A DYNAMIC MODEL OF RESIDENTIAL SORTING AND HEALTH FOR SENIORS

Sophie Mathes

Arizona State University

June 16, 2019
1. Introduction

Many policies that target environmental issues or issues of public health, affect people’s health in ways that differ across space. [Holland et al. (2016)] find that a growing electric vehicle fleet tends to reduce air pollution in areas with heavy traffic, but potentially increases air pollution in areas where the electricity to run the vehicles is produced. EPA’s national ambient air quality standards oblige counties with pollution levels above a certain cutoff to find ways to reduce air pollution, whereas counties just below the cutoff do not have to take any measures. All of this goes to say that one policy affects people’s health differently when they are located in different places. The aggregate costs and benefits of these policies crucially depend on how changes in local environments affect people’s health and how people respond to changes in environment by re-sorting across space.

This paper researches the interaction of health and location choice in both directions. It will explore how individual heterogeneity in health translates into different choices of residential location, and also how differences in local amenities in turn affect people’s future health outcomes. The analysis will focus on the senior population. Seniors are a natural choice to study residential sorting on amenities because the vast majority of seniors is retired and therefore labor market concerns can be ruled out as a confounding factor. Moreover, since seniors are physically more vulnerable to pollution than younger adults in terms of morbidity and mortality, public policies targeting pollution benefit this demographic the most. In addition to that, seniors are the fastest growing demographic age group of our time. By 2030 one in five US residents will be older than 65 with potentially huge economic consequences.

“Health Reasons” is among the top responses that seniors provide in the Health and Retirement Survey as a reason for their most recent move, and deciding where to live is a highly consequential decision. Localized amenities like the quality of health care, environmental amenities such as climate and air pollution, and opportunities for social interaction, affect health and longevity of seniors. [Chetty et al. (2016)] have documented striking differences in life expectancy across different regions in the US. Just recently, [Deryugina and Molitor (2018)] and [Finkelstein et al. (2019)] have shown that spatial differences in mortality are in fact causal.
This study combines the ideas of Tiebout (1956) and Grossman (1972) in a unified dynamic model of health and residential sorting. Individuals sort on amenities, based on preferences that are determined by their health and age type, and recognize how each location will potentially affect their health in the future. The estimation framework builds on Bayer et al. (2016), and extends it by introducing uncertainty about future health outcomes: When individuals choose a place to live in, they know the area-specific mortality rate and health transition probabilities. This stands to advance our understanding of the role of health in residential sorting. Prior studies have analyzed how individual differences in wealth, income, and preferences affect sorting outcomes (Epple and Platt, 1998; Epple and Sieg, 1999), tested how changes in amenities affect neighborhood demographics through sorting (Banzhaf and Walsh, 2008), and about how demographics and income help to explain heterogeneity in marginal valuation of amenities (Bayer et al. 2007, 2009). Recent work has added forward-looking behavior with respect to wealth (Bayer et al., 2016). In contrast, we know relatively little about how residential choices interact with health outcomes.

An individual is characterized by age and health and given this type and an individual random utility shock, chooses a residential location in order to maximize total lifetime utility. Total lifetime utility is the sum of discounted per-period utilities over the remaining years of life. The choice of a residential location determines the levels of amenities that the resident gets to enjoy. Per-period utility from each place is a function of local amenities and prices. can differ by health and age type. Future health is a function of both current health and current location. The model reflects tradeoffs between the quantity and quality of life. For example, places that are characterized by pleasant climate and high levels of cultural amenities, but also high levels of air pollution, might yield a high per-period utility, but affect future health negatively and hence shorten the remaining life span.

Panel data from the Center for Medicare and Medicaid Services (CMS) precisely track the residential locations of 7.3 million seniors, and the presence or absence of over 40 chronic health conditions from 2001 through 2011. Reduced form evidence suggests that negative health shocks trigger moves, leading to residential resorting.

The estimated structural parameters permit a novel, highly flexible approach to prospective policy analysis. Any policy that changes the provision of local amenities heterogeneously across space can be modelled. For example, regulations targeting ambient air pollution,
or changes to the local quality of health care such as the Hospital Readmission Reduction program, changes to local average temperatures and rainfall or the likelihood of extreme weather events, can be analyzed in terms of their valuation among seniors, and simulated with respect to their effects on migration flows.

Preliminary results show that valuation of the local quality health care increases as health worsens. Local amenity levels do a good job in explaining residential choices for younger seniors between the ages of 65 and 80, but a poorer job in explaining sorting for those past 80 years of age.

2. Related Literature

Common residential sorting models follow either a structure based on Epple and Platt (1998); Epple and Sieg (1999), where individuals have heterogeneous traits and therefore exhibit heterogeneous preferences, also known as “vertical sorting”; or assume that individuals with identical traits make heterogeneous choices, based on individual random utility (Bayer et al., 2009), “horizontal sorting”. A comprehensive review can be found in Kuminoff et al. (2013). This paper synthesizes both approaches. Individuals are modelled to be heterogeneous in health and age, thereby generating systematic heterogeneity in preferences across individuals, and in addition receive an individual random utility shock, such that otherwise identical individuals can be observed to make different choices.

3. Model

This model formalizes the following intuitive problem: Each period, seniors can move or stay in their place of residence. If they choose to move, they have to make another choice about where to move to. The state variables are current health status and current location. Future health evolves endogenously and is a function of current health status and current location. The sequence of events is illustrated in Figure [1]

At the beginning of the period, the individual observes their age and health type and realizes their random utility shocks $\epsilon_{i,j,t}$. Individuals then observe all possible location options.
Each location is characterized by its levels of amenities, probability of survival, and probability of transition into a different health type. If the individual decides to move, they incur a type and location-specific moving cost. At the end of the period, survival is determined conditional on current type and location, and conditional on survival and current location, the new health type is realized.

Each individual in every period solves the problem described in Equation 1. Individuals maximize utility by choosing their optimal residential location. $V^{\tau}_{t,j}$ stands for the total lifetime utility enjoyed by an individual of type $\tau$ in year $t$ in location $j$. They incur a type-specific moving cost $MC^{\tau}_{t}(j,l)$ if their initial location $l$ is not equal to their optimal location $j$, and the moving cost will be a function of the distance of the move.

$$\max_{j} V^{\tau}_{j,t} - MC^{\tau}_{t}(j,l) + \epsilon^{\tau}_{i,j,t}$$  \hspace{1cm} (1)

$\epsilon^{\tau}_{i,j,t}$ is the individual random utility, assumed to be distributed iid according to a Type I EV distribution. The total lifetime utility $V$ is comprised of the following components

$$V^{\tau}_{t,j} = u^{\tau}_{j,t} + s^{\tau}_{j,t} \cdot \beta E^{\tau}_{j,t} \left( \max_{k} V^{\tau'}_{k,j+1} - MC^{\tau'}_{t+1}(k,j) + \epsilon^{\tau'}_{i,k,j+1} \right)$$  \hspace{1cm} (2)

Notice that the per-period utility, the survival probability, and the expectation operator are all functions of type $\tau$ and location $j$. The expectation operator summarizes the uncertainty about the future health type $\tau'$. Per period utility is a function of local amenities $X_{j,t}$ and prices $p_{j,t}$, whereas the marginal utility of amenities and prices is type-specific.

$$u^{\tau}_{j,t} = X_{j,t} \alpha^{\tau} + p_{j,t} \gamma^{\tau}$$  \hspace{1cm} (3)
Table 1: Ten Most Frequent Chronic Conditions and Share of Seniors Diagnosed in 2001

<table>
<thead>
<tr>
<th>Condition</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypertension</td>
<td>58.8</td>
</tr>
<tr>
<td>Cataract</td>
<td>46.0</td>
</tr>
<tr>
<td>Hyperlipidemia</td>
<td>37.7</td>
</tr>
<tr>
<td>Ischemic heart disease</td>
<td>36.6</td>
</tr>
<tr>
<td>Anemia</td>
<td>31.6</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>28.8</td>
</tr>
<tr>
<td>Diabetes</td>
<td>20.5</td>
</tr>
<tr>
<td>COPD</td>
<td>17.1</td>
</tr>
<tr>
<td>Hypothyroidism</td>
<td>13.9</td>
</tr>
<tr>
<td>Glaucoma</td>
<td>13.5</td>
</tr>
</tbody>
</table>

4. Data

Information on individual location, age, and diagnosed chronic health conditions comes from a confidential panel dataset, built by the authors of Bishop et al. (2018). It is a national random sample of administrative records from the Centers for Medicare and Medicaid services (CMS). The panel contains annual observations of 7.3 million seniors in the years from 2001 to 2013. To put this in perspective, according to the Census in the year 2010 the total number of US citizens aged 65 years and older was 40.3 million. Individuals enter the panel when they turn 65, which is when they are automatically enrolled in Medicare, and leave the panel when they die. For each year that a person is enrolled in Medicare, their precise residential location is observed in form of their ZIP+4 code - a subunit of a ZIP code that equals approximately the size of a city block - together with a vector containing the presence or absence of around thirty common and less common chronic conditions. A “Top Ten” list of the most frequent conditions can be found in Table 1.

The unit of location choice will be a hospital referral region (HRR). An HRR is a geographic unit in which primary care providers refer to the same hospitals and specialized care providers, and is therefore a natural unit of choice to study residential sorting on health. HRRs are contiguous geographic units with a population of at least 120,000 individuals, and contains at least one hospital that performs major cardiovascular procedures and neurosurgery. There are 306 HRRs in the US, and roughly they can be thought of as mid-sized cities and their suburbs. Large metro areas usually contain multiple HRRs. The largest HRR in the sample houses 2.1 percent of the total sample population, the median HRR houses 0.5 percent of the sample population.
Individual locations in the dataset can easily be assigned to HRRs based on their ZIP code. Data on the amenity levels which each HRR provides come from multiple sources. Data on average temperature and rainfall is collected NOAA Weather Stations and publicly available. There are 12,230 weather stations across the country. The measurements of each station are averaged across one year and then averaged across all stations within an HRR.

Data on air pollution per HRR comes from EPA’s air quality monitors. These data are also publicly available. Specifically, ambient air pollutants ozone and particulate matter (PM 2.5) will be used because they are the most salient and most prevalent pollutants. The EPA operates 3,000 air quality monitors across the country, which yields neat coverage of data by HRR.

Data on temperature and precipitation levels in 2001 is drawn from the Global Historical Climatology Network Daily (GHCN Daily) data, provided by the National Oceanographic and Atmospheric Administration (NOAA), with the help of the R package rnoaoa. The data is publicly available. For all NOAA weather stations in the US active in 2001 there is a daily reading of the maximal temperature (in degrees Celsius) and the precipitation (in mm per square meter). Each station is assigned to the HRR that corresponds to the ZIP+4 centroid closest to the station by geocoordinates. The data per station is averaged by year, and then averaged across all weather stations within the HRR.

Data on housing prices is inferred from the 5 percent sample of the 2000 Census. Following the estimation strategy of Bayer et al. (2009), gross rents are regressed on housing characteristics and a PUMA specific intercept. The PUMA specific intercepts are taken to be the price premiums that have to be paid to live in a certain PUMA. Local rental prices, adjusted for housing characteristics, reflect the current cost of living in a certain place more clearly than housing values, which contain expectations about future price developments, and have been found to correlate most accurately with observable amenity levels (Banzhaf and Farooque, 2013).

Quality of health care by HRR is measured as the fraction of ambulatory care-sensitive hospital stays out of all hospital stays in the year 2001. This data is public and available at the

---

1PUMA specific rental prices are then aggregated into HRR units based on the Census crosswalks from PUMAs to block groups and from block group geocoordinates to ZIP codes. HRRs are defined as collections of ZIP codes.
Care-sensitive hospital stays are those that could have been prevented by timely ambulant provision of care. A common concern about outcome-based measures of hospital quality is that these do not accurately reflect a hospital’s quality if patients self-select into hospitals based on their health. In a recent working paper, Doyle et al. (2017) use the exogenous assignment of emergency patients to ambulance companies as an instrument for patient selection to different hospitals. They find that that publicly available outcome-based measures are in fact useful proxies for latent hospital quality. Also, Chandra et al. (2016) find evidence that hospitals which perform better on outcome-based measures exhibit higher market shares and higher growth rates, indicating higher underlying productivity.

5. Estimation

The estimation procedure involves several steps. First, the moving cost parameters and mean lifetime utility levels per type and place are estimated in a Maximum Likelihood estimation with a contraction mapping, according to Equations (4)-(7). The assumption that the individual random utility \( \epsilon_{i,j,t} \) is i.i.d. according to a Type I EV distribution with location parameter \( \mu = 0 \) and shape parameter \( \beta = 1 \). The feasibility of this distributional assumption is detailed in the Appendix Section A. Moving cost per type are parameterized as a quadratic function of distance in thousands of miles.

\[
LLF_t^T = \max_V \sum_l \sum_j \log P_{j,l}^T(l) \quad (4)
\]

\[
P_{j,l}^T(l) = \frac{\exp(V_{j,l}^T - MC(j,l))}{\sum_k \exp(V_{k,l}^T - MC(k,l))} \quad (5)
\]

\[
MC(k,l) = \gamma_0 \cdot \text{dist}(k,l) + \gamma_1 \cdot \text{dist}(k,l)^2 \quad (6)
\]

\[
s.t. \quad V_t^T = \lim_{x \to \infty} V_{x+1}^T = \lim_{x \to \infty} V_x^T + \log(\pi_{true}) - \log(\pi(V_x^T)) \quad (7)
\]

This procedure involves a normalization for each type since utility functions are invariant to constant shifts. This normalization inhibits the direct comparison of estimates across types and will be addressed in the second stage of the estimation.

To find the per-period mean utility values from lifetime utility values, Equation 2 can be rewritten as follows

\[ V_{j,t}^\tau = u_{j,t}^\tau + s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[ c_{EM} + \log \sum_k \exp(V_{k,t+1}^\tau - MC_{t+1}^\tau (k,j)) \right] \]  

(8)

This is possible because the expression \( E_{j,t}^\tau \left[ \ldots \right] \) is the expected maximum of a set of sums \( V_1 + \epsilon_1, \ldots, V_j + \epsilon_j \) where \( \epsilon_1, \ldots, \epsilon_j \) are i.i.d. according to a Type I EV distribution with parameters \( \mu = 0, \beta = 1 \). \( c_{EM} \) is a fixed value and equals the Euler-Mascheroni constant \( \approx 0.6 \), this is a result of the properties of the Type I EV distribution. Then, per-period mean utility values \( \tilde{u} \) are obtained from first-stage lifetime utility value estimates \( \tilde{V} \) according to Equation 9

\[ \tilde{u}_{j,t}^\tau = \tilde{V}_{j,t}^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[ c_{EM} + \log \sum_k \exp(\tilde{V}_{k,t+1}^\tau - MC_{t+1}^\tau (k,j)) \right] \]  

(9)

Place and type specific survival probabilities \( s_{j,t} \) and the health transition probabilities implicit in the expectation operator \( E_{j,t}^\tau \) are estimated in a separate procedure following the estimation strategy of Finkelstein et al. (2019). Period \( t \) estimates \( \tilde{V}_t \) are estimated with migration decisions and location decisions of individuals in the years 2001-2005, \( \tilde{V}_{t+1} \) are estimated using migration and location decisions in the years 2006-2011.

In the second stage, per-period utility values are decomposed onto prices \( p_{j,t} \) and local amenities \( X_{j,t} \) to obtain type specific utility parameters \( \alpha^\tau \) and \( \gamma^\tau \). These parameters can then be used to compute the marginal willingness to pay for amenities by type.

In order to do this, the normalization from the first stage needs to be addressed. Each \( \tilde{V}^\tau \) is equal to the true \( V^\tau \) minus a type specific normalization constant. The following Equation 10 rewrites Equation 9 with \( \tilde{V}^\tau = V^\tau - m^\tau \) to illustrate the relationship between the first stage estimates \( \tilde{u} \) and the true \( u \).

\[ \tilde{u}_{j,t}^\tau = \underbrace{V_{j,t}^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[ \gamma + \log \sum_k \exp(V_{k,t+1}^\tau - MC_{t+1}^\tau (k,j)) \right]}_{\text{true } u_{j,t}^\tau} \]  

\[ - \left( m_{j,t}^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[ m_{t+1}^\tau \right] \right) \]  

(10)

The “normalization bias” has two components: (1) a type-specific constant, and (2) the sum
of future type-specific constants, weighted by the product of place-specific survival and health transition probabilities. A type specific constant is no reason to worry when the second stage of the estimation includes a regression by type. To address point (2) the second-stage decomposition of $\tilde{u}_{j,t}^{\tau}$ includes fixed effects for all possible future health types $\tau'$. Practically, the product of survival probabilities and health transition probabilities $P_{j,t}(\tau, \tau')$ for all possible future type will be included as a set of variables in the second-stage regression.

$$u_{j,t}^{\tau} = a^{\tau} X_{j,t} + \gamma^{\tau} p_{j,t} + \delta^{\tau} \cdot \left( s_{j,t}^{\tau} P_{j,t}(\tau, \tau') \right)$$ (11)

In this regression, cost of housing $p_{j,t}$ is instrumented with the amenity levels of the nearest neighbor HRR in type space. To find the most similar HRR in type space, a principal component analysis is used to find the most important dimensions of joint variation for the amenities health care quality, air pollution levels, temperature, and precipitation. The Euclidean distance between all principal components determines the nearest neighbor. Other possible instruments are currently under consideration.

### 6. PRELIMINARY Results

How strongly do observed amenity levels correlate with the estimated per-period mean utility levels from the first stage? Figure 2 shows the adjusted $R^2$ of regressing mean utility levels on amenities and prices, before instrumenting for prices. It turns out that amenity levels and prices account for at least 20 percent of the variation in mean-utility levels across all types. For the young types, those aged 65 to 75, amenity levels in fact account for a large part of variation in per-period utility, up to 76 percent. Past age 75, amenity levels seem to correlate less with estimated mean utility levels, but the adjusted $R^2$ still ranges between 20 and 50 percent. It appears that for younger seniors, amenities account for a larger part of the variation in estimated utility levels than for older seniors. This is consistent with the notion that younger seniors seek out high-amenity places to spend retirement, while for older seniors, proximity to family and health care facilities is more important.

Figure 3 shows the estimates for monthly marginal willingness to pay for amenities. Health Type 1 is the healthiest type with 0 or 1 diagnosed chronic condition, Type 5 on the other
Figure 2: Adjusted $R^2$ of Per-Period Mean Utility Levels in the Second Stage, before Instrumenting for Prices. Amenity Levels Account for the Highest Share of Variation for Younger Seniors.
end of the spectrum has 8 or more diagnosed chronic conditions. The single most important amenity for all ages and all states of health appears to be the quality of health care. Health care quality is measured as the incidence of ambulatory care-sensitive hospital admissions per 1,000 Medicare enrollees. Ambulatory care-sensitive hospital admissions are admissions that could have been prevented by appropriate ambulatory care. The estimated willingness to pay for quality of health care is the highest of all amenities considered for each health and age type. The median willingness to pay for a one standard deviation increase in health care quality is 165 dollars per month (2001 USD).

The second most important appears to be temperature. Temperature is measured as average daily maximum temperature. For almost all types, the willingness to pay for 1 C higher average temperature is positive. The median is at 35 dollars per month. The willingness to pay to avoid ambient air pollution appears to have a trend in age. While younger types until age 80 appear to have a positive willingness to pay to avoid air pollution, as measured in standard deviations of PM$_{2.5}$, older types seem to have a negative willingness to pay. This suggests that air pollution is a factor in the location decision of younger seniors, but past the age of 80 other factors become more important. The willingness to pay to live in a more humid climate appears to have a trend in health. Within all age types, the healthier types seem to prefer more humid climates compared to the sicker types.

A full table of marginal utility estimates for all types and amenities can be found in Appendix Table 2.

References


(a) WTP for a 1 SD Increase in Health Care Quality, measured as Ambulatory Care-Sensitive Hospital Admissions.

(b) WTP to Avoid one Standard Deviation of Ambient PM$_{2.5}$

(c) WTP for 1 Celsius Increase in Average Daily Maximum Temperature

(d) WTP for 1 mm Increase in Average Daily Rainfall

Figure 3: Marginal Willingness to Pay per Month for Amenities in 2000 USD by Age and Health Type. Health Type 1 is Excellent Health, Type 5 is Poor Health.


7. Appendix

A. Normalizing shape parameter of $\varepsilon$

In the estimation process it is assumed that individual random utility $\varepsilon_{ij}$ is iid according to a Type I EV distribution (also known as: Gumbel distribution) with location parameter $\mu = 0$ and scale parameter $\beta = 1$. As a matter of fact, it is sufficient to assume that $\varepsilon$ is distributed according to any Gumbel distribution with $\mu = 0$. To show that $\beta$ can be normalized to 1, remember that the consumer’s optimal choice $j$ does not change if all options are divided by $\beta$.

$$\max_j \frac{V_1 + \varepsilon_{i1}}{\beta}, \ldots, \frac{V_j + \varepsilon_{ij}}{\beta} = \max_j \frac{V_1}{\beta}, \ldots, \frac{V_j}{\beta} = \max_j \tilde{V}_1 + \tilde{\varepsilon}_{i1}, \ldots, \tilde{V}_j + \tilde{\varepsilon}_{ij} \quad (12)$$

If $f$ is the density function of $\varepsilon$ with $\text{Gumbel}(0,\beta)$, and $y := \frac{\varepsilon}{\beta}$, then the density function of $y$ can be found through the following transformation

$$\int_a^b f(\varepsilon) \, d\varepsilon = \int_{\frac{a}{\beta}}^{\frac{b}{\beta}} f(\varepsilon(y)) \, \frac{d\varepsilon}{dy} \, dy = \int_{\frac{a}{\beta}}^{\frac{b}{\beta}} f(\beta y) \, \beta \, dy \quad (14)$$

$$= \int_{\frac{a}{\beta}}^{\frac{b}{\beta}} \frac{1}{\beta} \exp(-\left(\frac{\beta y}{\beta} + \exp(-\frac{\beta y}{\beta})\right)) \, \beta \, dy = f(\beta y) \quad (15)$$

$$= \int_{\frac{a}{\beta}}^{\frac{b}{\beta}} \exp(- (y + \exp(-y))) \, dy \quad (16)$$

This means that if $\varepsilon$ is distributed $\sim \text{Gumbel}(0,\beta)$, then $\frac{\varepsilon}{\beta}$ is distributed $\sim \text{Gumbel}(0,1)$. Notice that because $V$ has now been normalized to ensure $\beta = 1$, it is not possible to normalize $V$ further, e.g. to set one of the utility parameters equal to 1.
<table>
<thead>
<tr>
<th>Health type</th>
<th>Age 65-69</th>
<th>Age 70-74</th>
<th>Age 75-79</th>
<th>Age 80-84</th>
<th>Age 85-89</th>
<th>Age 90+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent (2000 USD)</td>
<td>-0.006 (0.008)</td>
<td>-0.004 (0.008)</td>
<td>-0.014 (0.011)</td>
<td>-0.027 (0.011)</td>
<td>-0.018 (0.011)</td>
<td>-0.027 (0.011)</td>
</tr>
<tr>
<td>Health Care</td>
<td>-1.063 (0.829)</td>
<td>-1.705 (0.932)</td>
<td>-4.302 (1.159)</td>
<td>-0.786 (1.159)</td>
<td>-3.15 (1.159)</td>
<td>-1.87 (1.159)</td>
</tr>
<tr>
<td>PM2.5</td>
<td>0.346 (0.352)</td>
<td>-0.216 (0.422)</td>
<td>-1.428 (0.377)</td>
<td>-1.601 (0.64)</td>
<td>-2.54 (0.64)</td>
<td>-0.87 (0.64)</td>
</tr>
<tr>
<td>Rainfall</td>
<td>0.546 (0.231)</td>
<td>0.129 (0.272)</td>
<td>-0.252 (0.223)</td>
<td>-0.285 (0.366)</td>
<td>1.542 (0.366)</td>
<td>0.159 (0.366)</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.351 (0.05)</td>
<td>1.092 (0.063)</td>
<td>1.374 (0.053)</td>
<td>1.77 (0.097)</td>
<td>1.009 (0.097)</td>
<td>0.227 (0.097)</td>
</tr>
<tr>
<td>Golf course</td>
<td>0.006 (0.006)</td>
<td>0.008 (0.008)</td>
<td>0.008 (0.007)</td>
<td>0.017 (0.011)</td>
<td>0.005 (0.011)</td>
<td>0.011 (0.011)</td>
</tr>
<tr>
<td>Health type</td>
<td>Age 70-74</td>
<td>Age 75-79</td>
<td>Age 80-84</td>
<td>Age 85-89</td>
<td>Age 90+</td>
<td></td>
</tr>
<tr>
<td>Rent (2000 USD)</td>
<td>-0.008 (0.006)</td>
<td>-0.001 (0.007)</td>
<td>-0.042 (0.015)</td>
<td>-0.04 (0.015)</td>
<td>-0.012 (0.015)</td>
<td>-0.018 (0.015)</td>
</tr>
<tr>
<td>Health Care</td>
<td>-1.091 (0.662)</td>
<td>-2.322 (0.949)</td>
<td>-6.165 (1.768)</td>
<td>-6.24 (1.591)</td>
<td>-1.837 (1.409)</td>
<td>-2.76 (1.28)</td>
</tr>
<tr>
<td>PM2.5</td>
<td>-0.682 (0.263)</td>
<td>-1.706 (0.4)</td>
<td>-2.065 (0.868)</td>
<td>-1.341 (0.782)</td>
<td>0.275 (0.273)</td>
<td>-0.432 (0.193)</td>
</tr>
<tr>
<td>Rainfall</td>
<td>0.494 (0.172)</td>
<td>0.504 (0.256)</td>
<td>-0.236 (0.466)</td>
<td>0.325 (0.468)</td>
<td>-0.781 (0.136)</td>
<td>0.14 (0.081)</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.885 (0.103)</td>
<td>1.597 (0.16)</td>
<td>1.521 (0.104)</td>
<td>1.367 (0.08)</td>
<td>-0.61 (0.10)</td>
<td>0.137 (0.081)</td>
</tr>
<tr>
<td>Golf course</td>
<td>0.004 (0.005)</td>
<td>0.002 (0.008)</td>
<td>0.019 (0.010)</td>
<td>0.025 (0.010)</td>
<td>0.015 (0.010)</td>
<td>0.011 (0.010)</td>
</tr>
</tbody>
</table>