The effect of weather on walking behavior among older adults

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Abstract

In this paper we examine how temperature and precipitation affect the probability that a retired American between the ages of 65 and 90 walks at least 2.5 hours per week using longitudinal data from the Consumption and Activities Mail Survey (CAMS), a subpanel within the Health and Retirement Survey (HRS). Walking behavior is linked with monthly temperature and precipitation data from weather station reports. Fixed-effect estimates reveal that higher temperatures are associated with a higher probability of walking at least 2.5 miles per week for females and we reject that the fixed and random effects estimates are the same. Random-effects estimates for males reveal that higher temperatures lower the probability of walking and we cannot reject that the fixed and random effects estimates are the same. Precipitation is not significantly associated with walking behavior for either gender.
Introduction

In this paper we examine how weather, specifically temperature and precipitation, affects the probability that a retired American between the ages of 65 and 90 walks at least 2.5 hours per week, the minimum recommend amount of moderate physical activity for older Americans (CDC, 2009). Although previous research has studied the exercise patterns of older Americans (Crespo, Keteyian, Heath & Semos, 1996; Dergance, Calmbach, Dhanda, Miles, Hazuda & Mouton, 2003) and the role of weather on physical activity (hereafter PA) (Eisenberg & Okeke, 2009; Matthews, Freedson, Hebert, Stanek, Merriam, Rosal, et al., 2001; Pivarnik, Reeves, & Rafferty, 2003; Zivin and Neidell, 2010), this is the first paper to address the latter relationship employing longitudinal data collected over several years. Doing so allows us to address the potential concern that individuals select where they want to live, and thus also select their climate. This is deemed location selection.

We focus on an older population because the impending retirement of the baby boom generation, and its subsequent transition to socially provided insurance (Medicare) makes elderly health and health related expenditures particularly important today (Lee & Skinner, 1999; Manton, Stallard, & Liu, 1993; Thorpe & Howard, 2006). We specifically study walking as an activity because it is by far the most common form of physical activity for older Americans (Simpson, Serdula, Galuska, Gillespie, Donehoo, Macera, et al., 2003). A great deal of recent research has recognized the benefits of walking in terms of both individual and public health (Blake, Mo, Malik, & Thomas 2009; Blumenthal, Babyak, Moore, Craighead, Herman, Khatri, et al., 1999; CDC, 2007; CDC, 2009; Gordon-Larsen, Hou, Sidney, Sternfeld, Lewis, Jacobs, et al., 2009; Le Masurier, Bauman, Corbin, Konopack, Umstattd, & Van Emmerik, 2008; Lee & Buchner, 2008; Nelson & Folta, 2009; USDHHS, 1996).
Simpson, et al. (2003) provide the most comprehensive accounting of walking behavior in the United States using data from the Behavioral Risk Factor Surveillance System (BRFSS) between 1987 and 2000. Walking is the most frequently reported PA for adults among forms that meet the CDC guidelines for regular physical activity (five or more times per week, for 30 or more minutes per walking session). Women tend to walk more than men: in 1987, 26.2% of men reported walking as one of their two most frequent forms of physical activity compared to 40.4% of women. The proportion of walkers increases over the time period. For example, 40.6% of men at least 65 years of age reported walking in 1987; by 2000 this proportion had risen to 44.2%. Moreover, the gap between males and females tends to decline with age: in 2000 the proportion of females at least 65 years old who reported walking was 45.4%. Finally, the data suggest that among males, it is consistently those 65 years old or above who walk the most. In contrast, walking is most common among females for those between age 55 and 64. Nonetheless, walking is clearly the most common form of PA among older Americans, both male and female.

A number of recent papers have catalogued seasonal variation in PA based on temperature and precipitation (Eisenberg & Okeke, 2009; Matthews, Freedson, Hebert, et al., 2001; Pivarnik, Reeves, & Rafferty, 2003). The analysis we conduct here is most similar to that of Eisenberg and Okeke (2009), because they also attempt to address the potential location selection issue. They find that at lower temperature ranges (<60°F) outdoor PA decreases as temperature decreases, with only partial substitution from outdoor toward indoor PA. Further, the extent of substitution depends on socio-economic status (SES): those with lower SES appear less able to move their activity indoors. However, at higher temperatures ranges (60°F to 80°F and >80°F), the relationship between temperature and physical activity is not statistically significant.
Methods

Data

Information about the time-use of older Americans is taken from the Consumption and Activities Mail Survey (CAMS), a biennial supplement to the Health and Retirement Survey (HRS) administered in 2001, 2003, 2005 and 2007. Both datasets are publicly available from the University of Michigan Institute for Social Research Survey Research Center. The survey instrument is mailed in mid-September and the majority of responses are received by mid-October. Unlike the American Time Use Survey (ATUS) or the BRFSS, both of which use a different group of respondents in each of its annual waves, the CAMS sample is longitudinal in nature (i.e. the same individuals are repeatedly sampled over time). The panel is unbalanced because of attrition, non-response and the addition of new participants, but 76.5% of all CAMS respondents provided walking data in at least two of the four waves and 40.0% responded in all four waves.

Respondents are prompted to self-report the actual amount of time spent in each of several activities even if this differs from usual. In the subsequent analysis, we utilize responses to the amount of time engaged in the following: walking in the previous week; working for pay in the previous week; and treating or managing an existing medical condition (hereafter, own health care) in the previous month. These activities are reported in each of the four waves. In addition, respondents are also asked to report whether they are physically disabled.

Responses to the amount of time working for pay and disability status are variables that are utilized to define the sample used for estimation. The decision to work can influence the decision to walk for two reasons. First, walking may be required as part of employment. Second,
working reduces the time available that can be allocated to walking for leisure. However, it is also possible that the ability or desire to walk can influence the decision of whether individuals work, or how many hours they work. Estimating the simultaneous determination of labor supply and walking behavior, while a potentially worthwhile undertaking, faces a number of non-trivial estimation issues. As older Americans face strong incentives to retire at age 65 because of eligibility for Medicare and full Social Security benefits, we avoid the simultaneity problem by restricting attention to individuals who are at least 65 years of age and do not report working for pay during the survey period (age is taken from the larger HRS survey). In addition, walking requires a minimum level of physical health. Thus, individuals who are above 90 years of age or self-report a physical disability are also omitted from the analysis.

Since CAMS does not ask respondents for their location of residence, this information must also be recovered from the HRS. As CAMS is administered in the fall, we link physical activity responses from 2001 to 2002 residences. In the publically available HRS data, the most disaggregated geographic identifier is the Census division.

Climate data are taken from the United States Historical Climatology Network (USHCN), which provides monthly average temperatures and total precipitation amounts from over 1200 weather stations across the continental United States. Although we know that the CAMS questionnaires are sent to participating households in the early fall, we do not know precisely on what day or days the forms are completed. Thus, we face two forms of aggregation from the base data, geographic and temporal. To handle the latter, the distances between the population centroid and every participating weather station in 2001 are calculated for each county in the United States. The five closest weather stations within 50 miles of the centroid (or all weather stations within 50 miles if there are less than five) are then used to calculate a distance-weighted
mean of the average monthly temperature and total precipitation for both September and
October. The arithmetic mean over September and October is then used as the average fall value
for 2001. A population-weighted average is then calculated over all counties in the Census
region to yield region-level fall averages for 2001. These calculations are repeated for 2003,

Estimation

Previous attempts to study the relationship between weather and exercise have tended to
compare the behavior of different individuals who experienced different types of weather, i.e.
cross-sectional (CS) analysis (Togo et al., 2005; Keenan, 2006; Eisenberg, D., & Okeke, E.,
2009; Pivarnik, J., Reeves, M., & Rafferty, A., 2003; Zivin and Neidell, 2010). Assigning causal
interpretations to such differences in behavior using CS data is difficult because individuals sort
themselves into climates by their long term residential decisions, i.e. the location selection issue
raised earlier. For example, if those who enjoy cross-country skiing sort into cold climates while
those who enjoy golf sort into hotter climates, the average treatment effect of temperature on PA
will be attenuated (i.e. odds-ratios are going to be biased toward unity). Indeed, location
selection could be problematic even if individuals did not expressly pick whether to live in warm
or cold climates based on physical activity opportunities. Any unobserved attribute that was
correlated with both climate and physical activity would bias coefficient estimates.

This selection issue in CS data and analyses has been recognized previously by Eisenberg
and Okeke (2009), who use state-level variation in weather and individual-level data from the
1993 to 2000 Behavioral Risk Factor Surveillance System (BRFSS) to examine the relationship
between weather and exercise. Unlike the CAMS data used in this study, which is longitudinal,
BRFSS is composed of repeated cross-sections, i.e. different individuals are interviewed each year. To control for location selection, they include state-month fixed effects so that identification comes from variations in weather and exercise behavior that are above or below monthly state averages. Intuitively, unobserved individual attributes that affect exercise behavior and are correlated with weather are assumed to be captured by the average weather patterns in a state. A recent working paper by Zivin and Neidell (2010) estimate a slightly different model of activity use than do Eisenberg and Okeke (2009) to account for location selection, using the 2003 to 2006 American Time Use Survey (ATUS). They employ year/month dummy variables along with county fixed-effects to capture the potential confounding influence of unobservable individual attributes that could be associated with physical activity behavior and weather.

With the longitudinal structure of CAMS, unobserved individual attributes can be modeled directly. For reasons unobserved to the researcher, some individuals are more likely to walk than other individuals. This feature can be built into to estimation model by including individual-specific constants. Using a latent-utility model, let \( Z_{it}(R) \) denote the unobserved utility to walking at least \( R \) hours per week for individual \( i \) in period \( t \). Then:

\[
Z_{it}(R) = \beta X_{it} + \mu_i + \varepsilon_{it}
\]

where \( X_{it} \) are the observed demographic and weather variables of respondent \( i \) in period \( t \); \( \mu_i \) is an individual-specific summary variable for unobserved attributes that influence the utility of walking but do not vary over time; and \( \varepsilon_{it} \) is a random error that is independently distributed logistic. The outcome of interest (here, whether the individual walks at least \( R \) hours per week), is then defined as:

\[
Y_{it}(R) = 1 \text{ if } Z_{it}(R) \geq 0
\]

\[
Y_{it}(R) = 0 \text{ if } Z_{it}(R) < 0.
\]
Although $\mu_i$ is included in the estimation model to control for unobserved time-invariant differences across subjects, these coefficients are not actually estimated. Even with multiple observations for each individual, estimating the set of $\mu_i$ (one for each individual in the sample) is unadvisable, since doing so would lead to inconsistent estimates of the parameters that matter, the $\beta$, which tell us the effect of the $X$'s (Hsaio, 1986; Chamberlain, 1980). One approach that overcomes this problem is the fixed-effects (within) estimator. Chamberlain (1980) demonstrates that $\sum Y_u(R)$ is a sufficient statistic for $\mu_i$ in the fixed-effects framework and the likelihood function reduces to the conditional logit over the individuals who moved from above the threshold $R$ to below the threshold or vice-versa during the survey period.

For those unfamiliar with the properties of the fixed-effect estimator, it is worth briefly pointing out some of the limitations of this estimation method. One drawback to fixed-effects is that respondents who were always above the threshold or always below the threshold do not provide any explanatory power. Intuitively, with fixed-effects we cannot learn about what causes individuals to change their behavior by studying individuals who did not change their behavior. Because of this, the number of observations actually available for estimation can fall dramatically. If $R$ is selected to maximize the number of available observations, then the threshold should be set to 3 hours of walking per week. Since only a few observations are lost by using the minimum recommended amount of moderate physical activity for older adults, we define our indicator variable to equal unity when an individual has reported walking at least 2.5 hours in the previous week (CDC, 2009).

A second issue with fixed-effect estimation is that it is impossible to recover the effect of explanatory variables that are constant over time for all individuals (see Baltagi, 1995; Woolridge, 2001). When a fixed-effect is included, all key relationships are identified based on
their deviations from the mean. Intuitively, we ask the data to tell us whether individuals were relatively more or less likely to walk (relative to their mean probability of walking) when the temperature was relatively higher (relative to the mean temperature they experienced). For variables that are constant over time, there are no observations above or below the mean value and thus, there is no way to recover the relationship. Algebraically, any variable that is constant is perfectly collinear with the included fixed-effect, $\mu_i$, and must be omitted from the estimation. This is highly problematic in cases where the relationship between the outcome and a time-invariant attribute (e.g. gender, race, education level) is of primary interest to a researcher.

Because the subsequent analysis is primarily focused on the role of environmental attributes that do change over time, namely temperature and precipitation, this is not a problem here. Moreover, the omission of observable time-invariant characteristics does not introduce bias in other coefficient estimates, as could happen when using cross-sectional instead of longitudinal data. Rather, the fixed-effect captures the potential confounding influence of all time-invariant confounders, both observed and unobserved (Woolridge, 2001).

Although it is impossible in a fixed-effects framework to recover the relationship between the outcome and time-invariant attributes, e.g. how gender influences the probability of walking, it is nevertheless possible to use our approach to examine how gender influences the relationship between temperature and walking. This is mostly easily accomplished by analyzing subgroups separately, i.e. estimating different coefficients for different groups. As previous research suggests that physical activity patterns and preferences differ between genders, males and females are analyzed separately. Unfortunately, the limited size of the CAMS sample prevents further stratification by race or socio-economic status.
A third issue with the fixed-effect framework, related to the previous one, is that attributes that do change over time will be imprecisely estimated if changes occur for only a small fraction of the sample. For example, although marital status can vary over time, in a fixed-effects specification, identification of the influences in the model is generated by observations on individuals who change their state over the observed time horizon, e.g. by looking at individuals who go from being married to being a widow(er). While some individuals in our sample do indeed change their marital status, the number of individuals doing so during the time period covered by our sample is quite small. This small proportion will tend to produce imprecise coefficient estimates that inflate standard errors.

Most importantly here, changes in marital status are likely to be uncorrelated with changes in temperature or precipitation. Hence, omitting marital status from the empirical specification should not influence the coefficient estimates of interest. Indeed, as a robustness check, we re-estimated the model including marital status and found that coefficient estimates on weather attributes were quantitatively similar, suggesting omission is not problematic for the purposes of the current study. A similar argument applies to other family structure attributes, e.g. presence of grandchildren in the home.

Because the estimation sample is restricted to fully retired individuals, household income is not included in main set of explanatory variables. Given the lack of labor income, changes in household financial resources are going to be driven by changes in stock/bond portfolios and the value of housing. We hypothesize these are uncorrelated with cross-regional weather variations and robustness checks confirm that including household income does not quantitatively affect the results presented subsequently. Therefore, we will only present the results that omit household income, though the results that include household income are discussed.
An alternative approach is to assume that $\mu_i$ is a random-effect distributed normal, $N(0, \sigma^2_\mu)$, where the variance is an estimable parameter. In this case, all observations—even those for individuals always above or below the threshold—are used in estimation; coefficient estimates for time-invariant characteristics can be recovered; and coefficient estimates are more precise, i.e. smaller confidence intervals. However, for estimates of $\beta$ to be consistent under the random effects assumption, $\mu_i$ must be independent of the observed characteristics. That is, a random-effects specification is valid when the potential issues with location selection are assumed away before estimation. Although this is an inappropriate a priori assumption, there are obvious efficiency gains from using random instead of fixed-effects, Therefore, a Hausman test is performed to compare the similarity of coefficient estimates under the two specifications. To do so, a random-effects specification is estimated over the same sample that is used for the fixed-effects estimation. Recall that this is a different sample than that available for the full random-effects estimation, which would also include individuals who were always above the threshold and always below the threshold.

**Results**

Descriptive statistics for the estimating sample are reported in Table 1. On average, respondents spend 4.7 hours per week walking. Although there are some exceptionally high reported values of weekly walking, the overwhelming majority of responses are reasonable: 90.5% are ten hours per week or less and 96.8% are twenty hours or less. The threshold of 2.5 hours of walking per week is nearly the median response. On average, individuals in the sample allocate just over 6 hours per month to their own health care. As evident from the standard deviation, however, to focus on the mean alone obscures quite a large amount of variation. Roughly 36.1% of individuals reported zero time
spent in own health care while one individual reported 744 hours in a month, equivalent to 24 hours per day over 31 days. In contrast, only 12.3% of individuals reported zero hours of walking per week. Nonetheless, 97.3% of health care responses were equal to or less than 31 hours per month, or approximately one hour per day. Less than 1% of the sample responses would imply more than 2 hours per day engaged in own health care. Overall, the majority of time-use responses both to the walking and own health care questions are plausible. Robustness of results to outliers is also examined.

The average fall regional temperature over the four waves is 64.2°F, which varied from a low of 62.6°F in 2005 to a 66.0°F in 2003. The variation in minimum and maximum temperature values is slightly larger. For example, 2001 had both the highest minimum and the lowest maximum. The difference in minima between 2003 and 2007 is 4.4°F while the difference in maxima between 2001 and 2005 is 4.3°F. The variation within regions (not reported) was also non-trivial. For example, the average temperature in Census region 3 (East North Central) ranged from 56.6°F in 2003 to 62.2°F in 2007. The average temperature in Census region 6 (East South Central) ranged from 64.1 in 2001 to 69.7 in 2007.

Before proceeding, it is important to recognize the limitations of these data relative to those utilized previously. With respect to effective variation, the current dataset is no more disadvantaged than using the BRFSS along with a state-month fixed-effects approach (Eisenberg and Okeke, 2009). A dataset with observations from Minnesota in February and Arizona in August may not produce more usable variation in temperature because the inclusion of fixed-effects effectively differences the average temperature from the observed temperature before estimation. If the observed temperatures are 30°F and 100°F in Minnesota and Arizona, respectively, but the average February temperature in the former is 35°F and the average August
temperature in the latter is 105°F, then the actual variation in temperature to be used in estimation with state-month fixed effects is 5°F for both.

The limitation of the current dataset is not the amount of temperature variation, but the range over which variation occurs. A temperature change of 5°F may have different effects at different temperatures. For example, a 5°F increase from 30°F degrees may increase walking greatly since the temperature is sufficiently high to prevent sidewalks from freezing, which might be especially important to the perceived safety of older people. In contrast, a 5°F increase from 90 degrees may decrease walking. While the subsequent results may be useful when considering temperature changes between 50°F and 80°F, extending our results to higher or lower temperatures is perhaps misguided. The temperature range covered in our dataset includes the average monthly temperature for six months in New York City (April to June and August to October). For Los Angeles, the temperature range covers the averages of ten months (all but July and August). For Houston, the temperature range covers the averages of seven months (October to April). For Chicago, the temperature range covers the averages of seven months (May to October). Therefore, while our dataset does not allow us to study all possible temperature ranges, it does allow us to account for a majority of the year in the majority of the county.

The first column of Table 2 reports odds-ratios from a fixed-effects (conditional) logit regression on the outcome of walking at least 2.5 hours per week on the sample of male CAMS respondents between 65 and 90 years of age who did not report working or being disabled (95% confidence intervals are in parentheses; statistical significance is noted for $P<0.01$ and $P<0.10$ to emphasize results that are alternatively much more or very nearly statistically significant at the 5% level). The second column repeats the analysis, but uses the random-effects specification. Odds ratios under random-effects are similar to those from fixed-effects and the null hypothesis
that they are equal cannot be rejected (based on the usual Hausman test). This suggests that the
efficiency gains from random-effects can be utilized here. For males, higher temperatures are
associated with a lower probability of walking at least 2.5 miles per week and the effect is
statistically significant at the 5% level.

For females (columns 3 and 4), however, estimation under fixed-effects yields
dramatically different results than estimation under random effects and here the Hausman test
strongly rejects equality in the coefficients. Unlike males, fixed effects estimation reveals that
every one degree increase in average fall temperature is associated with an increase in the
probability of walking at least 2.5 miles per week, though the estimate is only significant at the
10% level. No statistically significant association is found between walking and precipitation, for
either males or females. Note that another interesting difference between males and females is
the coefficient estimate on age. Although the odds ratio is less than unity for both samples,
implying that the probability of walking at least 2.5 hours per week decreases with age, it is only
statistically significant for females. We provide extended discussion in the next section.

Discussion

In this study we have used longitudinal data to explore the role that temperature plays in
determining whether elderly individuals achieve the CDC-recommended level of moderate
physical activity through walking. We found that the probability of walking at least 2.5 hours per
week is positively associated with temperature for females, but that the opposite is true for
males. In contrast, Eisenberg and Okeke (2009) did not find a significant relationship between
temperature and outdoor PA between 60°F and 80°F for either males or females. One
explanation for the differing results between their study and ours is the different ways in which
location selection is addressed: repeated cross-sections and state-month fixed-effects in the
former versus longitudinal data and individual fixed-effects in the latter. An alternative explanation is that the effect of temperature on the physical activity of older adults differs from the general population, and the response of older males differs from the response of older females.

But how to explain why relationship between weather and walking behavior differs by gender? Household production models (HPM) of health and leisure (Becker, 1965; Cawley, 2004; Grossman, 1972; Humphreys & Ruseski, 2009) provide an economic framework to do so. Walking can be thought of as an input in the production of the commodities health and leisure. These two activities provide satisfaction in the HPM framework: leisure might include simply sitting outside on a nice day, perhaps reading, but walking may also provide such pleasure. Poor weather (too hot, too cold or too wet) can be interpreted as increasing the effective cost and/or decreasing the marginal utility of engaging in outdoor PA. Thus, during periods of poor weather we would expect substitution away from outdoor PA like walking toward indoor activities, which become relatively cheaper.

Eisenberg and Okeke (2009) found that differences in economic resources influence an individual’s ability to substitute time across activities. Thus, one possible explanation for the opposing responses of males and females to temperature variation are underlying differences in household financial resources among older males and females. Cohen-Mansfield, et al. (2004) found that women are more concerned with the costs associated with available options for physical activity. Individuals with higher levels of income therefore have more available physical activity options and less difficulty paying for various forms of transportation to get to a more distant location. Using the 75th percentile of the household income distribution for the CAMS respondents (an imputed value of household income from all sources is provided in the
main HRS) as a threshold for high resource households, we compare males and females. We find that 38.5% of observations for males are above the threshold, compared to only 24.3% of females—a 59% difference. It is worth noting, however, that including household income in our regression specifications or interacting income with temperature did not affect coefficient estimates. Therefore, differences in household resources between males and females in our sample do not seem to explain the differences in responses we find here.

An alternative explanation for our gender result differences rests upon differences in underlying preferences for physical activity between genders. A survey on adult physical activity conducted by Keenan (2006) reports the reasons men and women gave for engaging in exercise: women engage in physical activity for health and weight reasons, while men report that they exercise as a way of socializing with others. Thus, higher temperatures may lead older males to replace walking with other outdoor social activities such as golf or tennis, while females increase their participation in walking as a low-cost way to improve health, weight, and stamina. This highlights a limitation of the current study (as well as others), but also an opportunity for future research. Longitudinal data that collected time use information on a disaggregated list of physical activities could be used to model substitution behavior across activities, which clearly stands as an important gap in the literature.

Another interesting result in our analysis is the statistically insignificant odds ratio on age for males. One would typically expect walking to decline with age as health deteriorated. Using a Lowess smoother, we estimated the relationship between age and walking behavior for males (not reported) and found that the walking/age-profile is decidedly humped-shaped, peaking at ages 72-73. It is possible that walking initially increases because males are transitioning toward walking from other, more strenuous forms of physical activity. This would be consistent with the
findings of Simpson et al. (2003), who found that the difference in walking participation between males and females narrows with age. Beyond the age 73, however, there is a clear decline in walking among males, which is consistent with increasing physical limitations associated with aging. A second explanation is that in a fixed-effect specification age is the same thing as including a linear time-trend. If older adults were becoming more aware of the importance of walking to improve their health during the observed sampling period, then the downward effects of age would be combined with the upward effects of awareness. We explored this by running a pooled regression with year dummy variables and indeed found that the odds ratio on age was less than one and statistically significant ($OR=0.983$, 95% CI=[0.969, 0.997]).

There are several other limitations to our study. Physical activity is self-reported and recalled. There may be benefits to using pedometers and time-use diaries in longitudinal data collection efforts to more accurately measure walking activity (Togo et al., 2005). In addition, data are aggregated both geographically and temporally. The availability of state or even county level identifiers would permit a more accurate description of the weather faced by survey respondents. Clearly, future work using more disaggregated longitudinal data could resolve this issue and would be a welcome contribution to the literature. Finally, the temperature ranges observed in our data preclude drawing conclusions about the relationship between weather and walking at more extreme temperatures. Longitudinal data collection that sampled individuals at different points during the year would be a useful tool for researchers.

Walking is clearly an important activity among older adults, improving both physical and mental health. We have shown than the decision to engage in walking depends upon weather conditions such as temperature. This research, and future research that might improve on what we have done, is important for at least two reasons. First, people in the U.S. are living to older
ages, and the costs of poor health in this population are increasingly important to consider. Second, while much uncertainty remains about global warming, the lead scientists who do this work (as represented by the International Panel on Climate Change) have continued to forecast average temperature increases in many areas of the United States that are in the range, or exceed the range of temperatures that we have considered in our analysis. If these changes are realized, our research suggests the possibility of benefits and costs related to health and walking. These should be further considered as we learn more about the changes realized in specific regions of the United States.
References


### Table 1: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking (hrs/week)</td>
<td>4.68</td>
<td>8.90</td>
<td>0</td>
<td>168</td>
</tr>
<tr>
<td>Walk at least 2.5 hrs/week</td>
<td>0.522</td>
<td>0.500</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Own health care (hrs/month)</td>
<td>6.25</td>
<td>26.78</td>
<td>0</td>
<td>744</td>
</tr>
<tr>
<td>Average fall temperature (°F)</td>
<td>64.15</td>
<td>5.02</td>
<td>55.37</td>
<td>74.10</td>
</tr>
<tr>
<td>2001</td>
<td>62.59</td>
<td>4.67</td>
<td>56.66</td>
<td>69.78</td>
</tr>
<tr>
<td>2003</td>
<td>63.06</td>
<td>5.43</td>
<td>55.37</td>
<td>70.95</td>
</tr>
<tr>
<td>2005</td>
<td>64.86</td>
<td>4.63</td>
<td>58.64</td>
<td>74.10</td>
</tr>
<tr>
<td>2007</td>
<td>66.02</td>
<td>4.55</td>
<td>59.79</td>
<td>73.76</td>
</tr>
<tr>
<td>Average fall precipitation (inches)</td>
<td>3.26</td>
<td>1.65</td>
<td>0.52</td>
<td>8.55</td>
</tr>
<tr>
<td>Age</td>
<td>75.32</td>
<td>6.17</td>
<td>65</td>
<td>90</td>
</tr>
<tr>
<td>Male</td>
<td>0.323</td>
<td>0.478</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: 2447 observations over 793 individuals. There are 577 observations from CAMS 2001; 625 from CAMS 2003; 650 from CAMS 2005 and 595 from CAMS 2007.
<table>
<thead>
<tr>
<th></th>
<th>Males Fixed-effects</th>
<th>Males Random-effects</th>
<th>Females Fixed-effects</th>
<th>Females Random-effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average fall temperature (°F)</td>
<td>0.961 (0.881 - 1.047)</td>
<td>0.963** (0.936 - 0.992)</td>
<td>1.056* (0.993 - 1.122)</td>
<td>0.990 (0.971 - 1.009)</td>
</tr>
<tr>
<td>Average fall precipitation (inches)</td>
<td>1.088 (0.949 - 1.247)</td>
<td>1.052 (0.965 - 1.147)</td>
<td>0.949 (0.866 - 1.040)</td>
<td>0.962 (0.906 - 1.021)</td>
</tr>
<tr>
<td>Age</td>
<td>0.946 (0.876 - 1.023)</td>
<td>0.994 (0.970 - 1.018)</td>
<td>0.887*** (0.837 - 0.940)</td>
<td>0.985* (0.970 - 1.000)</td>
</tr>
<tr>
<td>Own health care (hrs/month)</td>
<td>1.013 (0.995 - 1.032)</td>
<td>1.008 (0.994 - 1.023)</td>
<td>0.997 (0.993 - 1.002)</td>
<td>0.997 (0.993 - 1.001)</td>
</tr>
<tr>
<td>Observations</td>
<td>790</td>
<td>790</td>
<td>1657</td>
<td>1657</td>
</tr>
<tr>
<td>Groups</td>
<td>251</td>
<td>251</td>
<td>525</td>
<td>525</td>
</tr>
<tr>
<td>Hausman statistic</td>
<td>3.28</td>
<td>13.31***</td>
<td>13.31***</td>
<td>13.31***</td>
</tr>
</tbody>
</table>

Note: Coefficient estimates from logistic regression on CAMS respondents between the ages of 65 and 90 who do not work and are not disabled. 95% confidence intervals in parentheses. Hausman statistic is distributed $\chi^2(4)$.

*** p<0.01, ** p<0.05, * p<0.1