Focusing Your Walking Intervention's Message

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Abstract

Public policy makers seek to launch initiatives and preventive measures that reduce spiraling healthcare costs. One way they can do this is by encouraging their constituencies to engage in physical activity, such as walking. Although the health benefits of walking have been well documented, the factors that contribute to such behavior are not well understood. We analyzed the effect of factors that the literature has identified on walking behavior for "mature" adults, aged 40 to 65, and find that the "physical" infrastructure of a community, such as the presence of sidewalks, crosswalks, and signals for pedestrians, affects walking significantly. Our study suggests that policy makers would be well-advised to channel their efforts in building and improving the physical infrastructure that enable walking in their communities and to communicate the presence of these to their constituencies without explicitly recommending walking to them.

Keywords: Social Marketing, Physical Activity for Older Populations, Parallel Analysis, Community-wide Interventions.

Introduction

Mature adults, aged 40 to 65, have much to gain from increased physical activity. This age group is particularly vulnerable to complications associated with physical inactivity, including increases in the manifestation of cancer, cardiovascular disease, and diabetes, among others (Pearson et al., 2002; Albright et al., 2000; Haskell et al., 2007; Nelson et al., 2007). In addition, Andreyeva and Sturm (2006) found that regular physical activity in late middle age (54 to 69 years old) may lower health expenditures over time.

Mature adults are especially suited for walking as a primary form of physical activity. Not only is walking an enjoyable activity for many older adults, but it is also low impact and highly cost-effective. The time commitment required to experience positive health benefits from walking is similar to that of other, more demanding forms of physical activity. For example, several studies have found that walking burns about the same number of calories per mile as running or jogging (Health Enhancement Systems, 2004). The monetary costs of walking are extremely low; namely, expenses for comfortable clothes and a supportive pair of shoes. At the same time, the health-related benefits of walking are both extensive and well documented (US Department of Health and Human Services, 2007). Thus, it stands to reason that public health interventions to promote walking are an ideal approach to increase physical activity among older adults.

In this paper, we analyzed data collected from a social marketing campaign conducted in three communities in order to shed light on those factors affecting walking in adults aged 40-65. The contributions of our study are twofold. First, we identify factors which influence walking among mature adults. Equipped with this knowledge, policy makers may be better able to determine appropriate investment vehicles to make their communities more walking friendly to this group of individuals. Second, common sense indicates that there are numerous, interrelated factors which may affect the propensity to walk. Failure to reduce these factors to a smaller, more parsimonious set of variables may reduce the precision and accuracy of empirical results. To address this issue, we analyzed our data using a more accurate statistical technique for determining the number of factors to retain in exploratory analysis, namely parallel analysis (Patil, McPherson, & Friesner, in Press).

Given the benefits associated with walking, determining factors that influence the propensity to walk are important. Numerous studies have focused on the importance of environmental factors in increasing walking. For example, Forsyth et al. (2007) examined the relationship between the density of the residential environment and walking (along with other forms of physical activity). Higher population densities have many benefits in terms of more efficient uses of infrastructure; however, the authors caution that higher densities alone, like other built environmental features, do not appear to be the complete answer for inventions aimed at increasing physical activity. Further, Vojnovic et al. (2006) examined walking behavior in Michigan and suggest that urban planners and policy makers play a vital role in shaping the urban environment, which is a key facilitator of increased moderate physical activity in the United States. Addy et al. (2004) found that respondents who had good street lighting, trusted their neighbors, and used private recreational facilities, parks, playgrounds, and sports fields were more likely to be regularly active. Specifically, perceiving neighbors as being active, having access to sidewalks, and using malls are associated with regular walking. Saelens et al. (2003) examined neighborhood-based differences in physical activity and find that residents of high-walkability neighborhoods reported higher residential density, land use mix, street connectivity, aesthetics, and safety. Giles-Corti and Donovan (2003) reported that the relative influences of individual characteristics, social environmental, and physical environmental factors are equally important determinants of walking behavior. Therefore, a comprehensive approach to increasing walking is warranted. Interventions have also demonstrated the importance of policy and environment in limiting physical activity, including walking (Brownson et al. 2006).

Others have looked to media-based community interventions to promote walking. For example, Reger-Nash et al. (2002, 2005) conducted studies that targeted sedentary individuals aged 50-65 in West Virginia. Using a combination of paid advertisements, earned media coverage, public relations and community participatory planning as the intervention, the authors document statistically significant and sustained increases in walking-related activity among individuals in the target group. Reger-Nash et al. (2006) replicated this study among individuals aged 40-65 in Broome County, New York and report similar results. The focus of these longitudinal studies has been to demonstrate the effect of mass media campaigns on sustained increase in walking behavior.

This study extends these strands of literature in two important ways. First, and unlike the studies discussed at the beginning of this section, we investigated the determinants of walking behavior by focusing specifically on a cohort of adults aged 40-65. This is important from a policy perspective because this group of individuals is most likely to benefit from increased walking behavior. Moreover, the Reger et al. (2002, 2005, & 2006) studies focused on the cost effectiveness of social marketing campaigns to promote walking behavior among mature adults without explicitly analyzing the factors that induce or inhibit the likelihood that an individual will walk more. Our analysis, therefore, provides an important link between these two strands of literature.

A second problem affecting the studies intending to identify the determinants of walking behavior is that they focus on a plethora of different variables, many of which are interrelated. In a regression context, this may create problems such as severe multicollinearity, which distorts the precision (and potentially the accuracy) of any parameter estimates generated. Our study attempts to reduce this problem by incorporating parallel analysis into our empirical methodology. The value of parallel analysis is that it is less likely than its alternatives to identify extraneous (or unimportant) factors that influence the propensity to walk. As such, using parallel analysis reduces the likelihood that our analysis generates spurious and/or superfluous determinants of walking behavior. Our intent is to provide a concrete example of the benefits of this new methodology, in the hopes that it would be utilized in future, evidence-based, public investments aimed at increasing physical activity. This, in turn, would reduce the likelihood that those programs' funds are spent on ineffective interventions.

Methods

Sample

The sample comes from social marketing campaigns designed to increase walking among 40 to 65 year old adults. The campaigns (as well as the information collected from the campaigns) are similar in context, construct, and scale design to numerous other studies conducted in the literature (e.g., Carnegie et al. 2002; Reger et al. 2008). As a part of these campaigns, telephone survey data were collected by a well-established survey center from three communities (Morgantown, Huntington and Parkersburg) spanning 12 counties in West Virginia. These communities are interesting to study because they contain a wide range of topographic, socio-economic and urban/rural characteristics. The survey targeted adults between the ages of 40 and 65 (determined using a filter question in the survey). If more than two individuals aged 40-65 lived in the same household, the survey focused on the older of these individuals. Each survey took approximately 10 to 15 minutes to complete. The survey sampling procedure restricted respondents to households having land-based telephones. Completed baseline calls were made to 53 percent of eligible contacted residents in the sample area, representing 1,834 respondents. Follow-up phone calls were successfully made to 72 percent (n=1313) of those contacted at baseline. Surveys that were incomplete in areas germane to our analysis were eliminated from the sample, leaving a final sample of 634 observations.

Measures

Dependent Variable: Our initial dependent variable was based on the average amount of time people walked in a given week. However, because of the self-reported nature of our data (which may be subject to measurement error), as well as the fact that respondents exhibited an extremely wide range of walking times over the course of a given week, we did not use this variable directly. Instead, we created an ordinal step variable taking values between zero and three (Walkstep) which represents the average length of time in minutes that a respondent walks in a typical day. Values of zero identify individuals who walk less than fifteen minutes per day; values of one identify those who walk between fifteen and twenty-nine minutes; values of two identify those who walk between thirty and fifty-nine minutes; and values of three indicate an individual walks an hour or more. Thus, we can interpret our categories as inclusive of individuals who are inactive walkers, minimally active walkers, moderately active walkers and very active walkers. We find the median of Walkstep to be 2, which implies that a typical respondent walks between 30-60 minutes a day.

Independent Variables and Covariates: To identify those factors that influence walking behavior, as well as to control for any differences between the communities in our sample and those from other parts of the U.S., data on a number of additional variables were collected. These include the perceived importance of building sidewalks, making surroundings beautiful, reducing crime and increasing safety, promoting walking groups within the community, promoting the image of the community as being health-conscious and walking-friendly, and promoting the benefits of walking.

Data were also collected on covariates such as the location of the respondent's community, age, gender, marital status, ethnicity, weight, income, education and whether a health care professional has recommended walking to the individual as a form of exercise. Lastly, respondents were asked a series of fifteen questions about whether they could walk to a number of different locations, such as (but not limited to) a park, a store, a library, a post office, a restaurant, a pharmacy or a school. We created a variable that measures

Table 1:
Descriptive Statistics

Variable	Mean or Percentage	Std. Dev./Number Respondents
Walking Variable		
WalkStep	1.6215	1.1785
Non-Binary Explanatory Variables		
Respondent's Age	53.4054	6.3657
Respondent's Weight	173.8440	41.2812
Number of Places in the Community to which a Respondent could Walk	5.4874	4.7143
Community's Physical Environment Rating (see Table 2)	1.8118	0.8714
Town Evaluation Rating (see Table 2)	2.6601	0.7799
Community's Physical Safety Rating (see Table 2)	3.3147	0.7171
Binary (0-1) Explanatory Variables		
Respondent is Female	31.07	197
Respondent is Unmarried, but Lives with a Partner	3.31	21
Respondent is Divorced	16.25	103
Respondent is Married	68.77	436
Respondent is Widowed	4.42	28
Respondent is Legally Separated	0.79	5
Respondent's Income is under $15,000	4.42	28
Respondent's Incomes is between $15,000-$34,999	21.45	136
Respondent's Income is between $35,000-$49,999	21.92	139
Respondent's Income is between $50,000-$74,999	25.55	162
Respondent's Income is between $75,000-$99,999	12.30	78
Respondent's Income is $100,000 or higher	14.35	91
Respondent has no High School Diploma	4.89	31
Respondent has a High School Diploma	27.60	175
Respondent has some College Education, but no Bachelor Degree	19.24	122
Respondent has at least a Bachelor Degree	48.27	306
Respondent is Caucasian	94.64	600
Respondent is African-American	2.84	18
Respondent is a non-African-American Minority	2.52	16
Respondent Identified having a Friend with Whom They Walk	71.61	454
Respondent Stated that their Doctor did not Recommend Walking	4.57	29
Respondents Stated that a different type of Medical Personnel Recommend Walking	22.56	143
Number of Observations	634	

the total number of places that a respondent indicated that they could reach via walking, which should (in part) proxy for an individual's mobility.

Table 1 contains some basic descriptive statistics for each of these variables. The average age of respondents was 53 years old, and he or she weighed, on average, about 174 pounds. Only 31 percent of the sample was female, while nearly 69 percent of all respondents were married. Most households' incomes are between $15,000 and $75,000 a year, indicating that our cohort was primarily lower or middle class.

Respondents were also predominantly Caucasian, and either had a high school diploma or a four-year (or higher) college degree. Finally, over three-quarters of respondents indicated that they had a companion (either a person or pet) with whom they can walk, but only about a fourth reported that a health care professional recommended walking as a good way to obtain exercise.

Data Analysis

Two general themes guided our empirical methodology. First, because of the large number of variables in our data set, it was necessary to combine a number of related variables in order to ensure that the results were comprehensive, yet parsimonious. A second consideration was the generalizability of our data and empirical results. The data came from three communities in central Appalachia, which on a prima fascia basis may not be representative of communities in other parts of the U.S. To address this issue, it was necessary to control (or adjust) for any factors which may be community-specific (such as topographic conditions, demographic differences, economic characteristics, etc.) when identifying the determinants of walking behavior. To those ends, we employed a two-step methodology which addresses each of these considerations. The first step requires data aggregation and the second requires the application of an advanced regression model.

Data Aggregation

The first step required aggregating several independent variables describing characteristics of a community that make it more or less attractive for walking into fewer components or factors. For such data-reduction exercises, an exploratory factor analysis (EFA) is recommended (Patil et al. 2008). We used principal components analysis (PCA) for factor extraction, parallel analysis for factor retention, and varimax rotation for aiding the interpretation of factors as well as for reducing multicollinearity among the retained factors. It has been shown that this package of decisions is highly appropriate for conducting an EFA (Patil et al. 2008). The use of parallel analysis is especially crucial, since other factor retention criteria (for example, the eigenvalue greater than one rule) often lead researchers to identify too many factors that influence walking (Patil et al. 2008). As Patil, McPherson, and Friesner (in Press) indicate, this is problematic because too many latent factors may cause the policy makers to spread scare funds over a myriad of different

Table 2:
Component Matrix of Dataset (n=634, variables = 7) of Principal Component Analysis using Parallel Analysis (3 Components) and Varimax Rotation 1, 2

Variables		Component		
		1	**2**	**3**
1.	There are sidewalks on most of the streets in my neighborhood	0.796		
2.	My neighborhood streets are well lit at night	0.729		
3.	There are crosswalks and pedestrian signals to help walkers cross busy streets in my neighborhood	0.765		
4.	How much do you fear crime in your neighborhood?		0.833	
5.	Do you feel safe while returning to your home or residence when it is dark?		0.812	
6.	*Name of town* is very interested in promoting walking.			0.826
7.	Overall, how would you rate *Name of town* for walking?			0.744

1 The three components, in sequence of numbers indicated above, were labeled as Core Physical Environment, Physical Safety, and Town Evaluation.

2 Five variables that did not load significantly on any component: (a) The streets in my neighborhood are hilly, making my neighborhood difficult to walk in; (b) The surroundings are attractive while walking in my neighborhood; (c) There is so much traffic that it makes it difficult or unpleasant to walk in my neighborhood; (d) The speed of traffic on most nearby streets is usually slow (30 mph or less) (e) Name of town should be investing more tax dollars in sidewalks and trails.

many latent factors may cause the policy makers (and potentially irrelevant) interventions, thereby limiting the effectiveness of those funds. Please see appendix A for a brief synopsis of parallel analysis.

Results

Results of Data Aggregation

From 12 variables initially subject to PCA, 7 variables loading across three factors were retained (see table 2). The three factors were labeled Core Physical Environment (items loading on this component were related to the presence of sidewalks, presence of well-lit streets, and presence of crosswalks and pedestrian signals), Town Evaluation (items loading on this component were related to the town being very interested in promoting walking and the rating of the town for walking) and Physical Safety (items loading on this component were related to the degree of fear of crime in the neighborhood and the feeling of safety while returning home in the dark). We note in passing that, had one relied solely on the eigenvalue greater than one rule, EFA would have extracted an additional, superfluous factor, namely Traffic Conditions (items loading on this component were related to the amount and speed of traffic in the neighborhood). While it remains to be seen from the coming analysis whether and how the three factors extracted via parallel analysis influence walking, we can say that, had policy makers distributed scarce intervention funds based on EFA and the eigenvalue greater than one rule they would likely have misallocated a portion of those funds towards improving traffic conditions.

Advanced Regression Modeling

To address the second issue, we use advanced regression techniques. Regression is highly useful in this context because it employs a variant of the ceteris paribus assumption. That is, when interpreting a regression explaining the determinants of walking behavior, one examines each potential determinant holding constant, or adjusting for the effects of, all other factors included in the regression. Thus, usingregression, and including as many community-specific explanatory variables as possible should allow us to generalize our results to the population (of eldest household members aged 40-65) at large because any results obtained should be purged of the factors differentiating communities in Appalachia from those in other areas of the U.S., including California. Moreover, because any and all parameter estimates are interpreted on a marginal, and not a total basis, our results are less likely to be distorted by responses that are inflated or distorted because they include walking from all activities (i.e., employment) and not just for exercise.

Since our dependent variable, WalkStep, is a proxy variable taking one of four integer values, with higher values implying more walking activity, we used the most appropriate and parsimonious regression technique for such an ordinal variable, namely the ordered probit model (Greene 2000). (Please see appendix B for more details on this technique.) Given the large number of explanatory variables at our disposal, as well as the fact that few previous studies have performed a comprehensive analysis of the factors which induce walking, we chose to estimate an ordered probit model that is primarily linear in parameters and variables. The only three variables which were entered into our model non-linearly (i.e., quadratically) were our three aggregated variables: the community's physical environment, overall town evaluation and walkers' perceptions of physical safety. Given the cohort being analyzed, as well as the high benefits and low costs of walking, we suspected that these characteristics, more than any others, are the primary drivers of walking behavior. As such, a more thorough investigation of these variables was warranted. In addition, because these variables were constructed by aggregating a number of other variables, we allowed a quadratic specification to account for any possibly nonlinear relationships that may occur between walking behavior and our aggregated variables. In any case, while our specification was parsimonious, it should be considered as exploratory. Future work is necessary to determine whether our results continue to hold if one postulates a more complex functional form, or if one utilizes a related, but alternative regression technique such as the ordered logit model.

Lastly, we included all explanatory variables listed in Table 1, as long as they did not create perfect multicollinearity with the model's intercept. This would be the case, for example, if all six income variables were included in the regression, since the sum of these variables is, by definition, equal to one. In these instances, we follow the standard approach of dropping one of the collinear variables and interpreting all remaining variables relative to the omitted variable (Greene, 2000).

Results of Regression Model

Given the large number of explanatory variables, we summarize what we consider to be the crucial findings of our analysis in Table 3. Appendix C contains the full set of results for our ordered probit model. As evidenced by the chi-square test at the end of the table, the overall model was highly significant (p-value < 0.01), and was thus effective at characterizing and predicting self-reported walking behavior.

Examining Table 3, we found that explicit recommendations from medical personnel to walk or the presence of social support groups for walking do not affect the propensity to walk. We also found that people with high incomes ($100,000 or more) walk more, that divorced individuals walk more than non-divorced individuals, and that females are significantly more likely than males to walk. Individuals with less than a bachelor degree (i.e., those with and without a high school diploma, as well as those with some college education) are more likely to walk than do individuals who have a bachelor's degree or higher. Individuals reporting the ability to walk to a larger number of places (for

Table 3:
A Synopsis of the Ordered Probit Model Results[1]

Explanatory Variable	Sign of the Coefficient Estimate	P-Value
Number of Places in the Community to which a Respondent could Walk	+	0.0234
Community's Physical Environment Rating	-	0.0335
Town Evaluation Rating	+	0.9593
Community's Physical Safety Rating	-	0.1471
Physical Environment Rating Squared	+	0.0717
Town Evaluation Rating Squared	+	0.8362
Physical Safety Rating Squared	+	0.1797
Respondent is Female	+	0.0307
Respondent is Divorced	+	0.0546
Respondent's Income is $100,000 or higher	+	0.0839
Respondent has no High School Diploma	+	0.0536
Respondent has a High School Diploma	+	0.0003
Respondent has no Bachelor Degree	+	0.0045
Respondent Has a Friend with Whom They Walk	+	0.4999
Doctor did not Recommend Walking	+	0.1220
Respondents Stated that a different type of Medical Personnel Recommend Walking	-	0.5568
Chi-Square Test of Overall Model Significance (29 Degrees of Freedom)		0.0020

[1] Dependent Variable is WalkStep, an ordinal variable. Values of zero identify individuals who walk less than fifteen minutes per day; values of one identify those who walk between fifteen and thirty minutes; values of two identify those who walk between thirty and fifty-nine minutes; and values of three indicate an individual walks an hour or more.

example, a store or a park) were more likely to walk.

Among the three components derived after the principal components analysis, only Physical Environment of the Community had a significant effect on walking. Recall that this variable entered into our regression both linearly and quadratically.

Table 3 indicates that the linear term is negative and the squared term is positive, both of which are statistically significant. Further, the safety and beauty of a neighborhood also did not affect walking behavior.

Discussion

Accounting for approximately 250,000 deaths annually, the total annual health care costs associated with physical inactivity has been estimated at $251 billion (in 2003 dollars) in the United States alone (Chenoweth and Leutzinger 2006). Given this reality, public policy makers seek to use their resources as efficiently as possible. There is a growing literature which suggests that encouraging their constituencies to walk regularly, or engage in other physical activity, is a cost-effective way to reduce preventable disease and increase quality of life.

The main objective of this study was to identify different factors that had an effect on walking behavior among mature adults. In this regard, we present several results of particular interest. First, we found the "physical" infrastructure of a community, such as the presence of sidewalks, crosswalks, and signals for pedestrians, affected walking significantly. In a study focusing on the effect of the built environment on physical and mental health, Dannenberg et al. (2003) reached a similar conclusion. They found that street design and accommodation for safe pedestrian, bicycle, and wheelchair use, among other related factors, promote physical activity. Giles-Corti et al. (2003) found that similar physical infrastructure characteristics increase walking behavior in their examination of walking determinates in Western Australia.

Interestingly, explicit encouragement in terms of recommendations from doctors to walk does not affect the propensity to walk. This may be due to a number of factors. One, a doctor's recommendation is probably causing psychological reactance in individuals (Brehm & Brehm, 1981), thereby encouraging them to avoid the recommendation. Second, people who are recommended to walk may need more cues and support, besides just a verbal cue (e.g., King et al. 2008).

The presence of social support groups for walking also failed to exhibit a significant effect on walking. This finding is not consistent with those of Giles-Corti et al. (2003), who find that encouraging people to walk with others, or even with a dog, achieved higher levels of walking.

Our finding that people with higher incomes walk more may seem counterintuitive because as income increases, so does the value of one's time spent working or undertaking other activities (i.e., the "opportunity cost" of walking increases). One possible explanation for our finding is that at higher absolute levels of income, individuals may be able to afford engaging in leisure activities that are seen as beneficial, such as walking or other forms of physical activity. This finding is consistent with Siegel et al. (1995), who state that, "Persons at higher income levels were more likely to participate in some physical activity than were those at low levels (p. 708)." In this study, 70.3 percent of respondents who reported at least some physical activity during the past month were walkers. In addition, Kim et al. (2004) found that those with higher economic status were 1.6 times more likely to participate in healthy lifestyle behaviors, such as regular physical activity, healthy diet and lower levels of smoking and alcohol use, when compared with individuals of lower socioeconomic status. A second result is that mobility matters. If you have the ability to walk to more places, there is a good likelihood that you will, whether the reason is for pleasure, exercise or other reasons.

Our study suggests that policy makers would be well-advised to channel their effort in building and improving the physical infrastructure that enable walking in their communities and to communicate the presence of these to their constituencies without explicitly recommending walking to them. Moreover, the model is nonlinear (with a negative first order term and a positive second order term). Thus, there is a threshold level of improvements required in the physical environment to induce walking. In fact, improving the physical environment marginally may actually lead to less walking; major increases are needed to realize positive benefits (increased walking).

In identifying different factors that affected walking, we relied on parallel analysis, a more accurate statistical technique for determining the number of factors to retain in an exploratory factor analysis (EFA). The most popular criterion, the eigenvalue greater than one rule, has been shown to lead to the retention of more factors than warranted (Patil, McPherson & Friesner, in press; Patil et al. 2008). In our analysis, we encountered a similar finding; the use of the eigenvalue greater than one rule would have led to the extraction of one additional, superfluous factor. Moreover, of the smaller (three) number of factors extracted via parallel analysis, our ordered probit model identified only one of these factors as a significant determinant of walking. Clearly, policy interventions based on a naïve application of EFA, and using a less than optimal factor retention criterion, may be misleading, and scarce resources may be misallocated.

We offer a number of avenues for future research. Perhaps most importantly, we undertook what is essentially an exploratory data analysis using a self-reported walking metric. As a result, a number of less obvious relationships were discovered in this analysis which merit further study. For example, divorced individuals walk more and females walk more than males, especially females who are the oldest spouse or adult in the household. Also, we found that fear of the environment was not a significant factor in walking. This is not consistent with other studies (Sampson et al. 1997; Myers & Roth 1997). Future research relying on more informed theory, that use a better walking metric, and/or a combination of the two might alleviate these issues and provide additional policy insights.

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Appendix A

A Brief Synopsis of Parallel Analysis

Researchers make three important decisions while performing an exploratory factor analysis (EFA): factor extraction approach, factor retention criteria, and factor rotation strategy. Among them, psychometric literature suggests that the decision regarding factor retention criteria is the most important (Velicer et al. 2000). The most popular criterion for determining the number of factors to retain is the eigenvalue greater than one (EVG1) rule (Patil, McPherson & Friesner, in press, Patil et al. 2008). However, evidence in different streams of literature has demonstrated that the EVG1 rule leads to over extraction of factors (Patil et al. 2008). Consequently, researchers end up retaining more factors than necessary, which leads to findings which may lack parsimony and external validity (Patil, McPherson & Friesner, in press).

The first step of an EFA, factor extraction, identifies eigenvalues of a data set and the EVG1 rule leads to the selection of as many factors as the number of eigenvalues greater than one. In contrast, parallel analysis (PA) urges researchers to compare their dataset's eigenvalues with the 95th percentile eigenvalues generated from the factor extraction of randomly generated datasets with the same number of variables and sample size as theirs (Patil et al. 2008). Researchers retain as many factors as eigenvalues from their dataset, which are greater than corresponding eigenvalues from the randomly generated datasets.

Despite the significant accuracy of PA over the EVG1 rule, its use has not proliferated, primarily because of the technical nature of the method (for example, the determination of eigenvalues from randomly generated correlation matrices involves aspects of simulation and programming) and the non-availability of the PA option in popular statistical packages, such as SPSS and SAS (Patil et al. 2008). However, more user-friendly approaches for implementing PA, such as the web-based parallel analysis engine (Patil et al. 2007), are now available to aid researchers.

Appendix B

A Brief Introduction to the Ordered Probit Model

The ordered probit model is very similar to a binary probit (or logit) model, except that i) the dependent variable can take more than 0-1 values and ii) the ordering of the values has an intuitive explanation within the context of the problem being analyzed. In our case, higher values for our proxy variable imply a greater incidence of walking. Mathematically, the ordered probit model is based on the following structure (which follows Greene (2000) closely). Consider the process y*, which represents the amount of time per day an individual spends walking. In this case, a typical regression can be constructed as:

$$y_i^* = \beta_0 + \sum_{j=1}^{J} \beta_j X_i^j + \varepsilon_i \tag{1}$$

where i = 1,…,n denotes each observation in the sample, Xj, j = 1,…,J denotes a series of J explanatory variables, and ε is a normally distributed error term. If y* is directly observed without error, it is possible to estimate (1) via OLS. However, in our case we observe y (not y*), where:

$$
\begin{aligned}
y_i &= 0 \quad if \quad y^* \le 0 \\
y_i &= 1 \quad if \quad 0 < y^* \le \mu_1 \\
y_i &= 2 \quad if \quad \mu_1 < y^* \le \mu_2 \\
y_i &= 3 \quad if \quad \mu_2 \le y^*
\end{aligned} \tag{2}
$$

In this case, our observed variable y separates the true, but latent, variable into four mutually exclusive and collectively exhaustive categories. Moreover, it is assumed that the empirical proxy is not perfect; thus, it only approximates the true cutoff point between each of the four categories, which are represented in (2) by the mu parameters. For identification purposes, the first of the three mu parameters is normalized to zero, leaving two cutoff parameters for the four categories. Additionally, because the ordering of categories matters, the laws of probability require a well-formulated model to ensure that $0 < \mu_1 < \mu_2$.

Assuming a normal distribution, we arrive at the following probabilities, which are a trivial extension of the binary probit model:

$$
\begin{aligned}
\Pr ob(y_i = 0) &= \Phi(0 - \beta_0 - \sum_{j=1}^{J} \beta_j X_i^J) \\
\Pr ob(y_i = 1) &= \Phi(\mu_1 - \beta_0 - \sum_{j=1}^{J} \beta_j X_i^J) - \Phi(-\beta_0 - \sum_{j=1}^{J} \beta_j X_i^J) \\
\Pr ob(y_i = 2) &= \Phi(\mu_2 - \beta_0 - \sum_{j=1}^{J} \beta_j X_i^J) - \Phi(\mu_1 - \beta_0 - \sum_{j=1}^{J} \beta_j X_i^J) \\
\Pr ob(y_i = 3) &= 1 - \Phi(\mu_2 - \beta_0 - \sum_{j=1}^{J} \beta_j X_i^J)
\end{aligned} \tag{3}
$$

where Φ() represents the cumulative standard normal distribution (or CDF). Further assuming that all observations are independent of one another, one can construct a log-likelihood function:

$$
L = \sum_{i=1}^{n} \ln\left(\Pr ob(y_i)\right) \tag{4}
$$

which can be maximized over the betas to obtain coefficient estimates, standard errors and other traditional model diagnostics.

It is important to note one caveat of the ordered probit model, especially as it compares to OLS. In the OLS model, the parameter estimates can be directly interpreted as marginal effects. Because the ordered probit model makes use of the standard normal CDF, it is inherently nonlinear, and as such the parameter estimates are related, but not equivalent, to marginal effects. The implication is that, while one can interpret the signs and significance of the ordered probit parameter estimates in a manner consistent with those generated by OLS, one cannot directly interpret the magnitudes of the parameter estimates, especially within the context of marginal effects. As such, we confine our analysis to an investigation of signs and significance, not magnitudes.

Appendix C

Appendix C: Complete Ordered Probit Regression Results [1]

Explanatory Variable	Estimate	Std.Err.	t-ratio	P-value	
Intercept	1.7217	0.9628	1.7882	0.0737	*
Respondent's Age	0.0023	0.0074	0.3102	0.7564	
Respondent's Weight	-0.0006	0.0013	-0.4957	0.6201	
Number of Places in the Community to which a Respondent could Walk	0.0256	0.0113	2.2672	0.0234	**
Community's Physical Environment Rating	-0.6197	0.2916	-2.1255	0.0335	**
Town Evaluation Rating	0.0165	0.3239	0.0510	0.9593	
Community's Physical Safety Rating	-0.6788	0.4682	-1.4499	0.1471	
Physical Environment Rating Squared	0.1144	0.0635	1.8013	0.0717	*
Town Evaluation Rating Squared	0.0130	0.0630	0.2068	0.8362	
Physical Safety Rating Squared	0.1036	0.0772	1.3416	0.1797	
Respondent is Female	0.2517	0.1165	2.1607	0.0307	**
Respondent is Unmarried, but Lives with a Partner	0.3745	0.2558	1.4642	0.1431	
Respondent is Divorced	0.2624	0.1366	1.9219	0.0546	*
Respondent is Widowed	-0.0916	0.2263	-0.4048	0.6856	
Respondent is Legally Separated	0.1574	0.5202	0.3026	0.7622	
Respondent's Income is under $15,000	-0.0370	0.2472	-0.1495	0.8811	
Respondent's Incomes is between $15,000-$34,999	0.0360	0.1426	0.2522	0.8009	
Respondent's Income is between $35,000-$49,999	0.0571	0.1342	0.4253	0.6706	
Respondent's Income is between $75,000-$99,999	0.2334	0.1551	1.5052	0.1323	
Respondent's Income is $100,000 or higher	0.2726	0.1577	1.7284	0.0839	*
Respondent has no High School Diploma	0.3963	0.2054	1.9298	0.0536	*
Respondent has a High School Diploma	0.4390	0.1214	3.6152	0.0003	**
Respondent has no Bachelor Degree	0.3642	0.1281	2.8437	0.0045	**
Respondent is African-American	-0.0418	0.3506	-0.1191	0.9052	
Respondent is a non-African-American Minority	-0.0770	0.3430	-0.2246	0.8223	
Respondent Has a Friend with Whom They Walk	0.0697	0.1033	0.6746	0.4999	
Doctor did not Recommend Walking	0.4394	0.2841	1.5465	0.1220	
Respondents Stated that a Different type of Medical Personnel Recommend Walking	-0.0656	0.1117	-0.5877	0.5568	
Estimated Cutoff between Inactive and Minimally Active Walkers	0.6100	0.0482	12.6562	0.0000	**
Estimated Cutoff between Minimally and Moderately Active Walkers	1.1883	0.0620	19.1562	0.0000	**
Number of Observations	634				
Chi-Square Test of Model Significance (29 degrees of freedom)			55.8461	0.0020	**

* indicates statistical significance at the 10% level

** indicates statistical significance at the 5% level