.703**	.138**	.220**	.278**	.285**	.139**
Medium Education (M_EDU)			1.000	-.592**	-.157**	.086**	.157**	.107**	.218**	-.218**	-.166**	-.002	.284**	.068**	-.184**	-.005	.073**	.144**	.239**	.057**
High Education (H_EDU)				1.000	.251**	-.262**	-.074**	-.277**	-.468**	-.284**	.486**	-.559**	-.138**	-.496**	.649**	-.099**	-.218**	-.293**	-.330**	-.134**
Married (MAR)						-.778**	-.563**	-.616**	-.782**	-.087**	.263**	-.209**	-.441**	-.252**	.434**	.389**	.367**	.362**	.069**	-.054**
Never Married (NMAR)							.000	.435**	.728**	.195**	-.324**	.251**	.519**	.310**	-.568**	-.242**	-.264**	-.256**	-.168**	.046*
Separated, Divorced, Widowed (SDW)								.374**	.316**	-.081**	-.027	.101**	.033	.127**	-.008	-.314**	-.241**	-.240**	.086**	.028
No Vehicle (NOCAR)									.576**	.089**	-.241**	.209**	.216**	.139**	-.286**	-.267**	-.180**	-.166**	.156**	.054**
Female-headed Household (FHH)										.271**	-.352**	.398**	.436**	.482**	-.686**	-.396**	-.342**	-.323**	-.063**	.091**
Foreign Born (FB)											-.425**	.713**	-.184**	.551**	-.393**	-.101**	-.103**	-.120**	-.178**	.016
Foreign Born, U.S. Citizen (FB_US)												-.569**	-.107**	-.429**	.476**	-.052**	-.063**	-.087**	-.153**	-.065**
Speaks Spanish, English not well (SP_ENW)													-.139**	.806**	-.641**	.021	.067**	.134**	.076**	.081**
American Indian Women (AI_W)														-.061**	-.290**	-.118**	-.199**	-.213**	-.220**	.000
Hispanic Women (H_W)															-.787**	-.016	.015	.102**	-.078**	.087**
Non-Hispanic White Women (NHW_W)																-.077**	-.078**	-.141**	.007	-.105**
Travel Time Screenig (TT_Scr)																	.804**	.716**	.229**	.032
Travel Time Diagnosis (TT_Diag)																		.810**	.364**	.058**
Travel Time Treatment (TT_Trt)																			.321**	.069**
RUCA																				.090**

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

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

APPENDIX G

Appendix G. Interaction matrix of 3rd and 2nd order cross product terms to construct interaction terms.

3rd order Interactions			2nd order Interactions		2nd order Interactions		2nd order Interactions	
POV_Pers	No_Ins	AI_W	POV_Pers	AI_W	No_Ins	AI_W	POV_Pers	No_Ins
POV_Pers	No_Ins	H_W	POV_Pers	H_W	No_Ins	H_W		
POV_Pers	No_Ins	NHW_W	POV_Pers	NHW_W	No_Ins	NHW_W		
No_Ins	AI_W	FHH	FHH	AI_W	FHH	No_Ins		
No_Ins	H_W	FHH	FHH	H_W				
No_Ins	NHW_W	FHH	FHH	NHW_W				
POV_Pers	AI_W	FHH	FHH	POV_Pers				
POV_Pers	H_W	FHH						
POV_Pers	NHW_W	FHH						
TT_Scr	AI_W	No_Ins	TT_Scr	AI_W	TT_Scr	No_Ins		
TT_Scr	H_W	No_Ins	TT_Scr	H_W				
TT_Scr	NHW_W	No_Ins	TT_Scr	NHW_W				
TT_Scr	AI_W	POV_Pers			TT_Scr	POV_Pers		
TT_Scr	H_W	POV_Pers						
TT_Scr	NHW_W	POV_Pers						
TT_Diag	AI_W	No_Ins	TT_Diag	AI_W	TT_Diag	No_Ins		
TT_Diag	H_W	No_Ins	TT_Diag	H_W				
TT_Diag	NHW_W	No_Ins	TT_Diag	NHW_W				
TT_Diag	AI_W	POV_Pers					TT_Diag	POV_Pers
TT_Diag	H_W	POV_Pers						
TT_Diag	NHW_W	POV_Pers						
TT_Trt	AI_W	No_Ins	TT_Trt	AI_W	TT_Trt	No_Ins		
TT_Trt	H_W	No_Ins	TT_Trt	H_W				
TT_Trt	NHW_W	No_Ins	TT_Trt	NHW_W				
TT_Trt	AI_W	POV_Pers					TT_Trt	POV_Pers
TT_Trt	H_W	POV_Pers						
TT_Trt	NHW_W	POV_Pers						
RUCA	AI_W	No_Ins	RUCA	AI_W	RUCA	No_Ins		
RUCA	H_W	No_Ins	RUCA	H_W				
RUCA	NHW_W	No_Ins	RUCA	NHW_W				
RUCA	AI_W	POV_Pers					RUCA	POV_Pers
RUCA	H_W	POV_Pers						
RUCA	NHW_W	POV_Pers						

Appendix G. Continued.

3rd order Interactions			2nd order Interactions		2nd order Interactions		2nd order Interactions	
TT_Scr	FHH	No_Ins	TT_Scr	FHH				
TT_Scr	FHH	POV_Pers						
TT_Scr	FHH	AI_W						
TT_Scr	FHH	H_W						
TT_Scr	FHH	NHW_W						
TT_Diag	FHH	No_Ins	TT_Diag	FHH				
TT_Diag	FHH	POV_Pers						
TT_Diag	FHH	AI_W						
TT_Diag	FHH	H_W						
TT_Diag	FHH	NHW_W						
TT_Trt	FHH	No_Ins	TT_Trt	FHH				
TT_Trt	FHH	POV_Pers						
TT_Trt	FHH	AI_W						
TT_Trt	FHH	H_W						
TT_Trt	FHH	NHW_W						
RUCA	FHH	No_Ins	RUCA	FHH				
RUCA	FHH	POV_Pers						
RUCA	FHH	AI_W						
RUCA	FHH	H_W						
RUCA	FHH	NHW_W						
L_EDU	FHH	No_Ins	L_EDU	FHH				
L_EDU	FHH	POV_Pers						
L_EDU	FHH	AI_W						
L_EDU	FHH	H_W						
L_EDU	FHH	NHW_W						
L_EDU	TT_Scr	No_Ins	L_EDU	TT_Scr	L_EDU	No_Ins	L_EDU	AI_W
L_EDU	TT_Scr	POV_Pers			L_EDU	POV_Pers	L_EDU	H_W
L_EDU	TT_Scr	AI_W					L_EDU	NHW_W
L_EDU	TT_Scr	H_W						
L_EDU	TT_Scr	NHW_W						
L_EDU	TT_Diag	No_Ins	L_EDU	TT_Diag				
L_EDU	TT_Diag	POV_Pers						
L_EDU	TT_Diag	AI_W						
L_EDU	TT_Diag	H_W						
L_EDU	TT_Diag	NHW_W						

Appendix G. Continued.

3rd order Interactions			2nd order Interactions		2nd order Interactions		2nd order Interactions	
L_EDU	TT_Trt	No_Ins	L_EDU	TT_Trt				
L_EDU	TT_Trt	POV_Pers						
L_EDU	TT_Trt	AI_W						
L_EDU	TT_Trt	H_W						
L_EDU	TT_Trt	NHW_W						
L_EDU	RUCA	No_Ins	L_EDU	RUCA				
L_EDU	RUCA	POV_Pers						
L_EDU	RUCA	AI_W						
L_EDU	RUCA	H_W						
L_EDU	RUCA	NHW_W						
H_EDU	FHH	No_Ins	H_EDU	FHH				
H_EDU	FHH	POV_Pers						
H_EDU	FHH	AI_W						
H_EDU	FHH	H_W						
H_EDU	FHH	NHW_W						
H_EDU	TT_Scr	No_Ins	H_EDU	TT_Scr	H_EDU	No_Ins	H_EDU	AI_W
H_EDU	TT_Scr	POV_Pers			H_EDU	POV_Pers	H_EDU	H_W
H_EDU	TT_Scr	AI_W					H_EDU	NHW_W
H_EDU	TT_Scr	H_W						
H_EDU	TT_Scr	NHW_W						
H_EDU	TT_Diag	No_Ins	H_EDU	TT_Diag				
H_EDU	TT_Diag	POV_Pers						
H_EDU	TT_Diag	AI_W						
H_EDU	TT_Diag	H_W						
H_EDU	TT_Diag	NHW_W						
H_EDU	TT_Trt	No_Ins	H_EDU	TT_Trt				
H_EDU	TT_Trt	POV_Pers						
H_EDU	TT_Trt	AI_W						
H_EDU	TT_Trt	H_W						
H_EDU	TT_Trt	NHW_W						
H_EDU	RUCA	No_Ins	H_EDU	RUCA				
H_EDU	RUCA	POV_Pers						
H_EDU	RUCA	AI_W						
H_EDU	RUCA	H_W						
H_EDU	RUCA	NHW_W						

Appendix G. Continued.

3rd order Interactions			2nd order Interactions		2nd order Interactions		2nd order Interactions	
SP_ENW	TT_Scr	No_Ins	SP_ENW	TT_Scr	SP_ENW	No_Ins	SP_ENW	AI_W
SP_ENW	TT_Scr	POV_Pers			SP_ENW	POV_Pers	SP_ENW	H_W
SP_ENW	TT_Scr	AI_W			SP_ENW	FHH	SP_ENW	NHW_W
SP_ENW	TT_Scr	H_W						
SP_ENW	TT_Scr	NHW_W						
SP_ENW	TT_Diag	No_Ins	SP_ENW	TT_Diag				
SP_ENW	TT_Diag	POV_Pers						
SP_ENW	TT_Diag	AI_W						
SP_ENW	TT_Diag	H_W						
SP_ENW	TT_Diag	NHW_W						
SP_ENW	TT_Trt	No_Ins	SP_ENW	TT_Trt				
SP_ENW	TT_Trt	POV_Pers						
SP_ENW	TT_Trt	AI_W						
SP_ENW	TT_Trt	H_W						
SP_ENW	TT_Trt	NHW_W						
SP_ENW	RUCA	No_Ins	SP_ENW	RUCA				
SP_ENW	RUCA	POV_Pers						
SP_ENW	RUCA	AI_W						
SP_ENW	RUCA	H_W						
SP_ENW	RUCA	NHW_W						
SP_ENW	FHH	No_Ins	SP_ENW	FHH				
SP_ENW	FHH	POV_Pers						
SP_ENW	FHH	TT_Scr						
SP_ENW	FHH	TT_Diag						
SP_ENW	FHH	TT_Trt						
SP_ENW	FHH	RUCA						
MAR	TT_Scr	No_Ins	MAR	TT_Scr	MAR	No_Ins	MAR	AI_W
MAR	TT_Scr	POV_Pers			MAR	POV_Pers	MAR	H_W
MAR	TT_Scr	AI_W					MAR	NHW_W
MAR	TT_Scr	H_W						
MAR	TT_Scr	NHW_W						
MAR	TT_Diag	No_Ins	MAR	TT_Diag				
MAR	TT_Diag	POV_Pers						
MAR	TT_Diag	AI_W						
MAR	TT_Diag	H_W						
MAR	TT_Diag	NHW_W						

Appendix G. Continued.

3rd order Interactions			2nd order Interactions		2nd order Interactions		2nd order Interactions	
MAR	TT_Trt	No_Ins	MAR	TT_Trt				
MAR	TT_Trt	POV_Pers						
MAR	TT_Trt	AI_W						
MAR	TT_Trt	H_W						
MAR	TT_Trt	NHW_W						
MAR	RUCA	No_Ins	MAR	RUCA				
MAR	RUCA	POV_Pers						
MAR	RUCA	AI_W						
MAR	RUCA	H_W						
MAR	RUCA	NHW_W						
NMAR	TT_Scr	No_Ins	MAR	TT_Scr	NMAR	No_Ins	NMAR	AI_W
NMAR	TT_Scr	POV_Pers			NMAR	POV_Pers	NMAR	H_W
NMAR	TT_Scr	AI_W					NMAR	NHW_W
NMAR	TT_Scr	H_W						
NMAR	TT_Scr	NHW_W						
NMAR	TT_Diag	No_Ins	MAR	TT_Diag				
NMAR	TT_Diag	POV_Pers						
NMAR	TT_Diag	AI_W						
NMAR	TT_Diag	H_W						
NMAR	TT_Diag	NHW_W						
NMAR	TT_Trt	No_Ins	MAR	TT_Trt				
NMAR	TT_Trt	POV_Pers						
NMAR	TT_Trt	AI_W						
NMAR	TT_Trt	H_W						
NMAR	TT_Trt	NHW_W						
NMAR	RUCA	No_Ins	MAR	RUCA				
NMAR	RUCA	POV_Pers						
NMAR	RUCA	AI_W						
NMAR	RUCA	H_W						
NMAR	RUCA	NHW_W						

Appendix G. Continued.

3rd order Interactions			2nd order Interactions	2nd order Interactions	2nd order Interactions
NOCAR	FHH	No_Ins			
NOCAR	FHH	POV_Pers			
NOCAR	FHH	L_EDU			
NOCAR	FHH	H_EDU			
NOCAR	RUCA	No_Ins			
NOCAR	RUCA	POV_Pers			
NOCAR	RUCA	L_EDU			
NOCAR	RUCA	H_EDU			

KEY: Living Below Poverty (POV_Pers), W/out Health Insurance (No_Ins), Low Education (L_EDU), Medium Education (M_EDU), High Education (H_EDU), Married (MAR), Never Married (NMAR), Separated, Divorced, Widowed (SDW), No Vehicle (NOCAR), Female-headed Household (FHH), Foreign Born (FB), Foreign Born, U.S. Citizen (FB_US), Speaks Spanish, English not well (SP_ENW), American Indian Women (AI_W), Hispanic Women (H_W), Non-Hispanic White Women (NHW_W), Travel Time Screenig (TT_Scr), Travel Time Diagnosis (TT_Diag), Travel Time Treatment (TT_Trt), & RUCA