REGIONAL IMPACTS OF HEALTH CARE ACCESS AND UTILIZATION ON MIGRATION, EMPLOYMENT, AND HEALTH OUTCOMES

by

ANNE M. MANDICH

(Under the Direction of Jeffrey H. Dorfman)

ABSTRACT

This dissertation looks to examine the association of health access and utilization in terms of migration, employment, as well as health outcomes relating to preventable diseases. This work is outlined in four chapters. First, “Senior Migration: Spatial Considerations of Amenity and Health Access Drivers” begins this work by examining how local health care access plays into senior migration decisions. Next, we measure the ability of hospitals, particularly in rural communities, to attract non-health related employment and provide higher wage jobs to residents based on their education level in “The Impact of Hospitals on Local Labor Markets: Going beyond Input-Output Models”. Then, “Some State Vaccination Laws May Contribute to Greater Exemption Rates and Disease Outbreaks in the US” looks how both state health laws and up-take of Kindergarten Vaccine Exemptions are associated with preventable disease incidence. Finally, in “Who isn’t Vaccinating their Children? Examining the Demographics, Policies, and Shocks to Vaccination Rates in the United States over Time” we conclude with an extension of the first vaccine piece by analyzing both state level vaccine laws as well as the individual level characteristics associated with vaccine decisions.

INDEX WORDS: Migration, Hospitals, Autism, Vaccines, Health

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DEDICATION

To my loving family, friends, and immediate and greater community. This was possible due to the support of many and to whom I am deeply grateful.

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CHAPTER 1

INTRODUCTION

W. Clement Stone said, “You are the product of your environment. So choose the environment that will best develop you toward your objective.” If one’s objective includes having a healthy and successful life, one’s proximity to and utilization of health care plays a dynamic part in that objective. This dissertation looks to examine the association of health access and utilization in terms of migration, employment, and health outcomes relating to preventable diseases. This work is outlined in four chapters as summarized in the following.

Chapter 2 “Senior Migration: Spatial Considerations of Amenity and Health Access Drivers” begins this work by examining how local health care access plays into senior migration decisions. While previous studies have strongly suggested that natural amenities, such as nice weather, are strong pull factors for later-life migrants, it is less obvious if the highest natural amenity county destinations are also those with the quality health care access optimal for this migrant demographic. Utilizing a spatial Bayesian estimation strategy, we explicitly consider numerous drivers of later-life migration to examine the extent to which health access is a driver in location decisions. After controlling for local amenity spillovers, numerous measures of health care access that include hospital expenditures, hospital beds, and number of doctors, all weighted by county population, are positivity associated with later life migration decisions

Chapter 3 “The Impact of Hospitals on Local Labor Markets: Going beyond Input-Output Models” next examines the impact hospitals have on local employment and wages for both urban and rural communities. We measure the ability of hospitals, particularly in rural communities, to attract non-health related employment and provide higher wage jobs to residents based on their education level. Results find hospital employees with an associate’s degree can expect a 21.4%

wage premium, when compared to alternative opportunities, and those with a bachelor's degree can earn 12.2% more working in a hospital. Hospitals are shown to be positively related to overall employment as well as exhibit positive employment spill-over. For rural counties, a short-term general hospital is associated with 599 jobs in the county; 60 of which are hospital based and 499 are non-healthcare related. With the positive benefits on wages and non-healthcare job growth, hospitals have measurable positive labor market outcomes above their primary objective of providing health care access, particularly in rural counties.

Chapter 4 next looks at how both state health laws and utilization of vaccines are associated with preventable disease incidence. While health officials attest that immunizations are among the most successful and cost-effective interventions in public health, there remains an unvaccinated population in the United States. Our work analyzes how state-level vaccination exemption laws are affecting these trends. We measure how each component of states' kindergarten vaccination exemption law affect the state's vaccination exemption take-ups from 2002-2012 using CDC's Annual School Assessment Reports (SARS). We explore which types of laws (out of more than a dozen) increase, and which decrease, exemption rates in the state. Finally, we construct an index ranking state's exemption law effectiveness. We use this ranking to look at the association of preventable disease outbreak based on state's vaccination exemption laws and find statistically significant increases in pertussis incidence in state's with the least effective vaccine exemption policies.

Lastly, chapter 5 extends the work in chapter 4 to both examine state level vaccine laws as well as the individual level characteristics associated with vaccine decisions. Using the National Immunization Survey of 19-35 month old children in the US from 1994-2011, as well as state and annual policy characteristics, we utilize a multinational logit to measure factors contributing to parents' decisions to under or not vaccinate their children. Specifically, we measure the relationship between parent and child demographics and strictness of state vaccination exemption policy on vaccine take up. Similarly, years with more anti-vaccination news coverage (Jenny McCarthy) had a significant decrease in the number of up to date children.

CHAPTER 2

SENIOR MIGRATION: SPATIAL CONSIDERATIONS OF AMENITY AND HEALTH ACCESS DRIVERS

After a lifetime of working and saving, retirement can provide an opportunity for individuals to migrate to places which may have previously been less feasible under the constraints of family rearing and full time employment. For individuals who are in the labor force, employment opportunities will likely be of higher importance in the decision process to relocate rather than the locational attributes of a destination (Détang-Dessendre, Goffette-Nagot, and Piguet, 2008; Storper and Scott, 2009). However, for seniors who are no longer tied to the labor market, locational attributes, such as natural amenities, have been shown to be highly valued by retirees (Haas and Serow, 1993; Reeder, 1998; Duncombe et al., 2003; Gustafson et al., 2005; Oehmke et al., 2007; Rappaport, 2007; Poudyal et al., 2008; Wilmoth, 2010; Sharma, 2012). Natural amenities can be defined as environmental qualities that make an area appealing. Examples include mild winters, interesting landscape features, and lack of summer humidity. Approximately three fourths of U.S. counties that are classified as retirement designations fall into the top quarter of counties in a ranking of natural amenities (McGranahan, 1999).

While seniors may favor beautiful rustic landscapes (Longino and Bradley, 2003), one feasibility constraint for potential retiree migrants may be access to health care services.[1] Even if a migrant is currently in a good health state, statistically there is a higher probability of health complications with age. Not having adequate access to proper medical care could be a matter of life and death. Typically, high quality comprehensive medical centers are in large metropolitan cities that include connections to research universities and large health care networks. The extent

[1] We use the terms retiree migrant, senior migrant, and later-life migrant interchangeably in this paper. While there is not a perfect overlap between the sets, we believe the differences are very small.

to which health access is a positive driver in senior migration decisions is the thrust of this research.

An understanding of both the demand for health care access as well as retirement location decisions is important for policy makers and economic developers. Rural counties have long been second to their urban counterparts in terms of job growth-linked income gains (McGranahan and Beale, 2002). Incomes of retirees are assumed to be invariant to their location. Retirees may be more inclined to relocate to rural counties, since senior migrants are not constrained by local job market opportunities.

Rural counties can benefit from retiree in-migration through population growth, increased family incomes, greater economic diversity, and reduced unemployment rates (Longino and Crown, 1989). In-migrating retirees contribute to the sustainability of local businesses, churches, charities, and other civic activities (Levin, 2006). Many rural communities which do not believe they can attract employment-driven growth instead strive for retiree migration as a driver of economic development (Reeder, 1998; Deller, 1995; Shields et al., 2001; Federick, 1993; Keith and Fawson, 1995; Stallman and Siegel, 1995; Haas and Serow, 1990; Skelley, 2004; Das, Rainey, and Miller, 2009). Additionally, even non-rural policy makers have referred to retired migrants as being ‘‘pure gold” (Serow, 2003). Retirement migration has the ability to boost private spending, broaden the tax base, and improve the local economy’s service sector (Longino and Crown, 1989). This boost to local economies has been noted by politicians such as former Florida Governor Jeb Bush who felt retiree migration was an important economic development strategy and appointed a commission whose task was ‘‘to evaluate Florida’s competitive position in attracting retirees and to recommend ways to make Florida more retiree friendly’’ (Serow, 2003).

Given that some communities are treating retiree migration as an economic development tool, tax breaks may be used as an incentive to draw retiree migrants. Because retirees favor low cost of living areas (Conway and Houtenville, 2001), local officials could potentially attract migrants by decreasing taxes that directly affect retirees out of the labor force such as estate, inheritance, and gift taxes. However, it is unclear the success to which these tax incentives draw in migrants. Conway and Rork (2006) do not find an increase in in-migration for areas with lower relative inheritance taxes while Onder and Schlunk (2009) do find an increase in the inflow of retirees at the state level for states with relatively lower taxes. Given this ambiguity, identifying other non-tax local characteristics that may increase retiree migration is imperative. To draw these retiree migrants, the local government needs to be aware of the specific resources and amenities they have with the potential to attract retirees (Reeder, 1998; Louisiana Retirement Development Center, 2006; Lee and Stewart, 2010).

The goal of this paper is to examine drivers of retiree migration, with an emphasis on access to health services. Using spatial estimation techniques, the roles of local amenities as well as local health care access are explicitly considered in their ability to attract seniors. Due to different tastes and preferences between younger and older retirees, separate models will be estimated for migrants 60-74 and 75+ years of age. Additionally because the migrant relocating to Los Angeles County, CA is likely quite different than one relocating to Daniels County, MT, we also separate the models into rural, urban, and most urban counties.

We hypothesize that health access variables should be positive and significant drivers of migration for all retirees with an even larger importance to the oldest retirees. Simultaneously examining local amenities and access to health services as migration drivers creates an interesting potential contradiction. While rural areas will generally have higher natural amenities such as more green space and rustic appeal, it is the urban areas that typically have access to the most comprehensive medical care. While numerous preceding studies have looked at locational preferences of later-life migrants, to our knowledge none have explicitly considered the role of health access in location decisions utilizing a spatial estimation technique. Thus, considering this aspect of migration is a particular contribution to the literature.

The remainder of this paper is organized as follows. The next section discusses previous literature on this topic. Section III describes the data and sources. Section IV models the migration decision using a Bayesian methodology, with results outlined in Section V. Section VI concludes.

Background

When examining retiree migration, numerous studies have used the lifecycle theory model to explain migration decisions. (Litwak and Longino, 1987; Clark and Hunter, 1992; Walters, 2002; Conway and Houtenville, 2003; Wilmoth, 2010; Lovegreen, Kahana, and Kahana, 2010; Wilmoth, 2010; von Reichert, Cromartie, and Arthur, 2013) This theory projects that as an individual ages, migration decisions will reflect the lifecycle changes one is experiencing. Specially, the elderly can be categorized into having three major lifecycle changes that would drive different types of migration decisions. The first is the retirement/amenity movers. This class tends to be among the 'young old,' pension-rich, married, and in better health. The second class is the moderate/chronic disability movers. These are typically those who are poorer, widowed, older, and in need of informal care giving. This class is also termed a return migrant, as they often return to their state of birth or to the state of their children's residence. The third type of elderly migrants is the major disability movers. These are generally those who are moving to a formal care institution.

Certainly, these three types of movers have vastly different consequences for economic development at the county and state level. Those seeking economic development gains would be interested in attracting the "young" wealthy amenity migrants, and need to correctly market to this specific demographic. Natural amenities have been shown to be a driving factor in destination choices for these younger retirees (Schneider and Green, 1992; Duncombe, Robbins, and Wolf, 2003; Reeder, 1998; Gustafson et al., 2005; Oehmke, Tsukamoto, and Post, 2007; Poudyal, Hughes, and Cordell, 2008) as well as the total population (Rudzitis and Johansen, 1991; Nord and Cromartie, 1997; Beale and Johnson, 1998; Rudzitis, 1999; Deller et al., 2001; Knapp and Graves, 2006). This is especially seen in Poudyal, Hughes, and Cordell, (2008) whose results find that rural and biologically rich counties with substantial land use diversity and water amenities have great potential for attracting retirees. Walters (2000a, 2000b) as well as Sharma (2012) additionally find this is particularly the case among retirees with non-chronic disabilities and ample leisure time, as they can take advantage of climate-related recreational opportunities. Specifically, men aged 65+ not in the labor force are likely to spend 6–8 hours per day on leisure and sports and just under an hour on lawn and garden care (Sharma 2012).

While certain locational characteristics, such as natural amenities, have been extensively examined in previous work, the literature is less precise and lacking consensus when considering local health care access. Studies that have looked at the general relationship between health services and retirement migration typically use vague health indicators (Clark and Hunter, 1992; Knapp and Graves, 1989; Walters, 2002; Conway and Houtenville, 2003; Gale and Heath, 2000). Nonetheless, examples of the mixed findings of migration and health care access include

Carlson, et al, (1998) who find that survey respondents did not state that health care was a main factor in their migration decision as well as Jensen and Deller (2007) which predicts a higher concentration of doctors is associated with less in-migration. In contrast, Dwight (1985), Lee (1989), and Park, et al. (2007) find counties with the best health care services also have the highest increase in elderly population and healthcare access is an important factor in destination choice for prospective migrants. Poudyal, Hughes, and Cordell (2008) show a positive significant effect of hospitals per 1,000 residents on retiree migration. Walters (1994) measures an equal number of studies showing positive and negative or negligent impacts of health care services in attracting later life migrants. Oehmke, Tsukamoto, and Post (2007) states that while locational and natural amenities are vital drivers for those early in their retirement, retirees aged 70+ are more inclined to move to areas with more health service facilities. However, that study only looks at 68 rural counties in Michigan and thus has limited scope for generalizing its results.

These varying results as well as lack of medical access specificity variables provide opportunity for new insight. Seniors don't need access to just any medical services, but rather a particular set of medical services. The probability of suffering from heart disease and heart-related incidents such as stroke and heart attack increases with age, while treatable chronic conditions such as diabetes are also prevalent. We thus will use numerous measures of health services at the county level to capture overall health access as well as access to acute and chronic treatment options through health care expenditures, personnel, and infrastructure variables.

Additionally, the previous literature does not always to adhere to the theory that all retirees, and not just the oldest of the old, should demand access to medical services. Demand for health services by nature can be unpredictable (Arrow, 1963). People who undergo an unexpected calamity such as a stroke can go from a relatively high health state to a low health state very rapidly. The unpredictability of the need to access services suggests that people will demand reasonable access to hospital care not because they use it frequently, but because they realize the importance of such access in the event of a tragic situation. Thus, even if a 65 year old is relatively healthy, she should still demand reasonable access to care in case of an emergency. Also, demand for medical services is positively correlated with wage rates as well as higher levels of education (Grossman, 1972), which are both characteristics typical of the 'young-old' amenity migrants. Further, retirees are eligible for universal coverage under Medicare which gives recipients incentive to spend even when the benefits are far smaller than the costs (Murphey and Topel, 2006). Thus, the previous literature may not have sufficiently examined and explained the specific health access demand of retiree migrants, particularly those 60-74.

Finally, we will be looking at the drivers of later life migration while explicitly considering spatial spillover at the county level. Maza (2008) and Bolender and Kulcsar (2013) stress the importance of controlling for spatial dependencies as well as expanding the role of space to not strictly be confined to the own county, but also to include neighboring county's amenities. In their limited sample of interviews in counties with particularly large retirement migration rates, Bolender and Kulcsar find cases where migrants value healthcare, but are willing to drive across the county border, up to 30 minutes away, to reach the nearest hospital. One would expect the presence of a hospital, or any particularly attractive amenity, in a nearby county to have positive spillover effects to its neighbors, particularly in rural areas where a hospital's coverage area can cover numerous counties. Thus our motivation for using spatial models is purely to capture locational spill-over effects, not to identify any independent variables. We do not require strong functional form assumptions nor are we using spatial models for identification of independent variables as cautioned against in numerous studies

(Millian,2010; Pinske and Slade, 2010; and Gibbons and Overman, 2012). By including numerous health access measurements as well as accounting for changing migration preferences with age in a spatial framework, this work hopes to further extend this growing literature.

Data

The Census 2000 Migration Data DVD, obtained from the Population Division of the U.S. Census Bureau, contains the migration flow data used in this study. This dataset is based upon the 2000 Census long-form which asks each respondent if his/her current county of residence in 2000 is different than his/her county of residence in 1995. This therefore excludes all moves within the same county and helps to minimize the count of temporary moves, given the 5 year time window. This study uses a cross-sectional framework due to the challenges of examining later life migration over time as outlined in Conway and Rork (2010, 2014). Because interstate migration is a relativity rare event and changes in health care infrastructure are even rarer, detecting changes over time would be difficult. Additionally, because the Census long form was discontinued in favor of the American Community Survey, which has a smaller sample size and only measures 1 year migration decisions, the comparability and traction is also a challenge for recent years.

For the 2000 Census migration data, a limited selection of migrant characteristics are available that include age. This allows for exclusive examination of county level in-migration of migrants aged 60+. County level data was chosen since many of the desired independent variables are reported at the county level. Similarly, counties are a suitable level of geographical specificity when considering locational amenities since there can be high variability within a narrow geographical space.

Because we want to measure the extent to which migrants are choosing to move to areas with access to health services, in-migration is our chosen dependent variable. If we were to use an alternative measure of migration such as net-migration, we would not be measuring how many migrants can be attributed to local health access. Haas and Serow (1993) show that pull factors are more important than push factors in the migration process, thus in-migration measures the extent to which hospitals "pull" in migrants all else being equal. Further, net migration hides the true size of the flows in both directions, since a large in-migration may be partially or mostly offset by out-migration. Two counties with identical net migration could have in- and out-migration of very different magnitudes.

The data for the independent variables come from numerous sources. For county level natural resource variables, the USDA's data components for their natural amenity index are utilized which include: January mean temperature, January sunlight, July mean temperature, July humidity, topography code, and percent water cover. A set of recreational activity variables, such as number of golf courses and restaurants, was obtained from the County Business Patterns (CBP). The CBP is an annual series collected by the Census that provides county level business data such as number of establishments and employment counts classified by SIC industry code. Finally, health variables were obtained from the Area Resource File, which is a collection of data from over 50 sources such as the American Hospital Association, Bureau of Labor Statistics, and National Center for Health Statistics. The ARF is maintained by the U.S. Department of Health and Human Services and contains many county health and population characteristics.

Because the migration data is looking at migrants in 2000, all independent health and county characteristic variables are either for 1995 or 1990. If we were to use 2000 variables, we could create an endogeneity issue since it would be difficult to tell if the migration was determining county characteristics or the reverse. By using the lagged variables, the assumption is that it was this level of county amenities that induced a migrant to relocate to the respective location.

Separate models are estimated for the in-migration of those 60-74 and 75+ years old for rural, urban, and most urban counties. County population divisions we based upon the USDA's Urban Rual Continum Code. Counties in a metro area with 1 million or more residents are labeled "most urban", those which have less than 1 million residents but are still in a metro area are "urban", while all other counties are considered "rural". The dependent variable is log in-migration at the county level. The log of in-migration is chosen since when plotting the untransformed data there is a heavy tail due to many migrants moving to a few particularly large counties.

The independent variables are site characteristics that would influence retiree location decisions that include economic characteristics, natural and recreational amenities, and access to health services. The final variables used in estimation are listed in Table 2.1 and are generally self-explanatory with only a few needing further elaboration. The economic variables were chosen based on those previously used in the literature. Perc65 is percentage of the county population over 65 years old. Recreational amenities were selected based on activities typically favored by retirees. All these variables are a count of the number of each establishments per 100,000 residents. For the natural amenities, topography is a scale of 1 to 21 with the high end of the scale being a mountainous region and 1 being the plains. Humid measures the percentage of humidity in July and Sunjan is the number of sunny days in January. Finally, water is the percentage of county covered by water.

Health access is measured in three ways: hospital expenditure per 100,000 residents, number of hospital beds per 100,000 residents, and number of physicians per 100,000 residents. Hospital expenditure is broadest way to capture the climate of health access with doctors and beds being more specific. In the hospital analysis we further specify hospitals to be categorized by short term general care hospital beds, short term non-general care, and long term care beds. A short-term general hospital can be defined as having facilities and staff to provide diagnosis, care, and treatment of a wide range of acute conditions, whereas short term non-general hospitals provide treatment for a limited special group of acute conditions. Long-term hospitals have the infrastructure and personnel for the diagnosis, care, and treatment of a wide range of chronic diseases and have an average inpatient length of stay greater than 25 days. Because it's likely that the type of doctor in the county is important, we included both general practitioners and surgeon specialists as a way to capture both more basic services as well as full comprehensive care. Additionally, we also included the number of nursing homes per 100,000 residents within the analysis. According to the National Nursing Home Survey, in 2004 the number of 65 plus year olds living in a nursing home was 1.3 million, or 363 nursing home residents per 10,000 persons age 65 and older. In addition to being a long term care option, nursing homes provide a variety of uses for the elderly such as serving as a temporary location for those who have undergone orthopedic surgery or suffered a stroke to rehabilitate. Therefore, nursing homes could be important for all retirees and not just the oldest of the old.

Empirical Methodology

Particularly for states in which there are numerous small counties, it is highly plausible that nearby counties with good health services and/or other amenities will have a spillover effect for neighboring counties. Because it is inefficient to have a full service hospital in every county, hospitals in nearby counties will likely have a direct role when a migrant is considering a destination. In order to explicitly measure this spill over we use a spatial lag of X model (SLX). While an extensive explanation of the SLX model can be found in LeSage and Pace (2009), a brief summary is provided below.

Within the SLX framework, senior migration can be modeled as

$$y_i = \alpha + x_i\delta + w_iZ\gamma + \varepsilon_i \quad (1)$$

where y_i is the in-migration for county i, x_i is a (1 x k_1) vector of characteristics of county i that affect retiree migration, Z is an (n x k_2) matrix of county-specific characteristics where each column holds a particular characteristic and each row is a different county in the sample, w_i is a (1 x n) weighting vector that when multiplied by Z produces a vector with weighted average characteristics of counties nearby to county i, and ε_i is the stochastic term.

From equation (1) it can be seen that the model parameters to be estimated are α, δ, and γ. The variables in Z and x_i need not be identical or even overlapping. In our application, the variables in Z are a subset of the variables in x. The variables in x not in Z are excluded due to lack of spatial variability on a local (several county) scale. These variables are average January temperature, average July temperature, July humidity, and hours of sunlight in January.

Combining all the county observations to write the model in matrix notation, the (SLX) model can now be represented as

$$y = X\beta + \mathrm{WZ}\gamma + \varepsilon \quad (2)$$

$$\varepsilon \sim N(0, \sigma^2 V) \quad (3)$$

$$V = diag(v_1, v_2, .. v_n) \quad (4)$$

where X = [ι x_i] and ι is an (n x 1) vector of ones, X_i is the matrix formed by stacking the individual county's x_i vectors from equation (1), W is a similar stacking of the w_i weighting vectors, and $\beta = [\ \alpha\ \delta'\ ]'$. In the presence of heteroskedasticity, v_i are the county-specific error variances used to down-weight observations having large variances. Under a homoskedastic assumption, $v_i = 1$, for all i, and the error variance-covariance matrix reduces to the standard $\sigma^2 I$.

W, the stacked w_i weighting vectors, is a weighting matrix assigning weights based on the proximity of other counties to county i. Our W matrix identifies neighbors and neighbors of neighbors. Thus when multiplied by Z, this term will capture an indirect effect on migration from county characteristics up to two counties away. Because our analysis separates counties into rural, urban, and most urban specifications, this requires an adjustment to the normally square weighting matrix W. To illustrate, for the urban analysis which consists of 645 counties out of the total 3075 counties in our sample. Because we want the W matrix to include all neighboring counties and not just the 2 closest urban neighboring counties, W is a (645 x 3075) vector with appropriate weights for the 645 urban counties that is multiplied by the matrix Z which is (3075 x k_2) to produce WZ which is (645 x k_2) matrix. This allows us to ultimately model the direct effect of characteristics within only urban counties, as well as indirect effects of all neighboring counties regardless if they are urban.

The Bayesian Estimation Algorithm

As outlined in LeSage and Pace's *Introduction to Spatial Econometrics* (LeSage and Pace, 2009), these models can be estimated using a Bayesian methodology. Bayesian estimation is generally superior to classical approaches for spatial models such as ours because of the large number of parameters to be estimated. The modern, numerical approach to most Bayesian estimation algorithms lends itself well to such high-dimensional problems. The following outlines the Bayesian procedure utilized for the empirical results.

Bayesian estimation uses Bayes' Theorem to produce posterior distributions of the parameters. This is done by optimally combining user-provided prior information with the information contained in the data as summarized by the likelihood function. For the SLX model with heteroskedasticity present, thanks to the assumption of normally distributed errors, the full likelihood function has the form

$$\mathrm{L} = 2\pi^{-\left(\frac{n}{2}\right)}|\sigma^{-1}\mathrm{V}^{-\frac{1}{2}}|exp^{\left(\frac{-\mathrm{e}'\mathrm{V}^{-1}\mathrm{e}}{2\sigma^2}\right)} \tag{5}$$

where $e = y - X\beta - \mathrm{WZ}\gamma$ and β, γ, σ^2, and the v_i are the parameters to be estimated. Equations (6)-(8) below present our chosen prior distributions, as indicated using ω. To produce sound posterior estimates, the priors on β are informative and proper. We specify the prior on β and γ as a multivariate normal distribution and the prior on σ^2 as an inverse gamma density. We select a prior for v_i as a set of n iid $\chi^2(r)/r$ distributions, where r is the single parameter of the distribution. These priors can be written mathematically as

$$\omega(\beta'\gamma') \sim N(c, T) \tag{6}$$

$$\omega\left(\frac{r}{v_i}\right) \sim iid\ \chi^2(r), i = 1, \dots n \tag{7}$$

$$\omega(\sigma^2) \sim IG(a, b) \tag{8}$$

We select values that will produce relatively diffuse priors by setting c=0 and T=10,000 times the appropriate dimension identity matrix in the prior distribution for β and γ. This prior suggests a very vague prior inclination to expect regression parameter values near 0. While we believe the Bayesian approach is better-suited to this application than maximum likelihood or GMM, the impact on the actual empirical results based on our rather diffuse priors does not affect any of the qualitative implications.

As recommended by LeSage and Pace (2009), we set r = 4 in the χ^2 distribution as this will be diffuse enough to not overly downweight non-constant variances as well as outliers. Such a prior is equivalent to imagining that the prior information on σ^2 is based on a sample with four observations. In equation (8), a and b are both set to 0 to give a diffuse prior on σ^2.

By multiplying the prior by the likelihood function, the joint posterior distribution is obtained. The posterior distribution summarizes all the information we have about the location of the parameters being estimated. Because we cannot find measures such as means and standard deviations for this particular posterior distribution analytically, such measures must be estimated through numerical integration. This is done by the now common Gibbs sampler, which draws sequentially at random from a set of conditional posterior distributions of subsets of the parameters. While the joint posterior is too complex to deal with, correctly chosen subsets of parameters have standard distributions which can be handled easily in any econometric software package. The conditional distributions we use are (where "|" denotes conditioning on the following parameter values):

$$p(\beta'\gamma'|\sigma, V) \propto N(c^*, T^*) \tag{9}$$

$$c^* = (X'V^{-1}X + \sigma^2 T^{-1})^{-1}(X'V^{-1}y + \sigma^2 T^{-1}c) \tag{10}$$

$$T^* = \sigma^2(X'V^{-1}X + \sigma^2 T^{-1})^{-1} \tag{11}$$

$$p(\sigma^2|\beta, \gamma, V) \propto IG(a^*, b^*) \tag{12}$$

$$a^* = a + \frac{n}{2} \tag{13}$$

$$b^* = (2b + e'V^{-1}e)/2 \tag{14}$$

$$p\left(\frac{e_i^2 + r}{v_i}\middle|\beta, \sigma^2, v_{-i}\right) \propto \chi^2(r+1) \tag{15}$$

Our Gibbs sampler, a type of Markov Chain Monte Carlo sampling procedure, is used to generate draws from the posterior conditional distributions for all the parameters in the model.

By cycling repeatedly through equations (9)-(15) updating parameter values as we go with the most recent past draws of each parameter, we produce a set of draws that have been proven to converge to the joint posterior distribution (Chib, 1995).

Once an adequate number of values have been generated from the posterior distribution, we then can identify posterior means and credible intervals for the model parameters. The posterior means are estimated by the sample mean of the draws from the posterior simulation and credible intervals can be constructed by sorting the draws from smallest to largest and selecting the desired percentiles of the empirical distribution. Our posterior estimates were produced by carrying out 5,000 passes and discarding the first 1,000. To ensure convergence of our chain and, hence, validity of the estimates, these estimates were compared to longer runs and equivalent results are found. This creates confidence that our estimates are steady state values and the chain has converged to the full joint posterior distribution.

Results

To formally test for the presence of heteroscedastity, we can utilize the Bayesian framework to calculate posterior model probabilities for homoscedastic and heteroscedastic versions of the model. The odds ratio of these two probabilities is mathematically represented as

$$\frac{\mathrm{p(het)}}{\mathrm{p(hom)}} = \frac{\mathrm{p}(\mathrm{M}^{\mathrm{het}})\mathrm{p}(\mathrm{y}|\mathrm{M}^{\mathrm{het}})}{\mathrm{p}(\mathrm{M}^{\mathrm{hom}})\mathrm{p}(\mathrm{y}|\mathrm{M}^{\mathrm{hom}})} \tag{16}$$

where we set the prior probabilities for each of the models, $\mathrm{p}(\mathrm{M}^{\mathrm{i}})$ equal to 0.5. The marginal likelihoods are respectively represented as $\mathrm{p}(\mathrm{y}|\mathrm{M}^{\mathrm{i}})$, with the posterior model probability represented as $\mathrm{p}(\mathrm{M}^{\mathrm{i}}|\mathrm{y})$. The posterior model probability will reward the model that better fits the data averaged across all posterior supported values for the parameters. When these values are computed, the heteroscedastic version has a posterior model probability of approximately 1 and we thus invoke robust errors.[2]

Because W is not observable, the posterior model probabilities allow us to measure which W is best suited to the data. This avoids having to make strong functional form assumptions that could produce misleading results (McMillian, 2010; Pinske and Slade, 2010; and Gibbons and Overman, 2012).[3] Thus for the W matrix specification, we tested the posterior model probabilities of the spatial continuity matrix, W only including only one ring of neighbor, W having two rings of neighbors, up to W including the six nearest rings of neighbors The W best suited according to the probability testing was one with two rings of neighbors. Thus W is a matrix with rows that sum to 1 and non-zero entries for the county's own contiguous neighbors as well as the neighbors of those neighboring counties.

One advantage of using the SLX specification is the direct and indirect effects of each parameter on county in-migration are directly observable. The direct effect is δ, the coefficient on the variable of interest, which quantifies the impact on in-migration in the own county. The indirect effect, γ, is the coefficient on the weighted variables from surrounding counties, depicted in the results with W*. This indirect effect measures the amount of local spillover of counties in close proximity to the origin county. In our applications, the variables average January temperature, July humidity, sunlight in January, and humidity in July only have a direct effect and were omitted from being spatially weighted due to high spatial multicollinearity. These variables were only included in the X_i matrix and not the Z matrix since these variables are

[2] LeSage and Pace's Spatial Econometrics Toolbox was utilized to calculate all empirical results and are reported in Tables 2-6.
[3] In addition to pointing out strong functional form assumptions that previous spatial studies have invoked, these authors have cautioned against using spatial models for identification. We would like to explicitly note that we achieve identification by utilizing deep lags for all health care regressors that could possibly have introduced endogenity into the model. Thus our motivation for using spatial models is purely to capture locational spill-over effects, not to identify any independent variables.

generally almost identical for neighboring counties and thus do not need to be spatially weighted. Intuitively, it is generally not logical to move to a county because the neighboring county has nice weather since both counties likely have similar climates.

We use three different estimation strategies to measure access to care at the county level by health care expenditures, size of facility, and number of physicians. We choose these three proxies of health access to hopefully capture different nuances of health care access. We particularly want to capture which types of access really matter. For policy makers, spending more money on the health sector, or incentivizing doctors to relocate may be an easier solution than physically building or adding onto a hospital.

In addition to using three different measures of health access, we checked the robustness of our results by trying models with smaller age cohorts. Thus, in addition to the six models presented (most urban, urban, and rural counties, each for 60-74 and 75+ age groups), we also ran the model for the three county population categories for six age cohorts: 60-64, 65-69, 70-74, 75-79, 80-84, and 85+ year old categories. However, due to only small nuances in the results for the cohorts that are closest in age, we believe aggregating the migrants into just two age groups (60-74 and 75+) is appropriate: the youngest and oldest of the old. [4]

The following discussion of results will focus on selected drivers of later-life migration for both non-health and health access drives. Each table is divided into three columns for rural, urban, and most urban results. We limit our discussion to the signable variables based on the 90% credible interval (the Bayesian version of a confidence interval).

Non-Health Related Variables:

Keeping in mind that the dependent variable is log in-migration, we first focus on non-health related variables that would generally be considered pull factors in attracting migrants to

[4] Regression results from each cohort are available from the authors upon request.

an area. While the coefficients on the non-health variables are similar for all model specifications, our discussion will focus on the preferred results found in Table 2.2 (60-74 year olds) and Table 2.3 (75+).

Variables pertaining to the county's economic vitality generally perform as expected with a positive sign on log median income and log of home price. For rural counties, the positive coefficient of 1.65 on log home price for the youngest seniors is particularly of interest. While we try to control for numerous amenities that should be important to retirees, there naturally will be amenities that remain unobservable at the county level or are just not included in the model. The positive value on log home price is an indication that retirees value living in high quality areas. This is further confirmed with a negative coefficient on indirect home price, particularly for 75+ year old migrants.

Another important variable is the percentage of the county over 65 years of age. Increasing the number of county residents 65 and older by 1%, is associated with a 7.63% increase in in-migration for 60-74 year migrants and a 7.14% increase for 75+ year old in-migrants. This is likely an indication of a social-network aspect in relocation decisions, meaning that retirees prefer to locate to areas where they either already have friends or could easily meet people of a similar demographic with similar interests.

Variables associated with desirable natural amenities reveal different preferences based on county population. When comparing average January temperature for the youngest migrants across county population type, while January Temp is always positive and significant, urban counties have a larger magnitude compared to other counties. For example, if it were possible to increase the average January temperature by 1 degree Fahrenheit in a rural county, there would be an associated .014% increase of 60-74 migrants in rural counties whereas there would be an

.05% increase in in-migration for urban counties. Unlike rural counties, urban counties have a signable and negative value on average July temperatures. Topography and percent water in the county were positive and signable for both rural and urban counties, while only urban counties had a positive coefficient on average hours of sunlight in January. The combination of less humidity, less sunlight in January, and more water, suggest that migrants may be more amiable to relocate to cooler northern rural counties whereas those relocating to urban counties may prefer a southern climate.

With the exception of restaurants, cultural amenity variables such as libraries and museums did not perform particularly well. Keeping in mind that all these variables are weighed by county population, variables should be interpreted as X per 100,000 people.The number of restaurants per 100,000 people is signable and significant for urban counties. The overall weak performance of these variables seems particularly reasonable for rural counties as it is unlikely one would want to relocate to a rural area to have access to vast museums or libraries. An explanation for urban and most urban counties may be that quality and not quantity are important. For example, migrants may not prefer numerous museums in the county, but rather respected and established museums such as those found in major metropolitans like New York City or Chicago.

Health Services

Tables 2.2-2.7 have three different measurements of health services at the county level. Tables 2.2-2.3 have short and long term health care expenditures per 100,000 people. While small in magnitude, short term care expenditures is both positive and signable for all migrants 60 years and older in rural and urban counties. Given that the very eldest of the population are the highest users of nursing home care, the life course migration theory projects that then the eldest migrants should have a higher proportions of moves towards formal caregiving facilities. We find this relationship as the number of nursing homes per hundred thousand is not signable for migrants 60-74 years of age but is signable and significant for those 75+. Also, only the direct effect and not the indirect one is signable for nursing homes for those 75+, showing that having nursing homes in neighboring counties is not desirable but rather only those in one's own county are. This is consistent with previous work such as Conway (2011) that the migration decisions of the most elderly are predominantly those with more severe disability moving either to be closer to children or into formal caregiving. However given the small magnitudes of the health expenditure variables, further insight into the role of health infrastructure and physicians serve as robustness check to health access being positively associated with in-migration of retiree migrants.

When looking at health infrastructure, Table (2.4-2.5) has number of hospital beds by hospital type per 100,000 residents. Similar to health care expenditure, number of hospital beds is a positive driver of migration particularly for urban counties. Increasing the number of beds per 100,000 residents in a short term general hospital is associated with an increase in in-migration by .36% for 60-74 year old and .53% for 75+ year olds in urban counties. Similarly, non-general specialty hospitals have an associated increase in migration for younger and older later life migrants of .84% and 1.2% respectively. While non general specialty hospitals are less common and thus tend to be less accessible, there is a positive indirect effect for 60-74 year old migrants for both rural and most urban counties. This suggests that a migrant may only need to be within a reasonable commuting distance but not absolutely live in a county with such facility. When trying to improve local health care access, expanding or building a new hospital may be a more difficult option for county planners due to potentially large upfront costs, possible

Certificate of Need qualification, as well as the immobility of infrastructure. Despite these costs, we find that in some capacity hospitals are positively associated with in-migration for all counties. Thus hospital beds per 100,000 residents can considered a positive “pull” factor in attracting potential migrants. Particularly in rural counties with only one facility, these results align with Morton (2003) in that potential hospital closures could be a deterrent to migrants. While hospitals’ primary amenity to migrants is a facility in which to receive health care, they also act as a signal of the availability of physicians and medical personnel for routine care.

A more mobile aspect of health access is in terms of doctors. Relocating physicians to meet local demand is far more fluid and mobile than infrastructure construction. As seen in Table 2.6 and Table 2.7 both general practitioners as well as surgeon specialists are positive and signable for 60+ year old migrants. For rural counties, the combined direct and indirect effect of adding a one surgeon specialist per 100,000 has an associate in-migration increase of 12.02% and 8.2% for 60-74 year olds and 75+ migrants respectively. Similarly for urban counties, an additional surgeon per 100,000 residents can be associated with 5.3% and 11.9% more in-migration for 60-74 and 75+ year old migrants, respectively. General practitioners are also positive and signable for rural 60-74 year old migrants and older urban migrants. These findings suggest that health practitioners are positively associated with migrants’ location decisions. Additionally, given the consistent positive and large magnitude of the indirect effect of surgeon specialists, it appears that even if a specialist does not reside in one’s own county, specialists within a two county perimeter are a valuable amenity.

The poor performance of health practitioners in the most urban counties makes sense for numerous reasons. First, when one is moving to a major metropolitan with numerous hospitals, it is unlikely one would worry about access to comprehensive care or finding a primary care physician. Secondly, it seems plausible that the most urban cities have a large relative stock of doctors due to sorting. Because doctors are highly educated and earn high wages, many would prefer to live in a major metropolitan where there is access to cultural amenities such as museums and theatres as well as high quality restaurants. With the exception of less desirable pockets within cities, in the aggregate it seems reasonable that doctors would naturally tend to locate to large metropolitans over more rural locations with fewer cultural amenities.

When examining our three chosen indicators of health access: expenditures, hospital beds, and physicians, all results indicate that access to health care is positively associated with all later life migrants and not just the oldest of the old. Health expenditures and physicians are both significant and of the expected sign, expect for the most urban counties which are likely experiencing a threshold effect. Our findings on the positive association between both general practitioners as well as specialists could be of particular interest to community leaders interested in drawing later life migrants. Relocating doctors to meet local demand would be easier than attracting a new hospital without as high an upfront cost.

Conclusion

This study looks to gain further insight into the drivers of retiree migration when local spatial spillovers are explicitly controlled for in the estimation technique. Employing the Spatial Lagged Model gives both the indirect and direct effect of county characteristics on in-migration. Due to heterogeneous tastes as well as different impacts on an area’s economic activity, the dependent variable of retiree in-migrants is grouped into two age classifications: those 60-74, and 75+ years of age as well as by rural, urban, and most urban counties. Our independent variables examine numerous local amenities. Of particular interest among these variables is access to health services.

While we measure health services through three channels of health expenditures, hospital beds, and number of doctors, all measurements of health access conclude that health care access in the location destination is positively associated with later life migration. Especially when looking at physicians, the magnitude of these health access indicators is large and highly significant. While it is infeasible to have a large comprehensive hospital in every county, an encouraging result of this work for more rural counties is the positive association of physicians on senior migrants. Relocating doctors to meet local demand is a far more achievable goal than attracting a new hospital. In addition to health access being an important driver of migration, having a strong potential social network as measured by a large existing population of county residents 65 years and older, and desirable natural amenities can also help to pull in senior migrants.

One limitation of this study is that our model is only looking at locational characteristics and does not control for family networks. It is likely a nontrivial share of the oldest migrants are moving near family members to receive informal care, which our model cannot account for, and thus this missing effect results in a decrease in fit as age increases (von Reichert, Cromartie, and Arthun 2013). Also, a possibility for future research would be similar regressions using geographically weighted regressions (GWR) to allow for regionally-specific effects of different in-migration drivers.

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Table 2.1 Summary Statistics for Rural, Urban, and Most Urban Counties

	Rural	Urban	Most Urban
Variable	**Mean Std. Dev [Min Max]**	**Mean Std. Dev [Min Max]**	**Mean Std. Dev [Min Max]**
Log Migrants 60-74	5.248 1.107	6.867 0.985	8.208 0.862
	[0 , 9.161]	[3.61 , 10.594]	[5.7 , 10.903]
Log Migrants 75+	4.569 1.162	6.317 0.996	7.792 0.869
	[0 , 7.995]	[1.945 , 9.790]	[5.4 , 9.997]
Nursing homes per ht	0.041 0.042	0.033 0.019	0.028 0.012
	[0 , 0.752]	[0 , 0.154]	[0 , 0.070]
ST hosp expend per ht	36.936 37.784	60.676 59.11	80.94 67.44
	[0 , 972.98]	[0 , 455.031]	[0 , 513.006]
LT hosp expend per ht	4.549 27.445	7.146 19.033	12.068 18.47
	[0 , 486.372]	[0 , 277.430]	[0 , 128.482]
STG hosp beds per ht	0.413 0.453	0.322 0.275	0.336 0.247
	[0 , 4.984]	[0 , 2.401]	[0 , 2.241]
STNG hosp beds per ht	0.006 0.073	0.022 0.052	0.028 0.039
	[0 , 2.183]	[0 , 0.436]	[0 , 0.166]
LT hosp beds per ht	0.056 0.376	0.066 0.288	0.083 0.239
	[0 , 6.290]	[0 , 4.545]	[0 , 2.630]
General Practioners per ht	0.030 0.022	0.028 0.015	0.026 0.012
	[0 , 0.270]	[0 , 0.090]	[0 , 0.072]
Doctor Specalists per ht	0.016 0.030	0.047 0.057	0.100 0.079
	[0 , 0.999]	[0 , 0.721]	[0 , 0.531]
Unemployment	6.471 3.002	5.640 2.015	4.930 1.417
	[0 , 36.100]	[0 , 19.300]	[2.1 , 9.300]
Log Median Income	10.213 0.188	10.468 0.190	10.636 0.230
	[9.571 , 10.941]	[9.901 , 11.301]	[10.009 , 11.101]
Pop sq mi	37.956 42.133	226.053 248.78	2372.9 5672.85
	[0.2 , 788.4]	[1.4 , 2118.9]	[78.2 , 54246.8]
Log Home Price	10.624 0.352	11.053 0.546	11.550 0.488
	[9.615 , 13.122]	[0 , 12.426]	[10.64 , 13.062]
Perc 60-74	0.137 0.028	0.114 0.028	0.108 0.031
	[0.037 , 0.294]	[0 , 0.300]	[0.042 , 0.300]
Marinas per ht	0.002 0.010	0.002 0.004	0.001 0.002
	[0 , 0.286]	[0 , 0.036]	[0 , 0.017]
Restaurants per ht	0.187 0.115	0.168 0.055	0.179 0.047
	[0 , 1.571]	[0 , 0.522]	[0 , 0.427]
Movie theatres per ht	0.003 0.007	0.002 0.002	0.002 0.001
	[0 , 0.200]	[0 , 0.017]	[0 , 0.007]
Golf Courses per ht	0.002 0.006	0.002 0.003	0.001 0.001
	[0 , 0.100]	[0 , 0.022]	[0 , 0.009]
Libraries per ht	0.002 0.005	0.001 0.002	0.001 0.001
	[0 , 0.067]	[0 , 0.010]	[0 , 0.005]
Museums per ht	0.002 0.007	0.001 0.002	0.001 0.001

per ht denotes that the variable is a rate per 100,000 residents

Continued on next page

Table 1 – *Continued from previous page*

	[0 , 0.143]	[0 , 0.032]	[0 , 0.006]
Topography	9.123 6.626	8.290 6.376	7.734 6.724
	[1 , 21]	[1 , 21]	[1 , 21]
Percent Water	3.452 9.675	5.994 12.012	14.546 19.745
	[0 , 75]	[0 , 69.69]	[0.11 , 75]
January Temp	31.993 12.169	35.206 11.546	35.786 11.41
	[1.1 , 65.600]	[3.5 , 65.500]	[11.8 , 67.200]
Sunlight January	152.95 33.41	147.05 32.37	150.71 33.73
	[48 , 266]	[48 , 266]	[52 , 248]
July Temp	75.726 5.543	76.478 4.801	75.307 5.0
	[55.5 , 93.700]	[61.1 , 93.70]	[58.5 , 91.20]
Humidity	54.505 15.049	60.019 12.628	60.467 11.996
	[14 , 79]	[14 , 80]	[19 , 80]
Observations	2261	645	169

per ht denotes that the variable is a rate per 100,000 residents

Table 2.2 Hospital Expenditure Rates and Local Amenities: Migrants 60-75 years of Age

Dependent Variable: Log of 60-74 Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-21.803 ***	-14.840 ***	-17.091 **
	[-24.394 , -20.204]	[-19.155 , -12.177]	[-30.247 , -8.970]
ST Hosp Expend per ht	0.002 ***	0.002 ***	0.001
	[0.002 , 0.003]	[0.001 , 0.003]	[-0.002 , 0.002]
LT Hosp Expend per ht	0.001	0.002	0.000
	[0.000 , 0.001]	[-0.001 , 0.003]	[-0.007 , 0.004]
Unemployment	0.041 ***	-0.023	-0.066
	[0.029 , 0.048]	[-0.053 , -0.004]	[-0.186 , 0.008]
Ln Median Income	-0.086	1.193 ***	0.279
	[-0.371 , 0.091]	[0.831 , 1.417]	[-0.832 , 0.964]
Pop Sq Mi	0.007 ***	0.001 ***	0.000 *
	[0.006 , 0.007]	[0.001 , 0.001]	[0.000 , 0.000]
Log Home	1.651 ***	0.249 ***	0.156
	[1.487 , 1.752]	[0.156 , 0.307]	[-0.670 , 0.666]
Percent 65+	7.634 ***	3.596 ***	2.788
	[6.473 , 8.351]	[1.590 , 4.835]	[-2.302 , 5.931]
Marina per ht	-3.725 **	-24.635 ***	26.639
	[-6.400 , -2.073]	[-37.394 , -16.759]	[-25.042 , 58.540]
Restaurant per ht	-0.655 ***	4.281 ***	1.784
	[-0.981 , -0.455]	[3.229 , 4.930]	[-1.600 , 3.873]
Movie per ht	0.535	2.838	-10.722
	[-3.131 , 2.799]	[-21.063 , 17.591]	[-141.393 , 69.939]
Bowling per ht	1.123	9.039	91.885
	[-2.665 , 3.461]	[-14.751 , 23.724]	[-31.366 , 167.967]
Golf per ht	3.160	-3.319	-19.567
	[-1.560 , 6.074]	[-20.162 , 7.078]	[-115.503 , 39.653]
Library per ht	-1.599	-25.940 **	-94.078
	[-6.714 , 1.559]	[-49.664 , -11.296]	[-245.147 , -0.826]
Museum per ht	-15.282 ***	-25.560 ***	-75.216
	[-18.840 , -13.086]	[-42.451 , -15.134]	[-196.038 , -0.634]
Nursing Homes per ht	0.004	-0.004	-0.010
	[-0.003 , 0.009]	[-0.029 , 0.012]	[-0.106 , 0.050]
Topography	0.008 *	0.007	-0.012
	[-0.001 , 0.013]	[-0.006 , 0.014]	[-0.043 , 0.008]
Perc Water	0.067 ***	0.096 ***	-0.041
	[0.047 , 0.080]	[0.056 , 0.121]	[-0.158 , 0.031]
Jan Temp	0.014 ***	0.053 ***	0.038 ***
	[0.009 , 0.016]	[0.046 , 0.057]	[0.019 , 0.049]
Sun Jan	-0.001 *	0.006 ***	0.006 **
	[-0.002 , 0.000]	[0.005 , 0.007]	[0.002 , 0.008]
July	0.015 **	-0.035 ***	-0.008
	[0.005 , 0.021]	[-0.051 , -0.025]	[-0.048 , 0.016]
July Humid	-0.003 ***	-0.019 ***	-0.015 **

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents
Continued on next page

Table 2 – *Continued from previous page*

	[-0.006 , -0.002]	[-0.024 , -0.017]	[-0.027 , -0.008]
W*ST Hosp Expend per ht	0.001	0.001	0.000
	[0.000 , 0.001]	[-0.001 , 0.001]	[-0.003 , 0.002]
W*LT Hosp Expend per ht	0.001	0.000	0.000
	[-0.001 , 0.001]	[-0.002 , 0.002]	[-0.010 , 0.007]
W*Unemployment	0.030 ***	0.065 ***	0.156 ***
	[0.015 , 0.039]	[0.036 , 0.083]	[0.044 , 0.226]
W*Ln Median Income	0.667 ***	0.473	1.304 *
	[0.336 , 0.872]	[0.086 , 0.713]	[-0.009 , 2.115]
W*Pop Sq Mi	-0.001 ***	0.000	0.000
	[-0.001 , -0.001]	[0.000 , 0.000]	[0.000 , 0.000]
W*Log Home	-0.045	-0.024	0.371
	[-0.237 , 0.073]	[-0.128 , 0.040]	[-0.513 , 0.917]
W*Percent 65+	3.463 ***	3.082 **	6.180 *
	[2.053 , 4.334]	[0.594 , 4.618]	[-0.215 , 10.128]
W*Marina per ht	-2.971	-1.749	-9.993
	[-6.782 , -0.618]	[-10.713 , 3.784]	[-50.476 , 14.996]
W*Restaurant per ht	0.557 **	0.433	1.747
	[0.137 , 0.817]	[-0.726 , 1.149]	[-2.130 , 4.140]
W*Movie per ht	-9.332 ***	26.686 **	-40.323
	[-14.392 , -6.210]	[5.610 , 39.696]	[-159.369 , 33.162]
W*Bowling per ht	1.745	17.268 *	25.737
	[-3.720 , 5.119]	[-1.138 , 28.630]	[-68.570 , 83.950]
W*Golf per ht	4.984	-4.966	18.181
	[-1.494 , 8.983]	[-22.473 , 5.841]	[-46.235 , 57.944]
W*Library per ht	-7.044 *	12.670	43.728
	[-14.120 , -2.676]	[-4.338 , 23.168]	[-41.778 , 96.510]
W*Museum per ht	-8.486 ***	-5.386	-29.763
	[-13.727 , -5.251]	[-17.215 , 1.916]	[-90.575 , 7.776]
W*Nursing Homes per ht	0.006	-0.005	0.078 *
	[-0.005 , 0.013]	[-0.031 , 0.011]	[-0.022 , 0.139]
W*Topography	0.007	0.003	-0.003
	[-0.002 , 0.013]	[-0.011 , 0.012]	[-0.042 , 0.020]
W*Perc Water	0.036 **	0.011	-0.049
	[0.010 , 0.052]	[-0.035 , 0.039]	[-0.177 , 0.031]
R-Squared	0.896	0.909	0.863
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

Table 2.3 Hospital Expenditure Rates and Local Amenities: Migrants 75+ years of Age

Dependent Variable: Log of 75+ Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-26.430 ***	-11.876 ***	-18.737 **
	[-29.398 , -23.462]	[-16.342 , -7.410]	[-32.576 , -4.898]
ST Hosp Expend per ht	0.005 ***	0.003 ***	0.001
	[0.004 , 0.005]	[0.002 , 0.004]	[-0.001 , 0.004]
LT Hosp Expend per ht	0.001	0.002 *	-0.001
	[-0.001 , 0.002]	[0.000 , 0.004]	[-0.008 , 0.006]
Unemployment	0.027 ***	-0.051 ***	-0.118 *
	[0.014 , 0.041]	[-0.081 , -0.021]	[-0.246 , 0.010]
Ln Median Income	0.337 **	1.094 ***	0.024
	[0.003 , 0.672]	[0.717 , 1.471]	[-1.138 , 1.185]
Pop Sq Mi	0.007 ***	0.001 ***	0.000
	[0.007 , 0.008]	[0.001 , 0.002]	[0.000 , 0.000]
Log Home	1.720 ***	0.221 ***	0.257
	[1.532 , 1.908]	[0.125 , 0.317]	[-0.594 , 1.108]
Percent 65+	7.144 ***	3.232 ***	3.648
	[5.808 , 8.480]	[1.113 , 5.352]	[-1.638 , 8.934]
Marina per ht	-8.800 ***	-38.727 ***	3.491
	[-11.955 , -5.644]	[-52.327 , -25.128]	[-48.528 , 55.511]
Restaurant per ht	-1.326 ***	4.554 ***	2.000
	[-1.698 , -0.954]	[3.425 , 5.684]	[-1.552 , 5.552]
Movie per ht	3.438 *	7.956	12.600
	[-0.780 , 7.656]	[-16.993 , 32.906]	[-123.214 , 148.413]
Bowling per ht	5.633 **	15.524	67.200
	[1.259 , 10.007]	[-9.002 , 40.051]	[-61.524 , 195.923]
Golf per ht	0.792	-17.905 *	-41.011
	[-4.659 , 6.244]	[-35.563 , -0.247]	[-139.820 , 57.799]
Library per ht	-0.706	-14.943	-18.022
	[-6.562 , 5.149]	[-39.593 , 9.708]	[-180.077 , 144.033]
Museum per ht	-8.501 ***	-37.618 ***	-71.048
	[-12.663 , -4.339]	[-54.993 , -20.243]	[-197.078 , 54.982]
Nursing Homes per ht	0.019 ***	0.027 **	0.010
	[0.010 , 0.028]	[0.000 , 0.054]	[-0.090 , 0.110]
Topography	0.002	0.008	-0.015
	[-0.007 , 0.012]	[-0.005 , 0.022]	[-0.049 , 0.019]
Perc Water	0.038 ***	0.062 **	-0.044
	[0.014 , 0.062]	[0.020 , 0.104]	[-0.166 , 0.079]
Jan Temp	0.000	0.045 ***	0.032 ***
	[-0.005 , 0.005]	[0.038 , 0.052]	[0.013 , 0.052]
Sun Jan	-0.003 ***	0.004 ***	0.004 *
	[-0.004 , -0.002]	[0.002 , 0.006]	[-0.001 , 0.008]
July	0.045 ***	-0.040 ***	-0.006
	[0.034 , 0.057]	[-0.057 , -0.023]	[-0.047 , 0.035]
July Humid	-0.001	-0.020 ***	-0.015 **

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents
Continued on next page

Table 3 – *Continued from previous page*

	[-0.003 , 0.002]	[-0.025 , -0.016]	[-0.027 , -0.003]
W*ST Hosp Expend per ht	0.001 **	0.000	0.002
	[0.000 , 0.002]	[-0.001 , 0.002]	[-0.001 , 0.005]
W*LT Hosp Expend per ht	0.000	0.001	-0.002
	[-0.001 , 0.002]	[-0.001 , 0.003]	[-0.013 , 0.009]
W*Unemployment	0.018 **	0.080 ***	0.182 ***
	[0.002 , 0.035]	[0.049 , 0.110]	[0.066 , 0.297]
W*Ln Median Income	0.771 ***	0.370 *	1.619 *
	[0.390 , 1.152]	[-0.047 , 0.787]	[0.273 , 2.965]
W*Pop Sq Mi	-0.001 ***	0.000	0.000
	[-0.001 , 0.000]	[0.000 , 0.000]	[0.000 , 0.000]
W*Log Home	-0.378 ***	-0.032	0.332
	[-0.598 , -0.158]	[-0.138 , 0.074]	[-0.568 , 1.233]
W*Percent 65+	4.502 ***	3.478 **	4.604
	[2.859 , 6.145]	[0.876 , 6.081]	[-1.981 , 11.189]
W*Marina per ht	-3.423	-1.064	-3.474
	[-7.814 , 0.968]	[-10.564 , 8.437]	[-46.024 , 39.077]
W*Restaurant per ht	0.301	0.216	1.064
	[-0.188 , 0.790]	[-0.992 , 1.424]	[-3.042 , 5.169]
W*Movie per ht	-8.209 ***	31.041 **	-7.498
	[-13.882 , -2.535]	[8.732 , 53.350]	[-134.604 , 119.608]
W*Bowling per ht	0.326	15.359 *	35.752
	[-5.909 , 6.561]	[-3.710 , 34.429]	[-65.700 , 137.205]
W*Golf per ht	1.603	-7.688	20.162
	[-5.723 , 8.930]	[-26.203 , 10.826]	[-49.063 , 89.387]
W*Library per ht	-3.761	22.274 **	61.050
	[-11.721 , 4.200]	[4.640 , 39.907]	[-30.088 , 152.188]
W*Museum per ht	-4.505	-11.442 *	-5.111
	[-10.560 , 1.550]	[-23.906 , 1.021]	[-69.740 , 59.517]
W*Nursing Homes per ht	0.006	0.011	0.074
	[-0.006 , 0.018]	[-0.017 , 0.039]	[-0.032 , 0.181]
W*Topography	0.004	-0.006	-0.001
	[-0.007 , 0.015]	[-0.021 , 0.009]	[-0.042 , 0.039]
W*Perc Water	0.025 *	0.031	-0.021
	[-0.006 , 0.055]	[-0.017 , 0.078]	[-0.160 , 0.118]
R-Squared	0.875	0.903	0.849
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

Table 2.4 Hospital Bed Rates and Local Amenities: Migrants 60-74

Dependent Variable: Log of 60-74 Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-20.926 ***	-14.813 ***	-20.553 ***
	[-23.591 , 23.591]	[-19.336 , -9.464]	[-34.175 , -6.875]
ST Gen Beds per ht	-0.051 *	0.362 ***	-0.397
	[-0.002 , 0.014]	[-0.032 , 0.022]	[-0.116 , 0.077]
ST NonGen Beds per ht	0.239	0.837 **	5.517 ***
	[-0.113 , 0.011]	[0.177 , 0.546]	[-0.997 , 0.204]
LT Beds per ht	0.064 *	0.083	-0.121
	[-0.118 , 0.595]	[-0.021 , 1.696]	[2.301 , 8.732]
Unemployment	0.039 ***	-0.022	-0.023
	[-23.601 , -18.252]	[-19.354 , -10.271]	[-34.243 , -6.863]
Ln Median Income	-0.108	1.212 ***	0.480
	[0.027 , 0.052]	[-0.052 , 0.009]	[-0.147 , 0.101]
Pop Sq Mi	0.007 ***	0.001 ***	0.000 *
	[-0.410 , 0.194]	[0.839 , 1.585]	[-0.645 , 1.605]
Log Home	1.676 ***	0.250 ***	0.251
	[0.007 , 0.008]	[0.001 , 0.001]	[0.000 , 0.000]
Percent 65+	7.525 ***	3.337 ***	3.068
	[1.502 , 1.850]	[0.153 , 0.347]	[-0.586 , 1.087]
Marina per ht	-4.036 ***	-23.602 ***	31.844
	[6.300 , 8.749]	[1.224 , 5.449]	[-1.892 , 8.028]
Restaurant per ht	-0.689 ***	4.230 ***	1.386
	[-6.846 , -1.227]	[-37.066 , -10.139]	[-19.585 , 83.272]
Movie per ht	2.269	2.962	-15.718
	[-1.032 , -0.347]	[3.131 , 5.329]	[-2.084 , 4.855]
Bowling per ht	2.592	5.642	101.815 *
	[-1.564 , 6.103]	[-21.282 , 27.206]	[-146.057 , 114.622]
Golf per ht	2.071	-1.996	-9.622
	[-1.358 , 6.541]	[-18.522 , 29.807]	[-22.076 , 225.706]
Library per ht	-1.322	-26.325 **	-62.023
	[-2.790 , 6.931]	[-19.530 , 15.537]	[-104.352 , 85.108]
Museum per ht	-14.921 ***	-23.458 **	-77.522
	[-6.753 , 4.108]	[-51.141 , -1.509]	[-212.336 , 88.290]
Nursing Homes per ht	0.006	-0.005	-0.020
	[-18.734 , -11.109]	[-41.278 , -5.638]	[-201.468 , 46.423]
Topography	0.007 *	0.005	-0.016
	[-0.004 , 0.132]	[-0.064 , 0.229]	[-0.546 , 0.304]
Perc Water	0.070 ***	0.099 ***	-0.042
	[-0.002 , 0.016]	[-0.008 , 0.019]	[-0.048 , 0.016]
Jan Temp	0.012 ***	0.053 ***	0.039 ***
	[0.048 , 0.091]	[0.057 , 0.140]	[-0.159 , 0.075]
Sun Jan	-0.001 *	0.006 ***	0.006 **
	[0.007 , 0.017]	[0.046 , 0.060]	[0.020 , 0.058]
July	0.015 **	-0.036 ***	-0.015
	[-0.002 , 0.000]	[0.005 , 0.008]	[0.001 , 0.010]
July Humid	-0.004 ***	-0.019 ***	-0.016 ***

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*

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	[0.004 , 0.026]	[-0.053 , -0.019]	[-0.053 , 0.024]
W*ST General Beds per ht	-0.191 ***	-0.120	-0.497
	[-0.005 , 0.018]	[-0.031 , 0.024]	[0.023 , 0.227]
W*ST Non- Gen Beds per ht	0.589 **	0.552	4.159 **
	[-0.277 , -0.106]	[-0.334 , 0.095]	[-1.216 , 0.223]
W*LT Beds per ht	0.037	0.036	-0.719
	[0.116 , 1.061]	[-0.197 , 1.302]	[0.031 , 8.288]
W*Unemployment	0.027 ***	0.066 ***	0.159 ***
	[-0.006 , -0.002]	[-0.024 , -0.015]	[-0.028 , -0.004]
W*Ln Median Income	0.628 ***	0.450 **	1.506 **
	[0.013 , 0.042]	[0.035 , 0.096]	[0.047 , 0.272]
W*Pop Sq Mi	-0.001 ***	0.000	0.000
	[0.285 , 0.971]	[0.038 , 0.862]	[0.195 , 2.817]
W*Log Home	-0.072	-0.019	0.215
	[-0.001 , 0.000]	[0.000 , 0.000]	[0.000 , 0.000]
W*Percent 65+	4.048 ***	3.501 **	8.480 **
	[-0.274 , 0.129]	[-0.127 , 0.089]	[-0.662 , 1.093]
W*Marina per ht	-3.320 *	-2.655	-4.488
	[2.527 , 5.569]	[0.906 , 6.095]	[1.910 , 15.050]
W*Restaurant per ht	0.488 **	0.660	1.113
	[-7.341 , 0.701]	[-12.091 , 6.780]	[-44.855 , 35.879]
W*Movie per ht	-6.984 ***	25.333 **	-20.235
	[0.039 , 0.938]	[-0.548 , 1.867]	[-2.704 , 4.930]
W*Bowling per ht	4.051	17.983 *	-0.259
	[-12.328 , -1.639]	[3.187 , 47.479]	[-141.382 , 100.912]
W*Golf per ht	2.990	-5.800	11.721
	[-1.657 , 9.760]	[-1.103 , 37.070]	[-96.512 , 95.994]
W*Library per ht	-6.019 *	14.486 *	35.609
	[-3.767 , 9.746]	[-24.016 , 12.416]	[-53.455 , 76.898]
W*Museum per ht	-7.866 ***	-5.038	-27.984
	[-13.259 , 1.222]	[-2.980 , 31.952]	[-49.640 , 120.858]
W*Nursing Homes per ht	0.006	-0.004	0.125 **
	[-13.356 , -2.377]	[-17.479 , 7.402]	[-89.115 , 33.146]
W*Topography	0.007	0.005	0.004
	[-0.059 , 0.134]	[-0.128 , 0.200]	[-1.678 , 0.240]
W*Perc Water	0.033 **	0.006	-0.052
	[-0.003 , 0.016]	[-0.010 , 0.019]	[-0.035 , 0.043]
R-Squared	0.896	0.910	0.876
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

Table 2.5 Hospital Bed Rates and Local Amenities: Migrants 75+

Dependent Variable: Log of 75+ Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-26.177 ***	-11.637 ***	-22.375 ***
	[-29.142 , -23.558]	[-15.687 , -6.313]	[-36.294 , -8.376]
Short Term Gen Beds per ht	0.158 ***	0.538 ***	-0.410
	[0.012 , 0.030]	[-0.002 , 0.053]	[-0.104 , 0.096]
Short Term NonGen Beds per ht	0.379 *	1.183 **	6.968 ***
	[0.085 , 0.232]	[0.345 , 0.730]	[-1.053 , 0.232]
Long Term Beds per ht	0.076 *	0.062	-0.148
	[-0.036 , 0.794]	[0.277 , 2.089]	[3.568 , 10.369]
Unemployment	0.027 ***	-0.051 ***	-0.066
	[-29.335 , -23.019]	[-16.332 , -6.941]	[-36.374 , -8.377]
Ln Median Income	0.314 *	1.087 ***	0.273
	[0.013 , 0.041]	[-0.082 , -0.019]	[-0.196 , 0.065]
Pop Sq Mi	0.009 ***	0.001 ***	0.000
	[-0.037 , 0.664]	[0.694 , 1.481]	[-0.936 , 1.482]
Log Home	1.775 ***	0.227 ***	0.362
	[0.008 , 0.010]	[0.001 , 0.002]	[0.000 , 0.000]
Percent 65+	6.725 ***	2.641 **	4.164 *
	[1.574 , 1.975]	[0.130 , 0.325]	[-0.518 , 1.242]
Marina per ht	-9.321 ***	-37.145 ***	8.293
	[5.280 , 8.170]	[0.433 , 4.850]	[-1.072 , 9.400]
Restaurant per ht	-1.356 ***	4.529 ***	1.379
	[-12.595 , -6.047]	[-51.170 , -23.119]	[-45.455 , 62.042]
Movie per ht	4.143 *	7.041	0.207
	[-1.759 , -0.954]	[3.381 , 5.676]	[-2.265 , 5.023]
Bowling per ht	6.330 **	10.792	84.000
	[-0.401 , 8.687]	[-18.192 , 32.274]	[-139.612 , 140.027]
Golf per ht	0.236	-16.607 *	-32.282
	[1.690 , 10.971]	[-14.433 , 36.017]	[-45.411 , 213.412]
Library per ht	-0.005	-15.298	16.811
	[-5.414 , 5.886]	[-34.615 , 1.400]	[-134.549 , 69.986]
Museum per ht	-8.622 ***	-34.965 ***	-66.958
	[-6.282 , 6.273]	[-41.483 , 10.887]	[-142.299 , 175.921]
Nursing Homes per ht	0.021 ***	0.026 *	-0.004
	[-13.053 , -4.190]	[-53.485 , -16.446]	[-196.375 , 62.458]
Topography	0.002	0.007	-0.017
	[-0.004 , 0.156]	[-0.093 , 0.218]	[-0.600 , 0.304]
Perc Water	0.042 **	0.067 ***	-0.047
	[-0.008 , 0.013]	[-0.007 , 0.020]	[-0.051 , 0.016]
Jan Temp	-0.001	0.046 ***	0.035 ***
	[0.017 , 0.068]	[0.023 , 0.111]	[-0.170 , 0.076]
Sun Jan	-0.003 ***	0.004 ***	0.004 *
	[-0.006 , 0.004]	[0.038 , 0.053]	[0.015 , 0.055]
July	0.045 ***	-0.042 ***	-0.018
	[-0.004 , -0.002]	[0.002 , 0.006]	[-0.001 , 0.008]

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents
Continued on next page

Table 5 – *Continued from previous page*

July Humid	-0.001	-0.020 ***	-0.016 **
	[0.033 , 0.058]	[-0.060 , -0.024]	[-0.059 , 0.024]
W*ST Gen Beds per ht	-0.143 ***	-0.194	-0.103
	[-0.007 , 0.019]	[-0.016 , 0.040]	[0.011 , 0.228]
W*ST NonGen Beds per ht	-0.076	0.671 *	3.478 *
	[-0.239 , -0.046]	[-0.416 , 0.028]	[-0.874 , 0.668]
W*LT Beds per ht	0.025	0.080	-0.617
	[-0.633 , 0.482]	[-0.107 , 1.449]	[-0.917 , 7.873]
W*Unemployment	0.016 *	0.079 ***	0.186 ***
	[-0.004 , 0.001]	[-0.025 , -0.016]	[-0.028 , -0.004]
W*Ln Median Income	0.742 ***	0.353 *	1.856 **
	[-0.001 , 0.034]	[0.047 , 0.111]	[0.068 , 0.304]
W*Pop Sq Mi	-0.001 ***	0.000	0.000
	[0.339 , 1.146]	[-0.076 , 0.782]	[0.468 , 3.245]
W*Log Home	-0.389 ***	-0.027	0.137
	[-0.002 , -0.001]	[0.000 , 0.000]	[0.000 , 0.000]
W*Percent 65+	5.152 ***	4.129 **	6.679 *
	[-0.624 , -0.155]	[-0.142 , 0.088]	[-0.799 , 1.072]
W*Marina per ht	-3.602 *	-2.208	0.617
	[3.382 , 6.922]	[1.450 , 6.809]	[-0.171 , 13.530]
W*Restaurant per ht	0.269	0.425	0.544
	[-8.229 , 1.025]	[-11.994 , 7.577]	[-41.812 , 43.047]
W*Movie per ht	-7.107 **	29.299 **	10.485
	[-0.243 , 0.782]	[-0.855 , 1.705]	[-3.549 , 4.636]
W*Bowling per ht	2.296	16.896 *	-0.804
	[-13.293 , -0.920]	[6.355 , 52.243]	[-115.690 , 136.660]
W*Golf per ht	0.278	-8.255	16.557
	[-4.240 , 8.832]	[-2.812 , 36.605]	[-100.924 , 99.317]
W*Library per ht	-2.205	25.228 **	51.078
	[-7.516 , 8.073]	[-27.281 , 10.771]	[-53.361 , 86.476]
W*Museum per ht	-4.383	-10.283 *	-6.028
	[-10.660 , 6.249]	[6.645 , 43.810]	[-40.185 , 142.340]
W*Nursing Homes per ht	0.006	0.012	0.119 **
	[-10.664 , 1.899]	[-23.328 , 2.762]	[-71.472 , 59.416]
W*Topography	0.004	-0.004	0.004
	[-0.088 , 0.137]	[-0.089 , 0.250]	[-1.632 , 0.397]
W*Perc Water	0.022	0.024	-0.021
	[-0.008 , 0.015]	[-0.019 , 0.012]	[-0.037 , 0.044]
R-Squared	0.872	0.903	0.864
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

Table 2.6 Doctor Rates and Local Amenities: Migrants 60-74

Dependent Variable: Log of 60-74 Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-20.691 ***	-13.900 ***	-20.365 ***
	[-23.187 , -18.194]	[-18.232 , -9.569]	[-34.489 , -6.241]
ST Expenditures per ht	0.000	0.001 **	0.002
	[-0.001 , 0.001]	[0.000 , 0.002]	[-0.002 , 0.006]
LT Expenditures per ht	0.000	0.002 *	0.001
	[-0.001 , 0.001]	[0.000 , 0.004]	[-0.007 , 0.008]
General Practitioner per ht	1.563 **	-0.366	-0.150
	[0.253 , 2.873]	[-3.889 , 3.158]	[-11.176 , 10.875]
Doctor Specialist per ht	6.628 ***	2.843 ***	-344.737
	[4.830 , 8.426]	[0.954 , 4.732]	[-1061.308 , 371.834]
Unemployment	0.042 ***	-0.016	-0.066
	[0.030 , 0.053]	[-0.047 , 0.014]	[-0.190 , 0.059]
Ln Median Income	-0.132	1.212	0.381
	[-0.418 , 0.154]	[0.856 , 1.568]	[-0.797 , 1.558]
Pop Sq Mi	0.006 ***	0.001 ***	0.000 *
	[0.005 , 0.007]	[0.001 , 0.001]	[0.000 , 0.000]
Log Home	1.539 ***	0.224 *	0.096
	[1.371 , 1.707]	[0.130 , 0.318]	[-0.737 , 0.930]
Percent 65+	7.460 ***	3.987 ***	2.991
	[6.318 , 8.601]	[1.984 , 5.990]	[-2.168 , 8.150]
Marina per ht	-3.599 **	-25.156 **	27.621
	[-6.290 , -0.907]	[-37.960 , -12.352]	[-24.224 , 79.465]
Restaurant per ht	-0.753 ***	3.810 ***	2.123
	[-1.083 , -0.423]	[2.722 , 4.898]	[-1.339 , 5.586]
Movie per ht	0.745	-0.641	-15.853
	[-2.926 , 4.416]	[-24.658 , 23.376]	[-150.060 , 118.355]
Bowling per ht	2.025	10.348	81.212
	[-1.789 , 5.839]	[-12.525 , 33.221]	[-42.748 , 205.172]
Golf per ht	2.989	-3.950	-29.873
	[-1.754 , 7.733]	[-20.464 , 12.564]	[-127.430 , 67.684]
Library per ht	-2.447	-31.783	-79.148
	[-7.523 , 2.629]	[-56.228 , -7.337]	[-240.276 , 81.979]
Museum per ht	-14.934 ***	-25.605 ***	-78.091
	[-18.508 , -11.359]	[-42.282 , -8.928]	[-201.396 , 45.214]
Nursing Homes per ht	0.004	-0.005	-0.018
	[-0.004 , 0.011]	[-0.030 , 0.021]	[-0.114 , 0.079]
Topography	0.006	0.008	-0.011
	[-0.002 , 0.014]	[-0.005 , 0.021]	[-0.043 , 0.022]
Perc Water	0.066 ***	0.101 ***	-0.033
	[0.045 , 0.086]	[0.061 , 0.140]	[-0.153 , 0.086]
Jan Temp	0.013 ***	0.051 ***	0.038 ***
	[0.009 , 0.018]	[0.044 , 0.058]	[0.018 , 0.057]
Sun Jan	-0.001	0.006 ***	0.005 **
	[-0.002 , 0.000]	[0.005 , 0.008]	[0.001 , 0.010]

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

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Table 6 – *Continued from previous page*

July	0.015 ***	-0.037 ***	-0.003
	[0.005 , 0.025]	[-0.053 , -0.021]	[-0.044 , 0.038]
July Humid	-0.003 ***	-0.020 ***	-0.014 **
	[-0.006 , -0.001]	[-0.024 , -0.016]	[-0.026 , -0.002]
W*ST Expenditures	-0.001 **	0.000	0.003
	[-0.002 , 0.000]	[-0.002 , 0.002]	[-0.003 , 0.009]
W*LT Expenditures	0.001	0.001	0.001
	[-0.001 , 0.002]	[-0.001 , 0.003]	[-0.009 , 0.012]
W*General Practioner	-0.001	-5.840 **	6.635
	[-1.711 , 1.710]	[-9.997 , -1.683]	[-6.425 , 19.696]
W*Doctor Specialist	5.402	2.538 *	-5.405
	[3.294 , 7.510]	[-0.475 , 5.550]	[-14.942 , 4.131]
W*Unemployment	0.032 ***	0.063 ***	0.166
	[0.018 , 0.047]	[0.034 , 0.092]	[0.053 , 0.278]
W*Ln Median Income	0.768 ***	0.456 **	1.406 **
	[0.441 , 1.094]	[0.069 , 0.842]	[0.013 , 2.800]
W*Pop Sq Mi	-0.001 ***	0.000	0.000
	[-0.001 , 0.000]	[0.000 , 0.000]	[0.000 , 0.000]
W*Log Home	-0.092	-0.049	0.468
	[-0.287 , 0.102]	[-0.153 , 0.055]	[-0.455 , 1.392]
W*Percent 65+	3.804 ***	2.954 **	6.213 *
	[2.367 , 5.241]	[0.462 , 5.447]	[-0.332 , 12.758]
W*Marina	-3.357 *	-0.308 *	-10.332
	[-7.201 , 0.488]	[-9.263 , 8.648]	[-51.531 , 30.866]
W*Restaurant	0.371 *	0.587 *	2.152
	[-0.049 , 0.790]	[-0.586 , 1.761]	[-1.907 , 6.211]
W*Movie	-8.839 ***	26.025 **	-32.243
	[-13.826 , -3.853]	[4.799 , 47.251]	[-152.112 , 87.626]
W*Bowling	2.752	16.783 ***	26.096
	[-2.463 , 7.966]	[-1.615 , 35.181]	[-71.509 , 123.701]
W*Golf	4.754	-5.436	21.668
	[-1.676 , 11.184]	[-23.202 , 12.330]	[-42.803 , 86.139]
W*Library	-7.225 **	10.741	41.310
	[-14.223 , -0.227]	[-6.372 , 27.854]	[-50.432 , 133.051]
W*Museum	-9.022 ***	-4.444	-27.358
	[-14.152 , -3.893]	[-16.413 , 7.524]	[-88.049 , 33.332]
W*Nursing Homes	0.006	-0.002	0.067
	[-0.005 , 0.017]	[-0.028 , 0.024]	[-0.038 , 0.172]
W*Topography	0.008	0.001	-0.007
	[-0.002 , 0.017]	[-0.013 , 0.016]	[-0.046 , 0.032]
W*Perc Water	0.035	0.003	-0.057
	[0.010 , 0.061]	[-0.042 , 0.049]	[-0.191 , 0.077]
R-Squared	0.898	0.910	0.865
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

Table 2.7 Doctor Rates and Local Amenities: Migrants 75+

Dependent Variable: Log of 75+ Year Old In-Migrants			
	Rural	**Urban**	**Most Urban**
Constant	-25.347 ***	-10.449 ***	-21.894 ***
	[-28.231 , -22.462]	[-14.994 , -5.905]	[-37.089 , -6.699]
ST Expenditures per ht	0.002 ***	0.002 ***	0.003
	[0.001 , 0.003]	[0.001 , 0.003]	[-0.001 , 0.007]
LT Expenditures per ht	0.000	0.002 **	0.000
	[-0.001 , 0.001]	[0.000 , 0.005]	[-0.008 , 0.008]
General Practitioner per ht	2.986 ***	-0.476	1.231
	[1.480 , 4.492]	[-4.183 , 3.231]	[-10.537 , 12.998]
Doctor Specialist per ht	5.539 ***	3.695 ***	-426.416
	[3.521 , 7.557]	[1.737 , 5.654]	[-1194.076 , 341.245]
Unemployment	0.028 ***	-0.043 **	-0.112 *
	[0.015 , 0.041]	[-0.074 , -0.012]	[-0.246 , 0.021]
Ln Median Income	0.296 *	1.108 ***	0.205
	[-0.033 , 0.625]	[0.742 , 1.474]	[-1.050 , 1.461]
Pop Sq Mi	0.007 ***	0.001 ***	0.000
	[0.006 , 0.008]	[0.001 , 0.001]	[0.000 , 0.000]
Log Home	1.617 ***	0.185 ***	0.220
	[1.422 , 1.811]	[0.091 , 0.279]	[-0.674 , 1.114]
Percent 65+	6.858 ***	3.655 ***	3.856
	[5.519 , 8.197]	[1.549 , 5.762]	[-1.831 , 9.543]
Marina per ht	-8.596 ***	-39.714 ***	3.918
	[-11.681 , -5.510]	[-53.127 , -26.300]	[-52.667 , 60.503]
Restaurant per ht	-1.452 ***	4.000 ***	2.363
	[-1.832 , -1.073]	[2.886 , 5.114]	[-1.397 , 6.123]
Movie per ht	3.280 *	2.572	6.996
	[-0.924 , 7.485]	[-22.481 , 27.625]	[-133.156 , 147.149]
Bowling per ht	6.069 **	17.619	59.360
	[1.705 , 10.434]	[-6.112 , 41.351]	[-73.293 , 192.013]
Golf per ht	0.962	-19.599 **	-50.630
	[-4.324 , 6.247]	[-36.885 , -2.313]	[-156.451 , 55.190]
Library per ht	-1.270	-22.872 *	-13.700
	[-7.200 , 4.660]	[-48.382 , 2.637]	[-185.506 , 158.105]
Museum per ht	-8.320 ***	-36.815 ***	-79.723
	[-12.417 , -4.223]	[-54.500 , -19.129]	[-211.868 , 52.423]
Nursing Homes per ht	0.018 ***	0.026 *	0.002
	[0.009 , 0.027]	[-0.001 , 0.052]	[-0.103 , 0.107]
Topography	0.000	0.010	-0.013
	[-0.009 , 0.010]	[-0.004 , 0.023]	[-0.048 , 0.023]
Perc Water	0.037 ***	0.070 ***	-0.035
	[0.014 , 0.060]	[0.029 , 0.111]	[-0.162 , 0.091]
Jan Temp	0.000	0.043 ***	0.031 ***
	[-0.005 , 0.005]	[0.035 , 0.050]	[0.011 , 0.052]
Sun Jan	-0.003 ***	0.004 ***	0.004
	[-0.004 , -0.002]	[0.002 , 0.006]	[-0.001 , 0.008]

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents
Continued on next page

Table 7 – *Continued from previous page*

July	0.045 ***	-0.043 ***	-0.001
	[0.034 , 0.057]	[-0.060 , -0.026]	[-0.044 , 0.041]
July Humid	-0.001	-0.021 ***	-0.013 **
	[-0.003 , 0.002]	[-0.026 , -0.017]	[-0.026 , -0.001]
W*ST Expenditures	1.222	-6.868 ***	4.253
	[-0.718 , 3.163]	[-11.125 , -2.612]	[-9.615 , 18.120]
W*LT Expenditures	6.421 ***	4.622 ***	-3.856
	[4.011 , 8.831]	[1.485 , 7.759]	[-14.056 , 6.344]
W*General Practioner	0.022 **	0.078 ***	0.190 ***
	[0.006 , 0.039]	[0.047 , 0.108]	[0.071 , 0.310]
W*Doctor Specialist	0.889 ***	0.348 *	1.649 **
	[0.507 , 1.270]	[-0.059 , 0.754]	[0.198 , 3.100]
W*Unemployment	-0.001 ***	0.000	0.000
	[-0.002 , -0.001]	[0.000 , 0.000]	[0.000 , 0.000]
W*Ln Median Income	-0.456 ***	-0.070	0.389
	[-0.685 , -0.228]	[-0.178 , 0.038]	[-0.587 , 1.366]
W*Pop Sq Mi	4.860 ***	3.457 **	4.765
	[3.205 , 6.514]	[0.859 , 6.055]	[-2.253 , 11.784]
W*Log Home	-3.693 *	0.833	-3.417
	[-8.052 , 0.666]	[-8.483 , 10.149]	[-48.112 , 41.277]
W*Percent 65+	0.076	0.236	1.459
	[-0.413 , 0.565]	[-1.013 , 1.484]	[-2.961 , 5.878]
W*Marina	-7.921 **	29.306 **	-4.454
	[-13.713 , -2.130]	[7.278 , 51.334]	[-136.304 , 127.395]
W*Restaurant	0.821	14.914 *	31.078
	[-5.289 , 6.931]	[-3.985 , 33.812]	[-73.726 , 135.882]
W*Movie	1.559	-7.846	20.938
	[-5.894 , 9.012]	[-25.859 , 10.167]	[-48.941 , 90.817]
W*Bowling	-3.707	20.381 **	63.842
	[-11.642 , 4.227]	[2.523 , 38.239]	[-32.906 , 160.591]
W*Golf	-5.164 *	-9.504	-5.102
	[-11.018 , 0.691]	[-22.022 , 3.014]	[-72.214 , 62.010]
W*Library	0.006	0.014	0.070
	[-0.006 , 0.018]	[-0.013 , 0.041]	[-0.039 , 0.180]
W*Museum	-0.001 *	-0.001	0.004
	[-0.003 , 0.000]	[-0.003 , 0.001]	[-0.002 , 0.011]
W*Nursing Homes	0.000	0.002	-0.002
	[-0.001 , 0.002]	[-0.001 , 0.004]	[-0.013 , 0.010]
W*Topography	0.004	-0.009	-0.004
	[-0.006 , 0.015]	[-0.024 , 0.006]	[-0.045 , 0.037]
W*Perc Water	0.024 *	0.018	-0.031
	[-0.006 , 0.053]	[-0.029 , 0.065]	[-0.171 , 0.110]
R-Squared	0.878	0.906	0.851
Observations	2261	645	169

*Asterisks denote significance at the *10, **5, and ***1 percent credible intervals*
per ht denotes that the variable is a rate per 100,000 residents

CHAPTER 3

THE IMPACT OF HOSPITALS ON LOCAL LABOR MARKETS: GOING BEYOND INPUT-OUTPUT MODELS

In 2011, The Congressional Budget Office predicted that hospitals which qualify for certain federal subsidies will cost the federal government $23 billion over the 2012-2016 period.[5] Under normal market conditions, failing businesses are an indicator that the market does not have a sufficient preference for the good or service given the market price. However, because of moral hazard, adverse selection, and price distortion, hospitals do not function under normal market conditions. Thus, national and local governments have been willing to allocate resources to hospitals that otherwise would be losing money under the justification that hospitals provide numerous positive benefits for the local community.

On a national level, hospitals are an important part of the economy. In 2013, according to the BEA, Health Care and Social Assistance generated $1,195.8 billion in total value added and $2,033.1 billion in total output.[6] On a local level, hospitals provide a myriad of benefits that range from their primary function of providing medical access for residents, acting as an "export-base industry" through the inflow of federal Medicare and Medicaid payments, and supplying high-skill high-wage employment (Nelson 2009). While the general qualitative benefits of hospitals are intuitively apparent, estimation of these impacts involves some effort to isolate each one.

This study examines one aspect of hospitals' impact on local communities by measuring the relationship between hospitals and local labor markets in rural and urban areas. When

[5] These subsides are in the form of higher Medicare payments for struggling hospitals that qualify under the Critical Access Hospital, Medicare-Dependent Hospital, and Sole Community Hospital Programs.
[6] Hospitals were worth $749.4 billion in current-cost net stocks of private fixed assets, equipment, structures, and intellectual property products according the Bureau of Economic Analysis in 2013.

considering local labor markets, by far two of the most import factors are wages of local residents and employment opportunities in the community. Our formal research objective is to measure if hospitals, particularly in rural communities, attract non-health related employment, and if hospitals provide higher wage jobs to residents based on their education level.

Previous studies have primarily measured the economic impact of hospitals with Input-Output analysis. However, because of the limitations, particularly for rural counties (Holmes, et al., 2006), we measure employment and wage outcomes due to the presence of a hospital using two alternative model specifications. First, the differences in wages among health care versus non-health care workers is measured by statistically modeling workers' earnings conditional on educational attainment for years 2000 and 2010. Secondly, the relationship between hospitals and non-health related employment for years 2001-2010 for urban and rural counties is measured using regression analyses.

The remainder of this paper is organized as follows. Section II is a review of selected previous work, Section III describes the data and its sources. Section IV explains the empirical methodology and results, followed by a conclusion and summary in Section V. Because we are running separate analyses for employment and wages outcomes, Section III and IV have separate sub-sections for the employment and wage analyses.

Background and Previous Studies

The economic impacts of hospitals in urban versus rural communities are not uniform. While urban communities usually have multiple hospital options within a city that can cater to differing population and health demographics, rural counties generally rely on a single hospital provider. This difference is particularly evident when a rural hospital closure is considered.

When there are rumors of an urban hospital closure, the conversation is generally focused on health access for the population currently utilizing that hospital's services. In contrast, hospital closures in rural communities seem to include an additional serious concern for the closure's impact on the future of local economic development.

One example of this is in Clayton County, Georgia. When the area's only hospital was in jeopardy of being closed, community leaders fought together to keep it open. Policy makers were worried about the closure's impact on migration, stating that "people needing basic medical treatment would have had to leave due to a lack of healthcare professionals and healthcare facilities on this side of the county." They also were concerned over the quality of care, they stated that the "absence of a robust healthcare infrastructure would discourage many healthcare professionals from setting up practices in the county." Finally, they were also concerned over the future economic vitality of the area, with concerns that "very few companies will locate to an area where their workforce can't receive adequate medical care."

Generally, low population counties have been second to their urban counterparts in terms of job growth-linked income gains (McGranahan and Beale, 2002). While rural counties have the benefits of a lower cost of living and inexpensive land, it is difficult to compete with larger cities in terms of business support amenities, agglomeration, and access to a large pool of high skill labor. One major aid in rural economic development is the health sector. Generally, health jobs are second only to the education sector in terms of total employment for rural counties. Additionally, the health sector does not provide just average jobs, but high-wage high-skill jobs. This helps build a strong tax base and stimulates other local businesses when those wages are spent locally (Doeksen, Cordes and Shaffer).

While some studies have failed to find a relationship between hospital closure and economic outcomes (Probst, et al., 1999; Stensland, et al., 2002; Pearson, et al., 2003), there seems to be a consensus among rural policy makers that hospitals are critical for a rural county's economic vitality. Typically, beyond access to care, three additional benefits are attributed to hospitals in rural communities. Hospitals bring in high-skill high-paying jobs, hospitals are an important amenity to potential migrants, and hospitals are critical for attracting future business growth (Christianson and Faulkner, 1981; Mick and Morlock, 1990; Doeksen, Loewen, and Strawn 1990; Doeksen, Cordes, and Shaffer, 1992; Johnson, and Willoughby, 1997; Cordes, et al. 1999; Novack, 2003; and Doeksen and Schott, 2003).

Hospitals could also help local employees via inter-industry wage differentials. Numerous studies indicate that wages persistently vary across industries and businesses for workers with similar characteristics (e.g., Dickens and Katz 1987; Groshen 1991; Krueger and Summers 1988 ; Thaler 1989). Thus if a hospital which hires a large percentage of a rural population compensates their employees well, it could influence local labor market norms about wages and other employer practices. It may be that other businesses will have to adopt such practices if they wish to acquire high talent labor.

While these studies are among an extensive literature measuring the economic impact of hospitals, previous research has predominantly relied on Input-Output analysis. An exception to this is Lindrooth, Sasso, and Bazzoli (2003) who analyze urban hospitals closures using regression analysis. They find that when alternative care is available, there are potential efficiency gains when struggling urban hospitals close. Holmes, et al. (2006) measure the effect of rural hospital closures on rural communities using a fixed effect regression analysis. They find hospital closures in communities with only one hospital lead to higher unemployment and lower per-capita income. Bartik and Erickcek (2007) very thoroughly examine the relationship between the health sector and economic activity within a metropolitan area and finds above average wages for health sector employees holding worker characteristics constant. Capps, Dranoveb, and Lindrooth (2010) measure residents' welfare after a hospital closure and find total surplus (a measure of aggregate social welfare) in the local community can decline following hospital closures. Brooks and Whitaker (2010) similarly used regression analysis and found having a critical access hospital in a community leads to higher levels of retail activity.

This study compliments previous work by measuring hospitals' economic impact on local labor markets in a broader sense than possible with input-output models. In particular, we aim to capture non-production channel impacts such as how the amenity effects of having a hospital in a community might attract retiree migrants and attract new businesses (Mandich and Dorfman, 2014).

This study has two model specifications, one to measure the influence of hospitals on wage premiums and another for employment spillovers. For the wage analysis, we choose a linear regression model and analyze person level wages for both years 2000 and 2010. Measuring wages in these two time periods allows us to examine any changes in hospital impact on wages over time. This is particularly interesting given the recent significant recession in 2007-2009. Because of this individual-level wage data, we are able to interact education with hospital employment to measure the impact of health care employment on wages for various skill levels. This interaction has not been thoroughly explored previously, as most of the employment conversation around hospitals has centered on hospitals' ability to provide high skill, high wage employment such as doctors. This study thus contributes to the literature by specifically exploring hospital wage impacts on lower skill workers. We additionally contribute to the literature by measuring hospital employment spillover effects using regression analysis.

Employment outcomes are examined at the county level using panel data for 2002-2012. In order to control for local unobserved characteristics, regression analysis with county-level fixed effects was the chosen model specification. By running two regressions, one for total employment and another for local healthcare sector employment, we are able to calculate the total non-healthcare employment that is attributed to having a hospital in the county. This is the spillover effect. For clarity, this spillover is not equivalent to a job multiplier. Instead, job spillover can rather be thought of as the long run consequence of businesses being attracted to a location by the amenity of having a hospital. Finding a positive and significant employment spillover effect from hospitals would confirm rural policy makers' intuition that hospitals attract employment that is non-health care related, and that hospitals are an important factor for rural communities' economic development prospects.

Data

Because we have two separate analyses, one at the person level and one at the county level, the data are collected from two separate sources. As further described below, person level IPUMS data is used for wage premium calculations while county level hospital employment from the BEA is used for employment spillover measurement.

Wages

Individual level data used in the wage analysis include the 5 percent sample of the 2000 Census and the 1 percent sample of the 2010 American Community Survey from the Integrated Public Use Microdata Series (IPUMS). Summary statistics are reported in Table 3.1. To compute the dependent variable of log wage, the log of respondent's annual pre-tax wage and salary income was divided by the usual hours and weeks worked last year. Because this is self-reported and not administrative data, there is naturally noise in the data. We thus exclude all values below $5 per hour and then top code obvious outliers, conditional on education level, after graphing income by education level. This isn’t a perfect measurement of hourly income. However, because we use the full 5% IPUMS sample that consists of over 6 million observations in 2000 and over 1.8 million observations from 2010, we rely on the law of large numbers that while some estimates are imperfect, the averages of the final data series should be close to the true values.

The independent variables were chosen based on person level characteristics shown to impact earnings that include: race, age, sex, education, and working in an urban area. Because we want to measure whether there is a potential for a wage premium for historically underpaid workers based on race, we include a variable to distinguish black workers in our final estimation. Also, we only include workers of the traditional working ages of over 18 and less than 65 years of age.[7] Because education levels strongly predict future earnings, (Card and Lemiux, 2001), education is categorized into: less than a high school education, having a high school education or equivalent, some college, an associate’s degree, a bachelor’s degree, and, finally, a post graduate degree. Defining education into such fine categories allows us to estimate how employment in the health sector impacts people among numerous skill levels and not just highly skilled doctors and surgeons. We define hospital workers according the North American Industrial Classification System (NAICS) code of 622. Finally, because wages reflect cost of living, we include a dummy variable, urban, for whether or not the respondent works in an urban city center based on the PUMS classification.

[7] As a robustness check, we computed results including workers of all ages. The results were identical in sign and very similar in magnitude to those reported in Table 3.

We admit that this analysis is not perfect since people with the same education levels in different industries may have different mixes of majors and job skills, leading to some wage differentials. However, we believe that hospitals employ a wide enough array of people (health professionals, accountants, supply chain managers, custodians, receptionists, etc.) to make the comparison meaningful.

Employment

County level data for the employment analysis comes from the Area Resource File and the Bureau of Economic Analysis (BEA). Summary statistics are listed in Table 3.2. The Area Resource File is a collection of data from over 50 sources such as the American Hospital Association, Bureau of Labor Statistics, and National Center for Health Statistics. The Area Resource File is maintained by the Department of Health and Human Services and contains many county health and population characteristics. All county level characteristics in the analysis thought to impact employment were collected from the Area Resource File.

Total full-time and part-time employment by NAICS industry was obtained from the Bureau of Economic Analysis. Our employment analysis uses panel county-level data for 2002-2010 and is classified into aggregate employment and health care employment, defined by SIC code 8060. In order to more effectively capture the differences between urban and rural counties, we run separate analyses based on the population of the county. Using the 2013 Urban Rural Continuum Code, we run three analyses on the most urban (code = 1), urban (code = 2, 3) and rural (code ≥ 4) counties. Due to confidentially concerns, some counties have suppressed values for health care employment and thus we are missing those data. While we exclude these counties from our model, it should not hurt the analysis. Because the literature has shown that health care employment has positive benefits for rural counties, our analysis can be considered a lower bound since we do not observe counties where a hospital could potentially provide the greatest relative positive impact. [8]

While most of the variables in Table 3.2 are self-explanatory, a few deserve further explanation and motivation. In order to avoid a simultaneity bias, all hospital variables are lagged by 10 years. Thus it can be assumed that a business moved to an area with full knowledge of the health access and not the reverse. Because a major research hospital and a critical access hospital have different economic implications, we include three types of hospital classifications in the analysis: short-term general hospitals, short-term non-general hospitals, and long-term hospitals. A short-term general hospital can be defined as having facilities and staff to provide diagnosis, care, and treatment of a wide range of acute conditions, whereas short term non-general hospitals provide treatment for a limited special group of acute conditions. Long-term hospitals have the infrastructure and personnel for the diagnosis, care, and treatment of a wide range of chronic diseases and have an average inpatient length of stay greater than 25 days. The remaining independent variables include the log of median income in the county, the unemployment rate in the previous year, and the percentage of people employed in health care. The percentage of health care employment in the county is included to identify counties which particularly rely on hospitals as a major driver of employment opportunities.

[8] Because we are using a 10 year panel, we have a total of 17,613 observations for rural counties, 9,980 of which had either no health care employment or a suppressed value, representing 46% of the sample. Urban counties have 24% of the sample suppressed, with 1,915 missing values, and most urban had 798 suppressed values, representing 17% of the sample. However because the counties' economies that are surpressed, particularly extreme rural, would particularly benefit from having a hospital the suppression would likely only support our findings. Thus this data could be considered a lower bond estimation.

Empirics

Wages

Regression analysis is used to measure the person level wage premium associated with working in a hospital. A simple model specification uses an individual's log wage as the dependent variable with worker level characteristics as the independent variables. Specifically, we can mathematically represent this as

$$y = \beta_0 + \beta_1 X + \beta_2 hosp + u \qquad (1)$$

where y=log wage, X is a vector of person level characteristics, $hosp$ is a dummy for being employed within a hospital, and u is a robust standard error. The results from this simple model are reported in Table 3.3 column (1) and are consistent with the established labor literature with females earning less than males, and higher educational attainment producing a higher hourly wage. For this study, the analysis of greatest interest is how much more a worker can expect to earn if they are employed in a hospital conditional on one's educational attainment. As seen in model (1) for 2000 and 2010, overall employment in the health industry induces a 7.4% and 16.9% hourly wage premium over workers in other sectors. Essentially, in 2010 if person A is earning the national average of $51,000 in an alternative industry, by switching to work in a hospital, person A could expect to earn $59,619, or a wage premium of $8,619.

However, we should be initially cautious of this result. It could be that this wage premium is due to the disproportionate amount of high earners the health industry employs (i.e., surgeons) and may not be applicable to the total population. In order to test for this, we also model whether or not one receives a wage premium for working in the health industry based on one's level of education. By interacting hospital employment and education level, we can compare for each level of education how much more a person can earn being employed in a hospital. This allows us to analytically compare two people with a specific level of education who look exactly the same, except one works in the health industry and the other does not, and measure who makes more per hour and by how much. This can be done using a slightly modified regression model:

$$y = \beta_0 + \beta_1 X + \beta_2 hosp + \beta_3 hosp * educ + u. \tag{2}$$

Education specific results are shown in Table 3.3 column (2). We find a 21.4% premium in 2010 for hospital employees with an associate's degree compared to other people with an associate's degree. Similarly, a person with a bachelor's degree would earn 12.2% more, and one with post graduate education can expect a 7.7% wage premium over others with the same level of education. All three of these results are statistically and economically significant. In monetary terms, if a person with an associate's degree was making \$30,000 in an average-earning industry, they could be making \$36,420 working in a hospital. In this scenario, hospital employment would have a \$6,420 wage premium for those with an associate's degree. Considering that associate's degrees are generally two year programs with flexible program designs, this has major policy implications for creating medium-skill higher paying employment.

We find mixed results in hospital wage outcomes based on person characteristics. When measuring the presence of a hospital wage premium among black workers, there is not a significant relationship in 2000, and in 2010 there is a small negative relationship. However, we do find an 11.3% hospital wage premium among women in 2010. Hospitals have a strong demand for historically female dominated jobs such as administrative positions and nursing. Thus, hospitals have not only been employing a large proportion of females historically, but are also currently providing women with better paying jobs relative to outside options with the same education level.

Another interesting finding appears when comparing the 2000 and 2010 results. While these results are not perfectly comparable, as the 2000 results are based on Census long form data and 2010 relies on the American Community Survey[9], we see that none of the signs change. Incidentally, all the hospital employment magnitudes increase in 2010 compared to 2000. This is one signal for the durability of hospital's potential for positive economic impact. We also see a stronger link between education level and wage outcomes over time. For 2010, someone with a bachelor's degree can expect to earn 66.6% more per hour than someone without a high school diploma compared to 57.4% in 2000. This implies that the wage premium for higher education has increased in the past 10 years.

These results have important implication for policy makers. Our findings show that hospitals not only provide high-income high-skill employment (e.g., surgeons and doctors), but also have positive impacts for those with a lower level of education. For communities with a hospital present, workers with 2 or fewer years of post-high school education can find employment that pays significantly more than other opportunities for those with an associate's degree. Thus, hospital workers with an associate's, bachelor, or post graduate degree can expect a positive wage premium compared to outside opportunities.

Employment

Our next level of analysis measures the association between hospitals and jobs. We begin the analysis with Figure 3.1. Figure 3.1 graphs the percentage change in national total

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[9] Because 2000 was the last year the census used the long form, the ACS is now the standard for personal level data previous collected in the long form. For detailed information on the Census and ACS measurements see Gage, Linda. "Comparison of Census 2000 and American Community Survey 1999–2001 Estimates: San Francisco and Tulare Counties, California."

employment and percentage change in national health sector employment from 2002-2011. Two things are particularly striking in this graph. First, while health employment growth slows in 2004 and 2009-2011, hospital employment never drops. Over this time period, which includes a severe recession, health care employment is continuously increasing. Contrastingly, national employment does drop during 2008-2010. This would suggest that in the aggregate being employed in health care helps shield one from negative economic shocks, such as a recession. This is true for both urban and rural health sectors as graphed in Figure 3.2. Essentially, hospital jobs could be considered more "recession proof" than alternative employment opportunities.

To measure the implications of hospitals on local job markets, we measure county employment and presence of a hospital for 2001-2011. We use a linear regression model with panel clustered standard errors, time dummies, and county fixed effects. Mathematically this is represented as:

$$Y_{it} = X_{it}\beta + \delta yr_t + f_i + u_{it} \tag{3}$$

Where Y_{it} is the number of employed 18-64 year old individuals in the county and X_{it} contains annual county level characteristics, including type and number of hospitals present. Because there was a substantial recession during the selected time period, annual dummies, yr_t, are included to control for annual shifts in local employment. Similarly, because there will naturally be unobserved heterogeneity given the nature of county level data, county fixed effects, f_i are also included, as well as county clustered standard errors u_{it}.[10]

Another way we decrease the unobserved heterogeneity is categorizing the data based on how urban the county is. As seen in Table 3.4 the most urban counties have an average of 3.65

[10] We also tried a spatial version of this model which found that spatially lagged hospitals were not statistically significant for urban and rural counties. We did find spatially lagged hospitals were significant for most urban counties, however given our focus is primarily on rural hospitals we do not report these spatial findings. These are available by request.

short term general hospitals, whereas the most rural have an average of .98 short term general hospitals. By estimating equation (3) separately for the most urban, urban, and rural counties, we can observe how hospitals are affecting employment particularly in rural counties where there is likely only one hospital.

As shown in Table 3.4 county characteristics assumed to impact employment perform generally as expected. For all counties, the unemployment rate in the previous year is negatively associated with employment. Similarly, we also see that compared with the omitted year of 2001, the following years have more jobs than 2001 with the exception of the post-recession years of 2008 and later for Urban and Rural counties where the magnitude is noticeably smaller than the previous trend. As expected, log of income was universally positive for total employment in all counties; however, income was not significant for health related employment in the most urban counties and was actually negative in urban and rural counties. One explanation for this is that in urban areas, higher average incomes lead to higher demand for health services (perhaps due to the contribution of demand for elective procedures) while in rural areas which commonly have lower incomes it is possible that very low incomes correlate with higher demand for health services due to provision of Medicaid (and perhaps also Medicare).

Hospitals are positively associated with employment among all counties. Rural counties can attribute 559 jobs from having a short-term general hospital where urban and most urban counties can attribute 1,045 and 5,272 respectively. While these results seem intuitive given that hospitals are a major source of employment, an aspect of hospital economic impact we specifically want to measure is the number of non-health care jobs which can be attributed to the presence of a hospital.

We measure the non-healthcare employment gains related to hospitals through the following procedure. First, we save the results from equation (3) of the impact of hospitals on county employment. Then, we change the dependent variable Y_{it} in equation (3) to county health care employment. This gives us the number of health related jobs in the county due to having a hospital in the county. We can then subtract the impact hospitals have on health specific employment from total employment. This difference is the net non-health related job gains associated with having a hospital in the county. For example, as seen in Table 3.5, a short-term general hospital is associated with 559 total jobs in an average rural county. The table also shows that the expected gain in health care only employment associated with having a hospital in a rural county is 60 jobs for a short-term general hospital. Thus, the number of expected non-health care jobs a rural county would gain from a short-term general hospital is 559-60 = 499 jobs. Similarly, a short-term non-general hospital is expected to produce a gain of 216 non health related jobs for a rural county.

Hospital job spill-over is similarly present in the urban and most urban counties. Specialty hospitals had particularly high job gains. Short term non-general hospitals were responsible for 264 hospital jobs in urban counties and 852 non-hospital related jobs. Similarly, in the very urban counties short term non-general hospitals were associated with 1,351 health related jobs and 6,125 non hospital related jobs. Urban counties were also found to benefit from having long term care hospitals, which were associated with 292 hospital jobs in the county and 2,160 non-hospital related jobs. While urban hospitals do not usually employ the same percentage of the population as in rural counties, we do find that hospitals are positively contributing to urban counties' local job markets beyond the direct employment within the hospitals.

These results have definite policy implications for numerous reasons. First, these results show that businesses are attracted to communities that have access to health services, thus keeping a hospital open has consequences not only for the health access of residents, but also on the health of the local labor market and economy. Secondly, looking at the relationship between hospitals and non-health employment gives a much clearer picture of the true economic spill-over effect of hospitals. For example, if having a hospital in county x is associated with 60 jobs, but the hospital employs 60 people, this hospital has no spill-over effect since all of its job creation is internal. However, as Table 3.5 shows, this is not the case as all counties have positive spill-over employment gains from having a hospital net of the employment in the health care sector. Beyond traditional multiplier effects on hospital employee spending, hospitals appear to serve as an amenity in the business attraction process.

Conclusions

With positive benefits on wages and non-health related jobs growth, hospitals have measurable positive economic outcomes above their primary objective of providing health care. Our analysis finds that hospitals provide high wage jobs not only for the most educated population, but also among those with two and four year degrees. In 2010, hospital employees with an associate's degree could expect a 21.4% wage premium compared with those in other industries with the same level of education. Similarly, a person with a bachelor's degree would earn 12.2% more working in a hospital compared to outside opportunities.

In terms of jobs, overall employment is positively related to a strong health care presence in rural and urban counties. For rural counties, a short-term general hospital is associated with 599 jobs in the county, 60 of which are in health care and 499 which are non-health care related.

Urban counties were also found to benefit from having long term care hospitals, which were associated with 292 hospital jobs in the county and 2,160 non-hospital related jobs. The strong positive spill-over effect that hospitals have on non-health care employment suggests that hospitals are an important institution for job creation. Thus, hospital closures would not only affect direct health care employment, but also many other jobs in the community.

At a time when smart job creation and growth is critical, it appears the health sector can play a vital role particularly for rural counties' future economic growth. In short, hospitals have significant positive economic impacts on their local communities as measured through these labor market outcomes. It may be particularly advantageous for local policy planners to consider these outcomes when pursuing new businesses and striving to build strong communities. These results also have implications for local governments wrestling with decisions about whether to provide subsidies in order to keep their local hospitals open. When asked to provide local governmental funding in order to keep a hospital operating, these results help give local policy makers the numbers they need to make informed decisions.

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Figure 3.1: Percentage Change in Total and Hopsital Employment 2002-2011

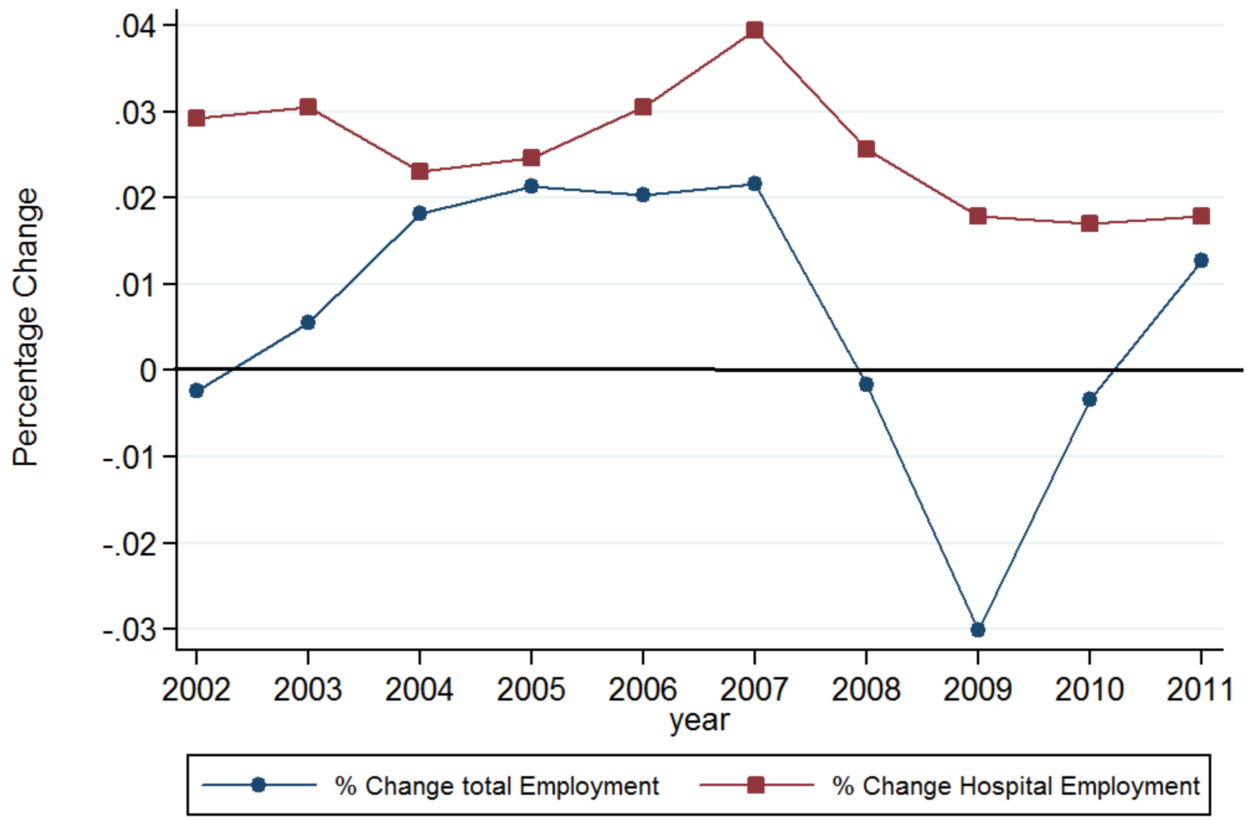

Figure 3.2 National Hospital Employment Change by Rural & Urban

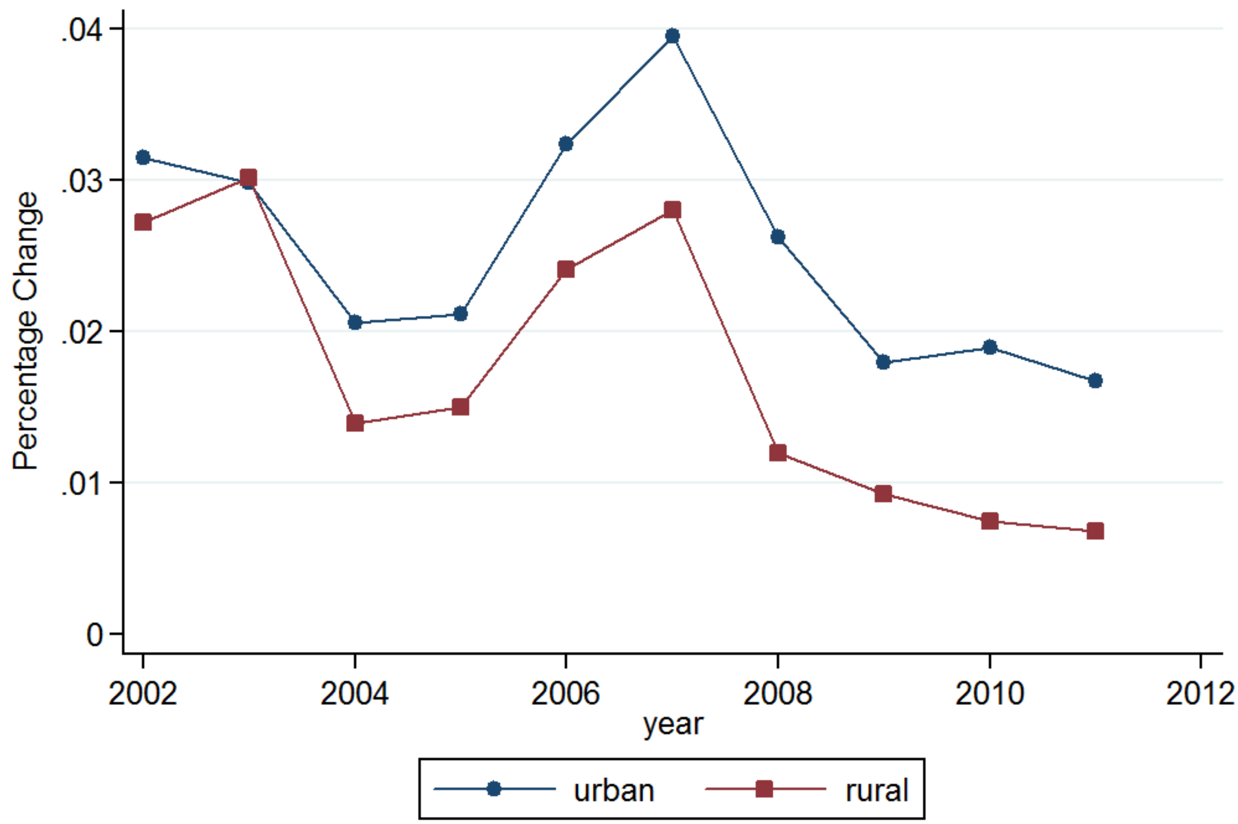

Table 3.1: Wage Descriptive Statistics

	2000				2010			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Ln Wage	2.642	0.590	1.61	5.298	2.881	0.651	1.609	9.462
Married	0.601	0.490	0	1	0.557	0.497	0	1
Black	0.099	0.299	0	1	0.097	0.296	0	1
Female	0.471	0.499	0	1	0.500	0.500	0	1
Age	39.1	11.8	18	64	41.0	12.9	18	64
Age Sq	1671.9	946.3	324	4096	1903.5	1070.6	324	4096
Urban	0.300	0.456	0	1	0.327	0.333	0	1
Less High School	0.127	0.332	0	1	0.073	0.259	0	1
High School	0.279	0.449	0	1	0.223	0.416	0	1
Some College	0.253	0.435	0	1	0.298	0.457	0	1
Associates	0.076	0.265	0	1	0.082	0.274	0	1
Bachelor	0.173	0.378	0	1	0.195	0.397	0	1
Post Bachelor	0.092	0.289	0	1	0.130	0.336	0	1
Hospital Employee	0.044	0.204	0	1	0.046	0.210	0	1

Table 3.2: Summary Statistics of Employment by County Type: 2002-2010

		(Count)	(Mean)	(Std. Dev)	(Min)	(Max)
Most Urban	Total Employ	3735	232846	464984	1929	5772756
	HC Employ	3090	27922	48280	45	533211
	Long term Hosp	3735	0.42	0.89	0	7
	Short Non-Gen Hosp	3735	1.23	2.96	0	37
	Short Gen Hosp	3735	3.65	6.70	0	97
	Ln Income	3735	10.45	0.26	9.71	11.68
	Unemploy	3720	5.54	2.15	1.60	20.50
	Perc HC Employ	3090	0.09	0.03	0.02	0.31
Urban	Total Employ	6426	71230	88566	519	620335
	HC Employ	4871	9751	10839	12	75854
	Long term Hosp	6426	0.15	0.44	0	4
	Short Non-Gen Hosp	6426	0.61	1.30	0	13
	Short Gen Hosp	6426	1.82	1.76	0	12
	Ln Income	6426	10.31	0.20	9.56	11.29
	Unemploy	6426	5.68	2.40	0	28.20
	Perc HC Employ	4871	0.10	0.04	0	0.37
Rural	Total Employ	17843	12822	22196	60	845120
	HC Employ	9567	1472	2447	0.00	62986
	Long term Hosp	17613	0.04	0.19	0	2
	Short Non-Gen Hosp	17613	0.04	0.21	0	3
	Short Gen Hosp	17613	0.98	0.72	0	6
	Ln Income	17843	10.22	0.22	9.30	11.73
	Unemploy	17613	6.13	2.88	0.60	25.50
	Perc HC Employ	9567	0.09	0.04	0	0.29

Table 3.3: Hospital Employment Wage Premium

	2000		2010	
Dependent Variable: Log Wage	(1)	(2)	(1)	(2)
Married	0.075***	0.075***	0.106***	0.106***
	(152.74)	(152)	(84.72)	(84.44)
Black	-0.031***	-0.029***	-0.063***	-0.059***
	(-40.99)	(-37.38)	(-33.33)	(-30.51)
Female	-0.221***	-0.225***	-0.203***	-0.207***
	(-476.79)	(-479.04)	(-176.56)	(-177.18)
Age	0.045***	0.045***	0.052***	0.052***
	(339.32)	(339.38)	(157.08)	(157.25)
Age sq	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(-259.47)	(-259.39)	(-126.14)	(-126.18)
Urban	0.086***	0.086***	0.084***	0.084***
	(126.29)	(126.78)	(51.63)	(51.9)
High School	0.128***	0.130***	0.172***	0.175***
	(181.6)	(182.75)	(85.23)	(85.68)
Some	0.278***	0.279***	0.349***	0.352***
	(368.29)	(365.06)	(163.9)	(163.23)
Assoc	0.326***	0.310***	0.398***	0.381***
	(338.37)	(311.04)	(160.84)	(149.45)
Bachelor	0.574***	0.572***	0.666***	0.662***
	(674.69)	(658.5)	(301.75)	(294.96)
Post	0.773***	0.774***	0.931***	0.931***
	(701.01)	(685.59)	(359.37)	(352.78)
Hospital Employ	0.074***	-0.048***	0.169***	0.015
	(68.03)	((-10.14))	(66.1)	(1.05)
HS*Hosp		-0.065***		-0.054***
		(-13.71)		(-3.65)
Some* Hosp		-0.014**		-0.020
		(-2.90)		(-1.36)
Assoc* Hosp		0.170***		0.214***
		(35.27)		(14.59)
Bach* Hosp		0.063***		0.122***
		(13.15)		(8.42)
Post* Hosp		0.026***		0.077***
		(4.56)		(4.85)
Female* Hosp		0.119***		0.113***
		(43.48)		(17.97)
Black* Hosp		-0.003		-0.025***
		(-0.88)		(-3.40)
Constant	1.344***	1.345***	1.269***	1.270***
	(546.89)	(547.47)	(196.35)	(196.43)
R-squared	0.297	0.299	0.331	0.332
N	5918257	5918257	1250703	1250703

t statistics in parentheses
Asteriks denote significance at the 0.05 (*), 0.01 (**), and 0.001 (***) level

Table 3.4: Total and Hospital Employment by County Type: 2002-2010

	Most Urban		Urban		Rural	
	(Total)	(Hosp)	(Total)	(Hosp)	(Total)	(Hosp)
Long term Hospital	2413	-1123 *	2451 ***	292 **	548 ***	53
	(0.58)	(-1.7)	(3.81)	(2.3)	(2.46)	(1.6)
Short Non-Gen Hosp	7476 ***	1351 ***	1116 ***	264 ***	312 **	95 ***
	(3.71)	(3.81)	(3.67)	(3.75)	(1.98)	(2.84)
Short Gen Hosp	5272 *	23	1045 *	66	559 ***	60 ***
	(1.83)	(0.04)	(1.67)	(0.5)	(3.83)	(2.67)
Ln Income	42920	-761	19892 ***	-1769 ***	1997 ***	-103 ***
	(1.38)	(-0.22)	(5.29)	(-2.92)	(7.5)	(-3.21)
Unemploy	-4887 ***	-617 ***	-651 ***	-77 **	-99 ***	-6 ***
	(-4.68)	(-4.32)	(-4.02)	(-2.07)	(-8.99)	(-3.07)
Perc HC employ	-215654	148023 ***	-53395 *	56239 ***	-12224 ***	9858 ***
	(-1.69)	(5.6)	(-1.69)	(6.53)	(-5.98)	(12.27)
yr2003	5222 ***	1071 ***	925 ***	297 ***	49 ***	28 ***
	(4.05)	(4.98)	(4.23)	(8.32)	(2.36)	(8.41)
yr2004	9707 ***	1672 ***	2024 ***	586 ***	179 ***	52 ***
	(4.24)	(5.01)	(5.31)	(9.17)	(5.33)	(9.93)
yr2005	10125 ***	1607 ***	2648 ***	793 ***	284 ***	73 ***
	(3.44)	(3.86)	(5.09)	(8.84)	(6.1)	(10.66)
yr2006	12048 ***	2162 ***	3506 ***	1123 ***	424 ***	104 ***
	(3.06)	(3.74)	(4.92)	(9.01)	(7.32)	(12.16)
yr2007	16665 ***	3090 ***	4153 ***	1474 ***	459 ***	141 ***
	(3.39)	(4.17)	(4.55)	(8.86)	(6.16)	(12.42)
yr2008	14227 ***	3230 ***	2866 ***	1656 ***	230 ***	154 ***
	(2.64)	(3.79)	(2.56)	(7.89)	(2.5)	(11.13)
yr2009	14820 ***	3906 ***	1798 *	1574 ***	-53	139 ***
	(3.14)	(4.65)	(1.73)	(8)	(-0.63)	(11.01)
yr2010	29868 ***	6169 ***	3039 **	1916 ***	120	167 ***
	(4.02)	(4.92)	(2.33)	(8.54)	(1.23)	(10.87)
Constant	-171398	21744	-112302 ***	21411 ***	-5319	1465 ***
	(-0.7)	(0.61)	(-2.88)	(3.29)	(-1.99)	(4.44)
N	3077	3077	4871	4871	9427	9427
R-Square	0.313	0.395	0.3521	0.4736	0.2263	0.4386

t statistics in parentheses
Asteriks denote significance at the 0.05 (*), 0.01 (**), and 0.001 (***) level

Table 3.5: Total and Hospital Employment by County Type: 2002-2010

	Most Urban			Urban			Rural		
	(Tot)	(Hosp)	(Net)	(Tot)	(Hosp)	(Net)	(Tot)	(Hosp)	(Net)
Long term Hosp	2413	-1123	3536	2451	292	2160	548	53	495
Short Non-Gen Hosp	7476	1351	6125	1116	264	852	312	95	216
Short Gen Hosp	5272	23	5249	1045	66	979	559	60	499

CHAPTER 4

SOME STATE VACCINATION LAWS CONTRIBUTE TO GREATER EXEMPTION RATES AND DISEASE OUTBREAKS IN THE US

In recent years, preventable diseases such as pertussis (whooping cough), measles, and mumps have been on the rise. While measles was largely eliminated in the United States by 2000, there has been resurgence in recent years. On January 13, 2015 health officials warned that a Disneyland visitor was linked to at least 7 cases of measles in California and 2 cases in Utah; 6 of those patients were not vaccinated. By March 2015, California had 133 confirmed measles cases, and 4 other states had cases linking back to the Disneyland visitor. For California, among measles cases for whom vaccination documentation was available, 57 were unvaccinated.[1]

Because vaccines rely in part on herd immunity for their effectiveness, this surge in disease has been popularly attributed to falling vaccination rates, particularly within local clusters, such as with the spread of measles in California from the infected Disneyland visitor.[1 2] While the U.S. does not have a national vaccination requirement, one way state policy makers incentivize people to vaccinate is through the educational system. Before a child can enter kindergarten in a any state, she must either be vaccinated or have a vaccination exemption. In most states kindergarten vaccination exemptions can be granted for medical reasons (i.e., the child has some physical ailment that prevents vaccination), religious reasons (e.g., vaccinations violate the parents' religious beliefs), or philosophical reasons (e.g., vaccinations are not in accordance with the parents' philosophical beliefs). Vaccination exemption rates vary significantly across the U.S. In 2012, exemption rates ranged from a low of approximately 0.45% in New Mexico to a high of 6.5% in Oregon (see Appendix 1).

If more parents do not vaccinate their children and instead opt for an exemption the U.S. could experience a general increase in preventable disease.[3, 4] If this association does hold, then state public health officials may want to advocate reconsidering state laws that ease the exemption process in order to avoid unnecessary illness. While numerous studies have examined vaccination exemption policy [3,5-10], to date few studies have been conducted that simultaneously, and dynamically, assess the impact of the multiple dimensions of exemption policy on exemption rates. [11] We extend this literature in three ways. First, we apply a comprehensive vaccine law database, which tracks over a dozen separate dimensions of state laws over time, permitting a longitudinal analysis. Second, we estimate a policy effectiveness model that evaluates the impact of each type of law on exemption rates, and use that model to construct an index of exemption policy effectiveness that weights each policy component by its contribution to overall exemption rates. This index supports a summary index measure of which states have the best composition of vaccine policies. Third, we will present evidence that states with the more effective bundles of policies (higher values of our summary index) also have lower rates of pertussis.

Vaccination exemption rates have drastically increased in the last 10 years, with almost all of the increase coming from religious and philosophical, or more generally "non-medical", exemptions. This increase in non-medical exemptions suggests that preferences for vaccines have changed in the last decade. One reason for this change in public perception is due to concerns about vaccine safety. For example, despite numerous reports showing no link between the MMR vaccine and autism, pockets of doubt remain among the public regarding the safety of that vaccine. Besides safety, some parents also question the effectiveness of vaccines.[12-13]

State policies may also be contributing to the observed increase in exemption rates. Every state has different exemption regulations as well as different language to describe and implement the laws. Some states have strict exemption submission laws that include a requirement that the state Department of Health approve all exemptions, whereas other states have almost no restrictions and parents can essentially "check a box" and send their child unvaccinated into school.[8, 12] For states with particularly easy exemption laws, the time cost in vaccinating one's child may be greater than the cost of filing an exemption. This is particularly true for parents who register their children for school at the last minute. If a child remains unvaccinated by the first day of kindergarten or first grade, it may be logistically impossible to vaccinate the child before the start of school; in such cases, filling out an exemption form at school may be the quicker and easier alterative. Similarly, for those who have high time costs to take their child to a clinic to be vaccinated because of work, lack of transportation, etc., filling out an exemption may be a lower cost option.[4]

A comprehensive list of exemption laws and definitions is presented in Table 4.1. The exemption laws range in stringency and purpose. For example, the category "*Use of Standardized State Form*," which identifies states with a standardized exemption application form, is likely not meant to hinder exceptions but rather unify and streamline the application. In contrast, "*Criminal/Civil Punishment*" indicates a type of regulation that assesses a penalty to either the child or parent for non-vaccination compliance, ranging from child expulsion to filing criminal charges of parent negligence. Thus not all components of vaccine exemption policy are equal, nor would we expect them to have the same impact on exemption rates.

This study measures the extent to which each of these state-level exemption policy components is associated with an increase or decrease in the actual number of vaccine exemptions filed in each state and year. From these estimated associations, we create a state level summary index that ranks states by their vaccination exemption law effectiveness. Finally, we also look at the association of exemption law effectiveness and preventable disease outbreaks.

Data

The kindergarten vaccination exemption data used in this study comes from the CDC *Annual School Assessment Reports* 2002-2012 (SARS).[14] These state-based surveys are the primary source of information on vaccination coverage of children in the U.S., and one of the only sources of exemption data available. However this data is not perfect as it relies on survey data from each state. Because of this sampling method, some of the challenges with the data include: some states only sampling select students vs. the entire state population, data is generally collected in the beginning of the school year when vaccination rates may be lower, and finally some states have missing years of data. Additionally, since the data are voluntarily given by the state, there is possible response bias where states with either particularly good or poor vaccine coverage have different incentives when reporting exemptions. To address these possible concerns, we run a series of robustness checks on our model to verify that any noise in the data is not impacting our conclusions.

We also include a set of state level, time-varying characteristics in our model collected from the *Area Resource File* (ARF).[15] The ARF is a collection of data from over 50 sources such as the American Hospital Association, Bureau of Labor Statistics, and National Center for Health Statistics. The ARF is maintained by the Department of Health and Human Services and contains many county health and population characteristics. We include measures of annual state-level socio-economic characteristics and economic conditions that could be associated with obtaining an exemption. These include: percent of the population that is Caucasian; percent of births that are very low birth weight; percent of the population that has earned a bachelor's degree or higher; state poverty rate; and the annual average unemployment rate.

Annual state specific vaccine exemption law data was obtained from the State Vaccination Requirements and Exemption Law Database, 2011.[16] This database is the most complete and comprehensive legal dataset on vaccination requirements available, and addresses 2,000 current US statutes and regulations from 50 states and the District of Columbia. Because of the volume of regulations and inconsistent policy language between states, trying to compare policies across states and time is not a simple task. We extracted our variables from this database by reviewing each state's vaccine laws and any changes over time, and then verified the database against each state's current department of health website information on vaccination exemption procedures.

This method of data collection differs from the previous work by Blank, et al. (2013) who identified state level vaccine laws by interviewing immunization program officials at the state level at one point in time. [11] Thus our data contrasts to that of Blank, et al. since our vaccine measurements are an abstraction of the actual regulatory language conducted by legal scholars and we can identify changes in laws over time. The dimensions of exemption laws we use, with definitions given by the legal database, are summarized in Table 4.1. [6, 11, 16] Indicator variables for each policy are included in our model of policy effectiveness.

Methods: Law Effectiveness Index

In order to measure each law component's effectiveness in reducing vaccine exemptions, we explore three regression analysis specifications that are designed for longitudinal data such as ours. We specify our model using a random effects estimator, a population average estimator, and a simple linear regression model with clustered standard errors (at the state level) for years 2002-2012. [17] The results were consistent across all three specifications, and our ultimate index of effectiveness was robust to model selection. For expositional purposes, we will present the random effects model results, though the full set of results are available upon request. Using the random effects model specification allows us to statistically control for annual year effects as well as unobserved state heterogeneity. Ultimately, this allows us to parse out the marginal effect each policy component has on exemption rates. [18]

Because not all laws are equally effective in making exemptions more difficult to obtain, it does not seem intuitive to create an index that weights each law component equally, though this is the approach taken in much of the existing literature. [3, 7, 9, 11, 19] It would be preferable to have a state ranking based on the total ability to reduce exemptions, not simply one that reflects the number of laws. Using the statistically significant regression coefficients as weights for such an index is a systematic way to combine the policies into a single summary statistic, which is preferable to the common practice of just summing the number of policy components a state has. Thus if one state has four relatively ineffective policies but another state has one very effective policy, the state with one effective policy should have a better (more effective at reducing exemptions) ranking than the other.

Our index is thus constructed by summing the statistically significant policy coefficients (from our exemption regression) multiplied by the corresponding indicator variables for whether the state has each policy component. (Excluding policies that are not significant is equivalent to giving them a weight of zero in the index.) We then grouped index numbers into four categories: Most Effective, Moderately Effective, Less Effective and Least Effective (corresponding to the highest to lowest quartiles of our index). Figure 4.3 presents a map of the 48 states (excluding

Alaska and Hawaii, for ease of presentation) according to their index rank in 2012. The darkest shaded states have the least effective policy, whereas the lightest states have the most effective policies. The complete index is available for all states each year from 2002 to 2012 upon request.

Policy Effectiveness Estimation

The dependent variable in our regression analysis is the total (medical, religious, and philosophical) state exemption rates. To see why we include all exemptions and not just non-medical exemptions, consider the case of Washington. In 2009, Washington had a change in policy that required parents or guardians to get a doctor's signature in order to obtain a vaccination exemption. While this successfully decreased the number of non-medical exemptions by 30% by 2012, it appears to have had an offsetting effect on medical exemptions which increased by 253% over the same time frame (from 309 to 1,092). This suggests that the change in policy may be incentivizing some people to obtain medical exemptions when they may previously have been more likely to obtain non-medical exemptions. In order to account for this and other possible substitution behavior, we look at policy effects on total vaccination exemptions.

In presenting the associations between each law component and the vaccine exemption rate, we highlight the results from our random effects regression analysis covering the years 2002-2010. Again, the dependent variable is the state's exemption rate (percent of kindergarteners with an exemption) and the independent variables include each policy component listed in Table 4.1, the state characteristics discussed above, and year indicator variables. The coefficients and standard errors from the random-effects model are presented in

Table 4.2 column 1 and discussed below; alternative models are presented in columns 2 though 4, but are not discussed in detail. As a robustness check, we ran a version of the model which excluded states with very low vaccine exemption survey response (<10%); excluding such states did not impact the results as can be seen in column 4 in Table 4.2.

We find having the Department of Health approve non-medical vaccination exemption applications has a statistically significant association with lower rates of exemption take-up by -1.12% ($p<0.05$) compared to states without such a policy. A priori, this seems to be one of the most difficult barriers to obtaining an exemption, since the Department of Health may be relatively strict in approving exemptions because of its interest in preserving herd immunity within the state. Consistent with previous research, states which allow philosophical exemptions had an +0.1% ($p<0.01$) higher exemption rate than states that do not allow philosophical exemptions. Because many states have required proof of immunity or religious certainty clauses with medical and religious exemptions, philosophical exemptions have the potential to be easier or less costly to acquire. Another law which was associated with lower exemption rates was the ability to be exempt from only specific vaccines instead of all vaccines (represented by the variable "Scalable"), which reduced exemptions by -0.7% ($p<0.05$) Also, criminal and civil punishment was statistically significant and associated with decreasing exemptions by -0.6% ($p<0.01$) compared with states without such a policy. Finally, within the past few years, numerous states have made administrative changes to their vaccination exemption laws and have adopted a standardized exemption form. While such polies are important for clerical accuracy and tracking, we did not find that they lower exemption rates but rather are associated with a +1.0% ($P<0.01$) increase in exemptions.

These results suggest that not all policies are created equal. While some states may have numerous laws related to exemption rates, if these laws are not effectively reducing non-medical exemption rates, then more is not necessarily better or more effective. Consequently, we constructed a state policy effectiveness index which aggregates the multiple dimensions of state exemption policy into one measure of effectiveness taking the estimated impact of each type of policy into account as seen in Figure 4.1.

Policy Effectiveness and Preventable Disease Outbreaks

Our constructed exemption law effectiveness index also allows us to examine whether states with more effective exemption laws also have fewer cases of preventable diseases. Table 4.3 shows the association between average incidence of pertussis per 100,000 people and our state level index ranking. Measuring pertussis incidence in terms of population allows a more uniform comparison mechanism since there is a wide range in state population sizes. As consistent with previous studies, while there is not a perfectly linear relationship between the index ranking and disease incidence, there is a general trend where states with less effective policies have higher average preventable disease rates per 100,000. [10] When comparing the average pertussis incidence over all of the years 2002-2012, there was an average incidence of 7.3 cases per 100,000 people (per ht) in the states with most effective policies and 16.06 cases per ht in the least effective policy states. This relationship is even more pronounced when we focused just on 2012, where the most effective policy states had an average of 16.45 cases per ht and the least effective policy cases had 54.19 cases per ht.

To test the validity of this perceived trend, we conducted a series of t-tests on the null hypothesis that the difference in average pertussis incidence was the same when comparing states with different policy effectiveness, as measured by our index focusing on the year 2012 data. We find statistically significant relationships among the comparisons. When comparing the least effective policy states to all other states, there are 38.67 fewer cases of pertussis per 100,000 among states with more effective policies ($p<0.01$). Additionally, when comparing the most and least effective policy states, the most effective states have 37.75 fewer cases per ht of pertussis ($p<0.01$) than the least effective policy states. These results hold when looking at the long run average pertussis incidence from 1995-2012.

Additionally, we also measured the association of pertussis incidence and state exemption policy effectiveness using regression analysis. As before, using a random-effects regression model with state characteristics variables and year dummies we find a statistically significant relationship between exemption laws and pertussis incidence. States with the most effective policies are associated with -7.02 fewer cases ($p<0.01$) of pertussis per 100,000 people than states with the least effective policies. Similarly, both states with somewhat effective and less effective policies had -6.55 ($p<0.01$) and -5.66 ($p<0.01$) fewer cases of pertussis per 100,000, respectively, than states with the least effective policies. These results suggest a statistically significant association between increased pertussis incidences and more ineffective vaccination exemption policy at the state level. The results are presented in an on-line appendix, and available upon request.

Conclusion

The goal of this research is to illuminate the relationship between various types of vaccination policies and state-level vaccination exemption rates, in order to aid policy makers and public health planners to target specific policy interventions that will decrease the number of exemptions given and ultimately reduce the incidence of preventable diseases. Our findings suggest that not all laws related to vaccination exemptions have the same impact on exemption take-up. For example, states' adoption of a standard exemption form may be useful for administrative purposes, but we find they are also associated with increases in the number of vaccine exemptions in those states. This is particularly important since the most popular recent policy reforms are these administrative changes.

However, we do find that other policies – such as requiring health department approval for non-medical exemptions, requiring a physician signature for an exemption, and having criminal or civil punishments for noncompliance – do have a statistically significant effect in reducing exemptions. For policy makers interested in decreasing the number of vaccine exemptions within their state, these specific regulations would be of particular interest. Finally, we also find a link between our constructed index of policy effectiveness and the incidence of preventable diseases. States that have the most effective portfolio of polices in our index have lower incidences of pertussis. Vaccine exemption policy is thus an important piece within a greater comprehensive plan of reducing preventable diseases. States thus have tools available to optimize their policies, if public health officials wish to decrease exemptions and disease outbreaks.

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[2] Disease outbreak is not a simple issue and besides non-vaccination, other influences such as possible vaccine failture may be confounding factors. Additionally as stated by the FDA, "While the reasons for the increase in cases of whooping cough are not fully understood, multiple factors are likely involved, including diminished immunity from childhood pertussis vaccines, improved diagnostic testing, and increased reporting. With its own funds plus support from the National Institutes of Health (NIH), the FDA conducted the study to explore the possibility that acellular pertussis vaccines, while protecting against disease, might not prevent infection." **(**Rodriguez, Jennifer and Padmanabhan. Nalini 2013. FDA study helps provide an understanding of rising rates of whooping cough and response to vaccination. FDA News Release, http://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm376937.htm) However estimating a comprehensive model of disease outbreak is beyond the scope of this study and we will only be focusing on the relationship between exemptions and disease incidence.

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implementation is beyond the scope of this study, we will use the Vaccine Exemption Law vernacular and assume for the remainder of the analysis that any current vaccination law is indeed being carried out by the state.

[17] Greene, William H. *Econometric analysis*. Pearson Education India, 2003.

[18] One specification that we do not use – though it is a strong candidate for use – is a fixed-effects regression (i.e., a model with state indicator variables). Fixed-effects models measure the impact of time-varying factors on the outcome, with all time-invariant heterogeneity (or unobservables) captured by the state indicator variables. One distinct advantage of fixed-effects models is that they are robust to time-invariant omitted variable bias (to which random-effects models are more susceptible). However, one disadvantage of a fix-effects model for our purposes is that variables that do not change within a state during the time period we examine cannot be included in the regression (being perfectly collinear with the state fixed effect). Four of the policy components do not change for some states over our time frame. So, if we used a fixed-effects model, those (potentially important) factors could not be considered. We thus face a trade-off: use all of the dimensions of policy in a random-effects framework (and rely more on cross-sectional variation and claim only to find associations); or use only some of the policy indicators in a fixed-effects model (and retain more capacity to make causal inferences, but limit the scope of those inferences). To decide which, we conducted a specification test by estimating our model with fixed-effects and compared the coefficients on the remaining variables to those from the full set in a random-effects specification. We found that the remaining policy coefficients were qualitatively very similar to the full random effect model; that is, dropping some dimensions of policy did not materially change the measured impact of the policy components remaining. Consequently, we conclude that the random-effects model with all policy dimensions does not suffer from meaningful omitted variables bias, and that we are able to use it in our analysis. We proceed on that basis. The full set of fixed-effects models are available upon request.

[19] Stadlin, S, Bednarczyk R A, Omer S B. Medical exemptions to school immunization requirements in the United States—association of state policies with medical exemption rates (2004–2011). *Journal of Infectious Diseases*. 2012; 206(7): 989-992

Table 4.1: Definitions and Number of States with each Vaccination Law in 2012

Provisional Admission	44
Use Standardized State Form	39
Notarization	14
Scalable Request	17
Submit Written Statement	46
DOH/school Approves Nonmedical Exemption	4
DOH/school Approves Medical Exemptions	3
Written Professional (Clergy) Statement	6
Non-physicians Can Not Sign Exemption Forms	20
Non-physicians Can Sign Exemption Forms	22
Criminal or Civil Charges	16
Annual Renewal	9
Philosophical Exemption Available	17

Provisional Admission	Partially vaccinated children or children who are missing immunization records may be admitted to school for a set period of time until records can be submitted or vaccines brought up-to-date.
Use of Standardized State Exemption Application Forms	Law states that there are standardized exemption forms.
Notarization of Exemption	Application Forms Laws that require exemption forms to be notarized prior to submission.
Scalable Request for Exemption to Only Particular Vaccines	Some states require that an exemption to vaccination, especially a non-medical exemption must be requested for all required vaccines. Scalable requests permit the parent or other adult to indicate which vaccine(s) exemption is being requested.
Submission of Written Statement Requesting Non-medical Exemption	Parents must to submit a written statement requesting a religious or philosophical exemption.
Requirements for DOH/school to Review/Sign/Approve Nonmedical Exemption Forms	This law is related to exemption to vaccination based on religion or philosophy or conscientious belief which requires the Department of Health at either the local or state level to review exemption applications/forms and decide whether to approve and sign-off on the applications.

Requirements for DOH/school to Review/Sign/Approve Medical Exemption Forms	Laws related to exemption to vaccination based on medical concerns that require the Department of Health at either the local or state level to review exemption applications/forms and decide whether to approve and sign-off on the applications.
Submission of Written Professional (e.g. Clergy) Statement For Religious Exemption	Requires a written statement be submitted by clergy or other professional who can support the parent's written statement indicating that vaccination conflicts with their religion.
Criminal and/or Civil Penalties Related to Vaccination Exemption	If a statute or regulation indicates that criminal or civil penalties are associated with various aspects of vaccination, including loss of state benefits or state benefit eligibility.
Non-physicians Can Sign Exemption Forms	This law permits that non-physician providers (physician assistants, nurse practitioners and others) can sign exemption forms.
Non-physicians Can Not Sign Exemption Forms	This law permits that only physician providers (MDs or DOs) can sign exemption forms.
Annual Renewal	Vaccine Exemption forms much be resubmitted annually.

Table 4.2:Regression Analysis Results for State Exemption Laws on Exemption Rates: 2002-2012

	Random Effect	Population Average	Clustered Errors	Clustered Errors 10% + Sample
Provisional Admission	-0.001	-0.0009	-0.0008	0.0004
	(0.0033)	(0.0032)	(0.0024)	(0.0025)
Standard Form	0.0103***	0.0103***	0.0104***	0.0088***
	(0.0033)	(0.0032)	(0.0027)	(0.0028)
Notarization	-0.003	-0.0028	-0.0028	-0.0006
	(0.0033)	(0.0033)	(0.0027)	(0.0025)
Scalable	-0.007**	-0.007**	-0.007**	-0.0061*
	(0.0032)	(0.0032)	(0.003)	(0.0034)
Written Statement	0.005	0.0049	0.0047	0.0043
	(0.0067)	(0.0066)	(0.004)	(0.004)
DOH reviews Medical application	-0.001	-0.0003	-0.0005	-0.0006
	(0.0048)	(0.0047)	(0.0025)	(0.0027)
DOH review Non-Medical applications	-0.0112*	-0.0113*	-0.0112*	-0.0106*
	(0.0067)	(0.0066)	(0.0059)	(0.0058)
Religious Sincerity	-0.002	-0.002	-0.0021	-0.0027
	(0.0084)	(0.0084)	(0.0051)	(0.0046)
Criminal	-0.006***	- 0.0063***	-0.0062	-0.0066
	(0.0025)	(0.0024)	(0.0044)	(0.005)
Non-MD Can't Sign	-0.005*	-0.0048*	-0.005*	-0.0048**
	(0.003)	(0.0029)	(0.0026)	(0.0025)
Non-MD Can Sign	-0.002	-0.0019	-0.0021	-0.0013
	(0.0026)	(0.0025)	(0.0024)	(0.0025)
Annual Submit	-0.003	-0.0028	-0.0027	-0.0028
	(0.0045)	(0.0045)	(0.0032)	(0.0033)
Philosophical	0.001***	0.0095***	0.0096***	0.0095***
	(0.003)	(0.0029)	(0.0032)	(0.0036)
State Characteristics	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Observations	468	468	468	395

Notes: Dependent variable is percent of Kindergarteners with an Exemption in a given state.
Asteristics denote significance by * p<0.10, ** p<0.05, *** p<0.01.

Figure 4.1 Exemption Effectiveness Ranking 2012

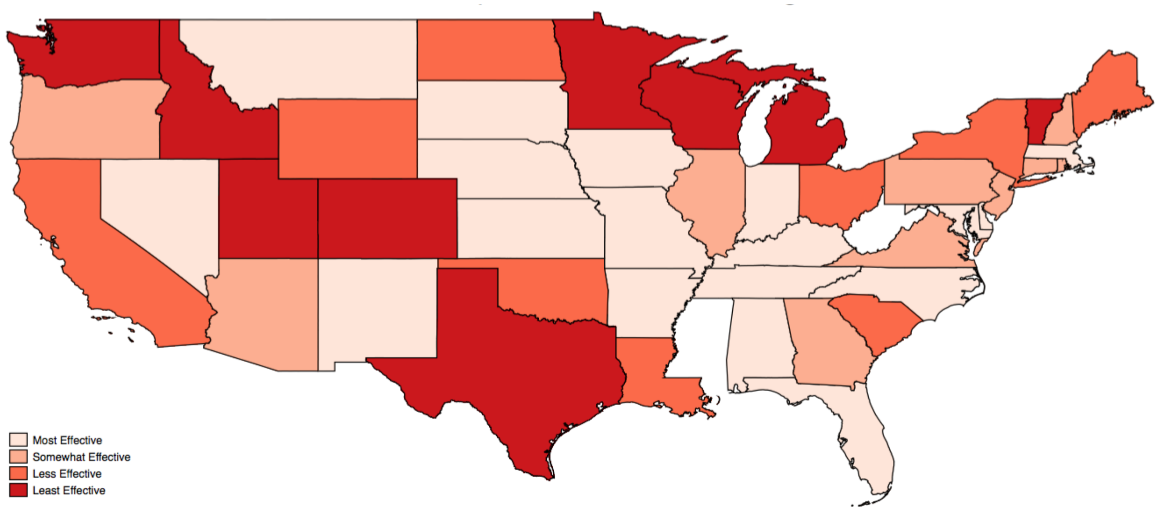


Figure 4.2: Percentage of Kindergarteners with Vaccine Exemptions: National Average 2002-2012

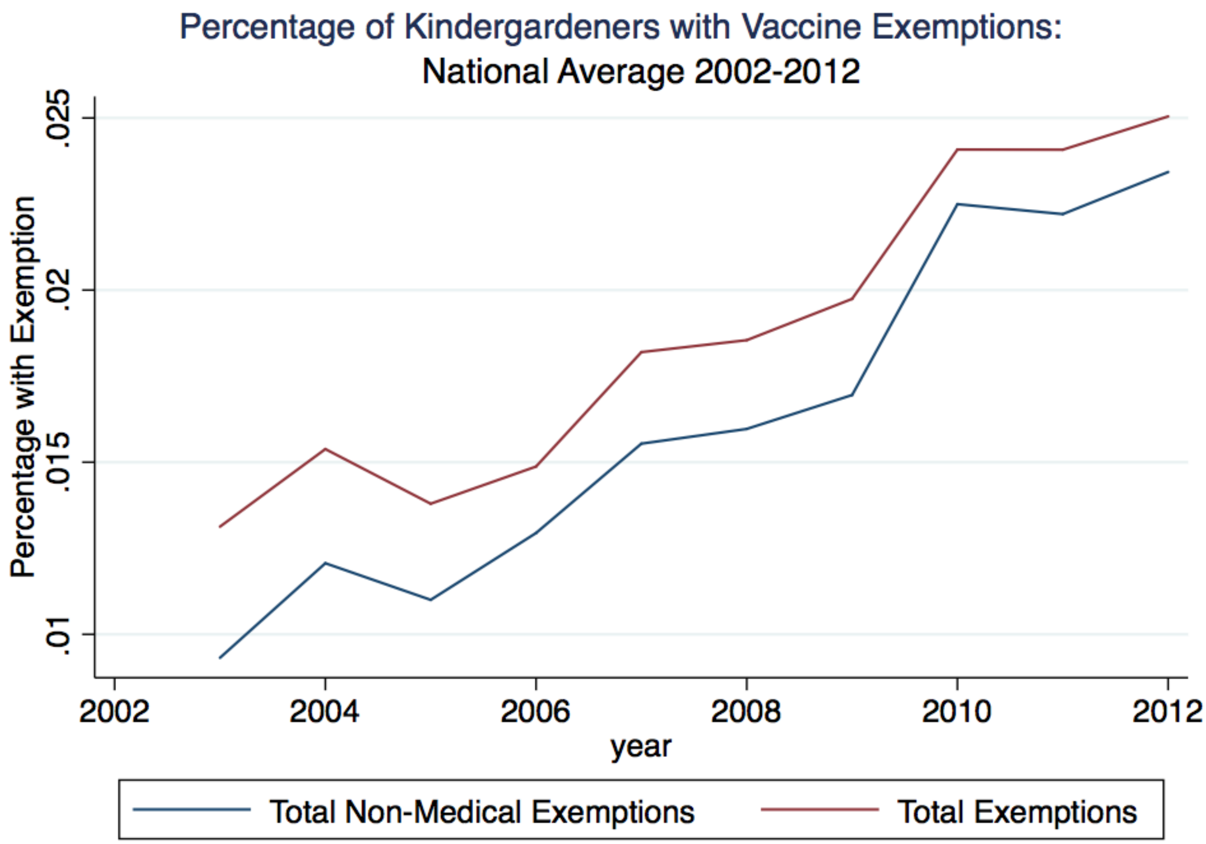


Table 4.3: Average Cases of Pertussis per 100,000 people by Index Ranking

	(1) 2002-2012	(2) 2012
Index=1 Most Effective States	7.30	16.45
Index=2 Moderately Effective States	6.07	11.97
Index=3 Less Effective States	7.53	18.14
Index=4 Least Effective States	16.06	54.19
National Average	8.43	22.63
Observations	539	49

Appendix 4.1: Index score, Percent with Exemption, and Incidence of Pertussis by State: 2012

	Index Rank	Pertussis	% With Exemption
Alabama	1	0.66%	4.4
Alaska	3	5.72%	48.26
Arizona	2	4.31%	17.24
Arkansas	1	1.10%	8.41
California	3	2.99%	2.09
Colorado	4	4.30%	28.8
Connecticut	2	1.74%	5.07
Delaware	1	0.70%	6.22
District of Columbia	2	1.60%	4.11
Florida	1	1.78%	2.98
Georgia	2	2.27%	3.21
Hawaii	2	2.50%	5.24
Idaho	4	5.86%	14.73
Illinois	2	6.05%	15.74
Indiana	1	1.56%	6.75
Iowa	1	1.65%	56.47
Kansas	1	1.10%	30.74
Kentucky	1	0.73%	15.2
Louisiana	3	0.66%	1.56
Maine	3	4.58%	55.45
Maryland	1	1.16%	6.27
Massachusetts	1	1.56%	9.75
Michigan	4	5.88%	8.55
Minnesota	4	1.61%	77
Missouri	1	1.80%	13.53
Montana	1	3.58%	54.62
Nebraska	2	1.73%	12.93
Nevada	1	2.50%	4.06
New Hampshire	2	2.55%	20.37
New Jersey	2	1.45%	15.74
New Mexico	1	0.48%	44.31
New York	3	0.70%	16.2
North Carolina	1	0.81%	6.28
North Dakota	3	1.80%	30.59
Ohio	3	2.33%	7.74
Oklahoma	3	1.36%	4.04
Oregon	3	6.54%	23.23
Pennsylvania	2	2.02%	15.24
Rhoda Island	2	1.47%	10.76
South Carolina	3	NA	4.74

South Dakota	1	1.79%	8.4
Tennessee	1	1.28%	4.72
Texas	4	1.76%	8.51
Utah	4	3.84%	55.72
Vermont	4	6.11%	103.03
Virginia	2	0.50%	7.64
Washington	4	4.98%	71.28
Wisconsin	4	4.50%	120.15
Wyoming	3	2.25%	10.76

*Pertussis per population is the number of cases in the state per 100,000 residents.

Appendix 4.2 : Policies by State for 2012

	Medical	Religious	Philosophical	Provisional Admission	Standardized State Form	Notarization	Scalable Request	Submit Written Statement	Written Clergy Statement	DOH Approves Nonmed	DOH/school Approval Med	Religious Belief Sincerity	Non-physicians Can Not Sign Forms	Non-physicians Can Sign Forms	Criminal/Civil Punishment	Annual Renewal
Alabama	1	1	0	1	1	0	0	1	0	0	0	0	1	1	1	0
Alaska	1	1	0	1	1	1	0	1	0	0	0	0	1	0	0	0
Arizona	1	1	1	1	1	0	1	1	0	0	0	0	0	1	0	0
Arkansas	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	1
California	1	1	1	1	1	0	1	1	0	0	0	0	0	1	1	0
Colorado	1	1	1	1	1	0	0	1	0	0	0	0	0	1	1	0
Connecticut	1	1	0	1	1	0	0	1	0	0	0	0	0	1	0	0
Delaware	1	1	0	1	1	1	0	1	0	0	0	0	1	0	1	0
DC	1	1	0	1	1	0	0	1	0	0	0	0	0	1	0	1
Florida	1	1	0	1	1	0	0	1	0	1	0	0	1	0	1	0
Georgia	1	1	0	1	1	1	0	1	0	0	0	0	0	1	1	0
Hawaii	1	1	0	1	1	0	0	1	0	0	0	0	0	0	1	0
Idaho	1	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0
Illinois	1	1	0	1	1	0	0	1	0	0	0	0	0	1	1	0
Indiana	1	1	0	1	1	0	1	1	0	0	0	0	1	0	0	1
Iowa	1	1	0	1	1	1	1	1	1	0	0	0	0	1	1	0
Kansas	1	1	0	1	1	0	1	1	0	0	0	0	1	0	0	0
Kentucky	1	1	0	1	1	0	1	1	1	0	0	0	0	1	1	0
Louisiana	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0
Maine	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	1
Maryland	1	1	0	1	1	0	1	1	0	0	0	0	0	1	1	0
Massachusetts	1	1	0	1	0	0	0	1	0	0	0	0	0	0	1	0
Michigan	1	1	1	1	1	0	0	1	0	0	0	0	0	1	0	0
Minnesota	1	1	1	1	1	1	0	1	0	0	0	0	0	1	1	0
Mississippi	1	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0
Missouri	1	1	0	1	1	1	0	1	0	0	0	0	1	0	1	1
Montana	1	1	0	0	1	1	1	1	0	0	0	0	1	0	0	0
Nebraska	1	1	0	1	0	0	0	0	1	0	0	0	1	0	0	0
Nevada	1	1	0	0	0	1	0	1	0	0	0	0	0	1	0	0

New Hampshire	1	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0
New Jersey	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	1
New Mexico	1	1	0	1	1	0	0	0	1	0	0	1	1	0	0	1
New York	1	1	0	1	1	0	1	1	0	0	0	0	1	0	0	0
North Carolina	1	1	0	1	1	0	1	1	0	0	0	0	1	0	0	0
North Dakota	1	1	1	1	0	0	0	0	1	0	0	0	1	0	0	1
Ohio	1	1	1	1	1	0	0	1	0	1	1	0	0	0	0	0
Oklahoma	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0
Oregon	1	1	0	1	0	0	0	1	0	0	0	0	0	1	0	0
Pennsylvania	1	1	0	1	1	0	0	1	0	0	0	0	0	1	0	0
Rhode Island	1	1	0	1	1	0	0	1	0	0	0	0	1	0	0	0
South Carolina	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0
South Dakota	1	1	0	1	0	0	0	1	0	0	0	0	0	1	1	0
Tennessee	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1
Texas	1	1	1	1	1	0	0	1	0	0	0	0	1	0	0	0
Utah	1	1	1	1	1	0	1	1	0	0	0	0	0	1	0	0
Vermont	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0
Virginia	1	1	0	1	1	0	1	1	0	0	0	0	0	1	0	0
Washington	1	1	1	0	1	0	1	1	0	0	0	0	0	1	0	0
West Virginia	1	0	0	1	1	1	0	1	0	0	0	0	1	0	0	0
Wisconsin	1	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0
Wyoming	1	1	0	1	0	0	0	0	1	1	0	0	0	1	0	0

Appendix 4.3: T-Tests for Changes in State's Incidences of Pertussis by Index Rank

	(1: Most vs. Other) Mean (T-test on Difference for other states) [Mean Other] [Mean Most]	(2: Least vs. Other) Mean [T-test on Difference for other states] [Mean Other] [Mean Least]	(3: Most vs. Least) Mean [T-test on Difference Least-Most] [Mean Least] [Mean Most]
Cases Pertussis 2012	9.77 (7.89) [26.22] [16.44]	-38.67 (8.24)*** [15.52] [54.20]	-37.75 (11.31)*** [16.45] [54.20]
Observations	49	49	27
Cases Pertussis 2002-2012	1.62 (1.21) [8.92] [7.31]	-9.16 (1.44)*** [6.91] [16.06]	-8.76 (1.99)*** [7.31] [16.06]
Observations	539	539	252

Notes: Asteristics denote significance by * p<0.10, ** p<0.05, *** p<0.01. Column (1) is the difference of mean cases of Pertussis per 100,000 people in the Most Effective states, Index=1, versus. all other states. Similarly column (2) is the difference in mean disease incidences in Least Effective states, Index=4, to all others. Column (3) is the difference between the Most and Least Effective policy states. The top panel is as average disease incidences over 1995-2012, whereas the bottom panel restricts the sample to 2012.

Appendix 4.4: State Exemption Effectiveness Index and State Pertussis Incidence: 2002-2012

	Random Effects	State Clustered Errors
Most Effective	-7.02***	-7.03**
	(2.13)	(3.08)
Moderately Effective	-6.55***	-6.56***
	(2.16)	(2.51)
Less Effective	-5.66***	-5.66*
	(2.23)	(2.99)
State Characteristics	Yes	Yes
Year Effects	Yes	Yes
Observations	490	490

Note: Dependent Variable is the number of cases of Pertussis per 100,000 residents in a state.

CHAPTER 5

WHO ISN'T VACCINATING THEIR CHILDREN? EXAMINING THE DEMOGRAPHICS, POLICIES, AND SHOCKS TO VACCINATION RATES IN THE US OVER TIME

Immunizations are among the most successful and cost-effective public health interventions available. "The success of vaccines in reducing disease-associated mortality is second only to the introduction of safe drinking water" (Plotkin and Plotkin, 2004). When the Centers for Disease Control and Prevention (CDC) released its list of the "Ten Great Public Health Achievements" of the 20th century, vaccinations were at the very top of the list (CDC, 1999). For those born in the 2009 US birth cohort alone, routine childhood immunization prevented approximately 42,000 early deaths and 20 million cases of disease" (Fangjun, et al., 2014).

Not only are vaccines extremely effective in disease prevention, they also have positive cost-benefit return ratios. Due to the routine childhood immunizations of the 2009 US birth cohort, a net savings of $13.5 billion in direct costs and $68.8 billion in total societal costs was saved respectively. The direct and societal benefit-cost ratios for routine childhood vaccination for the recommended 9 vaccines in 2009 were 3.0 and 10.1 (Fangjun, et al., 2014).

However, despite the economic and personal benefits that vaccines provide, there continues to be an under and non-vaccinated contingent in the US. This sub population appears to be on the rise since approximately 2000 (Figures 5.1 and 5.2). While numerous factors could be contributing to the increase, vaccine safety is a concern for a non-trivial part of the population. As an example, a Medline search over the past five years using the keywords "vaccine risks" scored approximately five times as many hits (2655 versus 557) as a Medline search using "vaccine benefits" as keywords.

Autism Spectrum Disorder has increased from effecting approximately 1 in 150 children in 2000 to 1 in 68 children in 2010[11]. In 1998, Andrew Wakefield published an article in the Lancet journal that claimed a link between autism and the measles mumps and rubella (MMR) vaccine. While this study has since been retracted by the journal (and all coauthors except for Wakefield) and thoroughly debunked by countless follow up studies, beliefs about the association of autism and the MMR vaccine persist. Additionally, the limited knowledge regarding how autism is contracted, as well as the concurrent increase in the number of recommended childhood vaccines during this time further perpetuates fears around the Lancet study. (Figure 5.6) Model and actress Jenny McCarthy in 2007 highlighted these fears when doing a nationally televised interview on Oprah, claiming she felt her son contracted autism after receiving the MMR vaccine.

The goal of this study is to better understand the population who are not fully vaccinating their children. Using National Immunization Survey data, we measure the association of child and parent level characteristics, state policies, and exogenous shocks (i.e., Jenny McCarthy) on the probability of a child being fully vaccinated. Specifically, we have three research questions as follow:

What demographic characteristics are associated with non-vaccination take-up?

What role does vaccination exemption policy have on vaccine take-up?

Is there association between pop culture (i.e., Jenny McCarthy) and vaccination rates?

[11] Some of the increase is due to redefining Autism Spectrum Disorders; however, this redefinition does not account for the entire increase nor the sheer prevalence of the disorder.

Background

In recent years a non-vaccinated and under vaccinated population has been on the rise and people are consequently getting sick. The number of children entering school whose parents are opting for a vaccine exemption rather than fulfilling the required vaccine schedule has been on the rise in the last decade (Sadaf, Alina, et al., 2013; Omer, S B., et al., 2009). In 2000, the United States declared that measles was eliminated domestically, meaning the disease was no longer native to the United States. However, in 2014 there were over 600 cases of Measles that primarily occurred among the non-vaccinated. In 2015, over 150 cases of measles spreading over 4 states would be traced back to a single unvaccinated Disneyland visitor. Pertussis (whopping cough) has also dramatically increased compared to its 2001 level as seen in Figure 5.5.

Because those with comprised immune systems, infants, or pregnant women cannot safely receive certain vaccines; this vulnerable population relies on herd immunity for protection against vaccine preventable diseases. Herd immunity sometimes referred to as "community immunity," is the phenomenon where there is little opportunity for a disease outbreak, since a critical portion of a community is immunized and thus the spread of disease is suppressed. The biggest worry for public health safety is losing herd immunity when those who should and can be vaccinated do not. Previous work has shown that the tendency of individuals to optimize based on self-interest can lead to vaccination levels that are suboptimal for a community, a classic free-rider problem. Optimal individual behavior can vary between universal vaccination and no vaccination, depending on the relative costs and benefits to individuals (Reluga 2006).

There are numerous costs of vaccinating oneself or one's child, one of which being the direct monetary cost. The literature has found that gaps in private health insurance coverage and out of pocket costs of vaccines are inversely related to being up to date on all recommended vaccines (Dombkowski 2004; Lee 2007; Molinari et al. 2007; Blewett, Lynn A., et al. 2008). Additionally, there are time costs associated with going to a clinic and receiving a vaccine. When one considers the time cost involved in either vaccinating one's kindergartener versus signing a vaccination exemption form, in many states the complexity of the exemption process, in terms of paper-work or effort required, was inversely associated with the proportion of exemptions filed. In many states, the process of claiming a nonmedical exemption requires less effort than fulfilling immunization requirements (Rota et al. 2001; Mandich and Bradford 2015).

There may also be an aspect of forgetting how contagious and serious vaccine preventable diseases can be. While older generations may remember polio scares or knew someone with polio, a parent of young children in the United States today is unlikely to have the same appreciation for the seriousness of the disease. In terms of measles, it does appear that when people "remember" or are mindful of disease implications, vaccine compliance increases. There is evidence that the prevalence of measles in the respondent's state of residence reduces the age in months at which the first measles vaccination occurs. (Philipson 1996)

An additional cost of vaccines is the potential for side effects. While vaccines undergo rigorous testing by the U.S. Food and Drug Administration, there remains serious concern over vaccine safety and effectiveness among the non-vaccinated. Some of these concerns include the view that vaccine preventable diseases are mild and/or uncommon; a mistrust of health professionals; mistrust in government and officially endorsed vaccine research[12]; one's cultural predispositions; alternative understandings of health; different perspectives of parental

[12] The FDA is responsible for evaluating the safety and efficacy of new vaccines. Subject to FDA approval, the Center for Disease Control, as well as other groups, including the American Academy of Pediatrics (AAP), provides recommendations pertaining to the use of a new vaccine and optimal vaccine schedules and doses.

responsibility; as well as the perceived link between autism and the MMR vaccine (Brown et al 2010; Kata 2010; Kennedy 2011; Sadaf, Alina, et al 2013; Song 2014). Instead of getting vaccine information from health professionals, non-vaccinated individuals are using media and non-official information sources.

This was especially true for the 2007 Jenny McCarthy Oprah interview. Model and actress Jenny McCarthy on a nationally televised interview on Oprah, claimed she felt her son contracted autism after receiving the MMR vaccine. While Jenny McCarthy was not the first person to make these claims (Wakefield 1999), her celebrity status as well as platform on Oprah made her a spokesperson for the anti-vaccine movement.. In Figure 5.7, McCarthy Autism News is prevalence of news stories relating to McCarthy and Autism per year, while Autism Vaccine News is the prevalence of news articles mentioning vaccines and autism. Here prevalence is measured as the relevant new story coverage in each year compared to the year with most coverage. This figure shows that McCarthy has had a non-trivial amount of news coverage, particularly after the Oprah interview in 2007, on this issue despite having no training in medicine or authority on the subject.

This study looks to extend the literature by both looking at the demographics of those who fully, partially, and don't vaccine their children as well as specifically considering the perceived autism risk in the decision to vaccine one's child. The "shock" of the Oprah interview helps us to measure the extent to which non-scientific media/news/pop culture (Jenny McCarthy) and erroneous fears of vaccine associated autism have on people's vaccination decisions.

Theory

Our theoretical model is a two-period model where a parent maximizes expected utility and accounts for the perceived costs of vaccination and perceived risk of disease. The theoretical foundation lies in the random utility model. For the i^{th}parent faced with J choices regarding their child's vaccination status, the utility of choosing J is

$$U_{ij} = X_i\beta_j + \epsilon_{ij}. \tag{1}$$

Thus if the parents makes choice J, it is because the Prob(U_{ij}>U_{ik}) for all other $k \neq j$. X_i is a vector of characteristics thought to be associated with vaccination decisions, β_j is the vector of coefficients associated with X_i and ϵ_{ij} is the error term.

Parents then must maximize their utility given their budget at time t. We will assume that parents only spend their income, I, on two goods, vaccines and X, where X is a numerarie to represent all other purchases and P is the cost of vaccine purchases. Thus the buget constraint is

$$I - P = X. \tag{2}$$

In addition to the monetary cost of purchasing a vaccine, the associated perceived risk involved with vaccinations will also enter the model. When a parent is choosing to vaccinate their child, the parent weighs whether the cost in terms of both price and possible perceived chance of autism outweigh the risk of the child contracting a preventable disease and possibly dying from that disease. We define the parent's perceived risk of the child developing autism from a vaccination as α, the perceived risk of contracting a disease as δ, and conditional on contracting a disease, the probability of dying from the disease as η. For simplicity, we assume that if a child contracts a disease there are two options, either the child heals and gains immunity from the disease, rendering a vaccination unnecessary, or the child dies. We also assume that the only way to contract autism is through the MMR vaccine and that parents would prefer their children to not develop autism such that the following conditions would hold. If the state of not having autism is represented by O and developing autism is A, then

$$\text{U(O, I-P)} > \text{U(A, I-P)} \tag{3}$$

$$\text{U(O, I)} > \text{U(O, I-P)} \tag{4}$$

$$\text{U(A, I)} > \text{U(A, I-P)} \tag{5}$$

$$\text{U(O, I-P)} < \text{U(O, I-P)} \tag{6}$$

Obviously all these options are superior to death where U=0.

As seen in Figure 5.1, we model a parent's decision in a two-period model, where in period 1 a parent can chose to vaccinate their child, then given this decision update their choice in period 2. We will examine the total utility of both periods as a weighted sum of the utility levels where β is a discount factor

$$U^* = U_1 + U_2\beta \tag{7}$$

Thus given the parent's utility function and perceived risk of autism, diease and death, a parent will only chose to vaccinate their child when the expected utility of vaccination, $EU_v^1$is greater than the expected utility of nonvaccination, EU_N^1. This can also be expressed for time period 1 as

$$EU_v^1 - EU_N^1 > 0 \tag{8}$$

$$EU_v^1 = \alpha U_1(\text{A}, \text{I} - \text{P}) + [1 - \alpha]U_1(\text{O}, \text{I} - \text{P}) \tag{9}$$

$$EU_N^1 = \delta[\eta * (U_1 = 0) + (1 - \eta)U_1(\text{O}, \text{I})] + [1 - \delta]U_1(\text{O}, \text{I}) \tag{10}$$

As we can see, the sign of both EU_v^1, and EU_N^1 are dependent on the parent's assigned values of α, δ, and η. The greater the perceived risk of autism, α, the quicker it will drive $EU_v^1 - EU_N^1 < 0$ and the parent will not vaccine their child. Similarly, as the percieved risk of δ and η approach zero, this will also lead to a non-vaccination result as U(O, I) > U(O, I-P).

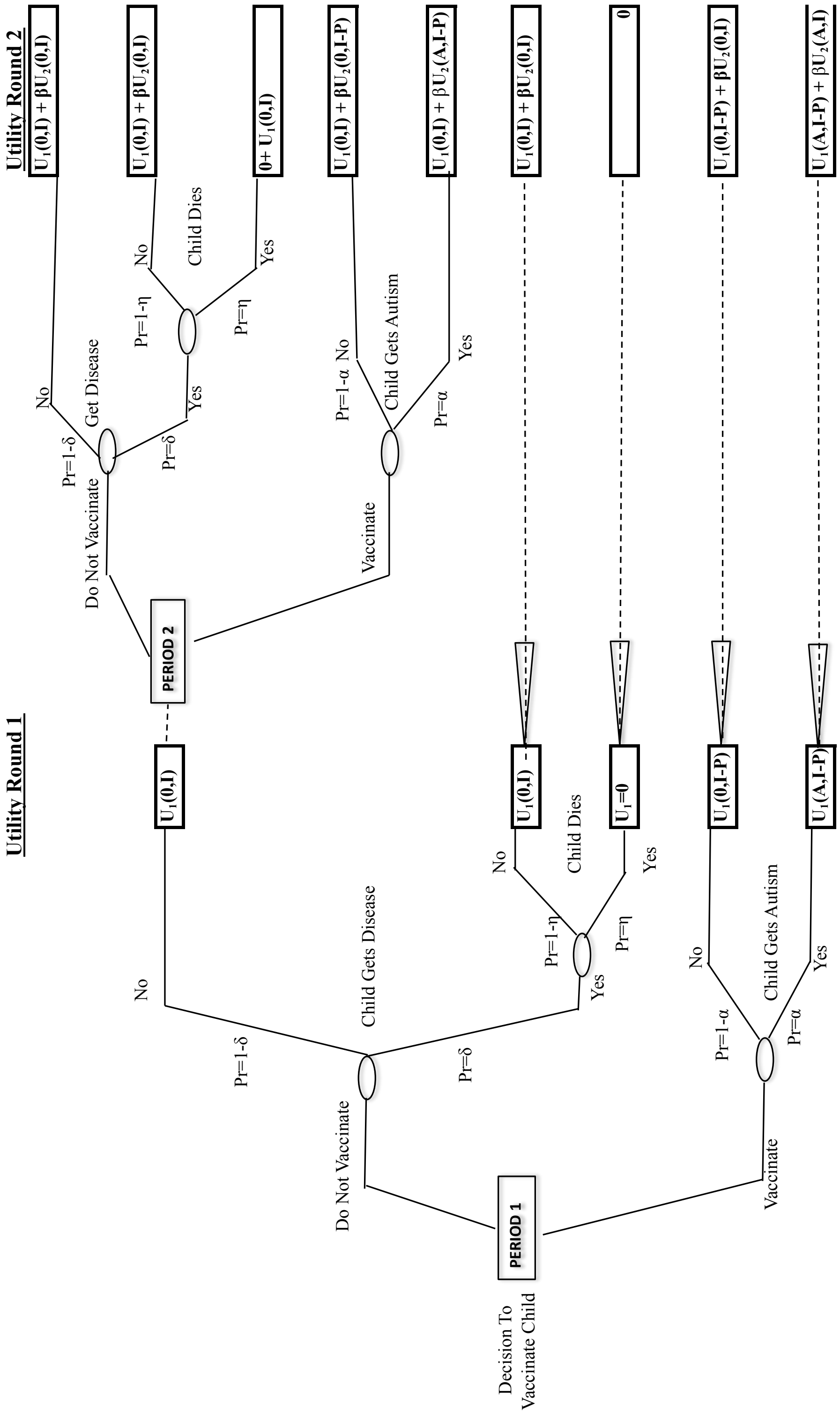
We examined each outcome of the decision tree by comparing first round utilty to second round utility in order to observe cases where parents would either always or never vaccinate. We find that most cases are not signable as the magnitude a parent assigns to α, δ, and η make comparisons ambigious. However, we do find one instance which is signable. We find not vaccinating in the second round, EU_N^2 is always preferable to not vaccinating in the first round, EU_N^1.

$$EU_N^2 - EU_N^1 = U(0,\mathrm{I})[\beta + 1 - \delta\eta\beta] - \delta U(0,\mathrm{I})[1 + \beta - \eta\beta - \eta] \quad (11)$$

$$= U(0,\mathrm{I})[1 + \beta + \delta[\eta - \beta - 1] \quad (12)$$

This result is interesting as it suggests that parents with concerns about vaccines would best maximize expected utility by delaying vaccination.

FIGURE 5.1



Utility Round 1
Utility Round 2
Decision To Vaccinate Child
PERIOD 1
Do Not Vaccinate
Vaccinate
Child Gets Disease
Pr=1-δ
Pr=δ
No
Yes
Child Dies
Pr=1-η
Pr=η
Child Gets Autism
Pr=1-α
Pr=α
U1(0,I)
U1=0
U1(0,I-P)
U1(A,I-P)
PERIOD 2
Get Disease
U1(0,I) + βU2(0,I)
0+ U1(0,I)
U1(0,I) + βU2(0,I-P)
U1(0,I) + βU2(A,I-P)
0
U1(0,I-P) + βU2(0,I)
U1(A,I-P) + βU2(A,I)

Data

Data come from the National Immunization Survey. This survey is conducted jointly by the National Center for Health Statistics (NCHS) and Centers for Disease Control and Prevention. The NIS is a list-assisted random-digit-dialing telephone survey followed by a mailed survey to the children's immunization providers. Data collection began April 1994 in order to monitor childhood immunization coverage. All children in the sample are 19-35 month olds. While the vaccine schedule is age sensitive, meaning a 19-month-old child has different vaccination requirements than a 4-year-old child, all children 19-35 months old have the same vaccine requirements and thus all children are comparable despite their age. While the NIS survey has both parents' responses as well as verified doctor data on the child's vaccines, we only use vaccine data that came directly from the immunization providers.

Three dependent variables were chosen for three different estimation specifications. Because the recommended vaccine schedule changes over the years observed in the study, we use two baseline measurements that are true for all years to measure whether or not a child has his/her recommended vaccines.[13] Up to date (UTD) basic is any child that has all doses of the Measles Mumps and Rubella (MMR), Diphtheria Tetanus and Pertussis (DTaP), and Polio vaccines. UTD 1995 is any child that has all doses of DTaP, MMR, Polio, and Hepatitis B vaccines. Because the Hepatitis B vaccine was not fully implemented into society until approximately 2000 (Figure 5.3), this estimation only includes years 2000-2012. Because of it's perceived association with Autism Spectrum Disorders; we also examine MMR vaccination compliance individually.

[13] On 13 December 2007, Merck & Co., Inc. voluntarily recalled 1.2 million doses of Haemophilus influenzae type b (Hib) vaccines that had been distributed since April 2007 for concerns regarding potential Bacillus cereus contamination (Huang, Wan-Ting 2010). A shortage of the vaccine persisted for 2007 and 2008 and we thus exclude Hib from our UTD classification.

Our chosen independent variables look to capture the person level demographics associated with vaccination decisions. We account for the race of the child by including dummies if the child is white, black, or Hispanic. Additionally, the sex of the child is also included. Autism is almost 5 times more common among boys (1 in 42) than among girls (1 in 189) (MMMR report 2014). Thus households who do not trust vaccines may even be less prone to fully vaccinate sons versus daughters given boys predisposition for autism. We also examine household and mother characteristics. Mother's education is measured categorically as having less than 12 years of education, high school, some college, or a college degree. The mother's age is also categorized into those <19 years of age, 20-29 years of age, and 30 plus years of age.

The number of children in the household was also considered with dummies for households with two to three children and those with four or more children. It could be that birth order has a role in a child being up to date on vaccines. Perhaps with the first child, the parent is particularly cautious and knowledgeable about vaccine schedules and doctor appointments compared to those with larger families. Income was also included in the estimation with dummies for those in the bottom 25% of earners in the sample and those in the top 75% of earners in the sample. Given that responses cover data from 1995-2012, as well as the income survey question being a range, we recoded the variables so all income was in 2010 dollars and best aligned the income brackets over the years of data into quartiles. This was the most comparable way to look at income over time given the data constraints.

Non-person level independent variables include state vaccination exemption policies and shocks to vaccination popularity. In Chapter 4, "Some State Vaccination Laws Contribute to Greater Exemption Rates and Disease Outbreaks in the US", an index was constructed measuring state's vaccination exemption policy effectiveness on Kindergarten vaccination exemption.

Essentially, this index measures which states have the best policies in making vaccine exemptions more difficult to obtain. The data used to construct the index is from the State Vaccination Requirements and Exemption Law Database, 2011 (ICPSR 34486). This index is included within our estimation to measure whether states with particularly strict vaccination exemption policies also have higher vaccination compliance for 19-35 month olds. Finally, we also include the prevalence of news stories that mention Jenny McCarthy + Autism as well as Vaccines + Autism. This is to better understand the association between a shock such as the Jenny McCarthy Oprah interview and a child being vaccinated.

Estimation

Given our two-period theoretical model, we express the probability of a child's vaccination status using a multinomial logit estimation strategy and standard maximum likelihood methods (Greene 1993). Within the multinomial logit framework, a child is in one of three categories, he is either up to date (UTD) on vaccines, is partially vaccinated, or is completely unvaccinated. At first glance, it may be tempting to invoke an ordered logit in favor of multinomial logit. We would argue that while ordered logit is preferable when there is a hierarchy of decisions, with vaccination status, these three statuses are not a progression but rather unordered groups. Parents who choose to give their children no vaccines are very different than those who choose to fully vaccinate or are late. It is highly unlikely that someone who has given their child no vaccines plans on doing so in the future, but rather it is more likely such parents have fundamentally different preferences for vaccines than parents of children with late or full vaccination status. Thus since these are such distinct categories, multinomial logit was the chosen specification.

The multinomial logit models the i^{th} child's probability of being in the j^{th} vaccination category. The general form of the MNL is

$$Prob(y_i = j) = \frac{e^{X_i\beta_j}}{\sum_{j=1}^{J} e^{X_i\beta_k}} \ , \ j = 1, \ldots J \tag{13}$$

The model in this study is represented as:

$$P_{jk} = \frac{e^{X_i\beta_j + \delta_j yr_i + f_{ji}}}{\sum_{j=1}^{3} e^{X_i\beta_j + \delta_j yr_i + f_{ji}}} \ , \ j = 1, 2, 3 \tag{14}$$

where β_j is the column vector of parameters for the chosen independent variables related to vaccination status. In addition to the exogenous variables accounted for in X_i, state fixed effects, f_i are included, as well as a nonlinear time trend to measure annual effects, δ.

As is, the parameters in (2) are unidentified since more than one set of parameters can generate identical probability values. To identify the parameters, we impose a common constraint by effectively normalizing the coefficients of the reference group to zero so the probabilities of all the choices sum to unity as seen in (15).

$$P_{jk} = \frac{e^{X_i\beta_j + \delta_j yr_i + f_{ji}}}{1 + \sum_{j=2}^{3} e^{X_i\beta_j + \delta_j yr_i + f_{ji}}} \ , \ j = 2, 3 \tag{15}$$

The estimated coefficients for each vaccination status can be interpreted as the effect of the X_i's on the likelihood of the child to be in that vaccination status relative to the reference group.

We report the marginal effects (partial derivatives) of (15) in Tables 5.2-5.4. These can be interpreted to represent the percentage change in P_{jk} or $P_{ji}$when there is a one percent increase in X_i.

Additionally, because the MMR vaccine is a single dose vaccine there are only two states: fully or UTD and non-vaccinated. Thus logit regression analysis is used to when examining the MMR vaccine.

Results

Basic:

The first specification is examining children and the following three vaccines: Measles Mumps and Rubella (MMR), Diphtheria Tetanus and Pertussis (DTaP), and Polio. The marginal effects of the state level vaccination exemption policies do not show a strong relationship between such policies and vaccination status. Initially, we thought parents might want to vaccinate their child in infancy in order to eliminate the future inconvenience of last minute catch-up vaccinations before the child enters kindergarten. These results suggest that perhaps either kindergarten entrance vaccine requirements may not play a role in the parents' current decision, or school age exemption laws do not impact infant vaccinations.

The association between Jenny McCarthy + Autism news articles and children either being partially vaccinated or fully vaccinated is significant with the correct sign. We can see that the more prevalent McCarthy + Autism news stories are, the less likely a child will be fully vaccinated and the more likely a child is partially vaccinated. This result reinforces the concern of the public making medical decisions based on non-scientific sources.

Because Autism Spectrum Disorders are more prevalent among boys, we also examine both sex of the child as well as an interaction term between McCarthy + Autism news articles and the sex of the child. We find that female children are .38% more likely to be fully vaccinated and are .3% less likely to be partially vaccinated. We also find a significant result that McCarthy

+ Autism news stories interacted with a dummy for a female child is associated with less partially vaccinated girls compared to boys. This further suggests that McCarthy's anti-vaccine autism arguments were particularly harmful to boys' vaccination rates.

The remaining child and household demographics performed very well. One surprising result was in terms of race. While it was not surprisingly that white was positive and significant in the probability a child is completely unvaccinated, it was not significant for partial or full vaccination. Traditional household performance variables performed as expected with less education being associated with higher probabilities of partial or no vaccinations whereas higher education is associated with full vaccination. Moms younger than 19 have a child who is 10.3% less likely to be fully vaccinated and Moms 20-29 years of age were .9% more likely to be partially vaccinated. Two interesting findings with household demographics came with income and number of children in the household. We find that birth order may be a substantial fact in whether a child is fully up to date on his or her vaccines. For example, a child who is in a household with two or three children is 2.2% less likely to be fully vaccinated and a child in a household with four or more children is 6.03% less likely to be fully vaccinated. Additionally, having more than two children in the household was also a positive predictor in a child being complexly unvaccinated. Finally, income also has an interesting result. While popular belief may be that non-vaccinators such as Jenny McCarthy are very wealthy, we do not find this. In fact, being in the top 25% of earners makes a child 1.5% more likely to be fully vaccinated, and being in the bottom 25% of earners has a .5% higher probability of being fully vaccinated.

1995:

As an additional measure, we also examine children based on the recommended 1995 vaccine schedule of having the MMR, DTaP, Polio, as well as Hepatitis B vaccines. Because in

1995 Hepatitis B was a relatively new vaccine, it wasn't until 2000 that it became fully implemented in the public. Thus this analysis is limited to 2000-2012.

We find that results are very similar to the first analysis. Again state vaccination exemption policies do not seem to have any association on vaccination take-up and Jenny McCarthy news presence has a significant impact on the probability a child is partially vaccinated. We don't find that white children are more likely to be fully vaccinated, but we do see that Hispanic child are both more likely to be fully vaccinated and less likely to be partially or non-vaccinated. Additionally, household and the child's mother's characteristics have the same signs and similar magnitudes as the first estimation.

MMR:

Finally, given that the Measles Mumps and Rubella (MMR) vaccine is the particular vaccine that is most strongly associated with autism, we examine our predictor variables with solely the one dose MMR vaccine. Again, we don't see much association with policy variables and MMR take up. With an increase in Jenny McCarthy news stories, a child is .006% less likely to have the MMR vaccine. Similarly, white and black children are .34% and .56% less likely to have the vaccine respectively. We do find that female children are .19% more likely to have received an MMR vaccine, which may again be related to boys' higher probability of autism.

Household variables performed in accordance with the previous estimations with children from larger families being less likely to be fully vaccinated and younger mothers being associated with a lower probability of having the MMR vaccine. Additionally, both the lowest and highest household incomes had a child who is .3% and .7% respectively more likely to have received the MMR vaccine.

Conclusion

Using the National Immunization Survey of 19-35 month old children in the US from 1994-2011, we measure the relationship between parent and child demographics, strictness of state vaccination exemption policy, and pop culture (ie. Jenny McCarthy) on vaccine take up. This is done using a multinomial logit estimation strategy on multiple vaccine combinations. For parent and child demographics, being white, coming from a household with many children, or having a young mother all significantly reduced the probability of a child being fully vaccinated. While state vaccination policies have been shown to be strongly related to vaccination exemption rates, we did not find an association between these policies and children between 19-35 months' vaccination status. Finally, these findings suggest that parents' vaccination decisions could be being influence by worries over autism and vaccines. Specifically, years with more Vaccination-Autism news coverage (Jenny McCarthy) were a significant factor in a child not having up to date vaccinations, particularly for male children. Additionally, female children being more likely to have the MMR vaccine is also a signal that parents may fear male children may contract autism from vaccines given boys' relatively higher frequency of having autism.

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Figure 5.2: Percentage 19-35 month olds Unvaccinated by Type of Vaccine: 1995-2012

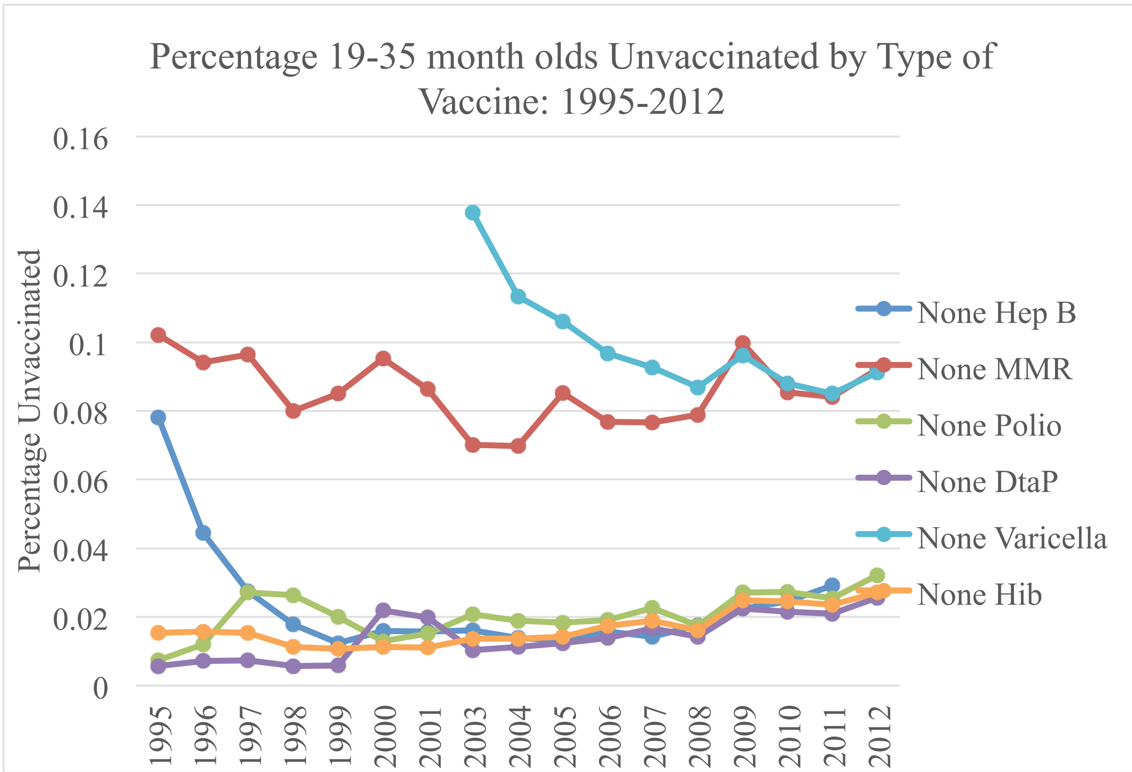

Figure 5.3: Percentage of 19-35 month olds Partially Vaccinated by Type of Vaccine 1995-2012

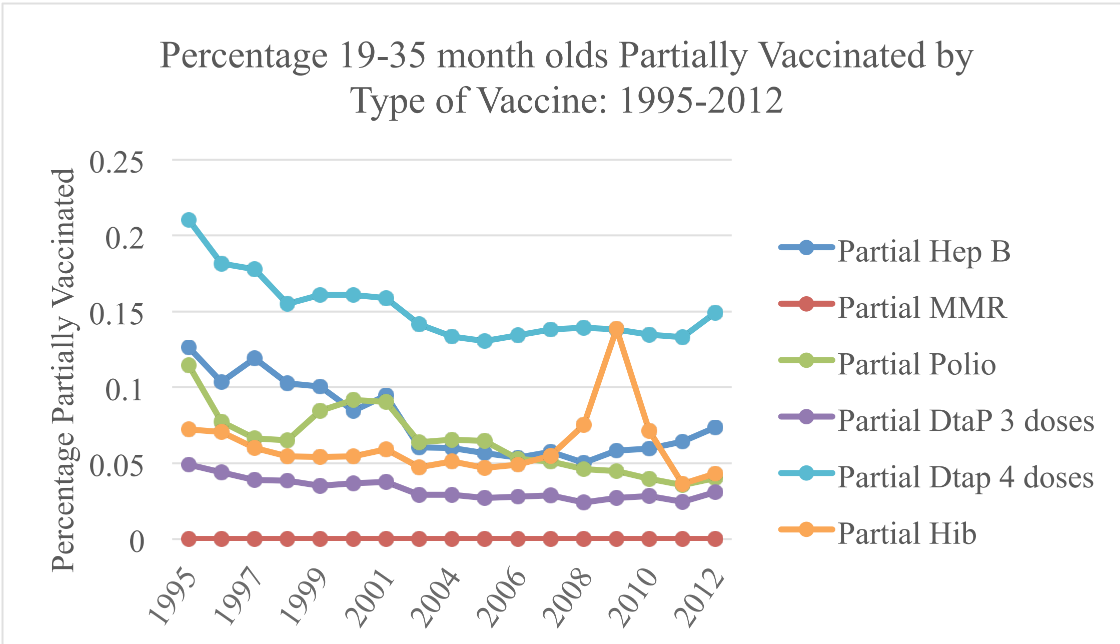

Figure 5.4: Percentage Up to Date by type of Vaccine

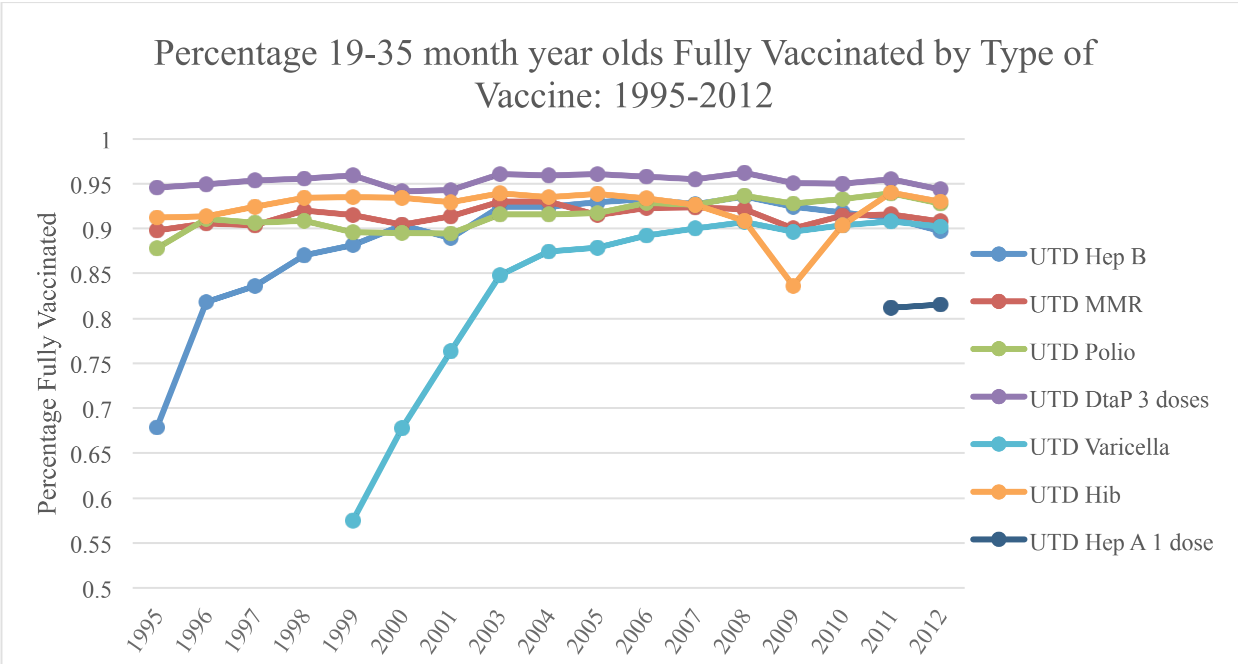

Figure 5.5: Incidence of Disease Over Time

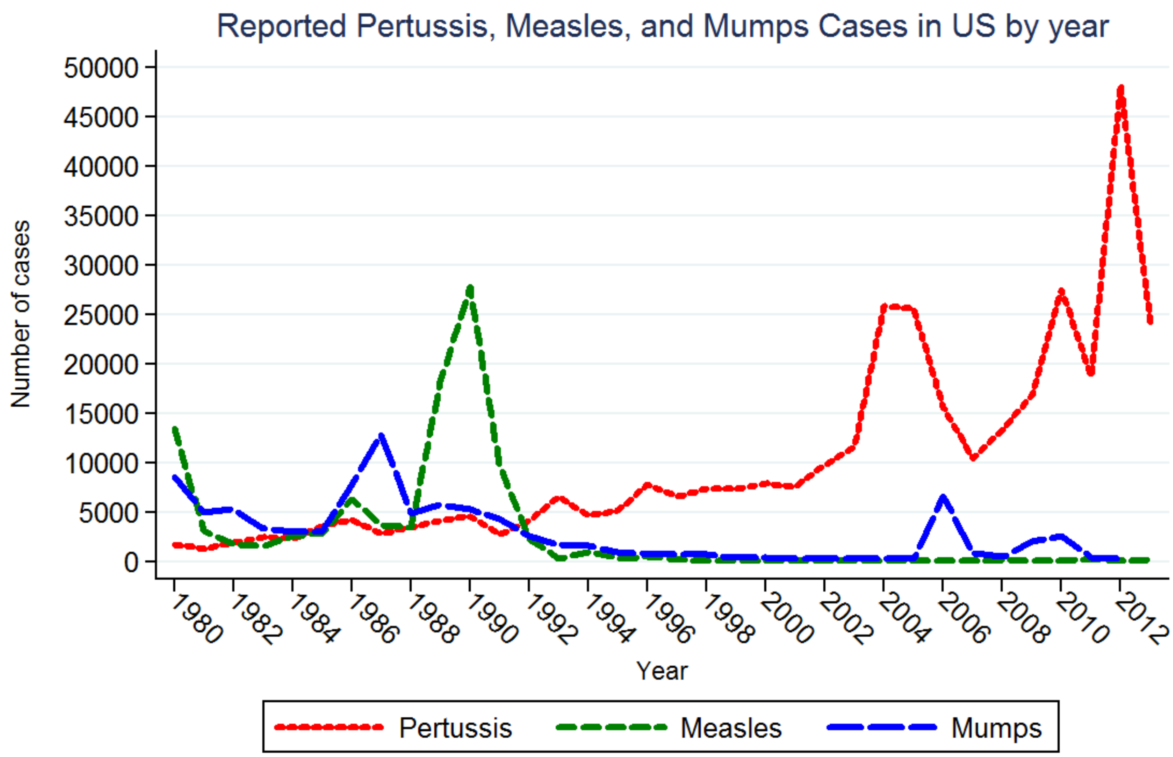

Figure 5.6: Changes in Vaccine Schedule over Time

1994 - 1995	Diphtheria*	Measles**
	Tetanus*	Mumps**
	Pertussis*	Rubella**
	Polio (OPV)	Hib
	Hepatitis B	
2000	Diphtheria*	Measles**
	Tetanus*	Mumps**
	Pertussis*	Rubella**
	Polio (IPV)	Hib
	Hepatitis B	Varicella
	Hepatitis A	
2005	Diphtheria*	Measles**
	Tetanus*	Mumps**
	Pertussis*	Rubella**
	Polio (IPV)	Hib
	Hepatitis B	Varicella
	Hepatitis A	Pneumococcal
	Influenza	
2010	Diphtheria*	Measles**
	Tetanus*	Mumps**
	Pertussis*	Rubella**
	Polio (IPV)	Hib
	Hepatitis B	Varicella
* Given in combination as DTaP	Hepatitis A	Pneumococcal
** Given in combination as MMR	Influenza	Rotavirus

Figure 5.7: News Article Frequency

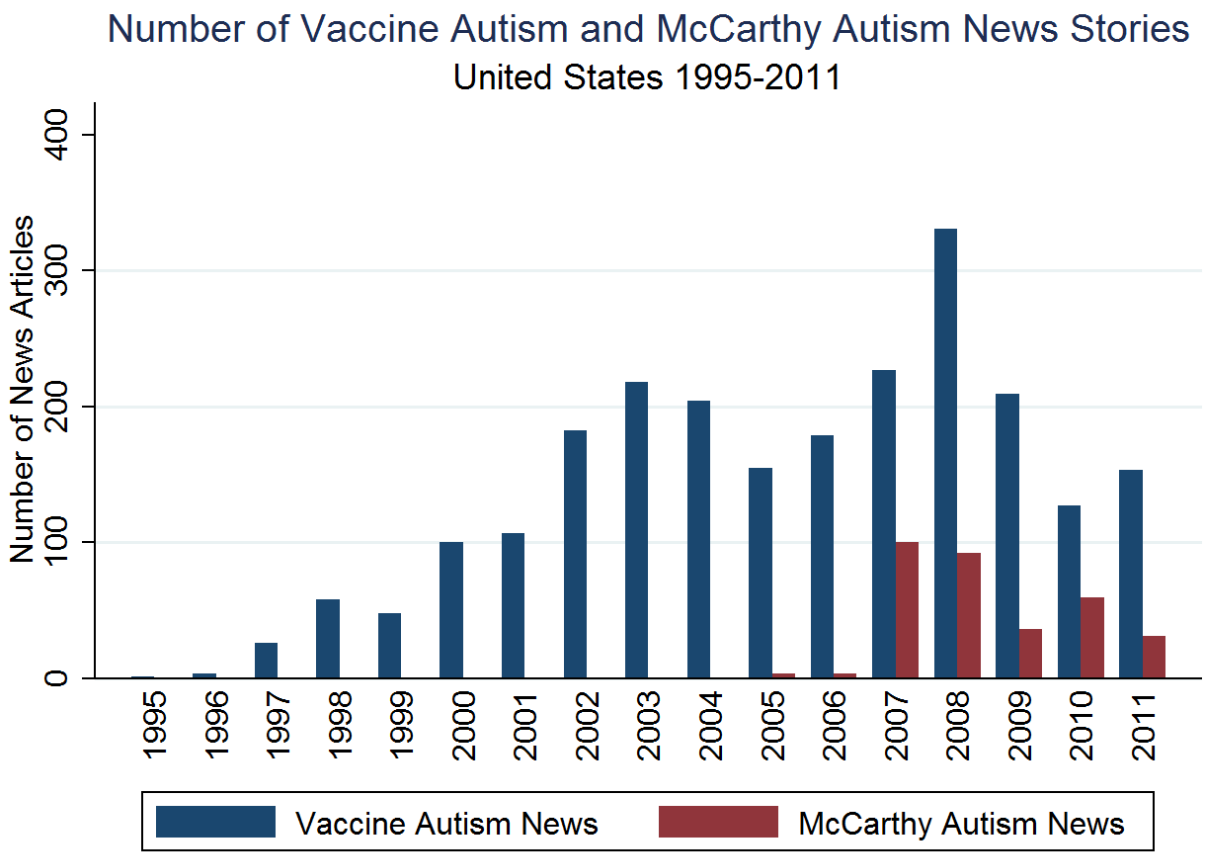

Table 5.1 Summary Statistics

	Mean	Count	Min	Max
White	0.614	359379	0	1
Black	0.127	359379	0	1
Hispanic	0.184	359379	0	1
Female	0.488	359379	0	1
Mom <12 Years Educ	0.121	359379	0	1
Mom HS Education	0.259	359379	0	1
Mom Some College	0.219	359379	0	1
Married	0.597	359379	0	1
2-3 Children in HH	0.606	359379	0	1
4+ Children in HH	0.127	359379	0	1
Mom < 19 years old	0.021	359379	0	1
Mom 20-29 years old	0.351	359379	0	1
Income Bottom 25%	0.175	359379	0	1
Income Top 75%	0.364	359379	0	1
Jenny and Autism News	16.67	342692	0	100
News Vaccines and Autism	134.1	342692	1	331

Table 5.2: Marginal Effects for "Basic" Vaccine Schedule

	None dy/dx	Part dy/dx	UTD dy/dx
Most Effective	0.00059	-0.0008	0.0002
	(0.00323)	(0.006)	(0.0067)
Somewhat Effective	0.0022	-0.0035	0.0012
	(0.00165)	(0.003)	(0.0035)
Less Effective	**0.004****	0.0048	**-0.0085****
	(0.0017)	(0.0033)	**(0.0037)**
News McCarthy	0.00001	**0.0001*****	**-0.0001*****
	(0.00001)	**(0.00002)**	**(0.00003)**
News Vax Autism	-0.000006	**-0.00003*****	**0.00005*****
	(0.00000)	**(0.00001)**	**(0.00001)**
News McCarthy*Female	0.00001	**-.00007****	0.00006
	(0.00001)	**(0.0003)**	(0.00004)
White	**0.004*****	-0.0007	-0.0033
	(0.00111)	(0.0021)	(0.0023)
Black	**0.007*****	**0.0131*****	**-0.0203*****
	(0.0013)	**(0.0024)**	**(0.0027)**
Hispanic	-0.00128	**-0.0069*****	**0.008*****
	(0.00123)	**(0.0023)**	**(0.0026)**
Female	-0.0009	**-0.003*****	**0.0038*****
	(0.00053)	**(0.001)**	**(0.0011)**
Mom < 12 yrs	**0.0087*****	**0.0146*****	**-0.0233*****
	(0.00099)	**(0.0019)**	**(0.0021)**
Mom HS	**0.0064*****	**0.012*****	**-0.0185*****
	(0.0008)	**(0.0014)**	**(0.0016)**
Mom Some	**0.0035*****	**0.0088*****	**-0.0123*****
	(0.0008)	**(0.0014)**	**(0.0016)**
Married	**-0.0049*****	**-0.0148*****	**0.0197*****
	(0.0007)	**(0.0013)**	**(0.0015)**
2-3 Kids HH	**0.006*****	**-0.0148*****	**-0.0218*****
	(0.00071)	**(0.0012)**	**(0.0013)**
4+ Kids HH	**0.0206*****	**0.0397*****	**-0.0603*****
	(0.00087)	**(0.0017)**	**(0.0018)**
Mom < 19 yrs old	0.00001	**0.01*****	**-0.103*****
	(0.0017)	**(0.0033)**	**(0.0036)**
Mom 20-29 yrs	**0.004*****	**0.009*****	**-0.014*****
	(0.0006)	**(0.0012)**	**(0.0013)**
Income <25%	-0.001	**-0.004*****	**0.0053*****
	(0.0007)	**(0.0014)**	**(0.0016)**

Income >75%	**-0.008*** (0.00074)**	**-0.007*** (0.0013)**	**0.0153*** (0.0014)**

Standard errors in parenthesis
Asteriks denote significance at the 0.05 (*), 0.01 (**), and 0.001 (***) level

Table 5.3: Marginal Effects for 1995 Vaccine Schedule: Years 2000-2012

	None	Part	UTD
Most Effective	0.0043	0.0013	-0.0056
	(0.004)	(0.009)	(0.011)
Some Effective	**0.0044***	-0.0034	-0.0009
	(0.002)	(0.0004)	(0.005)
Less Effective	**0.0053****	0.007	-0.012
	(0.002)	(0.0055)	(0.006)
News McCarthy	0.000007	**0.00007***	**-0.00008***
	(0.00001)	**(0.00004)**	**(0)**
News Vax Autism	-0.00001	**-0.00006*****	**0.00007*****
	(0.000008)	**(0.00001)**	**(0.00002)**
White	**0.0046*****	-0.00008	-0.0038
	(0.0012)	(0.002)	(0.0028)
Black	**0.007*****	**0.0156*****	**-0.022*****
	(0.0016)	**(0.003)**	**(0.0034)**
Hispanic	**-0.0031****	**-0.009*****	**0.012*****
	(0.0014)	**(0.003)**	**(0.0032)**
Female	-0.00043	**-0.0035*****	**0.004*****
	(0.0007)	**(0.001)**	**(0.0015)**
Mom < 12 yrs	**0.0079*****	**0.0085*****	**-0.016*****
	(0.0012)	**(0.003)**	**(0.0028)**
Mom HS	**0.0057*****	**0.0056*****	**-0.011*****
	(0.0009)	**(0.002)**	**(0.0021)**
Mom Some	**0.0027*****	**0.0039****	**-0.0067****
	(0.0009)	**(0.001)**	**(0.0021)**
Married	**-0.0037*****	**-0.0138*****	**0.018*****
	(0.0008)	**(0.002)**	**(0.002)**
2-3 Kids HH	**0.0054*****	**0.0128*****	**-0.0182*****
	(0.0009)	**(0.002)**	**(0.002)**
4+ Kids HH	**0.0215*****	**0.0414*****	**-0.063*****
	(0.001)	**(0.002)**	**(0.002)**
Mom < 19 yrs old	0.0005	**0.0087****	**-0.009****
	(0.002)	**(0.005)**	**(0.0048)**
Mom 20-29 yrs	**0.0052*****	**0.0072*****	**-0.012*****
	(0.0007)	**(0.002)**	**(0.0018)**
Inc <25%	**-0.0023*****	**-0.0036****	**0.006****
	(0.0009)	**(0.002)**	**(0.0021)**
Inc >75%	**-0.0083*****	**-0.0063*****	**0.015*****
	(0.0008)	**(0.002)**	**(0.0019)**

Table 5.4: Marginal Effects for having the MMR vaccine

	dy/dx
Most Effective	0.0059
	(0.0044)
Some Effective	-0.0023
	(0.0023)
Less Effective	**-0.0059****
	(0.0024)
News McCarthy	**-0.00006*****
	(0.00002)
News Vax Autism	**0.000006**
	(0.00001)
News McCarthy*Female	**.00009*****
	(.00003)
White	**-0.0034****
	(0.0015)
Black	**-0.0056*****
	(0.0018)
Hispanic	0.0011
	(0.0017)
Female	**0.0019*****
	(0.0007)
Mom < 12 yrs	**-0.011*****
	(0.0014)
Mom HS	**-0.009*****
	(0.0011)
Mom Some	**-0.006*****
	(0.0011)
Married	**0.009*****
	(0.0009)
2-3 Kids HH	**-0.011*****
	(0.0009)
4+ Kids HH	**-0.023*****
	(0.001)
Mom < 19 yrs old	**-0.0072*****
	(0.0023)
Mom 20-29 yrs	**-0.0073*****
	(0.0009)
Inc <25%	**0.0029*****
	(0.001)
Inc >75%	**0.007*****
	(0.0009)

CHAPTER 6

CONCLUSION

By examining the association of health access and utilization in terms of migration, employment, as well as health outcomes relating to preventable diseases, we arrive at numerous conclusions from this work.

When examining migration, using a Spatial Lagged Model measures health services through three channels of health expenditures, hospital beds, and number of doctors. All measurements of health access conclude that health care access in the location destination is positively associated with later life migration, especially when looking at physicians. Physicians being a positive draw for migrants is a particularly encouraging result for more rural locations as relocating doctors to meet local demand is a far more achievable goal than attracting a new hospital. In addition to health access being an important driver of migration, having a strong potential social network as measured by a large existing population of county residents 65 years and older, and desirable natural amenities can also help to pull in senior migrants.

We also find that through positive benefits on wages and non-health related jobs growth, hospitals have measurable positive economic outcomes above their primary objective of providing health care. Our analysis finds that hospitals provide high wage jobs not only for the most educated population, but also among those with two and four year degrees, especially in rural and urban counties. There is a strong positive spill-over effect in that hospitals are positively associated with non-health care employment. Thus, hospital closures would not only affect direct health care employment, but also many other jobs in the community.

We also looked at health access and preventable diseases through the route of vaccinations and vaccine preventable diseases. We looked to illuminate the relationship between various types of vaccination policies and state-level vaccination exemption rates, in order to aid policy makers and public health planners to target specific policy interventions that will decrease the number of exemptions given and ultimately reduce the incidence of preventable diseases. Our findings suggest that not all laws related to vaccination exemptions have the same impact on exemption take-up. We also find a link between our constructed index of policy effectiveness and the incidence of preventable diseases. States that have the most effective portfolio of polices in our index have lower incidences of pertussis. Vaccine exemption policy is thus an important piece within a greater comprehensive plan of reducing preventable diseases. States thus have tools available to optimize their policies, if public health officials wish to decrease exemptions and disease outbreaks.

Finally, we also looked at the roles between parent and child demographics, strictness of state vaccination exemption policy, and pop culture (i.e., Jenny McCarthy) on vaccine take up. For parent and child demographics, being white, coming from a household with many children, or having a young mother all significantly reduced the probability of a child being fully vaccinated. While state vaccination policies have been shown to be strongly related to vaccination exemption rates, we did not find an association between these policies and 19-35 months old children's vaccination status. Finally, these findings suggest that parents' vaccination decisions are being influenced by worries over autism and vaccines. Specifically, years with more Vaccination-Autism news coverage (Jenny McCarthy) were a significant factor in a child not having up to date vaccinations, particularly for male children. Additionally, female children being more likely to have the MMR vaccine is also a signal that parents may fear male children may contract autism from vaccines given boys' relatively higher frequency of having autism.