Human Mobility, Exposure to the Built Environment, and Health

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Abstract

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Neighborhood effects on health and behavior have been widely documented. Yet people do not spend all their time in their home neighborhoods. The places that people visit away from home may also have an impact on behavior. Using global positioning systems (GPS) records and self-reported travel diaries, this dissertation investigates associations between mobility patterns/activity spaces, environmental exposures, and health. It examines the level of agreement between GPS and travel diary data. It then presents a novel method for measuring exposure to point features, using fast food restaurants (FFRs) as an example data set, to estimate time spent in proximity to FFRs throughout the average day. Finally, it explores the relationship between the probability of being obese and exposure to residential property values across the entire activity space Travel-diary-reported visits to fast food restaurants and supermarkets were confirmed with GPS data 77% and 79% of the time, respectively. Findings show that participants spent 17 minutes per day within 100m of FFRs and that longer durations spent within 100m of FFRs significantly increased the odds of reporting an FFR visit, suggesting that duration of exposure to FFRs has an effect on visiting FFRs. Lastly, higher residential property values within participant activity space were associated with decreases in the odds of being obese, suggesting that being exposed to wealthier environments was protective of being obese.

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Chapter 1 : INTRODUCTION

The last 15 years have seen much research on the built environment and its effects on health and behavior thanks to technological advances in geographic information systems (GIS) and the concurrent proliferation of publicly available GIS data sets. Literature in this area has found that where one lives is associated with a wide range of health outcomes. Residential locations are associated with levels of walking[1–5] and physical activity.[6] Residents living in disadvantaged neighborhoods are more likely to suffer from a wide range of negative health outcomes[7] including obesity[8,9], poor mental health[10], and heart disease.[11,12]

Early studies relied heavily on the use of census tracts and other administrative boundaries to measure participants' residential environments. Yet such measures are sensitive to the modifiable areal unit problem (MAUP)[7,13] and require statistical analyses involving hierarchical/nested models to control for variation among residents who live in the same administrative units. Because many publicly available sources of data (e.g. the US Census and the National Health and Nutrition Examination Survey) provide data aggregated by administrative boundaries, administrative boundaries will continue to be relied upon for the foreseeable future. However, the use of GIS software has also allowed researchers to measure the environment near participants' homes using parcel-level data that are much finer-grained than data aggregated into administrative units; such data also allow measurements of built environment features using radial or network buffers around the homes.[2,14,15] The creation of individual-level disaggregate measures of environmental conditions for each participant, offer many strengths over administrative boundaries and reduces the need for hierarchical/nested models.

There are three main criticisms in research on health and the residential environment (measured using either administrative boundaries or GIS buffers): compositional, self-selection, and mobility critiques. First, critics suggest that findings may be due to the demographic composition of neighborhoods, rather than to the environmental context (the characteristics and features of the built environment) of the neighborhood.[16] Second, related to compositional effects is the issue of self-selection. People may be choosing to live in areas because of the health promoting or harming attributes of that area.[17] For example, people who like to engage in physical activity may prefer to live in areas with multiple options for physical activity. For both the compositional and self-selection critiques, health outcomes may be determined by pre-existing personal characteristics rather than, or in addition to, independent environmental effects.

The third major criticism is that while most studies have assessed the impact of home neighborhood on lifestyle and health, people do not spend all of their time within their home neighborhoods, and hence their behaviors may be influenced by non-home environments. This criticism has been given many names including the local trap[18], the residential trap[11], spatial uncertainty[15], and spatial polygamy.[19] If one assumes that the characteristics of the home neighborhood shape health and behavior, it follows that the environmental contexts of places visited outside home neighborhoods also shape health and behavior. The study of spatial mobility is still very new with few published studies. In a review of 131 studies that explored the relationship between the environment and cardiometabolic outcomes, Leal and Chaix found that 90% only considered the residential environment, ignoring the possible influence of the non-home environment.[20]

To help conceptualize the range of environmental contexts experienced away from home neighborhoods as well as spatial mobility patterns, researchers use the term 'activity space' to represent, "…the subset of all locations with which an individual has direct contact as a result of his day-to-day activities."[21]

A number of techniques have been created to measure activity spaces. Some studies have geolocated the self-reported locations of common activities.[22,23] Others have examined commute routes[24,25] and a smaller subset have used global positioning systems (GPS) records to obtain continuous objective measures of the built environment throughout the day.[26–28] From these different measurements the spatial extent and geometry of activity spaces has been represented and modeled in a number of ways (e.g. minimum convex polygons, standard deviational ellipses, kernel density estimations, and daily path areas) and used to capture a range of features and characteristics within the activity space (e.g., counts of supermarkets within activity space).[29–31] Rather than just representing an individual's residential environment, the activity space represents the totality of the environment the individual experiences over the course of daily life, not just the environment within proximity to the individual's home.

Shareck and colleagues[32] noted that measures of activity space include two domains: (1) "the extent to which one is mobile" which is influenced by socioeconomic and demographic characteristics along with work location and transportation options; and (2) "the characteristics of places and resources experienced during daily travels". A third domain of activity space and human mobility, in general, can be added to this framework: (3) time spent in subsets of activity spaces, because individuals spend different amounts of time at different locations and traveling between locations.[21] The influence of the temporal dimension of activity space has rarely been addressed in studies of built environment and health.

In this dissertation, three domains of spatial mobility/activity space are examined: the person, the environment, and time spent in distinct environments. Individual-level characteristics, traits, attitudes, and opinions inform where, why, and how individuals travel to certain places. At those different places, the individual comes into contact with and experiences different environmental contexts (e.g. levels of development density, property values, presence/number of food outlets, etc.) with these experiences varying in the durations of time spent there.

The shift from examining neighborhood environmental contexts to activity spaces and spatial mobility patterns brings with it the need for a more sophisticated understanding of the ways in which people come into contact with the built environment. Access and exposure are among the terms used to describe this contact in both neighborhood effects and mobility literature. Further, Chaix and colleagues[33] argued that intentional use of an environmental resource or characteristic (selective daily mobility) needs to be considered as well.

Using data from the Seattle Obesity Study II (SOSII), this dissertation investigates different methods for measuring exposure to and use of built environments. A study of health behaviors and obesity among residents of King County, Washington, the SOSII comprised a detailed behavioral survey, objectively measured mobility data from GPS records, subjectively measured mobility data from travel diaries, and objectively measured heights and weights. Given the recent advent of inexpensive GPS technology, objective mobility data is still new to the literature. Self-report data-collection methodologies, such as travel diaries, have been used much more extensively. Thus there is a need to better understand the level of agreement between the two data sources. In Chapter 2, GPS data were used to verify the accuracy of self-reported, travel log data on visits to fast food restaurants (FFRs) and supermarkets. In the process, it describes a method for objectively measuring selective daily mobility.

In Chapter 3 a conceptual framework for understanding exposure is specified, and an objective, time-based, GPS measure of exposure is introduced. Methods for identifying self-reported visits to FFRs employed in Chapter 2 were used to separate selective mobility from these exposure measures. In this chapter, exposure to FFRs is treated as a discrete measure (participants were either exposed to an FFR or not exposed). This study also explored the role of proximity to FFRs with the assumption that different proximities capture different ways in which people come into contact with FFRs.

Unlike FFRs, there are some built environment characteristics to which individuals are continuously exposed. Chapter 4 presents a method for measuring property values (a continuous exposure) as individuals travel throughout their daily activity spaces. Inside the King County urban growth boundary (which represents the majority of SOSII participants' spatial extents), participants are almost always exposed to residential property values.

Together, these three studies contribute to the literature by providing methods, objective measurements and the beginning of a theoretic framework for understanding how person/environment interactions beyond the home neighborhood are associated with health and behavior.

Chapter 2 : GPS OR TRAVEL DIARY

ABSTRACT

Background: Where people eat, shop for food, and how much time they spend doing so are related to their weight and health.

Objective: To verify the accuracy of visits to fast food restaurants and supermarkets reported in travel diaries in terms of location, specific establishment visited, and duration of visits using automated protocols within a GPS and GIS spatiotemporal framework.

Methods: The SOS II sample included 446 participants who responded to a survey, filled out a travel diary of places visited, and wore a GPS receiver for seven consecutive days between November2011 and October 2012. The tax parcels of fast food restaurants and supermarkets were geolocated based on the 2012 food permits from Public Health Seattle King County. Fast food and supermarkets visits recorded in the travel diaries were identified by the establishment brand name. GPS points corresponding to the reported visits were first selected by a temporal match of reported times of arrival and departures, using three time windows: the exact reported times; +/- 10 minutes of reported time arrived and left; and +/- 30 minutes. Second, GPS points were spatially matched to the establishment parcels in GIS to measure the duration of sensed visits. Travel diary visits were deemed GPS-verified when the brand names of the food establishments as reported and GPS-sensed visit matched. Sociodemographic differences were examined for reported, matched, and unmatched visits with respect for establishment and visit duration.

Results: One third of the participants reported 273 visits to fast food restaurants; 88% reported 1,102 visits to supermarkets. Of these, 77.3 percent of the fast food and 78.6 percent supermarket visits were GPS-verified using the +/-10-minute time window. The mean reported fast food visit duration was 14.5 minutes (SD 20.2), 1.7 minutes longer than the GPS measured visit; using the +/- 10-minute window for supermarkets, the same visit duration was 23.7 minutes (SD 18.9), 3.4 minutes longer than the GPS-measured visit.

Conclusions: Travel diaries provide reasonably accurate information on the locations and brand names of fast food restaurants and supermarkets participants report visiting. Further, the differences in reported and GPS–measured durations of visits to these establishments were under five minutes. GPS traces in a GIS framework are needed for a complete assessment of recall in self-reported measures.

BACKGROUND

Where people eat and shop for food affects their health. In particular, diet quality and weight status have been linked to the types of restaurants where people eat out and to the type of stores where they buy food. Generally, fast food restaurants are considered unhealthy food places[34], while supermarkets offer healthy food options.[35] However, difficulty in obtaining detailed and accurate information on the food places that people patronize has thwarted progress in research linking the food environment to health. A complete examination of the influence of the food environment on health needs to consider two types of data: data on people's routine exposure to that environment over the course of their daily lives, and data on food places that people willfully select to visit. Hence people's exposure to the food environment relates to both their activity space (where they live, work and travel) and to places they self-select to attend to their daily needs.[33]

Many studies have examined the effect of exposure to healthy or unhealthy food environments on various health outcomes. Most have conceptualized exposure as being related to the characteristics of the proximal environment, and specifically the home neighborhood. In a review of 131 studies on the relationship between the built environment and cardiometabolic outcomes, 90 percent of the studies looked only at exposures near residences.[20]

Some studies considered temporal proximity to home as defined by travel mode options such as driving, transit or walking. For example, Jiao and colleagues[36] measured food deserts based on the number of supermarkets within a 10-minute walk, bicycle ride, transit ride, or car ride from home. The more recent use of GPS and travel data has permitted researchers to explore exposure to the food environment over individuals' complete activity space.[24–28] However, these studies fall short of including the locational and temporal characteristics of exposure to self-selected food places. [33]Surveys have been the traditional instrument to capture self-selected activity related to food shopping or eating out. Studies using the American Time Use Survey (ATUS) have indicated that about 14 percent of the population is 'usually' engaged in the grocery shopping (of them 73 percent are women and 27 percent men). The average time spent grocery shopping per visit varied from 39 to 43 minutes not including travel. Goodman[37] found that women grocery shopped for an average of 42 minutes compared to 39 minutes for men; and Hamrick et al.[38] found that those under the age of 30 spend 43 minutes per day shopping compared to those between 30 and 54 who shop for 40 minutes. For the total population, an average of 6.2 minutes is spent grocery shopping on an average day. This average varies by demographic traits (e.g., employed people spend 5.4 minutes; and women spend 8.1 minutes).

Project-specific surveys have included information on the types of food establishments used, the frequency of patronage, and in some cases, the expenses related to the activities.[39,40] They typically do not provide information on the location and the name of the food places used.[41,42]

Multiday travel diaries have been used in mobility studies; they improve on surveys by yielding temporally fine-grained chronological data on activity as well as more precise definition of places visited (e.g., name of establishment, address, etc.) and mode of travel selected. Diaries can be trip-based (respondents filling in the time and place of the origin and the destination of a trip); or place-based (with the name and address of the places respondents stay at, the time of arrival at and departure from each place).[43] Both types of diaries can also record the activity being performed (e.g., meeting a friend, or eating), identify the location and name of places visited, the mode travel used, and the time spent in or between locations, places, or activities.

However, detailed, diary data remain self-reported and susceptible to recall or social bias and to other human errors. They are now often augmented by GPS-based objective data on time, location, and speed of travel. A few transportation studies have compared diary and GPS data. These studies have examined either the trips people reported taking or the places they reported visiting.

Among studies of trips, one study of 1,104 travel-diary-reported trips found that only 53.2% of the reported trips had any GPS data (the missing data appeared to be due to inconsistent wear of the GPS devices).[44] Of the remaining trips with GPS data, about 64% had trip origins and destinations that matched those of the diary (GPS-derived trip origins and destinations came from algorithms used to distinguish between trips and 'dwells,' or locations where participants were stationary).

Similarly, Chen and colleagues[45] compared travel surveys to GPS in an attempt to identify the transportation mode of reported trips in New York City. Their success rate ranged from 60 to 95% based on the mode of travel. Finally, Kelly et al.[46] aggregated the differences between reported and GPS–measured trip duration from eight studies. Reported trip durations were 4.4 minutes (28.6%) longer than the GPS trip duration.

Findings in studies of reported places visited have had similar results. In a validation study of an activity location questionnaire, researchers found that in 75% of self-reported locations were within 400 meters (about a quarter mile) of locations recorded by the GPS data.[47] Another study comparing GPS traces with reported visits to places found a 100% match with participants' homes, but matches of only 50 to 80% matches with commercial and religious establishment locations, suggesting that recall was place-specific.[48] A third study with a small number of observations comparing parents' reports of their children's locations to GPS data yielded a 48-percent match between the two datasets.[49]

GPS data have been called the "best practical standard" for identifying the location and duration of activity.[49] The data are not a gold standard because participants' adherence to study protocols cannot be controlled, and data reception is subject to errors (e.g. blocked, interrupted, or redirected communications with satellites which is often related to building architecture).[50]

The present study compares travel diaries to GPS data for visits to fast food restaurants and supermarkets from a large urban and suburban population assessed over a seven-day period. It uses GPS data to verify the accuracy of diary entries on the location and names of individual establishments visited and the duration of the visits. Based on a novel methodology to match GPS points associated with a reported visit, the study uniquely contributes to understanding the relative value of detailed self-reported and objectively sensed visits to two establishments shown to be related to health.

METHODS

Participants

Data (collected from November 2011 to October 2012) came from the Seattle Obesity Study (SOS) II, a longitudinal study examining weight change, the food environment, and mobility patterns in King County, Washington. Parcel-based sampling[51] was used to establish a sampling frame of residential units in 450,000 parcels within the King County Urban Growth Boundary (UGB). To provide equal distributions by socioeconomic status, residential units were selected based on one of three residential property values (<$199K, >-$200K–$299K, and >=$300K) and with the goal of matching the sample to the county-wide ratio of 58 single-family to 42 multifamily units. Parcel and assessed property value data came for the King County Assessor.[8,52] A commercial supplier matched addresses to phone numbers. Excluding duplicates and incomplete records, the sampling frame comprised 25,460 addresses and phone numbers.

Potential participants were sent pre-notification postcards followed by up-to-three telephone calls. Eligible participants were English-speaking, 18 to 55, mobile adults, who were the primary food shoppers in their households. Of the 712 eligible participants, 516 (72.5%) agreed to enroll in the study. An in-person meeting was scheduled, which could take place at a University of Washington location, at the participant’s home, or at another location of their choice. There were 291 participants who chose to meet in their homes. During the meeting, participants gave their written consent and were administered a computer-aided survey.

Data on participants’ age, gender, race, household income, education, number of adults and children 18 years old or under in the household, came from the survey. Their height and weight (shoeless and in street clothes) were measured using a portable stadiometer and a portable scale. Participants were also given a GPS receiver and a paper place-based travel diary and instructed on how to use them. All procedures and protocols used in the study were approved by the University of Washington Institutional Review Board.

Food establishment data in GIS

Fast food restaurants and supermarkets were identified using 2012 food permit records, which Public Health Seattle King County (PHSKC) collects for all businesses and institutions that serve food in the county. Food permits were geocoded using King County address point GIS layer (King County GIS Center, 2011) for reference within ArcGIS 10 (ESRI, Redlands, CA, 2010). The permits were classified into place or establishment types as previously described.[53] Fast food restaurants were nationally and/or regionally recognized chains that lacked table service and sold inexpensive food served in a short time span. Supermarkets were nationally and/or regionally recognized chains that sold a wide range of foods, including canned and frozen foods, fresh produce, and a variety of meat, fish and poultry. Place names were standardized to reflect the brand name of each establishment (e.g., McDonalds, Safeway). The tax parcels on which each food place was located were identified using the 2012 tax parcel GIS layer and PostGIS 1.5.3 (The PostGIS Development Group, 2008). There were 573 individual fast food restaurants and 199 supermarkets in the county.

Travel diary and GPS data

Each record in the travel diary included the name, address, time arrived and time left, and arriving travel mode for each place participants reported visiting during the seven-day assessment period. GPS traces were collected using GPS receivers (Qstarz BT-Q1000XT;

Qstarz International Co., Ltd., Taipei, Taiwan) recording longitude, latitude, speed, heading, satellite information, and precision data at 30-second intervals.

The travel log contained 16,433 visits to places reported by participants, which included home, work, recreation, shopping and other places. As with the food permit data, the names of all fast food restaurants and supermarkets in the travel diary were standardized by brand. Next, all of the places were aggregated by their unique spellings which resulted in 4,679 distinct place names for all 16,433 reported visits. This list was manually reviewed to identify and correct records with errant or alternative spellings of brand names (e.g. MacDonalds or McD, instead of McDonalds). Finally, the original place names for each travel diary record were compared to their standardized brand name to ensure that the brand names were not assigned in error. PostgreSQL 9.19 (The PostgreSQL Global Development Group, 2008) was used to identify travel diary place names corresponding to fast food restaurants and supermarkets in the GIS data.

Matching analyses

The analyses included participants ≥21 years old, who had complete survey data on personal and household characteristics; >3 days of assessment with both diary and GPS data; and were not working in a fast food restaurant or in a supermarket. To be included in the analyses, reported visits had to have GPS data and to be located inside King County, where GIS data were available for fast food restaurants and supermarkets.

GPS point records were associated with reported visits to food establishments using three steps: (1) reported visits were temporally matched to GPS points by selecting point records occurring within the reported window of arrival and departure times; (2) the matched GPS point records were spatially matched by identifying the points located inside a fast food restaurant or supermarket parcel in GIS; and (3) the food establishment brand name in the GIS data was compared to that reported in the travel diary.

Because participants typically reported visit durations in multiples of five minutes[43], GPS point records were matched to reported arrival and departure times of each visit using three time windows: (1) no time tolerance; (2) a +/- 10 minute time window (the reported arrival time minus ten minutes and the reported departure time plus 10 minute); and (3) a +/- 30 minute time window. The duration of GPS-sensed visits was calculated using the difference between the timestamps of the first and last GPS point records in each food establishment parcel.

Comparisons relying on chi-square analysis were made between participants who reported one or more visits to fast food restaurants or supermarkets during the assessment period and those who did not. Visit durations were calculated using travel log reports and GPS timestamps. Analysis of variance was used to for differences between reported and GPS-sensed mean visit durations for matched visits, as well as the mean differences between reported visit durations for matched and unmatched visits. Simple Pearson product-moment correlations tested the relationships between reported and sensed visit duration, and the parcel size to determine whether participants were simply passing by or through the food place.

RESULTS

Of the 516 participants in SOSII, 446 were considered in the analyses. The following were excluded from the analytic sample: two were <21 years old , five were working in a supermarket, ten had < three days of assessment, 28 lacked diary data and six lacked GPS data, five had poor data for both travel log and GPS, and 14 had incomplete survey data on personal and household characteristics.

Among the 446 participants, 150 reported at least one visit to a fast food restaurant, and 393 reported at least one visit to a supermarket (**Table 2-1**). Of the sample population, 82.7% was 40 years old or older; 69.3% was female; 79.8% White; 65.2% had a household income <$100,000; 63% had at least a college degree; almost 72% lived in households with two or more adults; the majority (55.8%) was married and did not live with children (53.8%) (Table 1). Participants reporting a visit to a fast food restaurant were more likely to be younger (24.0%) than non-visitors (13.9%); to have lower educational attainment (44.7%) compared to non-visitors (33.1%); and to be living with children than those who did not report a visit (56.0% versus 41.6%). There were no differences between participants who reported a visit to a supermarket and those who did not.

A total of 273 visits to fast food were reported (**Table 2-2**). Using the exact time reported in the travel diary, 65.2% (178) of the reported visits to fast food restaurants could be matched with GPS points within a fast food parcel; and 64.1% (175) could be matched to the same fast food brand name. Using the +/-10-minute and +/- 30-minute tolerances for matching the time recorded in the diary to that of the GPS, 77.3% (211) and 81.7% (223) of the fast food visits could be verified by GPS and by brand name, respectively.

A total of 1,102 visits to supermarkets were reported. Using the exact time reported in the travel diary, 74.6% (822) of these visits could be matched with GPS points within a supermarket parcel; and 73% (804) could be matched to the same brand supermarket name. Using the +/- 10-minute and +/-30-minute tolerances for matching the time window of the diary to that of the GPS, 78.6% (866) and 80.3% (885) of the supermarket visits could be verified by GPS and by brand name, respectively.

Matched visits to fast food restaurants included those of 72.7% of the participants who had reported at least one visit using the exact time match between diary and GPS, and 82.7% and 86.7% using the+/- 10-minute and +/- 30-minute tolerances, respectively. For supermarkets, 86%, 88.8%, and 90.1% of the participants who had reported at least one visit had at least one GPS-verified visit, using the exact time, and the +/- 10-minute and +/- 30-minute windows, respectively. The differences between participants with matched and unmatched visits were the same as those between participants with at least one reported and with no reported visits (**Appendix 2-A**)

The primary reasons why reported fast food visits could not be verified by GPS were: (1) the absence of GPS points in the time window provided in the diary (accounting for 7.3% of fast food visits and 6% of supermarket visits); (2) the GPS points recorded in the parcel were outside of the time window reported in the diary (varying from 0% to 17.3% of diary-reported fast food visits depending on the time window and 0 to 7.4% for supermarket visits); and (3) the GPS receiver did not change locations at any period within the time window, indicating that participants were either stationary or did not take the device with them during the reported time of the visit (4.4% of fast food visits and 4.9% of supermarket visits) (**Appendix 2-B**).

As reported in the travel diary, the mean duration of matched fast food visits (at the exact time window) was about 16 minutes (SD 21.6); measured by GPS (at the exact time window provided in the travel diary) the visit mean duration was 3.8 minutes shorter (**Table 2-3**, **Figure 1**). For the +/- 10 minute and +/-30 minute tolerances, mean diary-based visits were 1.67 and 1.62 minutes shorter, respectively. For supermarkets, the mean visit duration of matched visits reported in the travel diary was 24.3 minutes (SD 19); measured by GPS, the mean duration of visits was 7.4 minutes shorter using the exact time window provided in the travel diary. For the +/- 10 minute and +/-30 minute tolerances, the mean diary based visits were 3.37 and 1.95 minutes shorter, respectively. The correlation between the GPS-measured duration and diary-reported duration of fast food visits ranged from 0.97 ($p < 0.001$) at the exact time window, to 0.95 ($p < 0.001$) and 0.91 ($p < 0.001$) at the +/- 10 minute and +/- 30 minute tolerances. For supermarket visits the correlations were smaller; 0.77 ($p < 0.001$), 0.76 ($p < 0.001$), and 0.75 ($p < 0.001$) at the exact time, the +/- 10 minute tolerance, and the +/- 30 minute tolerance, respectively.

Considering differences in reported visit durations between matched and unmatched visits, unmatched visits to fast food restaurants and supermarkets were significantly shorter than matched visits using no time tolerance. Unmatched fast food visits were 6.2 minutes shorter and supermarket visits were 4.3 minutes shorter. Differences were not significant for either fast food or supermarket visits were not significant when using the +/- 10 minute and +/-30 minute time windows (**Table 2-4 & 2-5**).

DISCUSSION

The high proportion of matched visits indicated that travel diaries recorded reasonably accurately the location of visits and the business name of the fast food and supermarkets visited. The results showed a congruence rate between travel diary and GPS data that was as high, or higher, than those reported in previous studies. In previous studies matching rates have varied from a low of 48 percent[49] to upwards of 80 percent depending on the location type.[48] In this study, no population bias was detected between matched and unmatched visits beyond that of expected differences between fast food restaurant users and non-users.

Regarding visit duration, the diary-based and GPS measures were significantly correlated, although fast food visits had much higher effect sizes at all time windows and for both types of visits the correlations decreased as the time windows increased. On average the GPS–measured visits were shorter than those reported in the diaries. At the +/- 10 minute time window, the mean duration of GPS–measured visits was 11.5 percent and 14.2 percent shorter than the mean durations for reported visits to fast food restaurants and supermarkets, respectively. Similarly, matched visits had longer durations than unmatched visits.

The differences in mean duration between GPS–measured and diary-measured durations as well as the differences in diary-measured duration between matched and unmatched visits for both fast food and supermarket visits were highest at the exact time window. In comparing the differences in mean diary-reported visit durations between matched and unmatched visits, the differences were only significant at the exact time window for visits to either place. Overall, the decreases in mean duration differences from the exact time window to the +/- 10 minute suggest that time tolerances are needed when working with self-reported time measures. At the +/- 10 minute and +/- 30 minute tolerances, the smaller differences between reported and GPS–measured visit durations can be explained by the rounding of reported times and the use of multiples of five in reporting times. Transportation studies also found GPS-measured trip duration to be shorter than reported trip duration.[46] While the difference was larger for trips than for places visited, it suggested that in their reports, people inflate both travel and activity durations.

Our supermarket shopping visit duration was surprisingly different from those of ATUS, in which reported time spent grocery shopping was more than twice as long as either our reported or GPS-based visits. In ATUS, time spent in activity (including grocery shopping) excludes traveling to and from the activity. The difference suggested that in ATUS, people considered grocery shopping as a discrete activity, which was not associated with all visits to supermarkets, because the latter might include picking up a take-away meal, odds and ends for a special meals, or shopping for household items.

The +/-10 minute time window increased the number of reported visits that could be GPS-verified by at least 10 percentage points over the measurements done with no time tolerance (to 77.3% for fast foods and 78.2% for supermarkets). In contrast, the +/-30 minute window increased the number of matched visits by about 4% for fast food and by less than 1% for supermarket visits, suggesting that this larger tolerance likely exaggerated participants' error in recording the duration of a visit.

The larger tolerances also increased the possibility that a reported visit might have multiple matches (when GPS points within the time window are located inside two or more parcels both with same food outlet brand name). At the exact time window, neither fast food nor supermarket visits had multiple matches. Yet there were three fast food visits with multiple matches at the +/- 10 minute tolerance and seven at +/- 30 minutes. For supermarkets there was one visit at +/- 10 minutes and two at +/- 30 minutes. The larger time tolerances are capturing both actual visits and an instances in which a person was simply passing through a parcel on their way to somewhere else. Given the small gains from increasing the time tolerance from +/- 10 to +/- 30 minutes along with the increased possibilities for multiple matches, a +/- 10 minute seems to perform the best of the three windows. This finding differed from those of transportation studies where the 30 minute time window yielded better results in matching diary and GPS trip data.[44]

Parcel size (fast food median parcel size was 0.8 acres [IQR 0.5-1.2] and 3.4 acre [IQR 1.6-8.9] for supermarkets) was an appropriate spatial unit to capture GPS points related to a visit. Mean GPS travel speeds indicated that within-parcel sensed visit duration did not include travel to and from the places: speeds were near mean walking speeds at about 1.3 miles per hour (SD 1.2) for fast food restaurants, and 1.6 mph for supermarkets (SD 1.95) within the +/- 10 min time window (**Appendix 2-C**). Correlations between parcel size and speed of points (**Appendix 2-D**) were not significant for fast food visits, and although they were significant for supermarket visits at the exact time window and +/- 10 minutes tolerance, the correlations were small (in both cases r=-0.08). Correlations between parcel size and visit durations showed a similar pattern but with higher effect sizes (**Appendix 2-D**). At the +/- 10 minute tolerance the correlation was 0.22 ($p < 0.001$) for diary duration and 0.34 ($p < 0.001$) for GPS-measured duration (**Appendix 2-C**). People spend more time on larger supermarket parcels than they do on smaller ones. This is perhaps related to the higher speeds of travel on smaller supermarket parcels.

The study was limited to visits that were reported in travel diaries and therefore might suffer from recall or social bias, the latter bias being more likely for fast food restaurant (recognized as unhealthy places) than supermarket (healthy places) visits. Future studies should examine GPS traces to find out whether participants spent time in or near food establishments during the assessment period, which could help identify possible unreported visits. Furthermore, diary or GPS data are limited in their ability to characterize habitual behavior. The sample visited fast food restaurants an average of 0.34 (SD 0.47) times a week, among the 150 participants who reported visits the average was 1.8 (SD 1.3) visits a week. For supermarket visits the sample average was 0.88 (SD 0.32) visits per week and among those who reported one or more supermarket visits it was 2.8 (SD 1.8). In comparison, the Food Marketing Institute estimated that consumers average 1.6 supermarket visits per day.[54] No such data exist for fast food restaurant patronage, although eating at fast food restaurants two or more times a week has been shown to affect health[55] , and increases in weekly consumption of fast food were positively associated with BMI in young adults.[56]

CONCLUSION

More than 77% of visits to fast food restaurants and supermarkets that were reported in travel diaries could be verified by GPS and GIS in terms of their location and individual establishments being patronized. GPS–sensed visit durations were only 11.5 % and 14.2% shorter than reported for fast food restaurants and supermarkets, respectively. This suggested that travel diaries were a reasonable instrument to capture exposure by self-selection to the two types of places. However, while travel diaries are more cost effective to administer than GPS, they are more burdensome on participants, and suffer from recall and social bias, which could be detected with a GPS-based assessment of exposure in continuous space and time.

Table 2-1: Sample by reported visits

	Total (%)	Fast Food Restaurants: Respondent with =>1 reported visit		Respondent with no reported visits		p-value[a]	Supermarkets: Respondent with =>1 reported visit		Respondent with no reported visits		p-value[a]
		n	%	n	%		n	%	n	%	
N	**446 (100)**	**150**	**100**	**296**	**100**		**393**	**100**	**53**	**100**	
Age categories						0.017					0.472
21-39	77 (17.3)	36	24.0%	41	13.9%		71	18.1%	6	11.3%	
40-49	199 (44.6)	66	44.0%	133	44.9%		174	44.3%	25	47.2%	
>=50	170 (38.1)	48	32.0%	122	41.2%		148	37.7%	22	41.5%	
Gender						0.999					0.098
Female	309 (69.3)	104	69.3%	205	69.3%		278	70.7%	31	58.5%	
Male	137 (30.7)	46	30.7%	91	30.7%		115	29.3%	22	41.5%	
Race						0.954					0.165
Non-Whites	90 (20.2)	31	20.7%	59	19.9%		75	19.1%	15	28.3%	
Whites	356 (79.8)	119	79.3%	237	80.1%		318	80.9%	38	71.7%	
Annual household income						0.401					0.766
<50K	125 (28)	41	27.3%	84	28.4%		108	27.5%	17	32.1%	
50K - <100K	166 (37.2)	62	41.3%	104	35.1%		148	37.7%	18	34.0%	
>=100K	155 (34.8)	47	31.3%	108	36.5%		137	34.9%	18	34.0%	
Education						0.022					0.381
Some college or less	165 (37)	67	44.7%	98	33.1%		142	36.1%	23	43.4%	
College graduates	281 (63)	83	55.3%	198	66.9%		251	63.9%	30	56.6%	
Adults in household						0.057					0.659
Lives alone	125 (28)	33	22.0%	92	31.1%		112	28.5%	13	24.5%	
Two or more adults in household	321 (72)	117	78.0%	204	68.9%		281	71.5%	40	75.5%	
Marital status						0.118					0.363
Married	249 (55.8)	92	61.3%	157	53.0%		223	56.7%	26	49.1%	
Not married	197 (44.2)	58	38.7%	139	47.0%		170	43.3%	27	50.9%	
Children in household (age <=18)						0.005					0.977
No children	239 (53.6)	66	44.0%	173	58.4%		210	53.4%	29	54.7%	
Children	207 (46.4)	84	56.0%	123	41.6%		183	46.6%	24	45.3%	

[a] Chi-square analysis.

Table 2-2: Matched visits using travel diary, GPS, and brand names

	Fast food		Supermarkets	
	Number of visits (%)	**Number of participants with ≥ 1 reported visits (%)**	**Number of visits (%)**	**Number of participants with ≥ 1 reported visits (%)**
Total number (reported visits and participants)				
n	273 (100)	150 (100)	1102 (100)	393 (100)
GPS verified temporal-spatial match[a]				
No time tolerance	178 (65.2)	112 (74.67)	822 (74.59)	341 (86.77)
+/- 10 min	217 (79.49)	127 (84.67)	894 (81.13)	353 (89.82)
+/- 30 min	231 (84.62)	134 (89.33)	918 (83.3)	357 (90.84)
GPS and brand name match[b]				
No time tolerance	175 (64.1)	109 (72.67)	804 (72.96)	338 (86.01)
+/- 10 min	211 (77.29)[c]	124 (82.67)	866 (78.58)[e]	349 (88.8)
+/- 30 min	223 (81.68)[d]	130 (86.67)	885 (80.31)[f]	354 (90.08)

(a) > one GPS point inside time window and inside a GIS food place parcel.
(b) (a) above + brand name of food establishment in parcel GIS matches that in travel log.
(c) Three visits had two matches each.
(d) Seven visits had two matches each.
(e) One visit had two matches.
(f) Two visits had two matches each.

Table 2-3: Matched visit GPS and travel diary durations (minutes)

	Number of visits	GPS duration mean (sd)	Travel log duration mean (sd)	Pearson's r (p-value)
Matched fast food visits				
No tolerance	175	12.23 (20.84)	16.06 (21.64)	0.97 (0)
+/- 10 minutes	211	12.8 (20.16)[a]	14.47 (20.21)	0.95 (0)
+/- 30 minutes	223	12.81 (18.22)[a]	14.43 (20)	0.91 (0)
Matched supermarket visits				
No tolerance	804	16.89 (16.39)	24.27 (19)	0.77 (0)
+/- 10 minutes	866	20.3 (17.55)[a]	23.67 (18.92)	0.76 (0)
+/- 30 minutes	885	21.56 (18.21)[a]	23.51 (18.85)	0.75 (0)

[a] When a reported visit had multiple matches the GPS durations of matches were averaged.

Table 2-4: Reported visit durations for matched and unmatched FFR visits (minutes)

	Reported fast food visits mean duration (sd)=13.97 (18.72) n=273				
	Matched visits		Unmatched visits		
	Number of visits	Mean duration (sd)	Number of visits	Mean duration (sd)	p-value
No tolerance	175	16.06 (21.64)	98	9.84 (9.74)	0.010
+/- 10 minutes	211	14.47 (20.21)	62	11.94 (10.82)	0.380
+/- 30 minutes	223	14.43 (20)	50	11.44 (8.69)	0.348

Table 2-5: Reported visit duration for matched and unmatched supermarket visits

	Reported supermarket visits mean duration (sd)=23.21 (18.58) n=1102				
	Matched visits		Unmatched visits		
	Number of visits	Mean duration (sd)	Number of visits	Mean duration (sd)	p-value
No tolerance	804	24.27 (19)	298	19.97 (16.85)	0.001
+/- 10 minutes	866	23.67 (18.92)	236	21.25 (16.97)	0.095
+/- 30 minutes	885	23.51 (18.85)	217	21.77 (17.22)	0.248

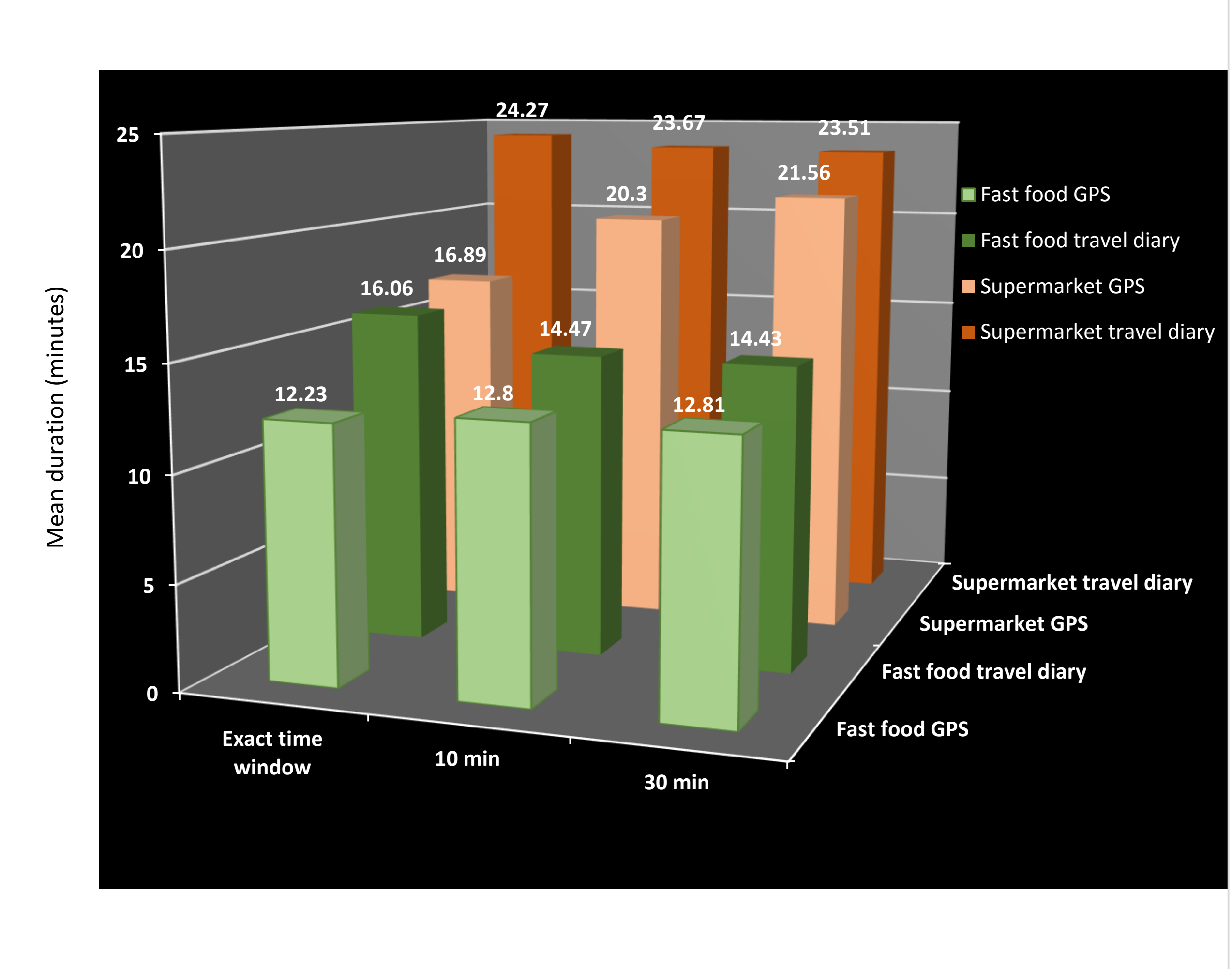

Figure 2-1: Mean duration of visits to FFRs and supermarkets (minutes)

Appendix 2-A: Population with matched and not matched visits (10 minute tolerance)

		Fast Food Restaurants					Supermarkets				
		Respondent with ≥ matched visit		Respondent no matched visit		p-value	Respondent with ≥ matched visit		Respondent no matched visit		p-value
	N (%)	n	%	n	%		n	%	n	%	
Overall	**446 (100)**	**124**	**100**	**322**	**100**		**349**	**100**	**97**	**100**	
Age categories						0.085					0.289
21-39	77 (17.3)	29	23.4%	48	14.9%		64	18.3%	13	13.4%	
40-49	199 (44.6)	54	43.5%	145	45.0%		158	45.3%	41	42.3%	
>=50	170 (38.1)	41	33.1%	129	40.1%		127	36.4%	43	44.3%	
Gender						0.893					0.501
Female	309 (69.3)	87	70.2%	222	68.9%		245	70.2%	64	66.0%	
Male	137 (30.7)	37	29.8%	100	31.1%		104	29.8%	33	34.0%	
Race			0.0%		0.0%	0.697		0.0%		0.0%	0.403
Non-Whites	90 (20.2)	27	21.8%	63	19.6%		67	19.2%	23	23.7%	
Whites	356 (79.8)	97	78.2%	259	80.4%		282	80.8%	74	76.3%	
Annual household income						0.146					0.887
<50K	125 (28)	32	25.8%	93	28.9%		98	28.1%	27	27.8%	
50K – <100K	166 (37.2)	55	44.4%	111	34.5%		128	36.7%	38	39.2%	
≥ 100K	155 (34.8)	37	29.8%	118	36.6%		123	35.2%	32	33.0%	
Education			0.0%		0.0%	0.006					0.534
Some college or less	165 (37)	59	47.6%	106	32.9%		126	36.1%	39	40.2%	
College graduates	281 (63)	65	52.4%	216	67.1%		223	63.9%	58	59.8%	
Adults in household						0.016					0.999
Lives alone	125 (28)	24	19.4%	101	31.4%		98	28.1%	27	27.8%	
Two or more adults in household	321 (72)	100	80.6%	221	68.6%		251	71.9%	70	72.2%	
Marital status						0.029					0.124
Married	249 (55.8)	80	64.5%	169	52.5%		202	57.9%	47	48.5%	
Not married	197 (44.2)	44	35.5%	153	47.5%		147	42.1%	50	51.5%	
Children in household (age <=18)						0.003					0.418
No children	239 (53.6)	52	41.9%	187	58.1%		183	52.4%	56	57.7%	
Children	207 (46.4)	72	58.1%	135	41.9%		166	47.6%	41	42.3%	

Appendix 2-B: Reasons why reported visits lacked matches

	Reported visits without matches N (%)					
	No tolerance		+/- 10 minutes		+/- 30 minutes	
Explanation	**Fast food**	**Supermarkets**	**Fast food**	**Supermarkets**	**Fast food**	**Supermarkets**
Reported food place name and food permit name differ but both are appropriate	3 (3.1)	1 (0.3)	3 (4.8)	1 (0.4)	3 (6.0)	1 (0.5)
Unable to determine	9 (9.2)	17 (5.7)	9 (14.5)	17 (7.2)	9 (18.0)	17 (7.8)
GPS receiver never moved	12 (12.2)	54 (18.1)	12 (19.4)	54 (22.9)	12 (24.0)	54 (24.9)
No GPS data	20 (20.4)	66 (22.1)	20 (32.3)	66 (28.0)	20 (40.0)	66 (30.4)
No parcel record	1 (1.0)	3 (1.0)	1 (1.6)	3 (1.3)	1 (2.0)	3 (1.4)
Points close but not inside parcel	5 (5.1)	68 (22.8)	5 (8.1)	68 (28.8)	5 (10.0)	68 (31.3)
GPS receiver error	0 (0)	2 (0.7)	0 (0)	2 (0.8)	0 (0)	2 (0.9)
Went to a different food place than the one named	0 (0)	6 (2.0)	0 (0)	6 (2.5)	0 (0)	6 (2.8)
Points inside parcel were outside reported time window	48 (49.0)	81 (27.2)	12 (19.4)	19 (8.1)	0 (0)	0 (0)
Total n reported visits without matches	98 (100)	298 (100)	62 (100)	236 (100)	50 (100)	217 (100)

Appendix 2-C: Descriptive statistics of matched visits[a]

	Fast food						Supermarkets				
Variable	**Mean**	**SD**	**Median**	**IQR**	**Max**		**Mean**	**SD**	**Median**	**IQR**	**Max**
No tolerance											
GPS duration(minutes)	12.2	20.84	4.67	2.08–13.8	156		16.9	16.39	12.2	5.36–24.3	145
GPS speed	1.04	1.1	0.72	0.34–1.34	7.16		1.57	1.95	1.15	0.68–1.83	32.3
# of GPS points	55.8	120.32	19	10–39	940		65.1	78.08	38	15–88	649
Parcel area (sq ft)	108000	223507.1	36400	23900–51500	1560000		255000	239695.36	148000	75500–425000	1260000
Reported – sensed time arrived (minutes)	-1.8	3.4	-0.42	-1.98–-0.11	0		-3.15	5.91	-0.425	-3.52–-0.1	0
Reported – sensed time left (minutes)	2.04	3.87	0.48	0.12–2.39	31.1		4.24	10.53	0.45	0.1–4.27	179
Reported – sensed duration (minutes)	3.83	5.39	2	0.83–4.31	45		7.39	12.35	2.84	0.5–9.22	179
10 min											
GPS duration (minutes)	12.8	20.16	6	3.16–13.8	160		20.3	17.55	16.3	8.18–28.1	145
GPS speed	1.31	1.16	0.99	0.535–1.68	6.86		1.71	1.69	1.31	0.82–2.06	20.6
# of GPS points	56.6	115.73	24	12–44	960		74	83.59	45	19–100	656
Parcel area (sq ft)	101000	211396.77	35000	22600–52400	1560000		247000	237759.22	146000	71300–386000	1260000
Reported – sensed time arrived (minutes)	-0.347	6.06	0.18	-1.87–2.82	9.95		-1.25	8.1	0.09	-3.12–2.38	10
Reported – sensed time left (minutes)	1.33	5.88	0.47	-1.66–3.5	31.1		2.12	11.32	-0.49	-2.44–3.47	179
Reported – sensed duration (minutes)	1.68	6.16	0.5	-1.33–3.58	45		3.36	12.59	0.17	-2.57–6.63	169
30 min											
GPS duration (minutes)	12.8	18.22	6.38	3.5–14.2	160		21.6	18.21	17	8.67–30.4	145
GPS speed	1.31	1.18	1.01	0.525–1.71	6.86		1.71	1.72	1.31	0.82–2.05	20.6
# of GPS points	53.8	102.07	25	14–44	950		77.3	87.38	47	20–101	659
Parcel area (sq ft)	101000	211990.93	33900	22100–52100	1560000		246000	237269.11	146000	71300–386000	1260000
Reported – sensed time arrived (minutes)	-0.378	11.79	0.28	-2.05–3.25	30		-0.15	10.37	0.15	-3.1–2.72	30

Reported – sensed time left (minutes)	1.24	9.1	0.55	-1.76–4.14	39.2		1.8	13.17	-0.48	-2.55–3.93	179
Reported – sensed duration (minutes)	1.62	8.49	0.48	-1.39–3.33	77.7		1.95	13.16	-0.17	-3–5.97	163
[a] When a reported visit had multiple matches the GPS durations of matches were averaged.											

Appendix 2-D: Correlations among GPS-measured variables of matched visits[a]

Comparison	Fast food Pearson's r (p-value)				Supermarkets Pearson's r (p-value)		
	No tolerance	+/- 10 min	+/- 30 min		No tolerance	+/- 10 min	+/- 30 min
Speed and reported duration	-0.25 (0.001)	-0.29 (< 0.001	-0.28 (< 0.001)		-0.09 (0.009)	-0.09 (0.008)	-0.09 (0.008)
Speed and GPS duration	-0.32 (< 0.001)	-0.37 (< 0.001)	-0.32 (< 0.001)		-0.22 (< 0.001)	-0.25 (< 0.001)	-0.23 (< 0.001)
Speed and duration difference	0.26 (0.001)	0.23 (0.001)	0.03 (0.627)		0.15 (< 0.001)	0.21 (< 0.001)	0.19 (< 0.001)
Speed and parcel size	0.07 (0.334)	0.08 (0.262)	0.13 (0.048)		-0.08 (0.025)	-0.08 (0.026)	-0.06 (0.061)
Parcel size and reported duration	0.03 (0.732)	0.04 (0.566)	0.03 (0.681)		0.22 (< 0.001)	0.22 (< 0.001)	0.22 (< 0.001)
Parcel size and GPS duration	0.04 (0.569)	0.09 (0.184)	0.13 (0.06)		0.3 (< 0.001)	0.34 (< 0.001)	0.34 (< 0.001)
Parcel size and duration difference (Reported – sensed duration)	-0.06 (0.405)	-0.17 (0.013)	-0.21 (0.002)		-0.06 (0.092)	-0.15 (< 0.001)	-0.16 (< 0.001)

[a] When a reported visit had multiple matches the GPS durations of matches were averaged.

Chapter 3 : A TIME-BASED, OBJECTIVE MEASURE OF EXPOSURE

ABSTRACT

Background: Exposure to the food environment has traditionally been measured by the counts of food outlets in proximity to individuals' homes. Advances in global positioning systems (GPS) technology have allowed researchers to count the numbers of food outlets in proximity to participants as they travel through their daily environments. However, GPS data can also measure the time participants spend in proximity to food outlets, thus helping estimate not only the spatial dimension of exposure but also the temporal exposure to environments of interests.

Objectives: We report on a novel, time-based measure of exposure to fast food restaurants (FFRs).

Methods: The Seattle Obesity Study II (SOS2) included 412 residents living within the urban growth boundary of King County, Washington, who were recruited using an address-based sampling method. Participants wore GPS receivers that recorded their locations at intervals of 30 seconds over seven consecutive days. Participants filled out a travel log reporting all of the places that they visited during that time period, and they also completed a computer-assisted questionnaire. The address of every FFR in King County was obtained from Public Health Seattle King County and were geocoded. Three day-level measures of FFR exposure were created using GPS traces: (1) FFR count, the daily count of FFRs in proximity to participants; (2)

duration, time per day spent in proximity to one or more FFRs; and (3) weighted duration, the duration spent in proximity to FFRs weighted by the number of FFRs in proximity. Each exposure was measured at four proximities, 21 meters, 100 meters, 500 meters, and a half mile. Self-selected exposure in the form of travel-log-reported FFR visits (as estimated using GPS traces) were excluded from analysis. Logistic regressions were used to examine associations between travel-log-reported visits to FFRs and each of the exposure measures at each of the proximities.

Results: The odds of reporting one or more visits to an FFR increased as time spent in proximity (at each measurement of proximity) to one or more FFRs increased. No relationships were found for FFR counts at any of the proximity measures. The odds of reporting FFR visits were significantly associated with the weighted duration in the 21- and 100-meter proximities.

Conclusions: Objectively measured duration of exposure to FFRs is significantly related to visiting FFRs. It offers a new approach to understanding the relationship between food environment exposures, mobility patterns, and health behaviors.

BACKGROUND

Higher levels of fast food consumption and visits to fast food restaurants (FFRs) are linked to higher body mass index (BMI), lower diet qualities, prevalence of type II diabetes, and related diminished health outcomes.[34,55,57,58] It has also been established that disadvantaged populations are more likely to live in proximity to a higher number of FFRs than more privileged populations.[59–61] Yet evidence of an association between residential proximity to FFRs and fast food consumption, visits, or health outcomes is mixed.[60,62] Fleischhacker and colleagues[60] identified only seven out of 15 studies reporting positive associations between the number of FFRs in proximity to residences and obesity prevalence. Researchers have hypothesized that the inconsistent findings are due to variations in levels of FFR exposure away from home neighborhoods.[23–27,63] Indeed, studies considering FFR proximity to schools or workplaces found associations with both BMI and fast food consumption.[64,65] However, such studies are rare: a review of 131 studies on the relationship between the built environment and cardiometabolic outcomes showed that 90 percent of the studies looked only at exposures near residences, six percent examined non-home exposures, and only four percent considered both home locations and other important locations.[20] Despite its limitations, this body of work has sparked interest in policy interventions to restrict where FFRs are allowed to locate.[66,67]

Most people are exposed to a range of locations in their daily lives—a phenomenon that Matthews and Yang[19] refer to as spatial polygamy. As a result, studies of exposure to the built environment (such as FFRs) need to consider participant mobility patterns and daily activity spaces.[19,31] Spatial mobility patterns tell a more complete picture about the relationship between the BE and health, than simply measuring the area near an individual's home. A small, growing body of literature started to address this issue.[23–27]

The field of exposure science conceptualizes exposure as the result of contact between a *stressor* (a factor or environmental trait) and a *receptor* (an organism or an organism's tissue).[68] Both stressor and receptor traits are causal factors in whether an exposure occurs. Stressor traits include both the location of the stressor in the environment and the concentration of the stressor at that location. Receptor traits include the receptor's mobility patterns, which in turn are related to lifestyle, social conditions, and behaviors.[68]

Chaix and colleagues[31] attempt to disentangle the relationship between receptor and stressor by identifying a triad of bi-directional causal pathways between an individual's environment, mobility patterns, and health outcomes: (1) *environment and mobility*--depending on the trait, the environment can lead to increases or decreases in mobility levels (e.g., walkable environments), yet higher levels of mobility may expose people to more and varied environments; (2) *mobility and health*--higher levels of mobility can lead to better health (e.g. walking as a form of passive exercise), yet healthier people are more mobile than unhealthy people; and (3) *environment and health*--environmental traits can positively or negatively impact health directly (e.g. air quality) or indirectly (e.g. facilitating behaviors that impact health), yet one's health status may influence one's choice of environments.

Using this conceptual framework, FFRs are stressor traits and the mobility patterns that bring an individual into contact with FFRs are receptor traits. Contact varies based on proximity between stressor and receptor: increasingly closer proximities leading first to increased likelihood of an FFR visit, followed by the purchase and consumption of fast food products. It is the consumption of fast food that eventually leads to increased BMI and related negative health outcomes. Exposure is moderated or mediated by such receptor traits as attitudes, preferences (e.g., for travel mode, food type, etc.), and health, which influence mobility and food selection. Exposure is also affected by such stressors as built environment characteristics (presence or absence, concentrations of FFRs) and travel options.

Measuring exposure and access both at home and away

Mobility studies of exposure to the food environment can add to knowledge gained from home- or other anchor-based studies. Anchor-based studies have typically measured the count of specific stressors (e.g., FFRs) within a given proximity to the anchor location. To date, studies that examined mobility through the food environment have continued to measure exposure by merely counting specific stressors near individuals (e.g., FFRs) used in previous home- or location-based studies.[69–72]. Current GPS technology allows for measurement of not just *the number of times* (counts) an individual comes into proximity of food outlets, but also *the actual time spent* (duration) in proximity to these outlets. Clearly, being exposed to a food environment for a short or a long period of time will affect exposure (e.g., driving by a fast food restaurant at 50 kmph versus walking by the same restaurant at 5 kmph can result in spending either 2 minutes or 20 minutes within 100 meters of the restaurant).

To our knowledge, our study is first to include time spent in proximity to food outlets as a measure of exposure. We refer to time-based, cumulative exposure measures, which have been used in the study of air pollution.[73–75] These studies quantify microenvironmental exposure (ME), which is the cumulative level of pollutant to which a person is exposed for a particular activity. ME exposure accounts not only for the concentration of pollutant present in the microenvironment, but also the duration of time that an individual spends in that microenvironment.[76] Exposure calculations explicitly differentiate between intensity and duration, although they may lead to the same outcome (e.g., (a) an exposure to a concentration of 10 pollution units for 2 hours and (b) an exposure to a concentration of 20 pollution units for 1 hour). In a food environment context, cumulative exposure can be estimated by multiplying the length of time of an exposure by the number of food outlets to which one is exposed during that time period. The cumulative exposure is thus the duration of exposure that has been weighted by the number of food outlets to which one has been exposed.

Importantly, measures of exposure duration are independent from travel mode, as different speeds of travel are captured by time. Burgoine and colleagues[24,25] used counts of and proximity to FFRs and takeaway restaurants as measures of exposure to the food environment. Because they did not have an exposure duration measure, they selected different proximity measures to account for exposure via different commute modes: a proximity of 500 meters for the shortest route from home to work for those who drove; and 100 meters for those who walked. Their assumption was that within a given time budget, higher speed travel provides access to a larger potentially available activity space. Unfortunately, however, there is no empirical basis for defining exposure "catchment areas" related to mode of travel. In addition, the relationship between mode of travel and speed is highly variable by time of day in cities where traffic congestion prevails. As a result, measuring exposure by duration and testing the effect of proximity by using a range of buffer size promises to better advance the field.

Previous studies have used a range of buffer sizes: 100 meters[24,25]; half-mile[26,27]; and up to eight kilometers.[77] Few studies present theoretical reasons for their choice of buffer size and little research has focused on testing which proximities are most effective at predicting health outcomes, food consumption, or food outlet visitation. Clearly, different buffer sizes will capture different aspects of the relationship between stressor and receptor that result in an exposure. Specifically, smaller proximities represent instances in which an individual is close enough to a food outlet to register its presence through sensory input—when the outlet is seen, heard or smelled. While larger proximities may represent the influence of cognitive factors related to individual attitudes, preferences, as well as knowledge and memory of food outlets.

This study introduces a new, small proximity of 21 meters (69 feet), which, as the maximum distance at which a human face can still be identified by another human, captures an individual's perception/recognition realm.[78] Interestingly, 19.8 meters (66 feet) is the width of many urban streets platted west of the Ohio River. A 21-m exposure relates to slow motion, either walking, slow bicycling, driving in congested traffic or stops at a traffic light. For slow modes of travel, exposure beyond 21 m will generally rely on cognition; an individual's knowledge of having a FFR nearby. Hence when FFRs are too far away to be directly experienced, there may be a very different relationship between receptor and stressor, one that is based on cognitive factors such as memory of food outlet location.

Last but not least in measuring exposure to the food environment is the important issue of spatial mobility bias.[33] Spatial mobility includes participants' selective mobility, or the locations a person chooses to visit as different from the places that to which a person is unwillingly exposed. Not filtering selective mobility from the activity space data may result in visits to a stressor and not the exposure to the stressor, predicting the health outcome.

The study

This study used objective measures of exposure based on GPS traces and built environment attributes in a GIS environment. It introduces two new measures of exposure (duration of time exposed, and duration of time exposed weighted by number of FFRs) and compares them to the conventional food environment exposure measures, i.e., the counts of FFRs in proximity to individuals based on their mobility patterns. The duration and the weighted duration are novel to food environment literature, with no other food environment studies using GPS data in this fashion. Further, exposure is measured using four different proximities between participant and FFR, using circular catchment areas around each FFR. The catchment area radii are 21 meters, 100 meters, 500 meters, and a half mile. The study accounts for the selective mobility bias by removing GPS/GIS data that are associated with travel-log-reported visits to FFRs.

METHODS

Sampling and recruitment

The sample frame was drawn from the approximately 450,000 residential tax parcels in the King County Urban Growth Boundary (UGB). Mandated by the state of Washington, the UGB is used to control real estate and infrastructure development, thus the vast majority of King County's population lives within the boundary. Identified using King County tax assessor data, residential property values for each parcel were weighted in three bands (<199k, >=200k to <299k, and >= 300k) to ensure socioeconomic diversity. The property bands were chosen based on previous research.[8,52] Single-family and multifamily units were also identified to ensure that the sample was proportionate to the county distribution of 58 and 42 percent respectively. The addresses from selected residential units on tax parcels were matched to telephone numbers by a commercial supplier. With a matching rate of 55 percent for single- and 40 percent for multi-family units, 25,460 addresses and telephone numbers were obtained after duplicate and incomplete records were removed.

The Battelle Memorial Institute Survey Research Group used the addresses to send out pre-notification postcards to potential participants. Eligibility was limited to English speakers over 18 without mobility issues and who were the primary food shoppers in their households. Battelle obtained verbal consent from 712 potential eligible participants whose contact information was then sent to SOS II research staff.

Data collection

SOS II staff contacted potential participants by phone to set up in-person meetings with 516 (72.5 percent) participants who agreed to enroll in the study. Participants were given the option of meeting at the University of Washington or at the location of their choice, including their homes. About 56 percent (291 participants) chose to meet at their homes. During the meeting, written consent was obtained, heights and weights were objectively measured, and a computer-aided questionnaire was administered by SOSII staff. Participants were also informed on how to fill out a seven-day, place-based travel log, and how to wear and recharge the Global Positioning Systems (GPS) receiver over the same seven days.

The travel log required participants to report the names, addresses and the times they arrived and left each place they visited during the course of the day. During this same period participants were also asked to wear a GPS receiver (Qstarz BT-Q1000XT; Qstarz International Co., Ltd., Taipei, Taiwan) that would record the latitude and longitude at intervals of 30 seconds. All data collection procedures and measures were approved by the University of Washington institutional review board. Participants with less than three consecutive days of travel log data or with noticeable errors in GPS data (e.g. if the GPS device did not record any data during the observation period) were excluded from the sample.

Dependent variable

There were 149 participants who reported at least one visit to a FFR in their travel log during the assessment period. Of those, 55 percent reported only one visit. Overall, the mean number of visits per participant for the whole sample was 0.67 (SD 1.2). Among those who reported one or more visits, the mean was 1.86 (SD 1.3). Given the skewed distribution, the number of visits was dichotomized to distinguish between those who reported one or more FFR visits and those who reported no visits during the observation period.

Survey variables

Participants filled out a computer-assisted questionnaire with the help of SOS II staff. Survey variables in this study include age, gender, race, education, self-reported household income, employment status, household size, marital status, and number of cars in household. Participants with missing responses to any of the questions or those who answered any of the questions with "Don't know/not sure", were excluded from the sample. Age was split into two groups: under 45 years; and 45 years or older. Race was dichotomized into non-Hispanic white and non-white or Hispanic participants. Self-reported annual income was trichotomized into three groups: under \$50,000; \$50,000 to \$100,000; and \$100,000 or higher. Education was split between those who had and had not earned college degrees. Employment status was dichotomized such that those who were classified as not employed included homemakers, students, retired, and those who were out of work or unable to work. Employed participants were those who reported being employed for wages or self-employed. Responses of 'divorced', 'member of unmarried couple', 'separated', or 'widow' were considered unmarried.

GIS data

Geocoding. ArcMap 10.2 (ESRI, Redlands, CA) was used to match participants' residential and primary workplaces addresses to a King County shapefile that represents each address in King County as a point corresponding to the centroid of the building associated with the address. Using a minimum match score of 100, 481 (93 percent) of the 516 eligible SOS II residential addresses were geocoded. The remaining addresses were geocoded manually using Google Maps to verify locations. For workplace addresses, 232 were matched using the 100 criterion and 138 were manually geocoded. For 146 participants no workplace was geocoded. The majority of these (117 participants) were due to blank responses, refusals, and participants being unsure of the address of their workplaces. Nine participants reported a partial or ambiguous work address (listing only the city name or just the zip code). Twelve worked in locations outside King County. Nine more did not give an address because they worked in multiple locations and were unsure of which address to report.

Commute distance. The airline distance between home and work was computed using the ST_Distance function in PostGIS and trichotomized to those who did not commute, those with commutes under the sample median of 5.22 miles, and those who commuted farther. The 60 participants with airline distances between home and work of under 125 meters (410 feet) were considered to be non-commuters. Participants who did not report a workplace address or who responded with a refusal or 'don't know/not sure' were considered to have no workplace address if they reported not being employed in the survey. Blank responses, refusals, and 'don't know/not sure' responses for participants who also reported being employed were treated as missing values and those participants were removed from the sample.

Fast food restaurant location data. Data on FFRs came from Public Health Seattle King County 2012 food permit records. The outlets corresponding to each permit were classified using a scheme presented in Moudon and team.[53] Venues were considered fast food restaurants if they were part of nationally or regionally recognized chains that lack table service and sell inexpensive food in a short time span. Each of the 573 fast food restaurants in the county was geocoded using the same technique as that used for the participant home addresses.

King County tax assessor data. Both residential density and residential property values came from the King County Tax Assessor parcel data. ArcMap 10.1 (ESRI, Redlands, CA) was used to count the number of residential units within an 800-meter radius of participants' homes. Due to positive skew, the variable was split at the sample median value of 1,892 residences. The same software and assessor data were also used to identify the average property value of a residential unit located on the participants' home parcel. Property values can be used as an objective measure of participant wealth in contrast to self-reported income.[8] If there was more than one residential unit on the parcel, the average property value of units on the parcel was obtained. The property values were then split into tertiles: $38,000 to $229,000; $229,000 to $326,000; and $326,000 or higher.

GPS data processing

For each participant, GPS points were first selected if they occurred during the assessment period (the period of time between the start time of the first place and the start time of the last place reported in the participant's the travel log). The mean number of days subjects reported in the travel log was 6.6 (SD 0.9).

GPS data errors are typically due to slow connectivity between satellite and device, physical structures that block satellite reception, and other environmental conditions (such as the state of the atmosphere) which can also hinder accurate measurement.[50] Criteria set by Tsui and Shalaby[79] and the Personal Activity and Location Measurement System (PALMS)[80] were used to identify and remove records under the above conditions. The following exclusion criteria were used; (a) having less than three satellites in view[79]; (b) when horizontal dilution of precision (HDOP) was greater than five[79]; and (c) when estimated speed of each point (calculated at the point level by averaging the distance/time between the preceding and subsequent GPS points) was greater than 130 kmph (81 mph), which is considered an excessive speed by both PALMS[80] and King County (the maximum speed limit in the county is 112.7 kmph, or 70 mph). Excessive speeds can cause connectivity errors but they may also be due to other measurement errors.[50,80]

To perform exposure analyses, the remaining GPS points were turned into line segments by linking each point with the point that followed in time. The time interval for each line segment was calculated by subtracting the timestamp of the segment's start point from that of its end point, with the end point serving as the start point for the next line segment. There were 11,119,350 line segments in the sample and the majority of segments (8,853,132 or 79.6 percent) had time intervals of ten seconds or less, and 99.86 percent of segments (11,103,838 segments) had intervals of 30 seconds or less. The 0.14 percent of segments with intervals longer than 30 seconds were due to missing GPS data as a result of problems such as when the satellite signal was obstructed, the GPS device malfunctioned, or when the device was turned off and then turned back on again at a much later period. Segments with shorter the time interval between points have greater accuracy in representing the path of travel between those points; therefore, line segments over 30 seconds were omitted from analysis. Collectively, line segments of 30 seconds or less create a spatio-temporal representation of participant travel patterns. The accuracy of line segments with shorter time intervals makes it possible to estimate the location of a participant at any point in time along the segment using linear interpolation.

Although all participants lived in King County, many spent part of one or more observation days outside the county. Only complete and partial line segments inside the county were selected. When a line segment crossed the county border, the segment was truncated and the time interval of the truncated segment that remained inside King County was estimated. The time interval of each partial segment was calculated using the length of the partial segment as well as the time interval and length of the complete segment (complete segment time interval * partial segment length / complete segment length).

To focus on the non-home and non-work place exposures, segments associated with geocoded home and work locations were removed from analysis. Based on previous studies[81], all complete and partial line segments within a 125-meter radial buffer of either location were removed. Together, the remaining partial and complete segments for each day comprised the daily travel path of each participant.

PostGIS 2.1 (The PostGIS Development Group. PostGIS. 2008) and PostgreSQL 9.19 (The PostgreSQL Global Development Group, 2008) in an R 3.2.1 programming environment (R Core Team, 2015) were used to process the data.

Exposure measures

We computed total FFR counts by summing all of the counts of individual FFRs within 21, 100, and 500 meters, and a half mile of GPS points representing participants' daily travel paths. In a GIS environment, the borders of multiple overlapping exposure areas were dissolved thus creating polygons depicting the land area with proximity to one or more FFRs. The duration of exposure was estimated by summing the intervals of the complete and partial GPS line segments intersecting these individual or multiple overlapping catchment areas (**Figures 3-1 & 3-2**).

To calculate the weighted duration of exposure, buffers around each FFR were left undissolved and intervals were summed for all of the complete and partial GPS line segments within individual and overlapping exposure areas. Leaving the buffers undissolved meant that intervals were weighted by the number of exposure areas they intersected with (**Figure 3-3**). For example, the time interval of a line segment inside a single buffer remained unchanged (multiplied by one FFR), however the time interval of a line segment inside two or more overlapping buffers was multiplied by the number of overlapping buffers (representing the number of FFRs).

Self-reported visits

The duration of self-reported visits was estimated by identifying GPS line segments that were both: (1) within the interval encompassing the time participants reported arriving at an FFR minus 10 minutes and the time reported leaving the FFR plus 10 minutes; and (2) the if the line segments were inside an FFR catchment area. The -/+ 10-minute tolerance was added to account for recall bias in the travel log.

Missing data and outliers

Participants with missing data for any of the survey variables were removed from the sample. Preliminary analyses revealed a participant with an FFR exposure duration of 144.4 minutes at the 21-meter catchment (in comparison the next highest value was 12.9 minutes). The outlier's data was removed from the study. After excluding participants with missing data, outliers, incomplete travel log data, and/or faulty GPS data, the final sample was 412 participants.

ANALYSIS

Means and standard deviations were calculated for each exposure measure at the four proximities by key variables representing domains that had previously been found to be associated with FFR visits: sociodemographics (age, gender, race, education, and employment status), commute characteristics (commute distance and number of cars in household), and household characteristics (household size and marital status). Residential density was also included to test for differences in exposure based on residential location. Analysis of variance (ANOVA) was used to test for significant differences in levels of exposure within each proximity by the key sociodemographic, commute, and household variables. Comparisons were made between participants who reported FFR visits and those who did not report visits. Chi-square analysis was used to test for associations.

Logistic regression models were run to predict the odds of a participant reporting an FFR visit by each exposure measure at each catchment size after adjusting for age, gender race, income, and education. A total of twelve models were compare differences in three exposure measures at the four different proximity sizes. Additional variables were selected based on their relationships with exposure or with the outcome. All analyses were conducted using R version 3.2.1. The following variables were used in all models: age, gender, race, education, income, number of cars in household, household size, commute distance, and residential density.

RESULTS

Of the 412 participants, 149 (36.2%) reported visiting one or more FFRs during the observation period, accounting for 276 visits. The majority of these participants (139) reported 254 visits to FFRs inside King County. We were able to identify corresponding GPS data for 182 (71.7%) of those visits (at the times participants reported visiting an FFR there were inside FFR catchment areas). About 58% (81 participants) of those who reported FFR visits had all of the visits verified by GPS, while 32 participants did not have any GPS data overlapping reported FFR visits.

Mean exposure by covariate

The means for the twelve exposure measures (duration, FFR count, and weighted duration each measured at four proximities) are presented in **Tables 3-1 to 3-3**. College-educated participants spent more time exposed to FFRs than those without college degrees. This was significant for three of the four duration proximities. Yet there were no significant differences in the counts of FFRs between those with college degrees and those without. For all three of the exposure measures and at every proximity, white participants had lower mean durations than non-white participants, however the association was only significant for duration at 500m and a half mile and for FFR count at 500m. Self-reported income was not significantly associated with exposure for any of the twelve measures and property value was significantly associated with only one measure (FFR counts at 100 meters).

Participants who lived in households of three or more residents had lower mean exposures than those who either lived alone or with one other person. The difference was significant for nine of the twelve exposure measures. Similarly, married participants had lower mean exposures as well, and the mean differences were significant for all but two of the exposure measures. These two variables are closely linked with 74.8 percent (175 participants) of married participants living in households with three or more residents. Among the unmarried, 79.2 percent (141 participants) lived in one- or two-person households. Related to smaller household size and non-married status, those in one- or no-car households had higher exposures. The mean differences were significant for three of the weighted duration measures (100-meter, 500-meter, and half mile proximities) and for the count of FFRs at the 21-meter proximity. In the remaining measures the one- or no-car households had higher means, but these were not statistically significant.

Employed participants had higher mean exposures than non-employed participants for all exposure measures. Yet the mean differences were only significant for FFR counts at all four proximities and for weighted duration at the 500-meter proximity. The mean difference in FFR counts at all proximities were also statistically significant for commute distance. Those with no commutes had the smallest FFR counts and those with above median commutes had the highest counts. In contrast, the mean differences in duration and weighted duration were not significantly associated with commute distance.

As expected, participants living in above median residential densities had higher mean exposure durations. These relationships were significant at the 500-meter and half mile proximities.

FFR visitors by covariate

Visiting one or more FFRS was significantly associated with a number of variables. Visitors to FFRs were more likely to lack a college degree, be married, live in households with ≥ 3 people and ≥ 2 cars, have commute distances > the sample median, and have residential densities > sample median (**Table 3-4**).

Among the tertiles of duration both the 21- and 100-meter proximities were significantly associated with FFR visits. None of the tertiles of FFR count were significantly associated with FFR visits. Weighted duration at the 21- and 100-meter proximities was also significantly associated with FFR visits. Regardless of whether the association was significant, the percentages of participants who reported FFR visits increased as the tertiles of all measures of exposure increased (**Table 3-5**).

Models

Variables for the regression models were chosen based on theoretic importance and performance in the previous tables. To prevent multicollinearity marital status was not included in the models. Instead, because nearly 75 percent of married households lived in households of three or more household was included. It is also theoretically and empirically linked both to exposure and FFR visitation (41 percent of those in households of three or more reported FFR visits compared to 31 percent of those in households of just one or two). Families with children are more likely to visit FFRs.

Similarly, although both commute distance and employment status were significantly associated with exposure, only commute distance was included in the models because only 17.3 percent of the employed participants had no commute. Further, commuting was significantly associated with FFR visits, while there was no such relationship based on employment status. The number of cars in the household is both a measure of household wealth and mobility. It was also associated with both exposure and FFR visits. For these reasons it was also included in the models. Because high density areas place people in closer contact with a wide range of services, participants living in high density areas are more likely to live near more FFRs. Therefore, residential density was included in the models to control for differences in exposure due to home location.

The odds of reporting one or more FFR visits were significantly and positively associated with the duration of exposure at all proximities (**Table 3-6**). At the 21-meter and half-mile proximities both Tertiles 2 (8.8 to 39 seconds) and 3 (39 seconds to 12.9 minutes) were significantly associated with increased odds of visiting an FFR. At the 100- and 500-meter proximities only Tertile 3 (17 to 190 minutes at 100 meters and 182 to 545 minutes at 500 meters) was significantly associated with FFR visitation. In all four models the odds for Tertile 3 were larger than the odds for Tertile 2.

For each of the four proximities, the odds of FFR visits were not significantly associated with the FFR count. For weighted duration, Tertile 3 was significantly associated with increased odds of FFR visits at both the 21-meter and 100-meter proximities. Those who spent between 41 seconds to 12.9 minutes per day within 21-meters of an FFR were 2.69 times (95%CI 1.53 to 4.73) more likely to report one or more FFR visits compared to those who spent 9.3 seconds or less per day in proximity to an FFR. Spending between 626 to 4420 minutes a day within 100 meters of a FFR significantly increased the odds of visiting an FFR by 3.07 (95%CI 1.76 to 5.36) compared to those who spent between 7 to 349 minutes in proximity to an FFR. Tertiles of weighted duration of exposure were not significant at the 500-meter or half-mile proximities.

In eleven of the twelve models only two other variables were associated with increased odds: education and residential density. College educated participants had decreased odds of reporting FFR visits compared to those with some college education or less. Only for FFR count at the 100-meter proximity was there no significant association with education (p=0.053). Living above the median density of 1892 units within 800 meters was associated with decreased odds of reporting an FFR visit. The odds of an FFR visit ranged from a low of 0.47 for duration at 21 meters to 0.54 (shared by duration at 100 meters, FFR counts at 100 meters, and weighted duration at a half mile).

DISCUSSION

This is among the first studies to use objectively measured duration spent within different proximities of a food establishment, as a measure of food environment exposure. Until now, food environment exposure has typically been assessed based on counts or densities in a given proximity to home, or simply the distance from home to the closest food outlet. This study suggests that objectively measured duration of exposure over the course of daily life better predicts behavior (visiting FFRs) than proximity to the number of FFRs. Increases in the odds of visiting a FFR for each tertile of duration at each of the four proximities suggests a dose-response relationship in which longer durations are associated with increased odds.

The lack of association with counts of nearby FFRs suggests that different exposure measures do not capture the same construct. Simply passing by an FFR while en route to a location may not be sufficient to entice a visit, but passing by the same FFR every day on the way to or from work or other places may indeed increase the odds of a visit, with the associated odds of increasing the consumption of fast foods, or of being overweight and/or obese.[24,25] In contrast to other studies, we examined all non-home and non-work related exposures, including those along participants' objectively measured commute paths.

While presenting a more complete measurement of actual exposure by combining FFR counts and duration, the weighted duration did not seem to offer any predictive advantages over simple duration. This may be due to the lack of influence that FFR counts had in predicting visits. The tertile value ranges for duration and weighted duration at the 21- and 100-meter proximities were similar. These similarities may explain the significant associations between weighted duration and FFR visits at these proximities.

Despite not being significantly associated with the odds of FFR visits, there was a significant association between above-median commute distances and higher counts of FFRs (Table 1). The act of commuting presents more opportunities for FFR exposure. Similarly, those who were employed also had significantly higher mean FFR counts than those who were not employed. Yet because the exposure occurs during the commute, the duration and weighted duration of the exposures are limited by the speed of travel. The lack of significant mean differences in duration or weighted duration for these variables suggest that the commute-related exposures were so brief relative to other travel as to be inconsequential.

The consistent association between high residential density and decreased odds of visiting an FFR in our models is a phenomenon that may be related to self-selection. Self-selection refers to the idea that people's choices of residential neighborhood may moderate or mediate the expected causal relationships between built environment characteristics and behaviors.[17] Huang and colleagues[82] identified clusters of residences in King County in which residents had high or low BMIs. Low–BMI clusters were found in areas with higher residential densities than the high–BMI clusters. People with lower BMIs tended to live near each other in high density neighborhoods while, those with high BMIs tended to cluster together in low density neighborhoods. Likewise, our research found that obese people are more likely to visit FFRs (43.6 percent of FFR visitors were obese compared to 27.8 percent of those who did not visit FFRs, p=0.002) and more likely to live in low-density areas (38.4 percent of those living under the median density were obese compared to 28.6 percent of those who living above the median, p=0.047) (data not shown). It is notable that after controlling for these locational differences, there was still a significant association between time spent in proximity to FFRs and the odds of visiting an FFR.

Where people choose to live is not only associated with FFR visits and BMI but also with household characteristics, many of which may be associated with visiting FFRs. In the sample, 63 percent (130 participants) of those who live in areas below the median density live in households of three or more ($p < 0.001$). In comparison, only 39.8 percent of those who live above the median density live in households of three or more. Further, as mentioned earlier those living in households with three or more are also more likely to be married and have children under 18 years living with them. Based on these findings it is very possible that married couples with children prefer less dense environments and this preference might be a driver in the higher rate of fast food visitation by those who live in below median density neighborhoods.

One further consideration in the relationship between residential density and FFR exposure is that differences in exposure based on density may be due either to exposures within the 800-meter area surrounding participants' homes (in which the density variable was measured) or due to participant mobility patterns. Participants may be more likely to travel to areas with residential densities similar to their own; those who live in high density areas may primarily travel to other high density areas and therefore having higher exposures to FFRs, while those who live in low density environments experience the opposite.

One of the goals of this study was to compare the different proximities to FFRs; however no solid conclusions can be drawn from the logistic regression results. Duration of exposure was significantly associated with FFR visitation at all four proximities and the count of FFRs was not significant at any of the proximities. Further, weighted duration was only significant at the 21- and 100-meter proximities, most likely due to the similarity between duration and weighted duration at these proximities. At the higher proximities, both the durations and counts greatly increased resulting in weighted duration values that were much larger than duration values for each tertile.

Limitations

We relied on self-reported data to control for spatial mobility bias. Visual inspection of GPS traces has found instances in which participants appeared to be visiting FFRs, yet these visits were not reported in the travel log. Instances in which the GPS points, overlaid on top of satellite imagery, show a trajectory from street or sidewalk to the FFR's building or drive-through window and then back to the street or sidewalk, were considered indicative of a visit. The most effective and accurate way to assess the actual number of FFR visits would be to visually review each participant's daily set of GPS traces. However, the brevity of some FFR visits (visits under three minutes in duration would be represented by a minimum of six GPS points even under favorable sensing conditions) could make it difficult to determine if an individual was just passing by an FFR, if they stepped inside briefly, or used the drive through service (in 2013 McDonalds was estimated to have a drive-thru speed time of 189.5 seconds per customer[83]). Therefore the actual number of FFR visits may be higher than the self-reported number.

Conversely we only able to identify GPS data for 71.7% of reported visits to FFRs in King County. To determine if our results were driven by FFR visits that were reported in the travel diary but not matched to GPS data, we repeated the analyses excluding the 32 participants whose visits were not GPS–matched. The results did not change substantially with all of the same exposure variables retaining significance in the models with the exception of the odds of Tertile 3 duration at 500 meters (odds=1.77, 95%CI 0.98–3.18). Given the advantages of larger sample sizes we opted to keep the 32 participants in the sample.

With the goal of introducing a new measure of exposure, this research did not consider the role other food outlets may play in whether one goes to an FFR. It is quite possible that the reason people in lower residential densities are more likely to report eating at an FFR is due to a more limited set of restaurant options. Further research should be done to investigate this possibility.

This study also relied on cross-sectional data gathered during the course of one week per each participant. While additional week-long measurements for each participant taken at monthly or yearly time intervals could help establish a causal relationship between FFR visitation and exposure, it may also be important to consider other measurement time frames. Matthews and Yang[19] speculate on the value of measurement periods lasting up to a month. Conversely, the seven days of data for each participant could be treated as longitudinal data. Visits to an FFR could be predicted using the exposure that precedes the visits. In this study we chose to average measures across days per participant for ease of interpretation. However other treatments of the data, for example with analysis explicitly incorporating temporal lags, may have higher predictive ability.

This study was unable to identify a proximity that was more effective in predicting FFR visitation than the others. Future studies could compare the drivers of fast food visits by exposure at different proximities to determine if specific drivers are associated with smaller or larger proximities. For example, hunger may be a stronger visit-determining factor with smaller buffers. If one is more likely to eat fast food when hungry, smaller exposure proximities may be more effective at predicting FFR visits than larger proximities, due to one's desire to sate their hunger as quickly as possible. Taste and cost may be more associated with higher exposures as both require knowledge about what specific FFRs offer and their locations relative to the individual.

CONCLUSIONS

This study introduces objectively measured duration and weighted duration of time spent in proximity to FFRs as two measures that are new to the study of exposure to the built environment. Applied to daily individual mobility patterns, the measures perform better at predicting FFR visitation than count-based measures of exposure used previously. Further, we were unable to identify a proximity measure that performed better than any other at predicting FFR visitation. Spending time within anywhere from 21 meters to a half mile of one or more FFRs can increase the odds of visiting a FFR.

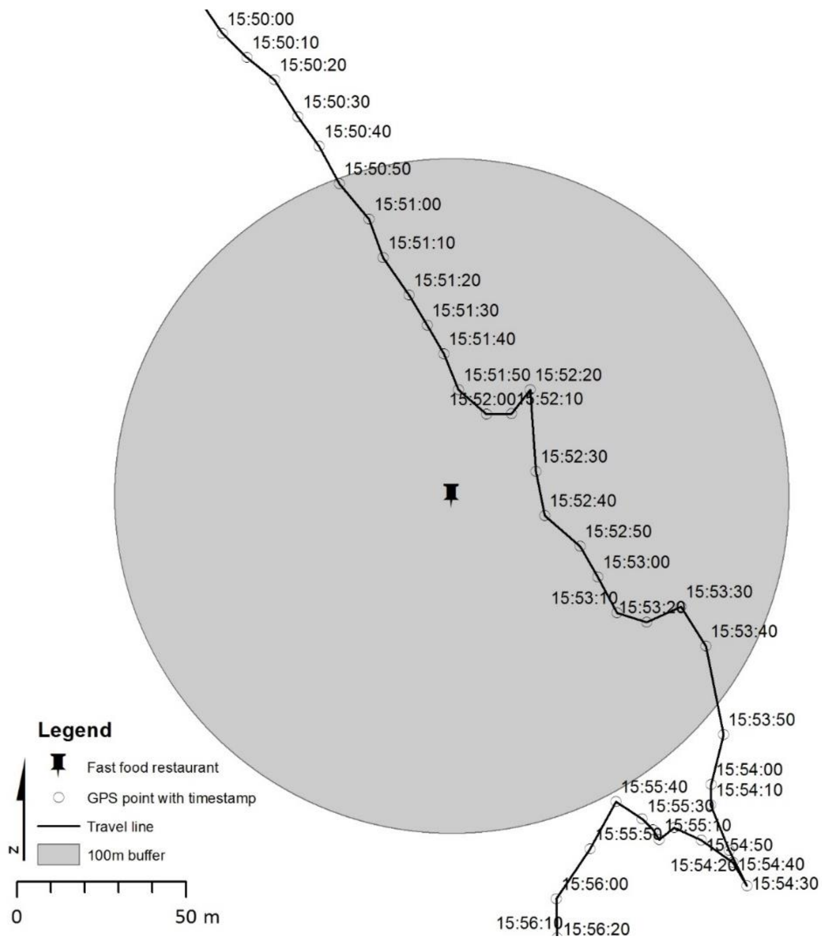

Figure 3-1: GPS points are sequentially connected by time of measurement and each FFR is buffered

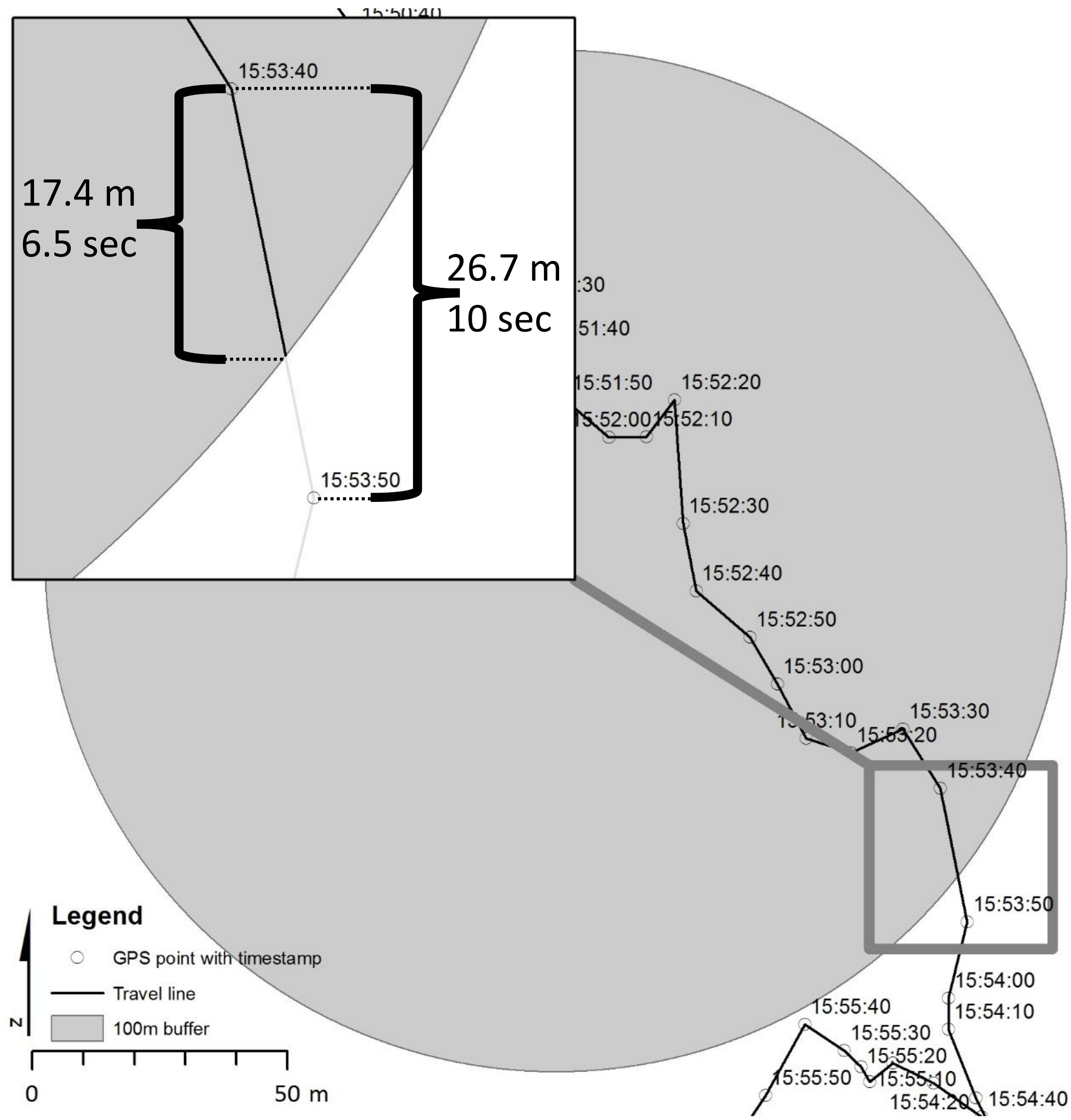

Figure 3-2: Estimating duration of exposure

Duration of exposure is estimated by summing the time intervals between GPS points inside buffers. Where line segments cross the buffer, the time interval of the portion of the line segment inside the buffer is estimated using the complete time interval (10 seconds) and the complete length of the segment (26.7 meters) as well as the length of the partial segment (17.4 meters). Partial time interval = complete segment time interval * partial segment length / complete segment length.

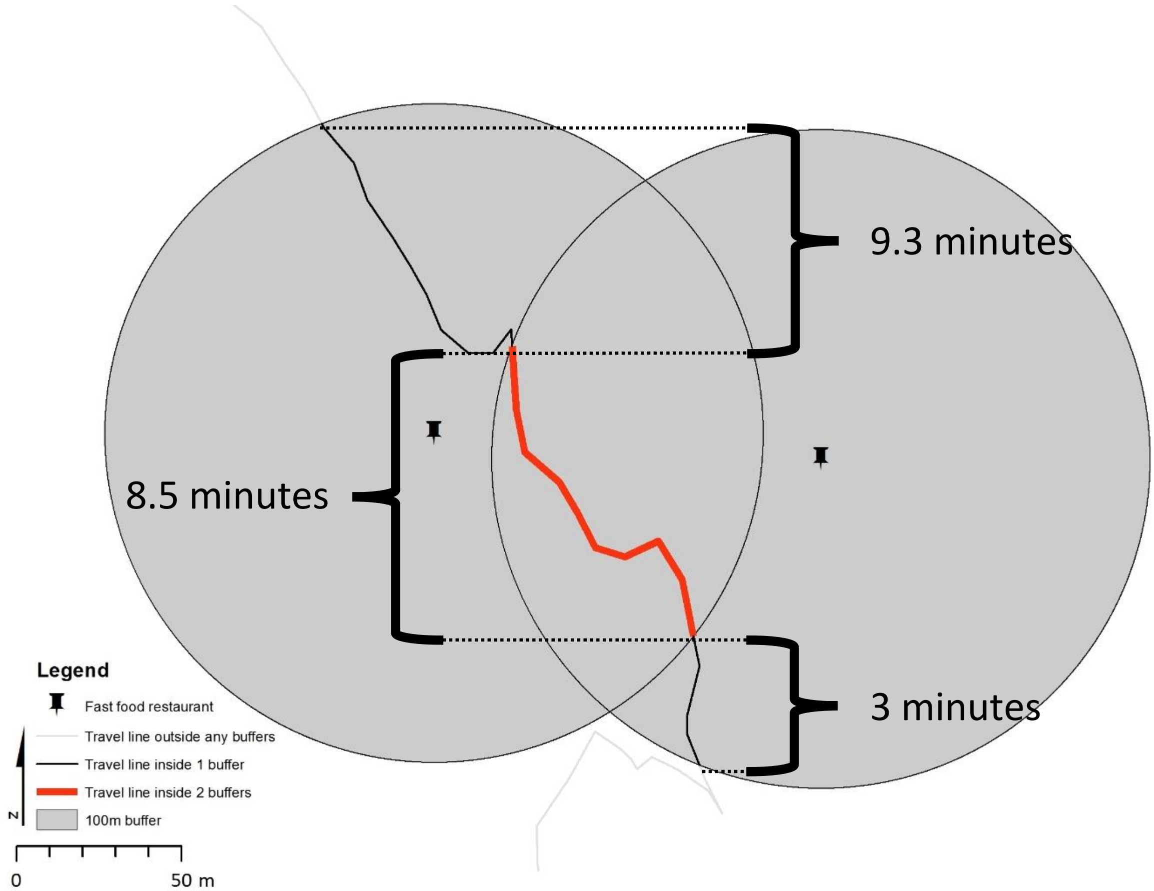

Figure 3-3: Estimating duration when two buffers overlap

When the buffers of two or more FFRs overlap, the duration is computed as the total time spent in one or more FFR buffers (9.3 minutes + 8.5 minutes + 3.0 minutes). The weighted duration weights the amount of time spent in multiple buffers by the number of overlapping buffers (9.3 minutes + (2 buffers * 8.5 minutes) + 3.0 minutes)

Table 3-1: Descriptive characteristics of duration of FFR exposure

		Duration in minutes[a] mean (SD)			
	N (%)	**21 meters**	**100 meters**	**500 meters**	**Half mile**
Total	412 (100)	0.99 (1.84)	17.04 (16.62)	84.8 (56.71)	117.73 (69.21)
Age					
< 45	157 (38.11)	1.03 (1.97)	**19.25 (20.96)**	89.84 (64.29)	123.75 (74.19)
≥ 45	255 (61.89)	0.97 (1.77)	**15.68 (13.13)**	81.7 (51.38)	114.03 (65.83)
Gender					
Female	293 (71.12)	0.98 (1.89)	16.37 (14)	83.54 (55.39)	116.38 (67.82)
Male	119 (28.88)	1.02 (1.74)	18.68 (21.77)	87.92 (59.96)	121.06 (72.71)
Race					
White	327 (79.37)	0.94 (1.87)	16.78 (17.28)	**81.26 (50.89)**	**113.69 (65.15)**
Non-white	85 (20.63)	1.2 (1.76)	18.04 (13.85)	**98.43 (73.8)**	**133.27 (81.6)**
Education					
Some college or less	157 (38.11)	0.87 (1.46)	**14.67 (11.48)**	**76.9 (53.11)**	**106.36 (64.81)**
College graduate	255 (61.89)	1.07 (2.04)	**18.5 (18.99)**	**89.67 (58.39)**	**124.73 (71.01)**
Income					
<$50K	118 (28.64)	0.95 (1.7)	16.39 (13.54)	84.78 (48.85)	117.56 (63.18)
$50K-$100K	151 (36.65)	1.14 (2.18)	17.7 (15.24)	86.1 (70.35)	118.15 (82.35)
≥ $100K	143 (34.71)	0.88 (1.55)	16.89 (20.06)	83.45 (45.95)	117.44 (58.41)
Employment status					
Employed	301 (73.06)	1.04 (1.88)	17.68 (17.27)	86.55 (56.27)	119.53 (69.36)
Not employed	111 (26.94)	0.86 (1.73)	15.3 (14.67)	80.07 (57.88)	112.85 (68.89)
Household size					
< 3 people	200 (48.54)	**1.19 (2.14)**	**19.63 (20.44)**	89.15 (65.11)	120.38 (75.81)
≥ 3 people	212 (51.46)	**0.81 (1.49)**	**14.59 (11.49)**	80.7 (47.24)	115.23 (62.43)
Marital status					
Married	234 (56.8)	0.84 (1.69)	**15.13 (11.97)**	**78.88 (48.47)**	**110.32 (60.76)**
Not married	178 (43.2)	1.2 (2.02)	**19.55 (21.03)**	**92.59 (65.33)**	**127.48 (78.06)**
Property value					
$38K – < $227K	136 (33.01)	0.91 (1.53)	17.88 (20.1)	88.43 (64.71)	118.42 (75.47)
≥ $227K – < $323K	137 (33.25)	1.23 (2.17)	17.39 (15.88)	84.01 (58.59)	115.19 (72.18)
≥ $323K	139 (33.74)	0.84 (1.77)	15.88 (13.31)	82.04 (45.57)	119.57 (59.57)
Cars in household					
< 2 cars	153 (37.14)	1.02 (1.63)	18.6 (14.7)	87.72 (61.5)	120.12 (73.38)
≥ 2 cars	259 (62.86)	0.98 (1.96)	16.12 (17.62)	83.08 (53.73)	116.33 (66.73)
Commute distance					
No commute	138 (33.50)	0.81 (1.51)	16.49 (14.59)	82.36 (53)	114.06 (62.09)
< median distance	137 (33.25)	1.02 (2.12)	16.2 (15.17)	83.82 (66.17)	120.98 (83.64)
> median distance	137 (33.25)	1.15 (1.86)	18.43 (19.69)	88.25 (49.91)	118.18 (59.77)
Residential density					

< median density	206 (50.00)	0.98 (1.84)	15.74 (12.39)	**78.86 (46.68)**	**107.37 (58.31)**
> median density	206 (50.00)	1 (1.86)	18.34 (19.93)	**90.75 (64.79)**	**128.1 (77.38)**

[a] Bold values indicate significant difference between means ($p < 0.05$).

Table 3-2: Descriptive characteristics of FFR counts

		Count of FFRs[a] mean (SD)			
	N (%)	**21 meters**	**100 meters**	**500 meters**	**Half mile**
Total	412 (100)	1.49 (1.08)	8.14 (4.45)	24.34 (13.16)	34.1 (18.88)
Age					
< 45	157 (38.11)	1.49 (1.08)	7.73 (4.03)	24.59 (13.11)	35.1 (19.56)
≥ 45	255 (61.89)	1.49 (1.07)	8.38 (4.69)	24.19 (13.21)	33.48 (18.46)
Gender					
Female	293 (71.12)	1.44 (1.01)	8 (4.15)	23.97 (12.66)	33.57 (18.49)
Male	119 (28.88)	1.61 (1.23)	8.47 (5.12)	25.26 (14.32)	35.38 (19.83)
Race					
White	327 (79.37)	1.48 (1.12)	8.03 (4.44)	23.85 (13.07)	33.39 (18.6)
Non-white	85 (20.63)	1.52 (0.91)	8.55 (4.5)	26.25 (13.41)	36.84 (19.81)
Education					
Some college or less	157 (38.11)	1.36 (0.96)	8.45 (4.87)	23.64 (13.99)	32.48 (20.04)
College graduate	255 (61.89)	1.57 (1.13)	7.94 (4.18)	24.77 (12.63)	35.09 (18.1)
Income					
<$50K	118 (28.64)	1.57 (1.22)	7.84 (4.36)	22.28 (13.48)	30.8 (19.59)
$50K-$100K	151 (36.65)	1.52 (1.04)	8.42 (4.9)	25.18 (14.05)	35.47 (19.54)
≥ $100K	143 (34.71)	1.4 (0.98)	8.09 (4.03)	25.15 (11.75)	35.36 (17.31)
Employment status					
Employed	301 (73.06)	**1.57 (1.12)**	**8.58 (4.48)**	**26.29 (13.58)**	**36.85 (19.32)**
Not employed	111 (26.94)	**1.28 (0.92)**	**6.92 (4.17)**	**19.04 (10.26)**	**26.62 (15.39)**
Household size					
< 3 people	200 (48.54)	**1.69 (1.22)**	8.49 (4.73)	**26.12 (14.74)**	**36.59 (20.99)**
≥ 3 people	212 (51.46)	**1.3 (0.88)**	7.8 (4.16)	**22.67 (11.25)**	**31.75 (16.36)**
Marital status					
Married	234 (56.8)	**1.3 (0.9)**	**7.67 (4.17)**	**22.73 (11.63)**	**31.86 (17.08)**
Not married	178 (43.2)	**1.73 (1.23)**	**8.74 (4.75)**	**26.46 (14.69)**	**37.03 (20.7)**
Property value					
$38K – < $227K	136 (33.01)	1.5 (1.01)	**7.91 (4.15)**	23.97 (14.05)	33.43 (20.58)
≥ $227K – < $323K	137 (33.25)	1.59 (1.08)	**9.07 (5.25)**	25.82 (13.93)	36.14 (19.69)
≥ $323K	139 (33.74)	1.38 (1.13)	**7.43 (3.69)**	23.25 (11.31)	32.73 (16.08)
Cars in household					
< 2 cars	153 (37.14)	**1.7 (1.18)**	8.22 (4.37)	24.8 (13.52)	34.82 (19.15)
≥ 2 cars	259 (62.86)	**1.36 (0.99)**	8.09 (4.51)	24.07 (12.96)	33.67 (18.74)
Commute distance					
No commute	138 (33.5)	**1.22 (0.84)**	**6.79 (4.06)**	**19.07 (10.14)**	**26.39 (14.48)**
< median distance	137 (33.25)	**1.51 (1.13)**	**7.61 (4.31)**	**21.88 (12.41)**	**31.06 (17.38)**
> median distance	137 (33.25)	**1.73 (1.17)**	**10.01 (4.37)**	**32.11 (13.06)**	**44.9 (19.41)**
Residential density					

< median density	206 (50)	**1.21 (0.87)**	8.37 (4.48)	24.19 (13.09)	32.91 (18.85)
> median density	206 (50)	**1.76 (1.19)**	7.9 (4.43)	24.49 (13.26)	35.28 (18.88)

[a] Bold values indicate significant difference between means ($p < 0.05$).

Table 3-3: Descriptive characteristics of weighted duration of exposure

	N (%)	Weighted duration in minutes[a] mean (SD) 21 meters	100 meters	500 meters	Half mile
Total	412 (100)	1.03 (1.87)	22.69 (21.96)	297.11 (247.36)	607.63 (526.94)
Age					
< 45	157 (38.11)	1.06 (1.98)	25.06 (26.5)	323.71 (272.05)	**674.52 (625.95)**
≥ 45	255 (61.89)	1.01 (1.81)	21.24 (18.53)	280.73 (229.87)	**566.45 (451.87)**
Gender					
Female	293 (71.12)	1.03 (1.93)	21.93 (20.37)	287.58 (238.7)	589.7 (529.98)
Male	119 (28.88)	1.04 (1.75)	24.56 (25.47)	320.58 (267.08)	651.76 (518.94)
Race					
White	327 (79.37)	0.98 (1.90)	21.87 (21.41)	**283.64 (225.4)**	591.86 (522)
Not white	85 (20.63)	1.24 (1.77)	25.85 (23.82)	**348.95 (314.27)**	668.29 (544.4)
Education					
Some college or less	157 (38.11)	0.92 (1.52)	20.59 (19.64)	266.56 (196.38)	**527.62 (388.32)**
College graduate	255 (61.89)	1.1 (2.06)	23.98 (23.22)	315.92 (272.74)	**656.89 (591.85)**
Income					
<$50K	118 (28.64)	0.97 (1.71)	23.36 (22.9)	302.1 (222.96)	619.08 (516.84)
$50K-$100K	151 (36.65)	1.18 (2.22)	23.5 (20.95)	296.42 (275.68)	607.91 (588.5)
≥ $100K	143 (34.71)	0.93 (1.59)	21.29 (22.3)	293.72 (236.25)	597.88 (466.38)
Employment status					
Employed	301 (73.06)	1.09 (1.92)	23.68 (22.42)	**313.79 (267.63)**	633.7 (533.95)
Not employed	111 (26.94)	0.87 (1.75)	20.02 (20.53)	**251.87 (174.46)**	536.92 (502.98)
Household size					
< 3 people	200 (48.54)	**1.23 (2.17)**	**26.45 (26.72)**	**336.97 (300.73)**	**709.38 (664.47)**
≥ 3 people	212 (51.46)	**0.85 (1.53)**	**19.15 (15.5)**	**259.5 (175.95)**	**511.64 (324.61)**
Marital status					
Married	234 (56.80)	0.88 (1.72)	**19.97 (16.81)**	**261.33 (177.86)**	**527.35 (412.23)**
Not married	178 (43.20)	1.23 (2.05)	**26.27 (26.93)**	**344.15 (310.66)**	**713.16 (633.5)**
Property value					
$38K – < $227K	136 (33.01)	0.97 (1.61)	24.13 (24.65)	326.13 (272.96)	670.01 (609.81)
≥ $227K – < $323K	137 (33.25)	1.27 (2.17)	23.25 (22.05)	286.21 (203.97)	584.3 (485.06)
≥ $323K	139 (33.74)	0.86 (1.78)	20.74 (18.89)	279.46 (258.98)	569.59 (474.84)
Cars in household					
< 2 cars	153 (37.14)	1.06 (1.68)	**25.51 (22.6)**	**331.76 (302.37)**	**684.72 (624.45)**
≥ 2 cars	259 (62.86)	1.02 (1.99)	**21.03 (21.45)**	**276.64 (206.09)**	**562.09 (454.96)**
Commute distance					

No commute	138 (33.50)	0.85 (1.53)	21.11 (17.85)	269.87 (240.51)	536.25 (436.35)
< median distance	137 (33.25)	1.03 (2.13)	21.66 (22.41)	284 (246.57)	630.98 (596.13)
> median distance	137 (33.25)	1.22 (1.91)	25.32 (24.98)	337.65 (251.51)	656.18 (532.78)
Residential density					
< median density	206 (50.0)	1.03 (1.88)	21.02 (17.84)	279.2 (193.79)	**533.98 (347.74)**
> median density	206 (50.0)	1.03 (1.87)	24.36 (25.36)	315.02 (290.63)	**681.28 (651.81)**

[a] Bold values indicate significant difference between means ($p < 0.05$).

Table 3-4: Descriptive characteristics of FFR visitors and non-visitors

	N (%)	No reported visits n (%)	Visit FF at least once a week n (%)	p-value[a]
Total	412 (100)	263 (63.8)	149 (36.2)	
Age				0.432
Younger than 45	157 (38.1)	96 (61.1)	61 (38.9)	
45 and older	255 (61.9)	167 (65.5)	88 (34.5)	
Gender				0.728
Female	293 (71.1)	185 (63.1)	108 (36.9)	
Male	119 (28.9)	78 (65.5)	41 (34.5)	
Race				0.999
White Non-Hispanic	327 (79.4)	209 (63.9)	118 (36.1)	
Non-White	85 (20.6)	54 (63.5)	31 (36.5)	
Education				0.007
Some college or less	157 (38.1)	87 (55.4)	70 (44.6)	
College graduate	255 (61.9)	176 (69.0)	79 (31.0)	
Income				0.874
<$50k	118 (28.6)	76 (64.4)	42 (35.6)	
$50k – > $100k	151 (36.7)	94 (62.3)	57 (37.7)	
≥ $100K	143 (34.7)	93 (65.0)	50 (35.0)	
Employment status				0.754
Employed	301 (73.1)	194 (64.5)	107 (35.5)	
Not employed	111 (26.9)	69 (62.2)	42 (37.8)	
Household size				0.044
One or two in HH	200 (48.5)	138 (69.0)	62 (31.0)	
Three or more in HH	212 (51.5)	125 (59.0)	87 (41.0)	
Marital status				0.041
Married	234 (56.8)	139 (59.4)	95 (40.6)	
Not married	178 (43.2)	124 (69.7)	54 (30.3)	
Property value				0.704
$38K – < $227K	136 (33.0)	90 (66.2)	46 (33.8)	
≥ $227K – < $323K	137 (33.3)	84 (61.3)	53 (38.7)	
≥ $323K	139 (33.7)	89 (64.0)	50 (36.0)	
# of cars in HH				0.022
< 2 cars	153 (37.1)	109 (71.2)	44 (28.8)	
≥ 2 cars	259 (62.9)	154 (59.5)	105 (40.5)	
Commute distance				0.005
No commute	138 (33.5)	87 (63.0)	51 (37.0)	
< median	137 (33.3)	101 (73.7)	36 (26.3)	
> median	137 (33.3)	75 (54.7)	62 (45.3)	
Residential density				< 0.001
< median density	206 (50.0)	111 (53.9)	95 (46.1)	
> median density	206 (50.0)	152 (73.8)	54 (26.2)	

[a] Derived from chi-square analysis.

Table 3-5: Descriptive characteristics of FFR visitors and non-visitors by FFR exposure measures

	N	No reported visits n	Visit FF at least once a week n	p-value[a]
Duration of exposure in minutes				
21 meters				
0-0.148	136	99 (37.6)	37 (24.8)	0.009
0.148-0.649	136	87 (33.1)	49 (32.9)	
0.649-12.9	140	77 (29.3)	63 (42.3)	
100 meters				
0-8.96	136	100 (38.0)	36 (24.2)	0.001
8.96-17.1	136	91 (34.6)	45 (30.2)	
17.1-190	140	72 (27.4)	68 (45.6)	
500 meters				
0-57.1	136	92 (35.0)	44 (29.5)	0.188
57.1-92.2	136	90 (34.2)	46 (30.9)	
92.2-500	140	81 (30.8)	59 (39.6)	
800 meters				
6.99-81.3	136	97 (36.9)	39 (26.2)	0.085
81.3-128	136	82 (31.2)	54 (36.2)	
128-545	140	84 (31.9)	56 (37.6)	
FFR count				
21 meters				
0-0.857	123	80 (30.4)	43 (28.9)	0.934
0.857-1.71	140	88 (33.5)	52 (34.9)	
1.71-8	149	95 (36.1)	54 (36.2)	
100 meters				
0-5.82	136	95 (36.1)	41 (27.5)	0.076
5.82-9.14	137	89 (33.8)	48 (32.2)	
9.14-27.2	139	79 (30.0)	60 (40.3)	
500 meters				
0-17	139	95 (36.1)	44 (29.5)	0.380
17-28.4	133	83 (31.6)	50 (33.6)	
28.4-78.6	140	85 (32.3)	55 (36.9)	
800 meters				
1 to 23	138	91 (34.6)	47 (31.5)	0.385
23-40.5	134	89 (33.8)	45 (30.2)	
40.5-115	140	83 (31.6)	57 (38.3)	
Weighted duration in minutes				
21 meters				
0-0.155	136	97 (36.9)	39 (26.2)	0.006
0.155-0.678	136	91 (34.6)	45 (30.2)	
0.678-12.9	140	75 (28.5)	65 (43.6)	
100 meters				
0-11.4	136	101 (38.4)	35 (23.5)	0.001
11.4-23.1	136	89 (33.8)	47 (31.5)	

23.1-194	140	73 (27.8)	67 (45.0)	
500 meters				
0-179	136	93 (35.4)	43 (28.9)	0.290
179-302	136	87 (33.1)	49 (32.9)	
302-1920	140	83 (31.6)	57 (38.3)	
800 meters				
6.99-349	136	91 (34.6)	45 (30.2)	0.424
349-626	136	81 (30.8)	55 (36.9)	
626-4420	140	91 (34.6)	49 (32.9)	

[a] Derived from chi^2 analysis.

Table 3-6: Logistic regression using robust standard errors to predict the odds of one or more FFR visits by exposure

	21 meters			100 meters			500 meters			Half mile		
	Odds	**95% CI**	**p-value**	**Odds**	**95% CI**	**p-value**	**Odds**	**95% CI**	**p-value**	**Odds**	**95% CI**	**p-value**
Tertiles of duration[a]												
Tertile 1	Ref			Ref			Ref			Ref		
Tertile 2	2.06	1.17-3.65	0.011	1.24	0.7-2.18	0.456	1.06	0.61-1.83	0.844	1.93	1.1-3.39	0.021
Tertile 3	2.8	1.58-4.96	0.000	2.89	1.65-5.07	0.000	1.72	1-2.94	0.046	2.16	1.22-3.83	0.008
Tertiles of counts[a]												
Tertile 1	Ref			Ref			Ref			Ref		
Tertile 2	1.26	0.73-2.18	0.408	1.16	0.66-2.04	0.601	1.32	0.76-2.3	0.323	1.06	0.6-1.86	0.849
Tertile 3	1.41	0.8-2.47	0.229	1.68	0.96-2.93	0.066	1.38	0.76-2.51	0.289	1.49	0.83-2.68	0.175
Tertiles of weighted duration of duration[a]												
Tertile 1	Ref			Ref			Ref			Ref		
Tertile 2	1.62	0.92-2.85	0.092	1.4	0.79-2.47	0.248	1.15	0.67-1.99	0.606	1.25	0.72-2.17	0.423
Tertile 3	2.69	1.53-4.73	0.001	3.07	1.76-5.36	0.000	1.47	0.86-2.52	0.158	1.15	0.67-1.99	0.600

[a] Adjusted for age, gender, race, education, income, number of cars in household, household size, commute distance, and residential density.

Chapter 4 : OBJECTIVE MEASURES OF EXPOSURE TO WEALTH

ABSTRACT

Background: Living in impoverished neighborhoods is associated with a wide range of negative health outcomes. Yet, people do not spend all their time in their neighborhoods.

Objectives: To measure exposure to wealth as the aggregated residential property value of participants' activity spaces beyond the home neighborhood using GPS records.

Methods: The Seattle Obesity Study II (SOS2) included 390 residents living within the urban growth boundary of King County, Washington, who were recruited using an address-based sampling method. Participants wore GPS receivers that recorded their locations at intervals of 30 seconds over 7 consecutive days and completed a computer-assisted questionnaire. Using GIS, parcel-level residential property values (land + improvements) from King County tax assessor data were smoothed into a continuous surface that comprised 30-by-30-foot cells, each measuring the mean residential property value per unit within 833m of cell centroids. For each participant, the property value of the location of each GPS record was then obtained. Three measures of wealth exposure were then created. Exposed wealth was created by averaging the GPS-obtained property values over the course of a day and then averaging across days. Exposed difference was the participant exposed wealth minus home neighborhood wealth, the property value per residential unit within 833m of participants' homes. The percentage of time spent in areas with the population above-median exposed wealth values was also calculated.

Results: Being white, college-educated, living in a household with < 2 cars, and being non-obese were associated significantly higher mean exposed wealth values. Exposed wealth was associated with a decreased odds of being obese (OR=0.62, 95%CI 0.39–1, p=0.046) after controlling for neighborhood wealth, SES, and demographics. Neither percent of time nor exposed difference were significantly associated with the odds of being obese after controlling for SES and demographics.

Conclusions: The amount of wealth to which one is exposed is associated with SES and demographics. Exposed wealth is also associated with a decrease in the odds of being obese.

BACKGROUND

Neighborhood effects on health are now widely documented. A growing body of literature has found that the residents of disadvantaged neighborhoods are more likely to suffer from a wide range of negative health outcomes[7] including obesity[8,9], poor mental health[10], and heart disease.[11,12].

Explanations for this relationship can be split into two categories: contextual and compositional.[16] Compositional explanations are based on the idea that the spatial clustering of individuals with shared characteristics is responsible for neighborhood effects on health. People of similar socioeconomic and demographic characteristics may choose or be forced to live in the same or similar neighborhoods. Therefore it may be the characteristics of the neighborhood's residents that are associated with a health outcome, not the physical characteristics of the neighborhood. Segregation and self-selection of residential location may be driving factors in compositional explanations.[17]

Contextual explanations are based on the features and characteristics of the neighborhood itself, such as the presence of fast food restaurants or sidewalks. The neighborhood composition may also include the social environment. Social capital, social networks, and social norms in the neighborhood may exert a strong influence on both positive and negative health outcomes.[84,85] Further, health-promoting resources are unevenly distributed among neighborhoods, with socioeconomically disadvantaged neighborhoods having fewer health-promoting resources.[86]

Bernard and colleagues (2007) suggest that access to neighborhood resources is determined by the following: the proximity of residents to resources; the social and civic rights of the society in which the neighborhood is located; the pricing mechanisms of resources in the neighborhood (pricing also affects whether or not a resource may locate in the neighborhood); and the level and type of informal reciprocity within the neighborhood's social networks. Others have similarly argued that the health of neighborhood residents is impacted at the individual level by social networks and social interactions[11,87] and at the group level by social capital or collective efficacy—the ability of multiple residents to advocate on behalf of the neighborhood.[88,89]

Often referred to as the local trap[18], the residential trap[11], spatial uncertainty[90], or spatial polygamy[19], one of the main criticisms of the neighborhood effects literature is that people frequently leave their home neighborhoods. It is reasonable to assume that the ability to leave one's home neighborhood and the places one goes on those trips also impact health outcomes. To date the research seems to bear this assumption.[25,26,81,91,92] Central to research on spatial mobility is the concept of the home range or activity space, which is defined by Golledge and Stimson[21] as "…the subset of all locations with which an individual has direct contact as a result of his day-to-day activities".

Considered by many to include both spatial and temporal elements, activity space has been observed and measured using a number of techniques.[29,30] Subjective measures of activity space are based on self-reported locations of activities performed outside the house[31,91,93] while objective measures rely on global positioning systems (GPS) data.[26,27,81]. In linking mobility an activity space to the relationship between inequality and health, Shareck and colleagues[29] identify two dimensions of mobility patterns that reflect the different the activity space metrics: “(1) the extent to which one is mobile; and (2) the characteristics of places and resources experienced during daily travels.”

Metrics of activity spaces are quite varied but are based on the size and geometry of the modeled activity space (e.g. minimum convex polygons, standard deviational ellipses, kernel density estimations, and daily path areas) as well as the built environment features and characteristics within the activity space (e.g., counts of supermarkets within activity space).[29–31] Different activity space metrics, therefore, can measure a range of mobility patterns including how far individuals travel, the places they travel to, the characteristics of those places, and the places within the modeled activity space that they did not visit.

Within Shareck et al.’s framework, one’s mobility potential is the factor that links inequality to differential health outcomes in built environment studies. A way of conceptualizing what is geographically accessible, mobility potential represents the degree to which an individual can move through space and time. This potential varies by socioeconomic factors with studies finding that disadvantaged individuals travel shorter distances[10], that unemployed people and part-time employees travel less than full time employees[10,26,94], and that those with less education are less mobile in general.[10,21] Yet high mobility potential does not necessarily translate into longer distances traveled. Individuals with higher levels of mobility potential may not need to travel much if all the resources they need are within a short distance of their homes. In contrast, individuals with lower mobility potential may have limited resources within their limited range thereby resulting in negative health outcomes. Those from more disadvantaged groups with higher mobility potentials may have more opportunities for contextual exposure to health-promoting resources—including social networks or social capital—outside their home neighborhoods.

High mobility potential may, however, also be the result of high social capital (at the individual- and/or neighborhood-level) or informal patterns of reciprocity among residents inside the neighborhood or between residents and outsiders. It is also quite possible that high mobility potential may strengthen social capital or patterns of reciprocity by allowing individuals or groups more social contact with each other.

The same factors identified by Bernard and colleagues[86] that explain access to health-promoting resources within the neighborhood can therefore be applied to the entirety of an individual's activity space. Those with higher mobility potential are more likely to have their social and civic rights respected, more able to afford higher quality health care, and have a wider range of health-promoting options available.

As mentioned earlier, individuals with similar or shared characteristics may live in similar neighborhoods which, in turn, may contribute to compositional explanations for relationships between neighborhoods and health. It is also likely that those with shared characteristics may have similar levels of mobility potential which may lead to visiting similar places when they leave their home neighborhoods. Indeed this is what Shareck, Kestens, and Frohlich[95] reported in a study of young adults between the ages of 18 and 25. Participants' non-residential neighborhood activity locations were in areas with area-level deprivation index scores that were similar to the scores of their home neighborhoods. Further, there were significant differences in both residential and non-residential levels of deprivation by educational attainment level. Those with a high school education or less had the highest deprivation levels both at home and away, while university students and graduates had the lowest.

The study of mobility patterns therefore reconciles some of the differences between compositional and contextual effects. In place of this dichotomy, Cummins, Curtis, Diez-Roux & Macintyre[96] argue for a *relational* perspective in which the relationship between person and environment is reciprocal and contingent on the timing of activities and the spatial location of those activities. That is to say, an individual may choose to visit, live in, or be excluded from, certain environments based on a variety of socioeconomic and demographic traits. These same traits may also be associated with the mobility potential. Both the visited and residential environments shape the individual's behaviors and health outcomes, which may then cause the individual to seek out new environments or reinforce the decisions to continue living in or visiting specific places. The relational perspective therefore emphasizes the need for more research on exposures outside the home neighborhood.

Very little research has investigated the impact of exposures to disadvantage outside the residential neighborhood. To date research on the topic has confirmed the relationship between disadvantaged neighborhoods and diminished health outcomes.[10,22,93] These studies have also found evidence for independent effects on health from the nonresidential places people visited as well as the time spent in those places.[93]

Inagami and team[22] used self-reported data recording where respondents engaged in specific activities by census tract. They found that the individuals living in disadvantaged census tracts who traveled to more advantaged census tracts reported better health. Vallée et al.[10] used the same measures to predict the odds of being depressed and found similar results. Those living in disadvantaged neighborhoods but who traveled to more advantaged areas were less likely to be depressed than those who stayed in their disadvantaged neighborhoods. But they also found the reverse effect for those living in advantaged neighborhoods. Having activity locations in less advantaged neighborhoods than one's own increased the likelihood of being depressed.

Sharp and team[93] created a measure of exposure similar to the ones used by Inagami et al. and Vallée et al., except that these exposures were weighted by the estimated time spent at specific activity locations. When those from disadvantaged areas spent more time in more advantaged areas the odds of reporting fair or poor health increased. And for those from more advantaged neighborhoods, spending more time in disadvantaged areas was also associated with an increased likelihood of reporting fair/poor health. It is possible that short-term exposure to increased neighborhood advantage was associated with better health as suggested by Inagami et al. and Vallée et al. but longer term exposures may be actually become deleterious.

These conflicting findings suggest that more research is needed. To date, the studies investigating exposure to disadvantage within the activity space have relied on self-reported locations of key activities. The limited range of activities in these studies (work, worship, receiving medical care, grocery shopping, and 'other') may not accurately account for all time, and hence may not reflect the full extent of an individual's activity space. For example, informal social encounters such as spending time at a friend's house are not included unless the respondent considers that activity to be an 'other' activity.

These studies also do not take into account travel routes or the entire scope of mobility patterns. In addition, the studies use census tracts as their measure of neighborhoods. The limitations with using administrative boundaries such as census tracts in built environment research are well documented.[7,8,19,97,98] In general, administrative boundaries in research are susceptible to the modifiable areal unit problem.[13] Notably, there is the potential for unmeasured variation of exposure both within and between tracts. For example, an individual living at the edge of a census tract may be more influenced by the environmental characteristics of the adjacent tract than their own.

This study used GPS data to measure daily individual-level exposure to advantage/disadvantage within the entirety of an individual's non-home activity space. Instead of relying on census-based indices of disadvantage, which come with both scaling and interpretability issues, this study used residential property values to capture wealth within an 833-meter radius of each participant's location in 30-second intervals. This radius was chosen for its comparability to Moudon and team's neighborhood wealth measure and because it is the maximum distance one can walk in 10 minutes.[8]

Property value is a measure of wealth that is easily scalable from the individual level to the neighborhood level. It also presents an objective alternative to using self-reported income as a measure of wealth and socioeconomic status. Further, property values capture aspects of wealth that income does not, such as the wealth of retired people living on limited incomes. Finally, property values are also linked to health outcomes. Using Behavioral Risk Factor Surveillance System (BRFSS) data, Drewnowski, Rehm, and Solet found that the zip codes with the lowest property values had the highest obesity rates in King County.[99] In a similar study using parcel-level data, Moudon and team (found that the odds of a participant reporting fair or poor health decreased with an increase in "neighborhood wealth," the aggregated property values within an 833-m radius of the participant's home.[8] At the individual level, lower property values on participants' home parcels were also associated with increases in the odds of being obese.[52]

The socioeconomic gradient in obesity prevalence has been widely documented with numerous studies showing that people with lower levels of income and education are more likely to be obese.[100–104] Further, Huang and colleagues[82] found that obese people were spatially clustered in low-income neighborhoods in the King County, Washington, and Christakis and Fowler[105] found that having a sibling or friend who was obese at one time period increased the odds of becoming obese at a later time period. Based on these findings, individuals' activity spaces may expose them to the social environments and resources different from those in their home neighborhoods. Individuals who travel to areas with lower or higher property values may therefore be exposed to social environments that can facilitate or protect against factors that could result in increases in body mass index.

In this paper we introduce three novel activity-space-based measures of non-home wealth exposure that were used to predict the odds of being obese. These measures rely on objective, spatio-temporal data obtained via GPS that were paired with parcel-level, residential property values. We further compared these wealth exposure measures to Moudon and team's neighborhood wealth measure[8], the property value per residential unit within an 833-meter radius of participants' homes.

HYPOTHESES

> **H1:** Neighborhood wealth will be negatively associated with an increase in the odds of being obese.
>
> **H2:** The wealth exposure measures in non-home neighborhoods will also be negatively associated with increased odds of being obese.

H3: The addition of wealth exposure to a model predicting obesity by neighborhood wealth will increase the magnitude of the association between neighborhood wealth and obesity.

METHODS

Data for this study come from the Seattle Obesity Study II (SOSII), an NIH NIDDK-funded study exploring relationships between the built environment and health in King County, Washington. The sample frame was drawn from the approximately 450,000 residential tax parcels in the King County Urban Growth Boundary (UGB). Mandated by the state of Washington, the UGB is used to control real estate and infrastructure development, thus the vast majority of King County's population lives within the boundary. Identified using King County tax assessor data, residential property values for each parcel were weighted in three bands (<\$199k, >=\$200k to <\$299k, and >= \$300k) to ensure socioeconomic diversity. The property bands were chosen based on previous research.[8,52] Single-family and multifamily units were also identified to ensure that the sample was proportionate to the county distribution of 58% and 42%, respectively. The addresses from selected residential units on tax parcels were matched to telephone numbers by a commercial supplier. With a matching rate of 55 percent for single- and 40 percent for multi-family units, 25,460 addresses and telephone numbers were obtained after duplicate and incomplete records were removed.

The Battelle Memorial Institute Survey Research Group used the addresses to send out pre-notification postcards to potential participants. Eligibility was limited to English speakers over

18 without mobility issues and who were the primary food shoppers in their households. Battelle obtained verbal consent from 712 potential eligible participants whose contact information was then sent to SOS II research staff.

Data collection

The research team contacted potential participants by phone to set up in-person meetings with 516 (72.5%) potential eligible participants who agreed to enroll in the study. Participants were given the options of meeting at the University of Washington or at the location of their choice, including their homes. About 56 percent (291 participants) chose to meet at their homes. During the meeting, written consent was obtained, heights and weights were objectively measured, and a computer-aided questionnaire was administered by the research team. Participants were also informed on how to fill out a seven-day, place-based travel log, and how to wear and recharge the Global Positioning Systems (GPS) receiver during the same seven days.

The travel log required participants to report the names, addresses and the times they arrived and left each place they visited during the course of the day. During this same period participants were also asked to wear a GPS receiver (Qstarz BT-Q1000XT; Qstarz International Co., Ltd., Taipei, Taiwan) that would record the latitude and longitude at intervals of 30 seconds or less. All data collection procedures and measures were approved by the University of Washington Institutional Review Board. Participants with less than three consecutive days of travel log data or with noticeable errors in GPS data (e.g. if the GPS device did not register any movement during the observation period) were excluded from the sample.

Sample

The sample comprised SOS II participants who had both GPS and travel log data. For each participant, GPS data were selected for analysis if a record was collected between the start and end times of the seven-day travel log observation period. Participants under 21 years of age and those with less than 3 travel log days were removed from the sample. Participants with missing responses for any of the survey data were also removed from the sample. For each participant GPS points were measured at 30-second intervals. Based on recommendations from the literature, records were excluded from analysis if there were fewer than 3 satellites in view, the horizontal dilution of precision was > 5, and the point's speed was > 81 mph.[79,80]

Geocoding

ArcMap 10.2 (ESRI, Redlands, CA) was used to match participants' residential and primary workplaces addresses to a King County shapefile that represents each address in King County as a point corresponding to the centroid of the building associated with the address. Using a minimum match score of 100, 481 (93 percent) of the 516 eligible SOS II residential addresses were geocoded. The remaining addresses were geocoded manually using Google Maps to verify locations.

Dependent variable

Each participant's height without shoes was measured using a portable stadiometer and a portable scale was used to measure weight in street clothes, also without shoes. Body mass index (kg/m^2) was calculated and dichotomized by obesity status (obese, BMI >= 30; non-obese, BMI < 30).

Survey variables

Participants filled out a computer-assisted questionnaire asking questions on health behaviors and demographics including: gender, age (<45; ≥45), race/ethnicity (non-Hispanic white; non-white or Hispanic), completed college degree (y/n), annual household income (<\$50k; ≥\$50k–<\$100k; ≥\$100k), home ownership (y/n), employed (y/n), marital status (y/n), number of cars in household (≤1;>1), and household size (≤2; >2). Variables were chosen for analysis based on their associations with obesity and mobility potential.

Residential property values

Using methods and definitions adapted from Moudon and colleagues[8], five wealth measures were derived from the 2011 King County tax assessor data which comprises data on residential property values (land plus improvement value) at the parcel level. The wealth measures include: personal wealth, neighborhood wealth, exposed wealth, exposed difference (exposed wealth minus neighborhood wealth), and percent time exposed to wealth (percentage of time spent in areas with property values above the sample median exposed wealth value). **Personal wealth** was calculated by identifying the parcel associated with each participant's geocoded home location and dividing the parcel's residential property value by the number of residential units on the parcel.

Neighborhood wealth and three wealth exposure measures (exposed wealth, exposed difference, percent time exposed) described below were computed using a SmartMap[106] of parcel-level residential property values smoothed into a spatially continuous surface. This process converted a vector map of residential parcels into a raster map of 30x30 foot cells, each cell measuring the average property value per residential unit of all the cells within an 833-meter radius. The 833-m radius is considered the cell's neighborhood and represents the average property value per unit of all parcels within a ten-minute walk from the cell's centroid. The continuous surface covers the majority of land within the King County urban growth boundary. Cells that were located in water bodies were assigned a null value. On land, null values indicated neighborhoods without any residential units within 833 meters. These areas were mostly in industrial, commercial, agricultural, or forested lands.

Neighborhood wealth is the residential property value per unit within 833 meters of each participant's home, which was considered the home neighborhood. Neighborhood wealth values were obtained by identifying the summarized property values from the SmartMap cells in which participants' homes were located.

The three measures of wealth exposure were computed by overlaying participant GPS data on the residential property value SmartMap. **Exposed wealth** is the average daily residential property value per unit within 833 meters of a participant's GPS points. Points within the participant's home neighborhood were excluded to contrast exposed wealth with neighborhood wealth. Property values for each point were obtained using the SmartMap. Values were averaged by day and then averaged across days, as shown in Equation *1*.

$$Exposed\ Wealth_k = \frac{\sum_{j=1}^{J} \frac{\sum_{i=1}^{n_j} PV_{ij}}{n_j}}{J} \quad (1)$$

Where:

J = number of days
n_j = number of points of j^{th} day
k = k^{th} participant
PV = residential property value of the i^{th} point on the j^{th} day.

The **exposed difference** was calculated by subtracting the neighborhood wealth values from the exposed wealth values. Participants with positive differences were, on average, exposed to non-home neighborhoods with higher property values than their own, while participants with negative differences were exposed to neighborhoods with values lower than their own.

$$Exposed\ Difference_k = Exposed\ Wealth_k - Neighborhood\ Wealth_k \quad (2)$$

Where k = k^{th} participant

The **percentage of time** spent in areas with residential property values above the sample median for exposed wealth (% time) was computed by identifying all of the GPS points inside raster cells with exposed wealth values that were above the sample median. Next, a time duration value was calculated for each GPS point. Because GPS records are taken at a single instant rather than over an interval, it was necessary to transform the instantaneous measure to a time interval measure. The point-level time valuewas computed by summing 1/2 of the interval between the focal GPS record and the previous record with 1/2of the interval between the focal and subsequent record. Next, the time duration values of all points inside SmartMap cells were summed per day to create a measure of total time measured spent in King County, in areas with residential property values. Then, the interval values for points in the above-median cells were summedFinally, the time spent in above-median property value areas was divided by the total time measured to calculate % time.

$$time\ duration_i = \frac{t_i - t_{i-1}}{2} + \frac{t_{i+1} - t_i}{2} \tag{3}$$

Where:
t_i = time of measurement for i^{th} GPS point for the k^{th} participant

$$\%\ time\ exposed_k = \frac{\sum_{j=1} \frac{\sum_{i=1} td_{ij}}{T_j}}{J} \tag{4}$$

Where:
td_{ij} = time duration of i^{th} GPS point when property value of i^{th} point > sample median exposed wealth on j^{th} day.
T_j = total time spent in areas with residential property values on j^{th} day
J = total number of days
k = k^{th} participant

ANALYSIS

The sociodemographic distribution of the sample by the 5 exposure measures (personal wealth, neighborhood wealth, exposed wealth, exposed difference, and % time) was examined using means and standard deviations. Analysis of variance was used to determine whether differences in means were significant. Correlations were conducted to explore the associations between the five exposure measures. Logistic regression was used to predict the unadjusted odds of being obese by the wealth exposure variables as well as the sociodemographic variables. The results of the previous analyses were used to inform the creation of logistic regression models using robust standard errors to predict the adjusted odds of being obese. Included in these models were age, gender, race, income, education, household size, home ownership, and number of cars in household. In the first model the odds of being obese was estimated for neighborhood wealth, a relationship that has been demonstrated elsewhere.[8] between neighborhood wealth and obesity was tested. To determine the role of exposed wealth in this relationship, the exposed wealth variable was then added to the model. Finally, an interaction term (exposed wealth * neighborhood wealth) was added to test for synergistic effects. Similarly, in the second model also explored the relationship between neighborhood wealth and obesity, however the % time measure was added rather than exposed wealth. In the last model, the odds of being obese was estimated using exposed difference. The sample was then stratified into 2 groups to estimate the odds of being obese for those with exposed difference values > 0 and again for those with values < 0.

RESULTS

Of the 516 subjects recruited for SOS II, 24 lacked GPS data and an additional 11 lacked travel log data. Two subjects under 21 years old were removed from the sample. Twenty-two more subjects were removed due to noticeable errors in GPS data or having fewer than 3 days of GPS or travel log data or more than three nonconsecutive days of either GPS or travel log data. The 19 subjects with missing, ‘not applicable’, ‘don’t know’, or ‘refused’ responses to survey questions used in this study were also removed the sample. Five of the subjects were excluded for meeting multiple exclusion criteria. These exclusions reduced the sample to 443 subjects.

From this reduced sample, two subjects were removed due to extremely outlying neighborhood and exposed wealth values (> 3 standard deviations from the mean). One subject had a neighborhood wealth value of $1,256K; the sample mean was $283K (SD $126K). The other subject had an exposed wealth value of $1,575K; however the sample mean was $270K (SD97K). The reduced sample (n=441) was then again assessed for outliers and subjects with values greater than two standard deviations from the sample mean for personal wealth, neighborhood wealth or exposed wealth were removed. Together there were 51 more subjects removed: 15 subjects had outlying values for personal wealth; 14 had outlying values for neighborhood wealth; 10 had outliers for exposed wealth; 6 had outliers for both personal wealth and neighborhood wealth, one had outliers for both personal wealth exposed wealth; 4 had outliers for neighborhood wealth and exposed wealth; and one had outlying values for all three wealth measures.

The 51 outliers were predominately wealthy: 37 (72.5%) had reported incomes greater than or equal to $100K a year. The mean personal wealth for the outliers was $550K (SD $215K), neighborhood wealth had a mean of $479K (SD $189K), exposed wealth had a mean of $342K ($102K), and the mean difference between exposed wealth and neighborhood wealth was -$136K ($203K). The outliers included a slightly higher percentage of women (76.5% of outliers), skewed older (54.9% were 45 or older), and there were more college graduates (88.2%). Approximately 82% were homeowners compared and 72.5% had ≥ 2 cars in the household. The outliers were in bigger households (62.7% lived in households with ≥ 3 people). Finally, the 15.7% of the outliers were obese (BMI => 30) 15.7%. The potential influence of these wealthy and non-obese subjects on models predicting obesity was the reason they were removed from analysis.

After removing all of the outliers, the analytical sample consisted of 390 participants. **Table 4-1** shows the sociodemographic distribution of the sample which was female (68.7%), < 45 years old (59.5%), white (79.2%),college graduated (59.7%). For the 3 categories of annual household the sample was close to evenly distributed (30.3% > $50K, 40.0% $50K < $100K, and 29.7%≥ $100K).

With a mean of $278K (SD $120K) the sample's personal wealth was about $21K higher than either the mean neighborhood wealth or exposed wealth sample, both of which were $257K, though the variation in neighborhood wealth was higher than that for exposed wealth (SD $76K and $58K, respectively) (**Table 4-1**). On average, when participants were outside of their home neighborhoods they spent 32% (SD 28%) of their time in neighborhoods with residential property values higher than the median value for exposed wealth ($259K) (**Table 4-1**). Exposed wealth was correlated with both personal wealth ($r=0.29$, $p < 0.001$) and neighborhood wealth ($r=0.47$, $p < 0.001$). (Data not shown).

Statistically significant differences in mean personal wealth values for various socio-economic and demographic variables showed that high personal wealth was associated with high levels of education, income, homeownership, having two or more cars per household, living in households of three or more people, being married, and being white. The same trends were found for neighborhood wealth. In both cases the mean wealth values were also significantly lower for obese participants. The personal wealth of obese participants was 18.5% lower than for nonobese participants, and the neighborhood wealth 11.6% lower (**Table 4-1**).

Differences in mean exposed wealth were found for race, education, and number of cars in the household. Non-white participants had exposed wealth values nearly 10% lower than those of white, non-Hispanic participants. Those without college degrees had exposed wealth values 9.7% lower than college-educated participants. The personal and neighborhood wealth values for those living in households with only one or no cars was 26.7% and 6.4% lower, respectively, compared to those in households with two or more cars. However, those in one or no car households had exposed wealth values that were 4.5% higher. Similar to personal and neighborhood wealth, obese participants had exposed wealth values 8.67% lower than non-obese participants (**Table 4-1**).

Exposed difference was associated with income, homeownership, marital status, number of cars per household, household size. Mean exposed difference values decreased with increased in the three income categories: < \$50K had a mean of \$21K (SD \$64K); \$50 to < \$100K had a mean of (\$4K (SD \$70K); and ≥ \$100K -\$29K (SD \$67K). Renters had a mean exposed difference of \$15K (SD \$60K) compared while homeowners (mean -\$6K; SD \$73K). Married participants had a mean exposed wealth value of -\$15K (SD \$69K) compared to unmarried participants (mean \$16K; SD \$68K). Households of ≤ 2 people had a mean exposed difference of \$10K (SD \$69K) compared to households with > 2 people (mean -\$13K; SD \$69K). The mean exposed difference for having≥ 2 cars in the household was -\$12K (SD \$70K) compared to \$17K (SD \$66K) in households with fewer cars.

Table 4-2 presents the unadjusted odds of being obese for each of the socio-economic, demographic, and wealth variables. Being white, having a college degree, being married, and living in households with 2 or more cars all significantly decreased the odds of being obese while being a renter significantly increased the odds. Of the 5 wealth exposure measures, only exposed difference was not significantly associated with decreased odds of being obese.

Presented in **Table 4-3**, the first model found that neighborhood wealth was significantly associated with a decreased odds of being obese after controlling for sociodemographic factors (β: 0.64; 95% CI: 0.46–0.89, $p < 0.01$). When exposed wealth was added to the model, the relationship stopped being significant (β: 0.76; 95% CI: 0.53–1.1, $p = 0.14$), however exposed wealth was significantly associated with decreased odds (β: 0.62; 95% CI: 0.39–1.00; $p < 0.05$). In the final step, the addition of the interaction term was not significant.

In **Table 4-4**, the addition of the % time variable to the model estimating obesity by neighborhood wealth was not significant (β: 0.56; 95% CI: 0.23–1.35; $p=0.19$), nor was the interaction term between neighborhood wealth and % time. Neighborhood wealth retained its significance with the addition of % time as well as the addition of the interaction term.

Though a scatterplot of exposed difference by obesity prevalence using locally weighted scatterplot smoothing (LOWESS) lines revealed a bell-shaped trend. As exposed difference approaches zero, the likelihood of being obese increases. After zero, the likelihood of being obese decreases as the exposed difference continues to increase (**Figure 4-1**). For this reason the model was then stratified by exposed difference at zero. In **Table 4-5**, exposed difference was not significantly associated with the odds of being obese in the analytical sample. Stratifying the sample did not change this relationship. Although the stratum with exposed difference values < 0, the odds of being obese did approach significance (β: 2.39; 95% CI: 0.98–5.81; p=0.05). As mentioned earlier, this variable was also not significant in unadjusted models (**Table 4-2**).

In each of the models, save one, having a college education significantly decreased the odds of being obese. When the sample was restricted to those with exposed differences > 0, have a college degree was not significantly associated with decreased odds of being obese

DISCUSSION

An explicit spatial and temporal framework for quantifying exposure to wealth offers new avenues for exploring health disparities. In general, we found that mobility patterns are clearly associated with a range of socio-economic and demographic variables. Confirming the work of Shareck, Frohlich and Kestens[29], we found that the property values of the places people visit away from their home neighborhoods and the routes they take to get there are directly related to socioeconomic status. Rich people travel to rich areas, middle-class people travel to middle-class areas, and poor people travel to poor areas. We also found some evidence that these non-home residential property value exposures may predict obesity prevalence.

Our research further confirmed the relationship between neighborhood wealth and obesity, with those living in richer neighborhoods having a decreased odds of being obese. However, this relationship was disrupted with the addition of the exposed wealth variable. This suggests that the residential property values of the locations people visit away from their home neighborhoods may have a stronger influence on the odds of being obese than the property values of their home neighborhoods, after controlling for income. No evidence of an interaction between neighborhood wealth and exposed wealth was found. We theorized that those who traveled to neighborhoods substantially different from their home neighborhoods would have more options available to them (in terms of both social and material resources) and that their health outcomes would be linked to what was available in those areas. Our results support this hypothesis. Caution must be taken with this interpretation as the odds of being obese for exposed wealth, though significant, had a high p-value and a wide confidence interval.

Models predicting obesity using the exposed difference variable did not show a significant relationship between exposed difference and obesity prevalence. However, when the sample was restricted to those with exposed difference values below 0, the odds of being obese increased by 2.39 with every $100K increase in exposed difference. This may suggest that those who travel to non-home neighborhoods with lower property values than their own may be more susceptible to the obesegonic factors of those non-home neighborhoods than those who travel to non-home neighborhoods with property values higher than their home-neighborhoods. Although this relationship was not significant, it approaches significance at an alpha of 0.05. A larger sample size may be useful in confirming this relationship. Conversely for those with exposed difference values greater than 0, the relationship did not approach significance. It was, however, it did decrease as hypothesized.

We also hypothesized that the % time spent in above-median exposed wealth areas would be significantly associated with decreased obesity. Unadjusted models showed a protective relationship between this % time variable and obesity prevalence. However, findings from the adjusted models suggest that neighborhood wealth and various sociodemographic characteristics explain the relationship between % time and obesity. Considering that we found a relationship between obesity and exposed wealth, it is logical to assume that the time spent in areas with high or low property values will also affect obesity. Other ways of measuring the time exposed to high property values need to be considered. For example, time durations could be measured for each tertile of exposed wealth, to quantify the number of minutes participants spent in each tertile.

Beyond the immediate health consequences of exposure to areas of different wealth, there are many other aspects of wealth exposure that merit further investigation. For example, we found that the exposed wealth of non-white participants was on average of $26K (approx. 10%) lower than those of white participants. This may be indicative of racial segregation or it may be related to the lower socioeconomic status of non-white participants. The personal wealth of non-white participants was about $31K or 10.9% less than white participants and about 33.3% (27 participants) of the non-white participants reported incomes between $50K and $100K compared to 41.7% (129 participants) of the white participants. A higher percentage of nonwhites also reported incomes of less than $50K: 38.3% of nonwhites compared to 28.2% for whites. Wealth exposure measures may reveal new insights into the interrelationships between segregation and economic disadvantage. However, larger sample sizes will be needed.

While we found a clear relationship between an individual's socioeconomic status and travel patterns, we do not know the reasons for that relationship. A next step in this research will be to determine if this relationship is due to workplace location. Presumably, there is a connection between one's socioeconomic status and the location of one's workplace (high-paying jobs will most likely be located in areas with high property values and low-paying jobs in areas with low values). Similarly there may be a connection between home and neighborhood property values and the property values of the areas close to the home but that are farther away than 833 meters. While individuals may run daily errands farther away than 833 meters, they may still run those errands close enough to their homes that there is little difference between their neighborhood wealth and wealth exposure measurements. It is more than likely that daily mobility selection[107] also plays a large role in the relationship between socioeconomic status and where people travel. Rich people may prefer to travel to rich areas and poor may prefer to travel to poor areas or may be barred access to rich areas. Indeed, one study[39] found that high SES participants shopped at expensive supermarkets while low SES participants shopped low-cost supermarkets. Our research also suggests that the issue of self-selection in housing choice[17] may be complicated by mobility patterns that introduce contextual exposures different from those experienced within the home neighborhood.

Although we found evidence of an association between wealth exposure and BMI, we were unable to speculate on the causality of this association due to the cross-sectional nature of these data. Further, we have not directly measured the hypothesized mechanism by which increased exposure to wealth decreases the odds of being obese. We speculate that when socioeconomic factors are controlled for, the relationship may be due to an individual's social connections with the people who live or congregate in the non-home neighborhoods areas visited by the individual. Christakis and Fowler[105] suggest a social contagion effect for BMI and found that having an obese friend, sibling, or spouse increased one's chances of becoming obese. Those with low exposed difference values may be more susceptible to the social contagion effect by traveling to areas with property values lower than that of their home neighborhoods. Data on social networks (especially on the physical locations or mobility patterns of social contacts) could greatly enrich our understanding of wealth exposure.

This study treats exposure to property values equally for all of the non-home neighborhood places traveled (as represented by GPS points). Yet the property values of some locations may have a stronger influence on obesity than others. For example, we know that shopping at high-cost supermarkets is associated with better health outcomes and high-cost supermarkets are more likely to be located in neighborhoods with high property values. [39] It is therefore logical to assume that a small number of GPS points located in the supermarket may be much more influential in causing or preventing obesity than points located at a movie theater or measured while driving. Limiting wealth exposure measures to specific activity areas would also make these measures more comparable to the methodology pioneered by Inagami and others.[22]

One of the main limitations of GPS data is that they only measure locations in terms of XY coordinates. More descriptive measures of the location are needed to understand where a person is (for example, at a specific school, church, or restaurant), why they are there, and what they are doing there. Connecting self-reported travel diary data to GPS is one potential solution. In future studies of wealth exposure, GPS data can be used to measure the time duration of visits to specific places reported in the travel diaries as well as the property value of those locations. This will allow us to compare the influence of property values in a wide variety of locations and better identify areas that may be more influential in promoting or inhibiting health.

Of more concern is that measurements taken at inconsequential locations may confound relationships. For example, a participant who drove through a very wealthy neighborhood may have a few GPS points with very high property values that are not reflective of the majority of places the participant visited. These points could skew the mean wealth exposure measures.

Further, the measurements may not accurately reflect the property values of where the participant was at the time. Property values measured at a GPS point represent a sample of the built environment within the point's calculated duration and distance traveled (1/2 the distance between the previous point and the focal point added to 1/2 the distance between the focal point and the subsequent point). Therefore GPS records with longer duration and/or distance values may less accurately reflect the exposed wealth for that participant within that time frame and spatial extent. In this study, records with excessively long time frames were not a serious concern. The vast majority of points in the sample (98.16%) had time duration values of 30 seconds or less. Accounting for only 1.84% of all points, longer time durations capture instances in which participants turned off their GPS receivers or the signal was blocked. The distance traveled during a point's duration was likewise examined. The maximum possible distance travelled for a GPS record in this study was 0.675 miles, given a maximum time of 30 seconds and a maximum travel speed of 81 mph. The daily average speed of GPS points per participant was 2.52 mph (SD 1.82) with a median of 2 mph. The maximum daily average speed per participant was 13 mph and came from a participant who traveled daily between Seattle and Tacoma, Washington.

A major limitation of this study is that the three wealth exposure measures presented here are very crude as there there are many potential levels of analysis. This study aggregated point-level data to the individual level by averaging SmartMap values obtained from individual GPS points per day and then normalizing the daily averages by number of days. However, this study could also be done as a multi-level analysis, in which the wealth exposure measures were aggregated at the day-level to control for within-subject variation across multiple days. The data could also have remained at the point level to capture variation among GPS points. Such finer-grained measures may have more sensitivity in uncovering relationships between variables.

CONCLUSION

Much research has explored the various ways in which characteristics of home neighborhoods may impact health, but most people do not spend all their time within their home neighborhood. They often travel outside of the home neighborhood over the course of a typical day. A growing body of literature is exploring the relationship to health of the places people travel outside their neighborhoods. Our research contributes to this literature with the introduction of three novel measures of objective exposure to wealth based on property values and GPS data (exposed wealth, % time, and exposed difference) we then compared these measures to personal wealth and neighborhood, previously examined measures that measure wealth at the parcel- and neighborhood-levels, respectively. We found that the places people go when they leave their home neighborhoods are a reflection of individual socioeconomic status. In addition, we have found evidence of a relationship between the exposed wealth of the places people travel to and their BMI. Wealth exposure offers a fruitful course of future research especially as it relates to selective daily mobility and self-selection.

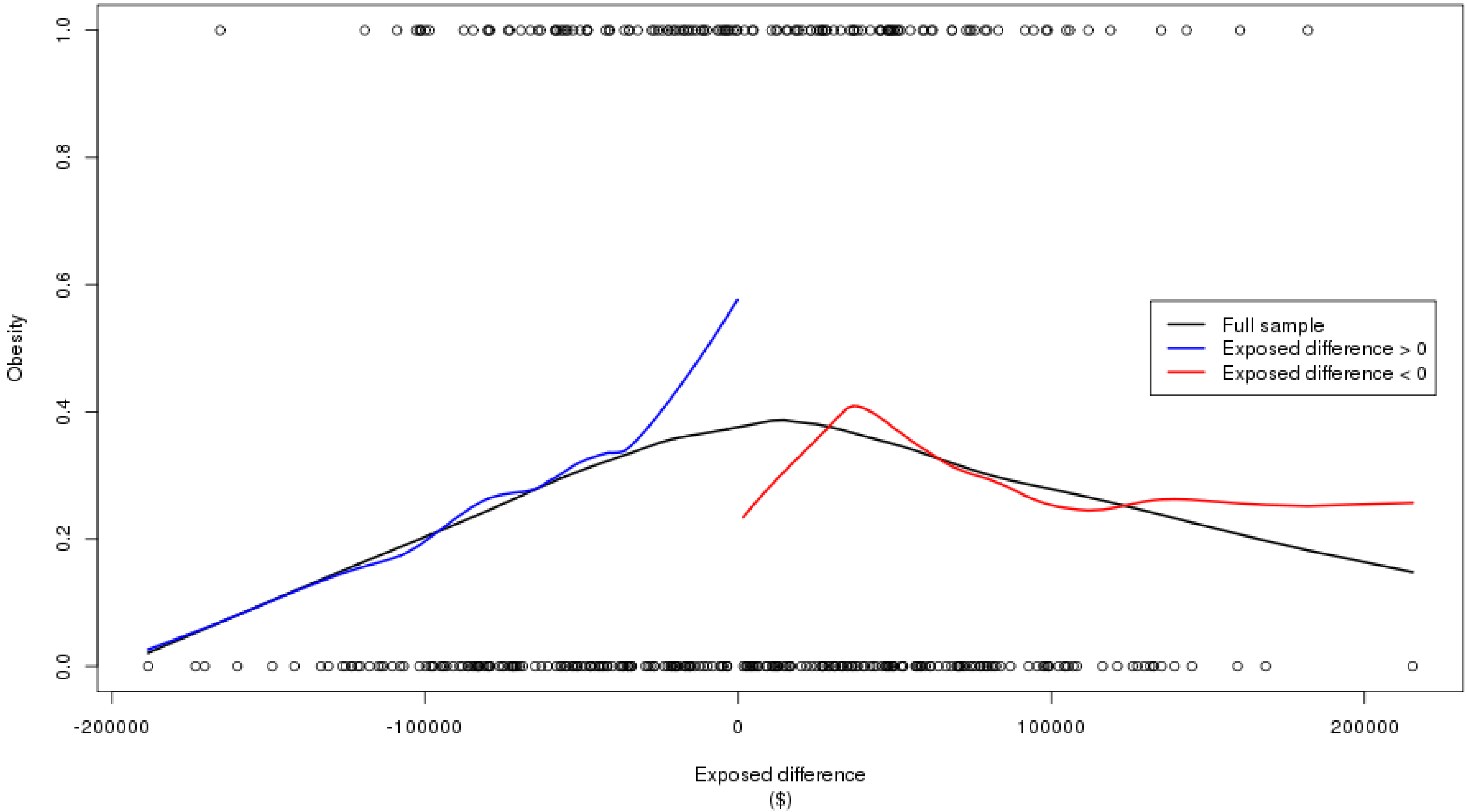

Figure 4-1: Scatterplot of obesity by exposed difference

Table 4-1: Descriptive characteristics of sample by wealth measures

			Personal wealth in $100K increments Mean (SD) [a]	Neighborhood wealth in $100K increments Mean (SD) [a]	Exposed wealth in $100K increments Mean (SD) [a]	Exposed difference in $100K increments[b] Mean (SD) [a]	% time exposed to areas with above-median exposed wealth values Mean (SD) [a]
Total	390	%	2.78 (1.2)	2.57 (0.76)	2.57 (0.58)	-0.01 (0.7)	0.32 (0.28)
Gender							
Female	268	68.72%	**2.9(1.22)**	**2.64(0.76)**	2.6(0.59)	-0.04(0.7)	0.34(0.28)
Male	122	31.28%	**2.51(1.1)**	**2.42(0.72)**	2.49(0.55)	0.07(0.7)	0.29(0.26)
Age							
< 45	232	59.49%	2.81(1.19)	2.57(0.76)	2.57(0.57)	0(0.73)	0.32(0.28)
≥ 45r	158	40.51%	2.73(1.21)	2.57(0.75)	2.56(0.59)	-0.02(0.66)	0.32(0.28)
Race							
Non-white	81	20.77%	**2.53(1.26)**	**2.4(0.75)**	**2.36(0.49)**	-0.03(0.65)	0.27(0.26)
White non-Hispanic	309	79.23%	**2.84(1.17)**	**2.62(0.75)**	**2.62(0.59)**	0(0.71)	0.34(0.28)
Education							
Some college or less	157	40.26%	**2.4(1.08)**	**2.37(0.73)**	**2.41(0.6)**	0.04(0.66)	**0.27(0.26)**
College graduate or higher	233	59.74%	**3.03(1.21)**	**2.71(0.74)**	**2.67(0.54)**	-0.04(0.73)	**0.36(0.28)**
Income							
< $50K	118	30.26%	**2.06(0.9)**	**2.36(0.65)**	2.56(0.59)	**0.21(0.64)**	0.32(0.28)
$50K – < $100K	156	40.00%	**2.74(0.95)**	**2.5(0.77)**	2.54(0.6)	**0.04(0.7)**	0.31(0.28)
≥ $100K	116	29.74%	**3.56(1.29)**	**2.89(0.73)**	2.6(0.54)	**-0.29(0.67)**	0.34(0.27)
Homeownership							
Own	290	74.36%	**3.05(1.12)**	**2.63(0.78)**	2.57(0.6)	**-0.06(0.73)**	0.33(0.28)
Rent	100	25.64%	**2(1.08)**	**2.4(0.65)**	2.55(0.53)	**0.15(0.6)**	0.29(0.26)
Employment							
Not employed	98	25.13%	2.65(1.32)	2.57(0.77)	2.59(0.61)	0.02(0.64)	0.34(0.27)
Employed	292	74.87%	2.82(1.15)	2.57(0.75)	2.56(0.57)	-0.02(0.72)	0.32(0.28)
Marital status							
Not married	180	46.15%	**2.37(1.01)**	**2.44(0.69)**	2.6(0.56)	**0.16(0.68)**	0.32(0.29)
Married	210	53.85%	**3.13(1.23)**	**2.69(0.79)**	2.54(0.59)	**-0.15(0.69)**	0.32(0.27)
Cars in household							
< 2 cars	149	38.21%	**2.27(1.02)**	**2.47(0.66)**	**2.64(0.52)**	**0.17(0.66)**	0.36(0.28)
≥ 2 cars	241	61.79%	**3.1(1.19)**	**2.64(0.8)**	**2.52(0.61)**	**-0.12(0.70)**	0.3(0.27)
Household size							
< 3 people	204	52.31%	**2.45(1.06)**	**2.49(0.73)**	2.6(0.55)	**0.1(0.69)**	0.33(0.28)
≥ 3 people	186	47.69%	**3.14(1.24)**	**2.66(0.77)**	2.53(0.6)	**-0.13(0.69)**	0.32(0.27)

Obesity prevalence							
Not obese	253	64.87%	**2.97(1.26)**	**2.68(0.77)**	**2.65(0.58)**	-0.04(0.74)	**0.35(0.28)**
Obese	137	35.13%	**2.42(0.97)**	**2.37(0.68)**	**2.42(0.56)**	0.05(0.62)	**0.27(0.27)**

Notes:
a) Bold values indicate significant difference between means ($p < 0.05$).
b) Exposed difference = exposed wealth – neighborhood wealth

Table 4-2: The unadjusted odds of being obese

	Unadjusted odds of being obese[a]		
	Odds	95% CI	p-value
Gender			
Female	Ref		
Male	0.96	0.61-1.51	0.845
Age			
< 45	Ref		
≥ 45	0.7	0.45-1.08	0.107
Race			
Non-white	Ref		
White non-Hispanic	**0.53**	**0.32-0.88**	**0.014**
Education			
Some college or less	Ref		
College graduate or higher	**0.4**	**0.26-0.61**	**0.000**
Income			
< $50K	Ref		
$50K – < $100K	0.65	0.4-1.08	0.091
≥ $100K	**0.48**	**0.28-0.84**	**0.009**
Homeownership			
Own	Ref		
Rent	**1.66**	**1.04-2.67**	**0.032**
Employment status			
Not employed	Ref		
Employed	0.64	0.4-1.04	0.066
Marital status			
Not married	Ref		
Married	**0.61**	**0.4-0.94**	**0.023**
Cars in household			
< 2 cars	Ref		
≥ 2 cars	**0.58**	**0.37-0.89**	**0.011**
Household size			
< 3 people	Ref		
≥ 3 people	0.72	0.47-1.1	0.121
Personal wealth	**0.65**	**0.53-0.79**	**0.000**
Neighborhood wealth	**0.56**	**0.42-0.75**	**0.000**
Exposed wealth[b]	**0.49**	**0.34-0.72**	**0.000**
Exposed difference	1.19	0.89-1.58	0.237
% time	**0.37**	**0.17-0.84**	**0.015**

Notes:
a) Bold values indicate significance ($p < 0.05$)
b) Exposed difference = exposed wealth – neighborhood wealth

Table 4-3: Logistic regression using robust standard errors to predict the odds of being obese by neighborhood wealth and exposed wealth [a]

	Model A[b]			Model B[c]			Model C[d]		
	Odds	95% CI	p-value	Odds	95% CI	p-value	Odds	95% CI	p-value
Age									
< 45	Ref			Ref			Ref		
≥ 45	0.74	0.46-1.19	0.213	0.73	0.45-1.18	0.191	0.73	0.45-1.18	0.188
Gender									
Female	Ref			Ref			Ref		
Male	0.81	0.49-1.35	0.411	0.79	0.47-1.32	0.359	0.79	0.47-1.32	0.361
Race									
Non-white	Ref			Ref			Ref		
White non-Hispanic	0.62	0.36-1.08	0.089	0.68	0.39-1.18	0.166	0.68	0.39-1.18	0.167
Income									
< $50K	Ref			Ref			Ref		
$50K – < $100K	0.94	0.51-1.74	0.848	0.9	0.49-1.67	0.745	0.9	0.49-1.67	0.744
≥ $100K	1.01	0.49-2.08	0.978	0.94	0.46-1.95	0.874	0.95	0.46-1.96	0.879
Education									
Some college or less	Ref			Ref			Ref		
College graduate or higher	**0.46**	**0.28-0.75**	**0.002**	**0.49**	**0.3-0.81**	**0.005**	**0.49**	**0.3-0.81**	**0.005**
Household size									
< 3 people	Ref			Ref			Ref		
≥ 3 people	0.84	0.49-1.43	0.505	0.83	0.49-1.43	0.504	0.84	0.49-1.43	0.509
Homeownership									
Own	Ref			Ref			Ref		
Rent	1.1	0.59-2.06	0.752	1.11	0.59-2.08	0.752	1.11	0.59-2.08	0.751
Cars in household									
< 2 cars	Ref			Ref			Ref		
≥ 2 cars	0.66	0.37-1.17	0.151	0.61	0.34-1.09	0.093	0.6	0.33-1.09	0.091
Neighborhood wealth[e]	**0.64**	**0.46-0.89**	**0.008**	0.76	0.53-1.1	0.138	0.69	0.14-3.34	0.643
Exposed wealth[e]				**0.62**	**0.39-1**	**0.046**	0.57	0.13-2.52	0.454
Neighborhood wealth * exposed wealth[e]							1.04	0.58-1.86	0.905

Notes:
a) Bold values indicate significance ($p < 0.05$); b) Model A = Odds of obesity by neighborhood health adjusting for age, gender, race, income, education, household size, homeownership, and cars in household; c) Model B = Model A + exposed wealth; d) Model C= Model B + interaction term; e) Wealth values in $100K increments

Table 4-4: Logistic regression using robust standard errors to predict the odds of being obese by neighborhood wealth and % time exposed[a]

	Model A[b]			Model B[c]			Model C[d]		
	Odds	95% CI	p-value	Odds	95% CI	p-value	Odds	95% CI	p-value
Age									
< 45	Ref			Ref			Ref		
≥ 45	0.74	0.46-1.19	0.213	0.74	0.46-1.19	0.205	0.73	0.45-1.18	0.196
Gender									
Female	Ref			Ref			Ref		
Male	0.81	0.49-1.35	0.411	0.8	0.48-1.33	0.382	0.8	0.48-1.34	0.392
Race									
Non-white	Ref			Ref			Ref		
White non-Hispanic	0.62	0.36-1.08	0.089	0.64	0.37-1.11	0.108	0.64	0.37-1.12	0.112
Income									
< $50K	Ref			Ref			Ref		
$50K – < $100K	0.94	0.51-1.74	0.848	0.92	0.5-1.69	0.781	0.91	0.5-1.67	0.760
≥ $100K	1.01	0.49-2.08	0.978	0.99	0.48-2.02	0.967	0.99	0.48-2.04	0.975
Education									
Some college or less	Ref			Ref			Ref		
College graduate or higher	**0.46**	**0.28-0.75**	**0.002**	**0.47**	**0.29-0.77**	**0.002**	**0.47**	**0.29-0.77**	**0.003**
Household size									
< 3 people	Ref			Ref			Ref		
≥ 3 people	0.84	0.49-1.43	0.505	0.85	0.49-1.45	0.534	0.86	0.5-1.48	0.590
Homeownership									
Own	Ref			Ref			Ref		
Rent	1.1	0.59-2.06	0.752	1.07	0.57-2	0.828	1.07	0.57-2	0.835
Cars in household									
< 2 cars	Ref			Ref			Ref		
≥ 2 cars	0.66	0.37-1.17	0.151	0.62	0.35-1.11	0.102	0.6	0.33-1.08	0.086
Neighborhood wealth[e]	**0.64**	**0.46-0.89**	**0.008**	**0.68**	**0.49-0.96**	**0.026**	**0.6**	**0.37-1**	**0.046**
% Time exposed				0.56	0.23-1.35	0.191	0.2	0.01-4.66	0.311
Neighborhood wealth * % time							1.49	0.46-4.8	0.499

Notes:
a) Bold values indicate significance ($p < 0.05$); b) Model A = Odds of obesity by neighborhood health adjusting for age, gender, race, income, education, household size, homeownership, and cars in household; c) Model B = Model A + % time exposed; d) Model C= Model B + interaction term; e) Wealth values in $100K increments

Table 4-5: Logistic regression using robust standard errors to predict the odds of being obese by exposed difference (exposed wealth - neighborhood wealth) [a]

	Model A Full sample n=390			Model B Exposed difference < 0 n=197			Model C Exposed difference > 0 n=193		
	Odds	95% CI	p-value	Odds	95% CI	p-value	Odds	95% CI	p-value
Age									
< 45	Ref			Ref			Ref		
≥ 45	0.76	0.47-1.21	0.243	0.96	0.45-2.04	0.919	0.59	0.31-1.15	0.120
Gender									
Female	Ref			Ref			Ref		
Male	0.87	0.53-1.43	0.581	0.82	0.36-1.86	0.628	1.01	0.51-1.97	0.983
Race									
Non-white	Ref			Ref			Ref		
White non-Hispanic	**0.57**	**0.33-0.99**	**0.044**	**0.39**	**0.16-0.91**	**0.027**	0.77	0.34-1.77	0.536
Income									
< $50K	Ref			Ref			Ref		
$50K – < $100K	0.94	0.51-1.73	0.834	0.85	0.3-2.41	0.751	0.94	0.44-2	0.868
≥ $100K	0.87	0.42-1.82	0.714	0.74	0.25-2.17	0.574	1.13	0.39-3.29	0.815
Education									
Some college or less	Ref			Ref			Ref		
College graduate or higher	**0.42**	**0.26-0.67**	**< 0.001**	**0.22**	**0.1-0.46**	**< 0.001**	0.76	0.39-1.49	0.416
Household size									
< 3 people	Ref			Ref			Ref		
≥ 3 people	0.8	0.47-1.35	0.388	1.08	0.46-2.54	0.859	0.57	0.27-1.22	0.144
Homeownership									
Own	Ref			Ref			Ref		
Rent	1.1	0.6-2.03	0.755	1.14	0.41-3.15	0.800	1.11	0.5-2.45	0.800
Cars in household									
< 2 cars	Ref			Ref			Ref		
≥ 2 cars	0.69	0.39-1.22	0.199	0.63	0.23-1.73	0.366	0.84	0.39-1.78	0.638
Exposed difference[b]	1.06	0.76-1.48	0.717	2.39	0.98-5.81	0.051	0.7	0.31-1.59	0.387

Notes:
a) Bold values indicate significance ($p < 0.05$); b) Wealth values in $100K increments

Appendix 4-A: Correlations of property-value-derived wealth measures.

Sample without outliers (n=390)

	Personal wealth	Neighborhood wealth	Exposed wealth	Exposed difference	% time
Personal wealth		0.58***	0.29***	-0.38***	0.15**
Neighborhood wealth	0.58***		0.47***	-0.69***	0.32***
Exposed wealth	0.29***	0.47***		0.32***	0.61***
Exposed difference	-0.38***	-0.69***	0.32***		0.15**
% time	0.15**	0.32***	0.61***	0.15**	

* p < 0.05; ** p < 0.01; *** p < 0.001

Outliers only (n=51)

	Personal wealth	Neighborhood wealth	Exposed wealth	Exposed difference	% time
Personal wealth		0.12	-0.36*	-0.29*	-0.28*
Neighborhood wealth	0.12		0.12	-0.87***	0.02
Exposed wealth	-0.36*	0.12		0.39**	0.50***
Exposed difference	-0.29*	-0.87***	0.39**		0.23
% time	-0.28*	0.02	0.50***	0.23	

* p < 0.05; ** p < 0.01; *** p < 0.001

Chapter 5 : CONCLUSION

In this dissertation three dimensions of mobility through activity spaces (person, environment, time) and three types of contact between person and environment (exposure, access, use/selective mobility) were considered. Elaborating on Golledge and Stimson's[21] definition, in the studies presented here, activity space comprises all of the places participants visited in King County along with the travel paths taken to get to these places. Activity space was measured with both GPS and travel diary instruments. For each of the three studies, different aspects of the activity space were measured. In Chapter 2, the activity space characteristics of interest were the supermarkets and fast food restaurants (FFRs) that were visited during each participant's observation period. For Chapter 3, the characteristic comprised the FFRs that participants came into proximity with at any of the four radial buffer sizes (21, 100, 500, and 800 meters). Finally, in Chapter 4, the residential property of the activity space was measured with 833m-radial buffers around each GPS point within King County.

In Chapter 3, a framework from exposure science is introduced in which exposure is considered the result of contact between a receptor and a stressor.[68] In adapting this framework to the food environment, the receptor is a person and the stressor (or enabler in the case of health promoting environments) is the environment. More specifically, the environment is the type of food outlet of interest. It is a person's individual traits and activity space that brings the person (receptor) into contact with a food outlet (stressor).

One of the novel aspects of this dissertation is that time is included as a dimension of the contact between person/receptor and environment/stressor. As discussed in Chapter 4, the size of one's activity space is limited by one's mobility potential, which is positively associated with socioeconomic status (SES).[29] Because people are mobile (and their mobility is a function of their SES and demographics), the contact between person and environment is constrained by time (and therefore also associated with SES and demographics).

One of the main conclusions from the research presented in this dissertation is that there are at least three types of contacts between receptor and stressor. In Chapter 2 the type of contact is use/selective mobility, measured both by GPS and travel diary. Previous research has relied on other types of contact (exposure and access) to predict use, which in turn leads to food consumption and the health outcomes associated with consuming that food. Yet as Chaix and team point out, many studies have failed to control for selective mobility/use in their exposure/access measures.[33]

As reported in Chapter 2, 77.3% and 78.6% of travel-log-reported visits (+/- 10 minutes) to FFRs and supermarkets, respectively, were able to be verified with GPS data. The use of both GPS and travel diaries in mobility studies therefore allows researchers the opportunity to verify participant responses to self-reported locations and better examine occurrences of use/selective mobility. The closest measureable proximity of receptor to stressor was used to measure selective mobility: instances in which individuals were measured to be within parcels associated with FFRs or supermarkets.

In Chapter 3, receptor/stressor contact is measured through 21m, 100m, 500m and 800m proximities to FFRs. Reported visits to FFRs that were verified with GPS records (using methods discussed in Chapter 2) were removed from the analysis to separate instances of selective mobility from unintended exposure. In addition to being one of the first studies to investigate duration of exposure to FFRs, it is also among the first studies of its type to rely on objectively measured locational data while controlling for selective mobility bias as recommended by Chaix and team.[33]

This study demonstrated that longer durations of exposure, especially at 21m and 100m proximities, were associated with increased odds of visiting FFRs. But it also suggested that different proximities between receptor and stressor captured different forms of contact. Closer proximities are more likely to be related to experiencing a place through direct sensory contact. Once outside of sensory range, however, the decision to eat at an FFR may be moderated by attitudes toward FFRs and cognitive processes (such as memory and knowledge of FFRs in the area). While attitudes have been included in past studies, few if any studies of health and environment included measures of individual cognition.

In addition, any built environment features that may affect behavior and health outcomes must be accessible to the individual. Bernard and colleagues[86] identify the following aspects of access at the neighborhood level, though these aspects can also be applied at the activity space level: (1) the proximity of residents to resources; (2) the social and civic rights of the society in which the neighborhood is located; (3) the pricing mechanisms of resources in the neighborhood (pricing also affects whether or not a resource may locate in the neighborhood); and (4) the level and type of informal reciprocity within the neighborhood’s social networks. Outside of sensory range, the individual wishing to visit an FFR needs to know: how far away they are from the FFR; whether the norms and laws of their society allow them to visit it; and how affordable the food is at the FFR. Conversely, access to an FFR or fast foods may be due to a friend or other social connection purchasing food for the individual. Farther distances between individuals and food sources may therefore suggest that accessibility, rather exposure, is the best way to describe the level of receptor/stressor contact.

In Chapter 4, the stressor/enabler of interest is the average residential property value within 833m of participants’ locations as they travel through space and time. The goal of the study was to reexamine the previously established relationship[8] between property values at the neighborhood level (neighborhood wealth was measured as the average property value per unit with 833m-radius of participants’ homes) and health using three new measures of property values that represent the activity space (exposed wealth, exposed difference, % time). Few studies have examined the property values of places visited outside of the home neighborhood and most of the locational data for those studies came from self-report. This study adds to that literature with objectively measured locational data that varies across time and space.

Exposed wealth (based on the average residential property value per unit within an 833m-radius of participants’ GPS records) was associated with a significant decrease in the odds of being obese after controlling for neighborhood wealth. However, neither exposed difference nor % time were found to have significant associations. Further refinement in how both of these variables are measured is necessary before making any conclusions about their associations with obesity.

Compared to FFRs, property value represents a different type of environmental trait that requires a substantially different method of measurement. Further, the hypothesized causal path from FFR exposure to health is based on the established relationship between eating fast foods and being obese.[34,55,57,58] Therefore, closer proximities to FFRs will present more potential opportunities to eat at FFRs, with access having the farthest proximity, and use/selective mobility having the closest. Proximity may be key in differentiating between exposure and access, with the key issues being the determination of which levels of proximity have which effects on behaviors.

In contrast, property values are a stressor/enabler that we are always in continuous contact with, and the hypothesized causal path between property values and health is less clear. At every level of measurement (parcel, neighborhood, and activity space), property value serves as a proxy measure for unmeasured contact (exposure, access and use) with health promoting resources either directly or through social networks.

The differences between the continuous contact of property values and the discrete contact of FFRs demonstrates the need for distinguishing between forms of contact between receptor and stressor. This is especially important when considering the proximities. While proximity is usually measured with radial or network buffers around an individual's GPS traces, or home or work locations, little research has been conducted on how sensitive model results are to the size of those buffers.[15] Yet as Chapters 3 and 4 suggest, the type of hypothesized contact between stressor and receptor (and the hypothesized health outcome associated with that contact) should determine the size of the proximity buffer.

This dissertation contributes to the establishment of a more detailed framework for how people connect with and experience the built environment over time. It also highlights the potential of objective GPS records in determining movement through space and time.

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