The Effect of Weather on Walking Behavior in Older Adults

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In this article, the authors examine how temperature and precipitation affect the probability that a retired American between the ages of 65 and 90 walks at least 2.5 hr/wk, using longitudinal data on walking frequency from the Consumption and Activities Mail Survey, a subpanel in the Health and Retirement Survey. Walking behavior is linked with monthly temperature and precipitation data from weather-station reports. The authors found that higher temperatures were associated with a higher probability of walking at least 2.5 hr/wk for women. In contrast, higher temperatures are associated with a lower probability of walking at least 2.5 hr/wk among men. Precipitation is not significantly associated with walking behavior for either gender.

Keywords: physical activity, elderly, climate, longitudinal data, location selection, Health and Retirement Survey

In this article 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 hr/week, the minimum recommended amount of moderate physical activity for older Americans (Centers for Disease Control and Prevention [CDC], 2009). Although previous research has been conducted on the exercise patterns of older Americans (Crespo, Keteyian, Heath, & Sempos, 1996; Dergance et al., 2003) and the role of weather in physical activity (Eisenberg & Okeke, 2009; Matthews et al., 2001; Pivarnik, Reeves, & Rafferty, 2003; Zivin & Neidell, 2010), this is the first article 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 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;
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 physical activity for adults among forms that meet the CDC guidelines for regular physical activity (five or more times a week for 30 or more min/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 with 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 men and women tends to decline with age: In 2000 the proportion of women at least 65 years old who reported walking was 45.4%. Finally, the data suggest that among men, it is consistently those 65 years old or above who walk the most. In contrast, walking is most common among women age 55–64. Nonetheless, walking is clearly the most common form of physical activity among older Americans, both men and women.

A number of recent articles have cataloged seasonal variation in physical activity based on temperature and precipitation (Eisenberg & Okeke, 2009; Matthews et al., 2001; Pivarnik et al., 2003). The analysis we conduct here is most similar to that of Eisenberg and Okeke, because they also attempted to address the potential location-selection issue. They found that at lower temperature ranges (<60 °F) outdoor physical activity decreases as temperature decreases, with only partial substitution from outdoor to indoor physical activity. Furthermore, the extent of substitution depends on socioeconomic status: Those with lower socioeconomic status appear less able to move their activity indoors. However, at higher temperatures (60–80 °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 data sets are publicly available from the University of Michigan Institute for Social Research Survey Research Center. The survey instrument is mailed in mid-September, and most responses are received by mid-October. Unlike the American Time Use Survey or the BRFSS, both of which use a different group of respondents in each of their 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, nonresponse, 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 it differs from the usual. In the subsequent analysis,
we use 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 asked to report whether they are physically disabled.

Amount of time working for pay and disability status are variables that are used 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, although a potentially worthwhile undertaking, entails a number of nontrivial estimation problems. Because 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 over 90 years of age or self-report a physical disability are also omitted from the analysis.

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

Climate data are taken from the U.S. Historical Climatology Network, which provides monthly average temperatures and total precipitation amounts from over 1,200 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 fewer 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, 2005, and 2007.

**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—that is cross-sectional analysis (Togo, Watanabe, Park, Shephard, & Aoyagi, 2005; Eisenberg, & Okeke, 2009; Keenan, 2006; Pivarnik et al., 2003; Zivin & Neidell, 2010). Assigning causal interpretations to such differences in
behavior using cross-sectional data is difficult because individuals sort themselves into climates by their long-term residential decisions—the location-selection issue raised earlier. For example, if those who enjoy cross-country skiing sort into cold climates and those who enjoy golf sort into hotter climates, the average treatment effect of temperature on physical activity 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 problem in cross-sectional data and analyses was recognized previously by Eisenberg and Okeke (2009), who used state-level variation in weather and individual-level data from the 1993–2000 BRFSS to examine the relationship between weather and exercise. Unlike the CAMS data used in this study, which are longitudinal, BRFSS is composed of repeated cross-sections; different individuals are interviewed each year. To control for location selection, Eisenberg and Okeke 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. In a recent working paper, Zivin and Neidell (2010) estimated a slightly different model of activity use than Eisenberg and Okeke did to account for location selection, using the 2003–2006 American Time Use Survey. They employed year and 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 we cannot observe in our data, some individuals are more likely to walk than other individuals. This feature can be built into an estimation model by including individual-specific constants. Using a latent-utility model, let $z_{it}(R)$ denote the unobserved utility of walking at least $R$ hr/week for individual $i$ in period $t$:

$$z_{it}(R) = \beta x_{it} + \mu_i + \epsilon_{it}$$

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 $\epsilon_{it}$ is a random error that is independently distributed logistic. The outcome of interest (here, whether the individual walks at least $R$ hr/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, because doing so would lead to inconsistent estimates of the parameters that matter, the $\beta$, which tell us the effect
of the \( x \)'s (Chamberlain, 1980; Hsiao, 1986). One approach that overcomes this problem is the fixed-effects (within) estimator. Chamberlain demonstrates that \( \sum y_i(R) \) 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 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, the threshold should be set to 3 hr of walking per week. Because 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 hr in the previous week (CDC, 2009).

A second problem 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 the researcher.

Because the subsequent analysis primarily focuses on the role of environmental attributes that 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—for example, 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, that is, estimating different coefficients for different groups. Because previous research suggests that physical activity patterns and preferences differ between genders, men and women are analyzed separately. Unfortunately, the limited size of the CAMS sample prevents further stratification by race or socioeconomic status.

A third problem 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 period, for example, by looking at individuals who go
from being married to being widowed. Although some individuals in our sample
do indeed change their marital status, the number 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 important 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 reestimated the model including marital status and
found that coefficient estimates on weather attributes were quantitatively similar,
suggesting that omission is not problematic for the purposes of the current study.
A similar argument applies to other family-structure attributes, for example, the
presence of grandchildren in the home.

Because the estimation sample is restricted to fully retired individuals, house-
hold 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 and bond portfolios and the value of housing. We hypothesize
that these are uncorrelated with cross-regional weather variations, and robustness
checks confirm that including household income does not quantitatively affect the
results. 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, $N(0, \sigma_\mu^2)$, where the variance is an estimable parameter. In this case,
all observations—even those for individuals always above or always below the
threshold—are used in estimation, coefficient estimates for time-invariant charac-
teristics can be recovered, and coefficient estimates are more precise, that is, they
have 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 or always below the threshold.

**Results**

Descriptive statistics for the estimating sample are reported in Table 1. On average,
respondents spend 4.7 hr/week walking. Although there are some exceptionally
high reported values of weekly walking, the overwhelming majority of responses
are reasonable: 90.5% are 10 hr/week or less and 96.8% are 20 hr or less. The
threshold of 2.5 hr of walking per week is nearly the median response.
Table 1  Descriptive Statistics

<table>
<thead>
<tr>
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<th>$M$</th>
<th>$SD$</th>
<th>Minimum</th>
<th>Maximum</th>
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<tbody>
<tr>
<td>Walking (hr/week)</td>
<td>4.68</td>
<td>8.90</td>
<td>0</td>
<td>168</td>
</tr>
<tr>
<td>Walk at least 2.5 hr/week</td>
<td>0.522</td>
<td>0.500</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Own health care (hr/month)</td>
<td>6.25</td>
<td>26.78</td>
<td>0</td>
<td>744</td>
</tr>
<tr>
<td>Average fall temperature ($^\circ$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 (in.)</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>

Note. 2,447 observations over 793 individuals. There are 577 observations from Consumption and Activities Mail Survey (CAMS) 2001, 625 from CAMS 2003, 650 from CAMS 2005, and 595 from CAMS 2007.

On average, individuals in the sample allocate just over 6 hr/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, and 1 individual reported 744 hr in a month, equivalent to 24 hr/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 hr/month, or approximately 1 hr/day. Less than 1% of the sample responses would imply more than 2 hr/day engaged in one’s own health care. Overall, most time-use responses to both 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 was 64.2 °F, which varied from a low of 62.6 °F in 2005 to 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, and the difference in maxima between 2001 and 2005 is 4.3 °F. The variation within regions (not reported) was also nontrivial. 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 used previously. With respect to effective variation, the current data set is no more disadvantaged than using the BRFSS along with a state-month fixed-effects approach (Eisenberg & Okeke, 2009). A data set 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 differentiates the average temperature from the observed temperature before estimation. If the observed temperatures are 30 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, 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 data set 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 may increase walking greatly because the temperature is sufficiently high to prevent sidewalks from freezing, which might be especially important to the perceived safety of older adults. In contrast, a 5 °F increase from 90 °F may decrease walking. Although 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 data set includes the average monthly temperatures for 6 months in New York City (April to June and August to October). For Los Angeles, the temperature range covers the averages of 10 months (all but July and August). For Houston, the temperature range covers the averages of 7 months (October to April). For Chicago, the temperature range covers the averages of 7 months (May to October). Therefore, although our data set does not allow us to study all possible temperature ranges, it does allow us to account for most of the year in most 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 hr/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 \( p < .01 \) and \( p < .10 \) 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 used here. For men, higher temperatures are associated with a lower probability of walking at least 2.5 miles/week, and the effect is statistically significant at the 5% level.

For women (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 men, fixed-effects estimation for women reveals that every 1 °F increase in average fall temperature is associated with an increase in the probability of walking at least 2.5 miles/week, although the estimate is only significant at the 10% level. No statistically significant association is found between walking and precipitation, for either men or women. Note that another interesting difference between men and women 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 hr/week decreases with age, it is only statistically significant for women. We provide extended discussion in the next section.
<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th></th>
<th>Women</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Fixed effects</strong></td>
<td><strong>Random effects</strong></td>
<td><strong>Fixed effects</strong></td>
<td><strong>Random effects</strong></td>
</tr>
<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 (in.)</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 (hr/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>1,657</td>
<td>1,657</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></td>
<td>13.31***</td>
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</tr>
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</table>

*Note. Coefficient estimates from logistic regression on Consumption and Activities Mail Survey 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 $\chi^2(4)$.*

* $p < .1$. ** $p < .05$. *** $p < .01$. 
In this study we used longitudinal data to explore the role 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 hr/week is positively associated with temperature for women but that the opposite is true for men. In contrast, Eisenberg and Okeke (2009) did not find a significant relationship between temperature and outdoor physical activity between 60 °F and 80 °F for either men or women. 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 that in the general population, and the response of older men differs from the response of older women.

But how to explain why the relationship between weather and walking behavior differs by gender? Household-production models 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 household-production-model 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 or decreasing the marginal utility of engaging in outdoor physical activity. Thus, during periods of poor weather we would expect substitution away from outdoor physical activity such as 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 men and women to temperature variation is underlying differences in household financial resources among older men and women. Cohen-Mansfield, Marx, Biddison, and Guralnik (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 compared men and women. We found that 38.5% of observations for men are above the threshold, compared with only 24.3% of women—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 men and women in our sample do not seem to explain the differences in responses we find here.

An alternative explanation for our gender differences rests in differences in underlying preferences for physical activity between genders. In a survey on adult physical activity, Keenan (2006) reported the reasons men and women gave for
engaging in exercise: Women engage in physical activity for health and weight reasons, whereas men report that they exercise as a way of socializing with others. Thus, higher temperatures may lead older men to replace walking with other outdoor social activities such as golf or tennis, while women increase their participation in walking as a low-cost way to improve health, weight, and stamina. This highlights not only 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 men. 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 men (not reported) and found that the walking/age profile is decidedly hump-shaped, peaking at age 72–73. It is possible that walking initially increases because men 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 men and women narrows with age. Beyond age 73, however, there is a clear decline in walking among men, 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, 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 1 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 of 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 that the decision to engage in walking depends on 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 United States are living to older age, and the costs of poor health in this population are increasingly important to consider. Second, although much uncertainty remains about climate change, 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 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


