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Essays in Health Economics: A Focus on the Built Environment

Thomas James Christian
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ESSAYS IN HEALTH ECONOMICS: A FOCUS ON THE BUILT ENVIRONMENT

BY

THOMAS JAMES CHRISTIAN

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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I wanted to briefly acknowledge the origins of the research. I was already interested in using prohibitively-long travel times to measure "access" when I read Nick Paumgarten's feature on extreme commuters, "There and Back Again: The Soul of the Commuter" by (printed April

16th, 2007 in *The New Yorker*). Robert Putnam's ideas discussed therein about the "triangle" between locations of home, work, and shopping–and what it means as that triangle gets bigger–were particularly helpful for organizing my thoughts for what later became my first essay, and potential future research. My second essay developed after hearing a radio interview (the December 15th, 2008 *On Point With Tom Ashbrook*: "Hunger in the USA") featuring Joel Berg, Executive Director of the New York City Coalition Against Hunger, who stated that the obesity and hunger paradox arises from healthy food inaccessibility. My third essay developed together with a dissertation committee member, Cynthia Searcy, based on prior research she had done and the dataset she had used.

I will long cherish many memories of times spent with friends made during my studies at the Andrew Young School. I look forward to more to come. I also really want to thank my Mom for everything.

I wanted to save the biggest thanks for last: It is my intention to never take anything for granted, and I am quite cognizant of my fortune for having had Inas Rashad Kelly as my dissertation advisor. I am very grateful for all her support, as without Prof. Kelly's continued readings (and re-readings), numerous suggestions, constant guidance, and encouragement, this project would not have been accomplished.

TABLE OF CONTENTS

LIST OF TABLES

ABSTRACT

ESSAYS IN HEALTH ECONOMICS: A FOCUS ON THE BUILT ENVIRONMENT

By

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The dissertation investigates how individual behaviors and health outcomes interplay with surrounding built environments, in three essays. We conceptually focus on travel behaviors and accessibility.

In the first essay, we hypothesize that urban sprawl increases requisite travel time which limits leisure time available as inputs to health production. We utilize the American Time Use Survey to quantify decreases in health-related activity participation due to commuting time. We identify significant evidence of trade-offs between commuting time and exercise, food preparation, and sleep behaviors, which exceed labor time trade-offs on a per-minute basis. Longer commutes are additionally associated with an increased likelihood of non-grocery food purchases and substitution into less strenuous exercise activities. We also utilize daily metropolitan traffic accidents as instruments which exogenously lengthen a particular day's commute.

The second essay tests whether the likelihood of food insecurity and "paradoxical" joint insecurity-obesity occurrences vary over the degree of urban sprawl. We utilize data from the Behavioral Risk Factor Surveillance System's Social Context Module merged with urban sprawl measures developed by Smart Growth America. We find significantly negative associations

between urban sprawl and the likelihood of food insecurity, and that insecurity is more likely in areas of less developed street connectivity. We find that joint outcomes are more likely in less sprawled areas and that likelihood is greater in areas of greater street connectivity, which fails to support theories proposing that healthy food inaccessibility is a determinant of joint outcomes.

The third essay evaluates research claims that walking and cycling to school increases students' physical activity levels in a predominantly urban sample. We utilize the third wave of the Survey of Adults and Youth–a geocoded dataset–to identify determinants of walking or cycling to school, and in turn to explore to what extent active travel impacts adolescents' weekly exercise levels. Consistent with the literature, we find that the distance between home and school is the largest influence on the travel mode decision. We also find no evidence that active travel increases the number of students' weekly exercise sessions. These results suggest that previous findings may not extend to all environments or populations.

ESSAY I: OPPORTUNITY COSTS SURROUNDING EXERCISE AND DIETARY BEHAVIORS: QUANTIFYING TRADE-OFFS BETWEEN COMMUTING TIME AND HEALTH-RELATED ACTIVITIES

Introduction and Motivation

Obesity-related diseases impose billions of dollars in medical expenditures on state and local governments each year (Wolf and Colditz 1998; Finkelstein et al. 2003). Because of the diseases' preventable perception, governments at all levels are enacting policies aimed towards reducing obesity rates while simultaneously seeking to understand underlying causes. A substantial literature now exists researching the economic causes of obesity (Finkelstein et al. 2005). One category of studies identifies strong spatial patterns of obesity, such as higher incidence in economically disadvantaged areas net of individual characteristics (Robert and Reither 2004). Within this vein there is an established positive association between urban sprawl and obesity (Ewing et al. 2003; Giles-Corti et al. 2003; Saelens et al. 2003; Frank et al. 2004; Lopez 2004; Rashad and Eriksen 2005; Zhao and Kaestner 2009). Still only a correlation, the most commonly asserted explanation is that suburbia imposes an automobile-dependent and sedentary lifestyle (Plantiga and Bernell 2005).

This essay's purpose is to quantify trade-offs between commuting and health-related activities for the purpose of examining commuting as a possible pathway explaining spatial patterns of health outcomes. Given that urban sprawl–here referring to decentralized, car-centric urban form–increases distances between people and places and that greater distances increase requisite travel time (Levinson and Wu 2005), then at constant labor time each additional minute spent commuting must directly diminish available leisure time by one minute. We conjecture that resulting leisure time loss to indirect health consequences. First, there are reduced exercise time possibilities. Second, there is reduced time for meal preparation, inducing substitution into meals of lower time cost, which often effectively means processed or non-grocery meals less healthy than meals assembled from base ingredients (Cutler et al. 2003). Third, reduced time for traditional sit-down meals might promote increased secondary eating (i.e., snacking), which is not unhealthy *per se* but could be in an unhealthy food environment, a concern of health policy makers (French et al. 1997; Jacobson and Brownell 2000). Lengthier commutes may also limit meal frequency, which is linked to increased body mass (Hamermesh 2009). Fourth, commute time could be drawn from sleeping time, and sleep deprivation–which affects appetite-regulating hormones–is associated with obesity (Gangwisch et al. 2005).

In addition to time directly lost, commuting may also indirectly affect behaviors throughout the day. Commuting increases stress levels (Koslowsky et al. 1995) and may also magnify perceptions of time pressure. If commutes are either physically draining themselves or reduce sleeping time, attributable lethargy may impede sufficient exercise achievement or induce substitution into less strenuous daily activities, at a cost of reduced energy expenditures. Thus, the spill-over of these indirect effects into non-commuting time further debilitates health production.

A counterargument claiming that commuting lengths are unrelated to health outcomes is supported by data suggesting that increases in Americans' commuting times are moderate relative to the increase in obesity. From approximately 1980 to 2000, the obesity rate increased 106% while the average journey to work measured by the decennial Censuses increased only 17.5% –which in absolute terms is only ten additional minutes daily at the median.[1] However,

[1] The age-adjusted obesity prevalence for adults aged 20-74 was 15.0 in the 1976-1980 National Health and Nutritional Examination Survey (NHANES) II and 30.9 in the 1999-2000 NHANES (Source: CDC). The median journey to work was 21.7 minutes in 1980 and 25.5 minutes in 2000 (Source: U.S. Census).

Levinson and Wu (2005) argue that Census measures do not account for growing metropolitan areas and understate the true commuting length increase.[2]

Moreover, the complex mechanisms of time's input into health outcomes are not currently fully understood. Leisure time loss occurs within a context of increasingly low-cost, energy dense foods, which are linked to obesity (Drewnoski 2004). Long commutes themselves may be symptomatic of deleterious spatial isolation exemplified by inaccessibility to local public goods and amenities such as parks for exercise (Plantiga and Bernell 2005) and by inaccessibility to nutritional consumption opportunities such as grocery stores (Larsen and Gilliland 2008),[3] both of which jointly reinforce obesity outcomes. Ultimately, the scope of this essay is not to analyze the determinants of the increase in obesity since the 1980s but rather to uncover an association between commute times and behavioral patterns which may promote obesity and related complications in the long-run.

The remainder of the essay is structured as follows: we develop a simple theoretical model and analytical framework. We then describe the dataset and principal measures. The next section discusses the primary empirical analysis–OLS results suggest highly significant trade-offs between commuting and exercise, food preparation, and sleep time; the commuting time trade-off exceeds the labor time trade-off on a per-minute basis; disaggregating commutes by active and sedentary transit modes reveals that active mode commuting does not affect individuals' non-travel exercise behaviors but sedentary commuting time does; sample stratifications identify further relationships, particularly that obese individuals and residents of the most sprawled metropolitan areas trade off commuting and food preparation the greatest

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[2] Other data sources illustrate increased traffic congestion: for example, the Texas Transportation Institute reports annual hours spent in traffic delay per traveler increased 164% over the period 1982 to 2004.

[3] Healthy food inaccessibility is the consumption-side analog to the spatial mismatch hypothesis (Kain 1968), economics' long-standing theory of spatial inaccessibility in the labor market. Indeed, spatial mismatch might increase certain individuals' commutes, further limiting leisure time.

extent; and using metropolitan area fatal traffic accidents as instrumental variables increases the estimated trade-off between commute and both exercise and sleep time. We then pursue analytical extensions using the data–activity time data augmented with strenuousness scores suggest that commuting induces substitution into lower intensity exercise activities; longer commutes are associated with a higher likelihood of non-grocery food purchases; employed individuals compensate for time lost by increasing eating, sleeping, and socializing time, only; and the obesity-sprawl association persists despite controlling for commute time. Finally, we conclude by summarizing the essay's main contributions and limitations. We present all tables following the conclusion and explain the time use variables' construction in the appendix.

Theoretical Motivation and Empirical Strategy

Becker (1965) theorizes utility as a function of *n* compository Z goods, themselves (ultimately) functions of leisure time (*l*) and *m* monetary (*x*) inputs. We focus on one particular Z good, "Health", and subsequently not only health's derived demand but derived "demand" for its *k* number of health-related input activities. Health has many other determinants, represented by the vector $\boldsymbol{X}_h$:

$$Utility = U\left(Z^{Health}\left(\boldsymbol{X}_h, \boldsymbol{Activity}_k(\boldsymbol{x}_m^k, l^k)\right), \boldsymbol{Z}_{n-1}\right)$$

Total daily time (τ) is uniformly constrained to $\tau = w + \boldsymbol{l}_q + c$. Holding minutes worked (w) constant, increases in commuting time (c) must necessarily be met with decreases in aggregate leisure time ($\boldsymbol{l}_q$, a vector of q non-market activities), although every individual activity need not decrease. It is straightforward to add wage and prices to the constraint (though without gains to insight within the scope of this essay).

Increasingly limited leisure time progressively constrains time available for input-to-Health activity *k*. Consider activity *k* with *m* monetary inputs $\boldsymbol{x}_m^k$ and a single leisure time input

l^k. For a given individual allocating time and monetary inputs to maximize utility, the total change in the optimal allocation of activity *k* as commuting constrains inputs is:

$$\frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial c} = \left(\sum_m \frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial \boldsymbol{x}_m^k}\frac{\partial \boldsymbol{x}_m^k}{\partial c}\right) + \frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial l^k}\frac{\partial l^k}{\partial c}$$

Which, because $l^k = \tau - h - \boldsymbol{l}_{q-1} - c$, and so $\frac{\partial l^k}{\partial c}$ = -1, reduces to:

$$\frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial c} = \left(\sum_m \frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial \boldsymbol{x}_m^k}\frac{\partial \boldsymbol{x}_m^k}{\partial c}\right) - \frac{\partial Activity^k(\boldsymbol{x}_m^k, l^k)}{\partial l^k}$$

The first term represents activity reduction due to decreases in monetary inputs and the second term represents activity *k*'s reduction due to lost leisure time, both resulting from commuting time increases. The term $\frac{\partial x_m^k}{\partial c}$ is a theoretically negative pure income effect–commuting constrains income-generating time available for labor (*w*) and also imposes a per-mile cost (manifested as fuel prices or automobile maintenance). Unfortunately, adequate monetary input data do not exist and so the first term represents a source of error in empirical estimation. However, one can consider specific activities' relative input intensities–time versus money–to infer the magnitude of the bias.

The empirical focus of this essay is the estimation of $\frac{\partial Activity^k(x_m^k, l^k)}{\partial c}$, the change in activity *k* due to commuting. Previous empirical time use analysis employs multinomial Tobit models (see Mullahy and Robert 2008) to estimate activity shares of total time with respondent characteristics as regressors. However, in terms of modeling activity trade-offs we are aware of only Basner et al. (2007), who use adjusted linear regression analysis. To our knowledge no advanced econometric techniques presently exist modeling time-use trade-offs, and certainly not which account for endogenous selection.

I model individual *i*'s (in location *j* at time *t*) time spent participating in each of *k* health-related activities as a function of time spent commuting (c_{ijt}). We hold time spent working (w_{ijt}) constant to ensure that increases in commuting time must be met with decreases in leisure time, only. We also include a vector of control variables $\boldsymbol{X_{ijt}}$:

$$\boldsymbol{Activity_{ijt}^{k}} = \beta_0^k + \beta_1^k c_{ijt} + \beta_2^k w_{ijt} + \boldsymbol{\beta^k X_{ijt}} + \varepsilon_{ijt}^k$$

The primary statistic of interest is β_1^k, the associated change in activity participation time for a one-unit increase in commuting time. However, inadequately addressing self-selection may yield biased estimates. Theorists since Plantiga and Bernell (2005) have recognized how the failure to acknowledge sprawl's endogeneity might lead to misguided interpretation.[4] In the current framework, individuals giving little utility value to health might rationally locate on the urban fringe, apply the time they do not use for health-related activities towards commuting, and enjoy better consumption bundles following cheaper housing costs. It is naïve to solely attribute such health-related activity reductions to time constraints while disregarding individuals' health or residential location preferences.

It is difficult to disentangle these unobservable factors from long-run equilibria. In the short-run, however, c_{ijt} is not completely determined by the individual alone. Various random and external influences affect short-run commute length: consider congestion levels, poor weather affecting roadway conditions, or public transportation irregularities. A single day's commute is conceptually decomposable into long- and short-run factors:

$$c_{ijt} = \bar{c}_{ij} + c_{ijt}^e$$

$$\text{where } c_{ijt}^e = c^e\left(\boldsymbol{\Omega_{ijt}}\right)_{ijt}$$

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[4] Eid et al. (2008) empirically demonstrate a spurious sprawl-obesity association due to self-selection. Plantiga and Bernell (2007) also find evidence of selection bias. In contrast, randomized experimental design evidence from the Moving to Opportunity housing voucher program shows an obesity reduction in the target group (Kling et al. 2007).

Individuals choose $\bar{c}_{ij}$, the long-run average commute (what might be reported on a Census form). Although there is certainly a trade-off between $\bar{c}_{ij}$ and leisure time, self-selection creates an identification problem. However, there exist unintentional short-run (daily or single trip) deviations from $\bar{c}_{ij}$, represented by the term c^e_{ijt}. Structural variation in c^e_{ijt}–arising from an identifiable set of random, exogenous factors $\boldsymbol{\Omega}_{ijt}$–is exploitable in instrumental variable procedures.[5] Statistically acknowledging such variation essentially introduces randomness into non-experimental data and allows more persuasive causal arguments.

Data

Description of the American Time Use Survey

I utilize the American Time Use Survey (2003–2008) as our primary dataset. The American Time Use Survey (ATUS) is an annual, nationally representative cross-sectional survey, administered by the Bureau of Labor Statistics (BLS) since commencing in 2003. A monthly ATUS sample is randomly drawn from respondents recently completing the BLS's Current Population Survey (CPS). Respondents chronologically list what they consider to be their primary activities and the activities' durations beginning with 4am on the previous day through 4am on the day of the interview, a twenty-four hour period referred to as their "diary day". The BLS labels each activity with one of approximately four hundred activity categories. Only respondents' primary activities are recorded; secondary or tertiary activities performed simultaneously are omitted. The ATUS also records where each activity took place, or transit

[5] Using these instruments implicitly presumes individuals do not sort on $\boldsymbol{w}_{ijt}$ nor do they anticipate variability in c^e_{ijt} in residential location decisions, or that behavioral responses are identical between $\bar{c}_{ij}$ and c^e_{ijt}.

mode for travel activities. The BLS additionally matches time diaries and CPS demographic information.[6]

The U.S. Department of Agriculture in conjunction with the National Institutes of Health-National Cancer Institute has delivered the Eating and Health Module (EH Module) of the ATUS for the 2006 and 2007 cohorts. Because the ATUS only records primary activities, eating concurrent with other activities–such as “snacking” while working or watching television–is ignored. However, the EH Module addresses respondents’ secondary eating behaviors by recording how many minutes respondents were eating during another primary activity. The EH Module includes several additional items, including self-reported height and weight from which body mass index (BMI) is calculated,[7] respondents’ roles in household meal preparation, and households’ relation to the poverty line.

The CPS provides numerous socioeconomic items. We include standard control variables: age, gender, race and Hispanic status, education, marital status, number of children, an indicator for the presence of a child 0-1 years, household income,[8] disabled worker status, and employment status. Employment status is disaggregated into broad occupation categories to acknowledge physical exertion variation across occupations: “White collar” workers are those in management, business, financial, and professional occupations; “Service” workers are those in service, sales, or office administrative support occupations; and “Blue collar” workers are those

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[6] For further details, the reader is referred to Hamermesh et al. (2005), who write a descriptive overview of the ATUS. One characteristic of the ATUS is low response rate (below 60%); there is no evidence that non-response is due to individuals being “too busy”, though nonresponse has been linked to weak community integration (Abraham et al. 2006). Additionally, ATUS respondents are found to have a greater propensity towards volunteering (Abraham et al. 2009).

[7] Body Mass Index is calculated as kg/m^2. Individuals are defined as obese if their BMI is greater than or equal to 30. We correct self-reported height and weight with algorithms derived from regressing actual height and weight on reported height and weight from National Health and Nutritional Examination Survey data (for ages 21-65, only–other ages’ BMIs are recoded as missing).

[8] Household income is reported by bracket set. We recoded income as the midpoint of the household’s income bracket to construct a continuous income variable. The exception was the top bracket, where We increased the label’s value by 50% ($150,000 to $225,000).

from farming, fishing, forestry, construction, extraction, installation, maintenance or repair, production, and transportation occupations. We additionally distinguish self-employed and hourly workers who may have more and less flexible work schedules, respectively. We code an indicator equal to one if the respondent is enrolled in school. We code an indicator variable "smoker" equal to one if the respondent reported any time using tobacco (or marijuana) products, which will proxy for some individual health preferences. We code a severe weather indicator equal to one in instances in which rainfall equaled or exceeded 0.6" or snowfall equaled or exceeded 0.1" inches on average over the respondent's metropolitan area their diary day.[9]

I model time participation in four health-related activities: (1) aggregate exercise, which is the summation of total time spent in thirty-five individual exercise and sport activities; (2) total time spent preparing food; (3) the total time spent eating as a primary activity; and (4) total time spent sleeping. We also model time socializing and watching television–which together comprise two-thirds of Americans' waking leisure time–as benchmark comparisons. We detail all time variables' construction in the appendix.

The analysis's principal explanatory factor is time spent commuting. Modeling travel behavior with the ATUS is difficult, as explained by Brown and Borisova (2007). The issue is that the ATUS segments each travel episode by destination purpose. If a commuter brings a child to school before traveling to work, the ATUS only categorizes the school-to-work portion as work-related travel. The home-to-school portion is classified separately, even if it is a routine occurrence that arguably should also be included as part of the "commute". Ignoring such segments means that the ATUS-tabulated "travel related to work" underestimates commutes for individuals making stops between work and home–estimated at about one third of all commute

[9] Weather data are from the National Climactic Data Center. "Average over the respondent's metropolitan area" means the average recorded rainfall or snowfall totals for all weather stations within the metropolitan area.

trips (p. 10). To accommodate commuting trips with multiple purposes, We manually calculate individual commute times from ATUS diary activity logs using Brown and Borisova's definition of a commute: all travel time for any purpose from the time the respondent leaves home until arrival at work, and *vice versa*. A respondent's total commuting time is the summation of all qualifying travel time.[10]

Instrumental Variables

The survey's cross-sectional design creates the primary impediment to causal inferences. To mitigate selection bias, an ideal instrument set will explain the diary day's commuting time yet also be uncorrelated with health-related activity time. For most commuters, the degree of traffic congestion is a primary determinant of the daily variation in time traveling between home and work. The Department of Transportation reports the largest sources of congestion as bottlenecks, traffic incidents, work zones, and poor weather. In terms of validity as instruments, bottlenecks are non-random, weather conditions influence health-related time allocation, and to our knowledge no nationally-representative dataset exists detailing construction zones by location and day.

I focus on fatal traffic accidents to proxy highway congestion.[11] Fatal accident occurrences are exogenous to the individual and would create the magnitude of congestion that would saliently impact traffic flow. We use fatal accident records from the Federal Highway Administration's Fatal Analysis Reporting System and aggregate hourly tallies by CBSA for each diary day. We limit the recorded accidents to those occurring on National Highway System roads during "rush hours"–between 6am-9am and between 4pm-8pm on non-holiday weekdays–

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[10] As Brown and Borisova (2007) acknowledge, this definition itself is problematic because the ATUS only records one day and so the researcher cannot ascertain which stops are routine and which are not.

[11] In addition to fatal accidents, we experimented with gasoline prices, hazardous material spills, annual (metropolitan) highway expenditures, and an indicator for the Monday after fall daylight savings switches, which are known in traffic circles to be associated with heavier congestion (Vanderbilt 2008).

in order to more precisely match commuters and relevant incidents. We then match the daily metropolitan accident counts to each individual's geographical location (CBSA), diary date, and the times of day in which the respondent was commuting.

I distinguish each accident by the time of accident occurred to construct two dichotomous instruments: whether an accident occurred during the respondent's journey from home to work (the morning commute) in the respondent's metropolitan area on their diary day, and whether an accident occurred during the respondent's journey from work to home (the evening commute). This distinction is because accidents occurring during the morning hours may have a different effect than evening hour accidents for two reasons: (1) the working population's shift towards the urban core during work hours means that accidents occurring when the populace is more centralized will affect more people in denser circumstances, and (2) the timing of the work day may mean that one trip is more flexible than the other with regards to the journey's timing, allowing workers to adjust their departure times in case of (anticipated) congestion more for one than the other, lessening any congestion impact.

Sample Construction and Summary Statistics

The full sample is constructed as follows: when ATUS samples from survey years 2003 through 2008 are aggregated, 85,645 observations comprise the full set. Given the focus on a work-related activity–commuting–We limit the sample to working age (18-65) adults residing within identifiable urban labor markets, specifically the respondent's Core Based Statistical Area (CBSA).[12] These criteria result in the omission of 18,464 individuals from rural (non-metropolitan) counties, and then 10,410 individuals outside of the age range. Next, individuals

[12] A CBSA is a geographic entity defined by the U.S. Office of Management and Budget containing an urban core of at least 10,000 people.

with incomplete records are dropped: 7,035 individuals with missing household income,[13] an additional 403 with missing weather data, and an additional 31 with missing occupational categories are excluded.

Lastly, to construct a sample which permits meaningful comparisons and which will produce inferences with reasonable generalizability, we limit the sample to individuals falling under loosely-defined "traditional" commuting schedules. Essentially, night shift workers are dropped. Commuters are eligible for inclusion if they arrived at work between 4:30am and 6pm, and also arrived at home between 10am and 11:30pm. Moreover, any individual–working or not working–identified as beginning or ending the day away from home is omitted. Together, these criteria resulted in the loss of 2,810 further observations. The final dataset includes 46,496 full observations.

The instrumental variables sample is further reduced. For this procedure, We omit the 32,005 non-commuters for two reasons: (1) traffic accidents are inapplicable to non-commuters, and more importantly (2) selection into commuting arises from a decision to select into labor force participation the specific diary day, an additional source of endeogeneity. Finding a factor to explain the labor decision would likely encompass a catastrophic event such as severe weather or illness which would also affect health-related activity time, invalidating the factor as an instrument. Second, we omit the 741 commuters who did not use a car during any portion of their commute, for whom traffic accidents are also irrelevant. Third, we omit 1,731 respondents whose journey to work or returning home was less than ten minutes, as these individuals are least likely to have used highway roads, where relevant traffic accidents took place.

[13] In the sizeable number of observations with missing income data, 93.4% refused to provide the information, 6.4% said they did not know, and 0.3% left the item blank.

The remaining IV sample is reduced to 12,019, for which the instrument's coverage is limited–only approximately 1.33% of commuters qualified as having one or more fatal traffic accidents occurring within their metropolitan area during rush hours on their ATUS diary day. Moreover, although accidents occur everywhere, they are 1.26% more likely {p-value < 0.000} in bigger cities (Atlanta, Boston, Chicago, Houston, Los Angeles, New York, Philadelphia, and Phoenix), a particular segment of the sample distribution. Ultimately, however, results will be conditional on CBSA, which captures location effects. However, because the impact of traffic accidents may be more pronounced in larger often more congested cities, we employ a second IV sample further restricted to residents of the fifteen most populous metropolitan regions.[14] The limited IV sample encompasses 4,282 observations.

Full summary statistics are included in Tables 1 and 2. Table 1 presents summary statistics for all ATUS variables and Table 2 lists summary statistics for variables taken from the EH Module. Table 3 presents selected activity time-use averages for three particular types of individuals within the ATUS sample: those with zero commutes, those ±10 minutes of the 50-minute daily commuting time median and those with total commuting times of 180 minutes or greater, following the U.S. Census definition of an "extreme commuter".[15] We limit the "no commute" group to those working (at home) at least four hours to provide a meaningful comparison with commuters, who implicitly allocate time to labor. The fourth column reports Analysis of Variance F-Statistics under the null hypothesis that activity means are equal across commuting length groups.

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[14] The fifteen most populous regions, based on 2008 Census estimates, are New York, Los Angeles, Chicago, Dallas, Philadelphia, Houston, Miami, Atlanta, Washington, Boston, Detroit, Phoenix, San Francisco, Riverside/Bernardino, and Seattle.

[15] Approximately 2.23% of commuters in the ATUS sample spent 180 minutes or more of the diary day commuting, which is comparable with U.S. Census estimates–2.47% of employed Americans had a journey to work of at least 90 minutes in 2003.

Most activities decrease with commute time: extreme commuters sleep 44.7 minutes (9.5%) less than non-commuters; they also spend 10.1% less time in primary eating, 38.3% less time preparing food, and 63.3% less time exercising. Not all activities strictly decrease as commutes lengthen–television watching rises then falls over commute length. Lastly, there is no evidence of any significant difference in socializing time averages across groups. For all other activities at least one group's mean is significantly different.

Analytical Results

All regressions include labor market participation time, age, gender, race, ethnicity, employment information, disability status, school enrollment, marital status and child information, education, household income, smoking indicator, severe weather indicator, and indicators for CBSA and ATUS diary date. There are time indicator variables coded for the day of the week, the month, and the year of the ATUS diary day. There is also a holiday indicator equal to one if the diary day coincided with New Year's Day, Easter, Memorial Day, the Fourth of July, Labor Day, Thanksgiving, or Christmas. We report standard errors clustered by respondents' CBSA in parentheses.[16]

OLS Results

I report full ordinary least squares coefficients modeling activity time allocation in Table 4, where each column's heading indicates the activity used as dependent variable. All time use variables are in minutes, so coefficients on commute and labor time are interpretable as per-minute trade-offs. There is evidence of strongly significant negative associations between commute length and exercise, food preparation, sleeping, socializing, and television viewing times. Each minute spent commuting is associated with a 0.0257 minute reduction in exercise

[16] We also generate but do not report both unadjusted standard errors and Seemingly Unrelated Regression (SUR) standard errors. Geographical clustered errors are the smallest; unadjusted and SUR errors are larger and relatively similar to each other. Ultimately, the choice of errors used in no way affects significance.

time, a 0.0387 minute reduction in food preparation time, a 0.2205, minute reduction in sleep time, and comparatively a 0.0226 and 0.1740 minute reduction in times spent socializing and viewing television, respectively. The largest estimated activity trade-off with commuting is with sleep time; certainly, sleep-loss implications permeate many facets of life beyond nutritional health outcomes.

Although highly significant, the coefficients are small in magnitude. The median 50 minute commuter loses only 1.29 minutes in exercise, 1.94 minutes of food preparation, and 11.03 minutes of sleep. However, these calculations are a single day's trade-offs, only, and effects may cumulate. The growth in obesity rates since the 1980s is equivalent to 100-150 additional calories per day–"three Oreo cookies or one can of Pepsi" (Cutler et al. 2003, p. 100)–and so slight behavioral changes daily can produce dramatic results. Ignoring the extrapolation and assuming moderate 280 calorie per hour exercise, an additional hour commute is associated with a 1,414.6 lesser caloric expenditure due to lost exercise over a 235 working day year.[17] If short-run exercise differences are unsubstantial in the short-run, there are also additional nutritional effects, evidenced by reduced food preparation time, which are unfortunately impossible to precisely measure using ATUS data. Modest coefficients are also consistent with the hypothesis that time constraints are a small but meaningful factor among an array of complex causes determining health outcomes.

There is no significant evidence of a trade-off between commuting and primary eating time. One interpretation for the absence of a significant association is that eating is a highly valued activity and individuals resist allocating away eating time. Additionally, eating is characterized by the ability to be performed concurrently with other activities and so eating time is particularly prone to measurement error given that the standard ATUS only measures primary

[17] A pound of body fat is the equivalent of approximately 3,500 calories.

activities. We analyze secondary eating time–and additional dietary behaviors–using the EH Module in Section V below.

Comparatively, the labor time coefficient is consistently significantly negative across activities, suggesting that there is also a negative trade-off between labor time and health-related activities. In particular, these findings support Ruhm's (2005) explanation of improved health outcomes in economic downturns due to recovered leisure time resulting from unemployment. In comparison to the commuting time coefficient, the labor time coefficient is statistically indistinguishable for exercise {p-value = 0.8071}, but the commuting coefficient is statistically greater in magnitude than the labor time coefficient with respect to food preparation {p-value = 0.0053}, sleep {p-value = 0.0001} and television times {p-value = 0.0247}. On a per-minute basis, commuting is associated with a greater amount of time traded-off with these activities than labor time is. The exception is time spent socializing, where the trade-off with labor time exceeds that with commuting time {p-value = 0.0001}.[18]

Lastly, the comparative coefficient magnitudes across activities suggest the limited health impact policies solely seeking to reduce commute (and labor) time might have–a one-minute reduction in commute time increases television watching over six times more than it increases exercise. The inefficiency of such a policy is measureable by the degree to which time savings are diverted into activities unproductive to health. An effective policy should *also* channel reclaimed leisure time specifically into health production.

[18] One of Putnam's (2000) principal inferences is that solitary commuting results in fewer social interactions and ultimately reduced social capital. Although the data suggest that work more than commuting is associated with less socializing time, there is probably a significant amount of on-the-job socializing not being captured by the ATUS.

Active and Sedentary Commuting Mode Comparisons

A valid critique of the commute measure is that respondents engaged in utilitarian exercise–walking or cycling as a transit mode[19]–bias coefficients. Individuals with longer active-mode commutes will need less non-travel exercise, but it would be incorrect to characterize their exercise trade-off with commuting as unhealthy since some exercise is achieved via transit. There is legitimate potential for bias: 10.9% of ATUS commuters reported some active commuting portion, and 3.8% reported active commuting portions of thirty minutes or greater. Because the ATUS identifies mode of transportation, we disaggregate total commute time into an active portion and two sedentary portions–"engaged" and "passive"–to separate this confounding factor. The active mode portion is total minutes of the commute spent walking or cycling, the "engaged" sedentary mode portion is total minutes spent operating a vehicular mode (such as driving a car), and the "passive" sedentary mode portion is total minutes spent as a non-operating passenger of a vehicular mode. The motivation for separating engaged and passive sedentary modes is that for some public transit users, commuting time is highly productive (with regards to work or certain leisure activities), which may free up time for health-related activities more than those employing engaged sedentary modes. We present commute time coefficients disaggregated by both active and sedentary mode usage times in Table 5.

With respect to exercise, the time trade-off appears to come entirely from sedentary commuting. Both of the sedentary commuting coefficients are significant, though statistically indistinguishable {p-value = 0.3797}. Despite the expected bias from utilitarian transit, there is no evidence of a significant trade-off between exercise and active commuting. Individuals do not consider active commuting a form of utilitarian exercise to the extent that it crowds-out non-

[19] Using active modes of travel is a commonly-prescribed solution in the popular media for individuals who feel they cannot find time to exercise. Of course, the surrounding built environment greatly influences the decision to walk (Saelens et al. 2003) or cycle (Rashad 2009).

travel exercise behaviors. Similar to exercise, only sedentary commuting time coefficients are significant with respect to food preparation.

Disaggregation reveals significant associations between commuting and eating time, whereas the aggregated commuting time coefficient is insignificant. Specifically, the passive commuting time coefficient is significantly *positive*–perhaps passive commuters apply time saved by in-transit productivity towards traditional sit-down meals. It is less clear why only passive commuting–and to a weaker extent active commuting–affects socializing time. One possibility is that passive commutes allow unrecorded secondary socializing opportunities which are not characteristic of engaged commuting.

For sleeping and television times, the coefficients on active and both sedentary commute times are significant. Moreover, for television the active commuting coefficient exceeds the sedentary commute modes' coefficients in magnitude {p-value = 0.0402}. One explanation is that active commuters have less affinity for and are more willing to trade off sedentary activities such as watching television, which illustrates the potential endogeneity inherent in modal choice. The commute mode coefficients are statistically indistinguishable for sleeping {p-value = 0.6366}.

Censored Regression Results

All time participation dependent variables are constrained to the twenty-four hours observed in the diary day. Previous time-use analyses often employ Tobit models to accommodate censoring of activity times, while other researchers propose that OLS is adequate for most studies' purposes (Stewart 2006). The issue is whether observed zero values result from observational windows which are too brief or whether they represent true nonparticipation.[20]

For comparison, we calculate censored-regression coefficients for exercise, food preparation, eating, and sleeping activities. All regressions are left-censored at 0; there are no activity participation observations at the upper bound of 1440 (total minutes in a day) and so right-censoring is unnecessary. Table 6 displays marginal effects, calculated as the change in activity time conditional on being uncensored, for commute time–both aggregated and disaggregated into active and sedentary portions–and labor time.

After accounting for censoring, most of the relationships from OLS results remain with slight changes in magnitude: each minute spent commuting is associated with a 0.0294 minute reduction in exercise time, a 0.0295 minute reduction in food preparation time, and a 0.2203 minute reduction in sleep time. Commuting time is again insignificant with respect to eating time. When commute time is disaggregated, again only sedentary commuting modes are significant with respect to exercise time, only passive commuting is associated with eating time, and both active and sedentary commuting time are significantly related to sleep time. The primary difference from OLS results is that the censored-regression active commuting coefficient is now weakly positively significant for food preparation. One explanation for this also involves transit mode self-selection: individuals who actively commute are more health-conscious and invest greater amounts of time in (healthy) meal preparation.

Commute Time Coefficients by Sample Stratifications

Table 7 presents OLS coefficients for commute time with respect to exercise, food preparation, eating, and sleeping time stratified by different subsamples to identify differences in

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[20] Foster and Kalenkoski (2008) provide a succinct overview of the OLS-vs-Tobit debate and empirically illustrate that results are often qualitatively comparable between Tobit and OLS models. Throughout the remainder of the essay we continue to predominantly employ OLS.

commuting time response among different populations. The subsamples we analyze are: males, females, three age groups (respondents aged 18-34, 35-49, and 50-70), white, nonwhite, households with children, commuters only, "non-errand" commuters (commuters making no stops between home and work), white collar employees, service occupation workers, the obese, the non-obese, households above 90th percentile income, and under 185% of the poverty line. We also utilize the Smart Growth America metropolitan sprawl index–first used by Ewing et al. (2003) to link obesity and urban sprawl–to investigate whether the commuting time-use trade-offs vary over urban form.[21] We group the bottom quartile of the sample with respect to the sprawl index, which by the index's design are residents of the *most* sprawled metropolitan areas, and the top quartile of the distribution (the residents of the least sprawled areas).

Subsample results suggest that males trade off exercise with commuting more than females (coefficients are -0.0345 and -0.0145), but females trade off food preparation more than males (coefficients are -0.0202 and -0.0483). The exercise trade-off with commuting decreases with age, the food preparation trade-off increases with age, and sleep trade-off dips in middle age and then rises. White respondents trade off exercise while there is no evidence that nonwhites do, and non-obese individuals trade off exercise while there is no evidence that obese individuals do. The commuting coefficient is significant the greatest number of occurrences within the sleeping time category–in all fifteen subsamples–and is significant for the least number of coefficients (three of the possible fifteen) within the eating time category.

[21] See www.smartgrowthamerica.org. The index is constructed so that lower values indicate areas of greater urban sprawl. Ewing et al. (2003) use both a county-level and metropolitan sprawl index and find stronger relationships with the county-level index. Because commuting may involve crossing county lines, we exclusively use the metropolitan-level index and recognize that results using the index are conservative. One caveat is that the index was constructed using Census 2000 data and so does not align with the 2003-2008 ATUS time span. Urban form changes slowly but it is true that the measure is more outdated wherever urban structure changed more rapidly.

When commuting is significant within the eating category, it is positive for service workers and the obese. Given the relationship between caloric intake and obesity, there may be certain individuals who react to longer commutes by spending more time eating–perhaps in response to commuting stress–which leads to weight gain. In contrast, the commuting coefficient is significantly negative for the subsample of those commuting directly between home and work. Perhaps the decision to run errands as part of a commute is also influenced by unobservable individual characteristics.

One noticeable result is the magnitude of the coefficient within the food preparation category for the obese subsample, which at -0.736 exceeds every other subsample's coefficient. Perhaps obese individuals are most willing to trade off food preparation time for commute time, due to some inherent trait. If foods requiring less preparation time also promote obesity, this effect will self-reinforce. Additionally, those in the bottom quartile of the Smart Growth sprawl index–residing in the *most* sprawled areas–trade off food preparation for commuting more than individuals residing in the least sprawled metro areas. This finding is consistent with a hypothesis that obesity is higher in areas of greater sprawl because individuals preferring low time cost, less nutritious meals self-select into these areas.

Instrumental Variables Results

To circumvent self-selection bias, we incorporate fatal traffic accidents as exogenous factors increasing commute time into the analysis. We display first stage results in Table 8 detailing metro-area fatal traffic accidents' effect on commuting time. Both accident indicator coefficients are significantly positive, as expected–traffic accidents proxy congestion which lengthens travel time. A morning incidence of a metropolitan-area fatal traffic accident is associated with a 27.2 minute longer daily commute and an evening incidence is associated with a 14.9 minute longer commute. The F-statistic testing the instruments' joint contribution to the model is 10.96 {p-value < 0.0000}, satisfying the greater-than-10-F-statistic rule-of-thumb for sufficiency (Staiger and Stock 1997).[22]

Table 8 also presents commuting time OLS coefficients using the reduced sample, commuting time IV coefficients, and both the χ^2 and F-statistics from and J-Hansen and Durbin-Wu-Hausman tests (with p-values in braces), respectively. The J-Hansen over-identifying restriction tests demonstrate that fatal traffic accidents are inappropriate for use as instruments when modeling eating time. In turns out that incidence of an evening accident is associated with 6.79 additional minutes of eating per day {p-value = 0.0233}.[23]

If using accidents as instruments yields consistent estimators, then the Durbin-Wu-Hausman tests indicate that endogeneity bias does not statistically influence OLS commuting coefficients' estimates in the full IV sample, and so using OLS results is appropriate. It may be that combinations of control variables, including the smoking and disability indicators, proxy for unobservable health preferences, the theoretically confounding factor. Future work should particularly seek to identify additional instruments or alternative identification strategies to compare results.

For sleep time, the Hausman test almost passes weak evidence of endogeneity and moreover among the four outcomes sleep time is the only activity for which the commuting IV coefficient is significant {p-value = 0.1294}. Interestingly, the IV coefficient point estimate is more than double in magnitude that of the OLS estimate, suggesting that a one-minute increase

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[22] The severe weather indicator, although not a valid instrument, is also a random external factor potentially influencing traffic. Unreported results indicate the coefficient if positive as expected–a value of 0.3350–but insignificant {p-value = 0.784}. It may be that the thresholds used to code the variable are insufficient to affect travel speed. The weather variable is also more weakly matched to individuals, since unlike traffic accidents it is not possible to tie weather conditions to specific times of the day.

[23] When incidence of a morning accident is alone used as a single instrument, the Hausman test fails to demonstrate evidence of bias {p = 0.1193}, and both OLS and IV coefficients are insignificant.

in commuting time decreases sleep time by 0.7499, and the commuting IV coefficients for exercise and food preparation times similarly increase in magnitude, although insignificant. This is unexpected because the theoretical bias–location self-selection by health preferences–increases coefficient magnitudes. IV coefficients should then be of lower magnitude, not greater.

Table 9 displays estimates using the sample of commuters in the fifteen most populous metropolitan areas. Morning and evening accidents are now combined into a single diary day accident indicator to accommodate the smaller sample size and still produce a joint F-statistic greater than ten. In first stage results, a fatal traffic accident occurrence is associated with an additional 17.01 minute daily commute. In second stage results, there is now Hausman test evidence that endogeneity bias affects the commuting time coefficients for exercise and sleep time. As in the full IV sample, reduced sample IV coefficient magnitudes increase: an additional minute of commuting is associated with 0.1457 fewer minutes exercise and 1.3720 few minutes sleep time. The IV coefficient's point estimate under sleep is less than "-1"–implying that indirect effects are present since the associated sleep loss exceeds the one-minute attributable to commuting time –although the estimate is not statistically different from negative one {p-value = 0.5319}.

The populous metropolitan area sample reinforces the evidence of increased trade-offs between commuting and both exercise and sleep time. Consistent with predictions of Becker's (1965) composite good theory, these time-intensive activities might be particularly prone to increased time constraints relative to food preparation and eating, which involve relatively more monetary good inputs. Given the theoretical direction of the endogeneity bias due to unobservable preferences, future research should seek to replicate these findings, to ensure their robustness across estimation strategies.

One alternative possibility is that individuals respond to lengthened commutes due to congestion differently than they respond to more typical commuting portions. Time spent stalled in traffic might increase stress disproportionately to typical commuting time, debilitating commuters' willingness to engage in health-related activities and consistent with the increased IV commuting coefficient magnitudes. It is not possible to directly measure stress in the ATUS; however, the survey does capture time spent in sleeplessness, which may proxy for stress levels. Neither morning {p-value = 0.9364} nor evening {p-value = 0.4756} traffic incidences are significantly associated with increased sleeplessness, so there is no empirical evidence of bias, though future research must consider of instrumental variables' potential indirect effects. Measuring commuting time's indirect effects will enable a more definitive understanding of the mechanisms influencing health-related activity time reductions.

Tests and Extensions

MET Analysis: An Examination of Physical Activity Intensity

Caloric expenditures vary by activity. If longer commutes are physically draining, one potential byproduct from traveling is that individuals substitute into less intensive activities resulting in reduced energy expenditure for a given quantity of exercise time. To test this possibility, we match activity times to MET intensity values Tudor-Locke et al. (2009) construct for ATUS activity categories to calculate MET minutes. A "MET" (or "metabolic equivalent") is a unit commonly used to gauge the intensity of a physical activity and "MET minutes" are the minutes spent in an activity multiplied by that activity's MET value. A MET is defined as the ratio of energy expenditure in an activity to expenditure at rest.[24] For example, a MET value of 2.0 indicates that the activity requires twice as much energy than if the person were resting. The

[24] A MET value of 1.0 is equivalent to a metabolic rate consuming 3.5 milliliters of O_2/kg body weight per minute.

ATUS MET values range from the low of 0.92 (sleeping) to 10.0 (doing martial arts or playing rugby).

Using these intensity values, we calculate "MET minutes", defined as individual *i*'s participation in activity *k* weighted by *k*'s MET intensity, summed over a set of activities:

$$MET\ Minutes_i = \sum_K (i'\text{s time in activity } k)\ (\text{MET intensity for activity } k)$$

We construct two MET minute indexes: the first where *K* is limited to ATUS exercise activities only and a second where *K* is limited to all other non-exercise leisure activities day. We use exercise MET minutes as an outcome variable regressed on commuting time (and all other factors). MET minutes combines time in activities with the activities' degree of strenuousness and thus roughly proxies caloric expenditures. We then include aggregate time spent exercising as an additional control and regress again. MET minutes are the aggregated product of activity time and strenuousness, or alternatively, MET minutes are average MET values weighted by activity time participation. Therefore, holding time constant investigates regressor associations with average strenuousness of the set *K*. While Table 4 regressions analyze *quantity* of exercise, regressing exercise time augmented with MET intensity analyzes *quality* of exercise. We then repeat the substitution test using the set of non-exercise leisure activities to test for associations between lengthier commuting times and substitution into less strenuousness non-exercise time uses. We display coefficients for pooled and disaggregated commute times, labor time, and exercise/leisure time controls in Table 10.

The first three columns of Table 10 use exercise MET minutes as an outcome variable. The first column's significantly negative commute time coefficient shows that lengthier commutes are associated with lower MET minutes. In the second column we control for exercise time to examine variation in average MET intensity related to commuting and labor time. In this instance, commute time maintains negative significance, and so there is significant evidence that commuting induces substitutions into lower exercise intensities, because longer commutes are associated with lower average MET values, holding exercise time constant. This result is consistent with the hypothesis that longer commutes produce a lethargic side effect. An additional 41.7 minutes of commuting is associated with exercising on average intensity one MET lower. There is no evidence of an analogous substitution due to labor time. The third column repeats the second column's model with commuting time now disaggregated by active, engaged, and passive transit modes. There is no evidence that walking or cycling is associated with substitution into lower intensity exercises, but there is weak evidence that engaged mode and strong evidence that passive mode commuting times are associated with lower-intensity exercises. An additional 16.47 minutes only of passive commuting is associated with exercising at an intensity level an average of one MET lower.

In the fourth column, the set of *k* is all non-exercise activities; commute time is disaggregated by mode and non-exercise leisure time is held constant. All commute and labor time coefficients are significantly positive. This suggests that the average strenuousness level of non-exercise activities increases with both commuting and labor time. The active commuting time coefficient point estimate is the largest, although all commuting mode coefficients are statistically indistinguishable {p-value = 0.4695}. The labor time coefficient, however, is statistically distinct from the commuting coefficients {p-value < 0.0000}.

Is it possible that commuting and labor produce an invigorating effect which increases non-exercise activity intensity? Two alternative possibilities are (1) that individuals manage their schedule so that work day leisure activities are busier and more strenuous, days off from work are characterized by more relaxed activities, and so this result arises from intertemporal activity arrangement. Additionally, (2) because sleeping and television–inherently sedentary time uses–are the activities most traded off with commuting and labor time, their trade-off raises the non-exercise leisure time average MET intensity score. An interesting extension would transpose MET minutes to caloric expenditures and calculate net caloric expenditures associated with commuting time.

An Extension to Analyses of Eating and Food Preparation Behaviors

Commuting is consistently insignificant with respect to eating behavior in pooled samples. However, primary eating time is particularly prone to measurement error due to omitted secondary eating–time spent eating while engaged in another primary activity. The EH Module indicates a non-trivial amount of secondary eating–respondents' average time spent eating secondary to another activity was 22.34 minutes, or 18.7% of the total minutes they ate. Although the data do not show an association between commuting and primary eating, it is possible that commuting affects secondary eating time, for instance by providing an environment–such as a car–in which to snack. To test this hypothesis, we utilize the EH Module's secondary eating information. We regress secondary eating time in minutes on commuting time and labor time (here both scaled to *hours*). OLS results are in the first column of Table 11.

EH Module data do not demonstrate any evidence of an association between total secondary eating and either commuting or labor time. It appears that neither commuting nor work time are associated with differences in eating time in either traditional meal settings or while concurrent to other activities. These results may be moot, however, given evidence that the frequency of eating episodes–not the minutes spent eating–explains ATUS respondents' BMI values: fewer eating episodes are associated with higher BMI scores (Hamermesh 2009).

Certainly, time constraints imposed by longer commutes might force individuals to eat fewer meals throughout the day.

To test this possibility, we examine whether commuting time is associated with the number of diary day primary and secondary eating episodes.[25] Negative binomial regression coefficients are presented in the second and third columns in the top half of Table 11. The coefficients on commute time are insignificant for both primary and secondary eating episodes– there is no evidence of an association between time spent commuting and the number of meals throughout a day. The coefficient for labor time, however, is positively (weakly) significant with respect to primary eating episodes. Recalling that in Table 4 there is a negative relationship between labor and primary eating times, the overall evidence suggests greater labor time is associated with less primary eating time overall, but with more meals throughout the day, and does not influence secondary eating behaviors.

Although eating time is not associated with commuting time, increased time constraints due to commuting might influence the type and health quality of meals prepared and consumed, especially given that the ATUS demonstrates a trade-off between commuting and food preparation times. Reduced food preparation time resulting from lengthier commutes may increase the consumption of pre-prepared, often less-healthy meals obtained from either full- or limited-service food establishments. To further investigate this, we code an indicator variable equal to one if the respondent reported any time spent purchasing non-grocery food items.[26] Probit regression marginal effects using this indicator as the dependent variable are presented in the bottom half of Table 11. Each probit regression's sample is differentiated by self-reported

[25] Primary and secondary eating episodes are coded as having four if the number reported was four or greater; this is approximately the top 1% of each distribution.

[26] The indicator is constructed as equal to one if ATUS variable t070103, indicating minutes spent "purchasing food (not groceries)", is greater than zero. The BLS's description of activities that might be classified as t070103 include "paying the pizza delivery person", "paying for meal at restaurant", or "buying fast food".

household food preparation duty roles obtained from the EH Module: the first column uses the pooled module sample, the second column is those identifying as the household primary meal preparers, the third column is those who identify as sharing meal preparation duties, and the fourth column is those who are neither primary meal preparers nor share duties.

For primary meal preparers and those uninvolved in meal preparation (and the pooled sample overall), the data suggest a significant positive correlation between increased commute length and purchase of non-grocery food items. In contrast, longer labor hours are negatively associated with the likelihood of non-grocery food purchases for the pooled sample and those without principal meal preparation roles, although at a much smaller magnitude. Assuming an eight hour work day and one hour total commuting time, the combined effects would net negative for those without meal preparation duties but positive for the pooled sample overall.

The evidence suggests that longer commutes of primary meal-preparers are associated with non-grocery food purchases, meaning it is less likely foods consumed in such instances are unprocessed base grocery items. Again, one should be cautious in making inferences regarding the healthiness of this outcome, but increased "take-out" is unhealthy if respondents either do not or are not able to choose healthy non-grocery food items. Quality grocery stores have largely migrated out to the suburbs where they are unreachable to the inner city poor (Eisenhauer,2001), while fast food establishments are ubiquitous within disadvantaged neighborhoods (Block et al. 2004). Residents of such neighborhoods–a particularly immobile subpopulation–substitute towards fast food following lower time and money costs, though at higher health costs.

Intertemporal Substitution

One limitation of the ATUS is its single day observational window and it is completely unknown how respondents spend other days. The evidence so far indicates there are robust decreases in some due to commuting and labor time, but very possibly respondents compensate for lost activity time on days off from work. Connolly (2008) already demonstrates evidence of intertemporal substitution of activities based on weather patterns both the day previous to and after the ATUS diary day.

To test for intertemporal substitution, we take a categorical comparison approach to detect increased health-related activity participation times for employed individuals not working on their ATUS diary day relative to individuals without jobs. First, we code a dummy variable indicating respondents that do not have a job; those included are either unemployed or not in the labor force. Second, we code another dummy variable indicating the respondent is employed but reported *no labor time* during the particular ATUS diary day. The reference group is employed individuals that worked on their diary day. We run a new set of regressions modeling time spent in activity k as follows:

$$\boldsymbol{Activity}_{ijt}^{k} = \alpha_0^k + \alpha_1^k(not\ employed)_{ijt} + \alpha_2^k(employed; no\ labor\ time)_{ijt} + \boldsymbol{\alpha^k}\mathbf{X_{ijt}} + \varepsilon_{ijt}^k$$

Intertemporal substitution would be evident as employed individuals increasing health-related activities upwards on days off from work relative to individuals without jobs, who do not work any day and have no need to compensate. The difference in activity k time between employed individuals not working and individuals without jobs is the difference between coefficients α_2^k and α_1^k. Therefore, evidence of intertemporal substitution will manifest as the linear combination $\alpha_2^k - \alpha_1^k > 0$. A positive combination demonstrates that employed individuals compensate for time lost in health-related activities due to commuting and labor requirements by increasing participation on days they do not work or commute, relative to unemployed and labor force non-participants. We present estimates for α_1^k, α_2^k, and $[\alpha_2^k - \alpha_1^k]$ across different activities in Table 12.[27]

All estimates of α_1^k and α_2^k are significantly positive, reaffirming evidence of increased activity involvement in the absence of work and commute. With regards to intertemporal substitution, the only instances of significantly positive differences between α_2^k and α_1^k are with respect to eating, sleeping, and socializing, suggesting employed individuals compensate by eating an additional 3.3 minutes, sleeping on average an additional 26.0 minutes, and socializing an additional 3.5 minutes on days they do not work, relative to those without jobs. Furthermore, $[\alpha_2^k - \alpha_1^k]$ is statistically *negative* for both food preparation and television activities–it appears that employed individuals spend less time daily preparing food (8.0 minutes) and watching television (9.7 minutes) on days they do not work relative to those without jobs. Perhaps employed individuals are inherently less likely to spend time preparing food, meaning efforts to increase healthy food preparation by shortening work and commute time burdens would be ineffective. However, this characteristic could also result from inertia–habits of consuming low time cost food carried over a work-week of time-constrained days.

Reduced Form: Associations Between Commute Time and Obesity

If longer commutes are associated with reduced health-related activity time, do ATUS data also show that respondents with lengthier commutes are more likely to be obese? While results may be illustrative, modeling a cumulative outcome–body mass–as a function of a single day's activities is problematic. Results must be received with caution.

[27] Commute time and work time are omitted in these regressions because the time savings effect of having no work or commute is fully captured by α_1^k and α_2^k. Any effect of employment status is incorporated into α_2^k, which calculates the difference between employed individuals working and not working. Additionally, employed individuals serve as the reference group so occupational indicators (white collar, blue collar, service) are superfluous and are also omitted.

To investigate an association between obesity and commute we run regressions using respondents' BMI and obesity status as outcomes and diary day commute and labor times as explanatory variables, with standard controls. We also include the Smart Growth American sprawl index as a regressor to attempt to replicate the sprawl-obesity association of previous research. If the inclusion of commute time removes the significance of sprawl, it would validate commuting as the latent pathway driving the sprawl-obesity association. However, if sprawl remains significant independent of commuting, then there must be other factors characteristic of sprawl besides lengthy commutes associated with obesity.

The first and second columns of Table 13 present probit regression marginal effects with respondents' obesity status as the dependent variable ordinary least squares and the third and fourth columns repeat displaying results with respondents' BMI as the dependent variable, excluding and including commute and labor times, respectively. Both commute and labor times are scaled to hours in these regressions. The sample (of 2,852) is limited to the respondents completing the EH Module who journeyed to work on their diary day.

The first row of Table 13 indicates that the commute time coefficient is significantly positive with respect to obesity status (although only at the 90% confidence level) but not BMI; this weakly replicates previous research correlating commute length and body mass (Walsleben et al. 1999; Lopez-Zetina et al. 2006). Labor time, on the other hand, is insignificant in every regression. Commute length may be associated with body mass due to either causality or self-selection, but there is no demonstrable relation to body mass and the diary day's work time. Table 13 also displays the coefficients for white and blue collar occupations (service sector employment is the reference group), which might capture more cumulative labor effects. However, none of these coefficients are significant.[28]

Lastly, the sprawl index coefficients are statistically significant in each model, and always display the expected negative sign. This replicates previous research and for the first time demonstrates that the relationship between urban sprawl and body mass is detectable using ATUS data. Commute time and sprawl are both significant in the obesity models, which suggest that although there is evidence linking commuting time with behaviors which may contribute to obesity outcomes, there must be additional factors characteristic of sprawl besides commuting which are associated with increased mass.

Conclusions

This essay hypothesizes and tests a pathway explaining how the built environment might lead to poor health outcomes. Specifically, we test the putative claim that Americans have insufficient leisure time due to long commutes (and work hours) to either exercise or prepare healthy meals. We find highly significant evidence that commuting is associated with modest reductions in exercise, food preparation, and sleep behaviors. Moreover, commuting is often associated with greater trade-offs than labor time, on a per-minute basis. Sample stratifications reveal further relationships, particularly that obese individuals and residents of the most sprawled metropolitan areas trade off commuting and food preparation with the greatest magnitude. We also find evidence that longer commutes increase the likelihood of non-grocery food purchases and induce substitution into lower intensity exercises. To the possibility of intertemporal substitution we find evidence of increased eating, sleeping, and socializing times, only, during non-work days. Lastly, we find the association between urban sprawl and greater body mass

[28] Lakdawalla and Philipson (2002) find differences in body mass across occupations of differing levels of strenuousness using refined measures, but the ATUS data do not demonstrate significant differences across coarse occupational categories.

persists even after controlling for commute time. All together, longer commutes are associated with behavioral patterns which over time may contribute to poor health outcomes.

This essay contributes to a cross-disciplinary field of developing research within the intersection of health and urban economics. The effects of the built environment on resident health are a topic of increasing interest in public health fields, while the built environment itself is an equilibrium outcome which theories in both urban economics and expenditure-side local public finance seek to explain. Future research should continue to incorporate this simultaneity.

Despite the link to the built environment, the results of this research are of general interest beyond the connection to sprawl and commuting. Understanding healthy activity time trade-offs to due to work and work-related travel will be of broad interest to health, urban, and labor policy makers. For example, marginal commuting costs are commonly conceptualized as both the wage value of lost time and additional gasoline costs of sitting in slow or idle traffic, and both congestion and environmental externalities are also recognized. However, health consequences of lost leisure time are additional–but usually unaccounted for–commuting costs, and are relevant towards informing policy. Future researchers could attempt to calculate in monetary terms the impact of commuting on health, using results from this essay.

In addition to extending emerging research investigating time use trade-offs (e.g., Basner et al. 2007), this essay is the first in which external factors are exploited as instruments in order to make causal inferences in activity time trade-offs. Incidences of dairy day metropolitan-area fatal traffic accidents are found to significantly explain commuting time, and so add to the existing literature's stock of external factors able to be merged into the ATUS dataset (Hamermesh et al. 2006; Connolly 2008; and Krueger and Mueller 2008). ATUS data continually demonstrate that external factors produce salient results in the survey, supporting ATUS usability in evaluating the effects of an expanding variety of natural experiments.

This study has several limitations, particularly relating to the cross-sectional nature of the data. A more valid design would resample respondents over days with varying commute and labor times to allow for within subject analysis. Another alternative to mitigate selection bias is to focus analysis on those for whom "commute" is not a choice variable, such as the adolescents of commuting parents.[29] Secondly, most of the inferences about eating behaviors are based on observations of food preparation times, instances of non-grocery food purchases, and conjectures on what these imply about an individuals' dietary intake. Information on precisely which foods individuals consumed would be invaluable. Third, monetary prices are omitted from the study, which are a key economic determinant in explaining behavior. There exist metropolitan-level price indexes such as that constructed by the American Chamber of Commerce Researchers Association (ACCRA), but crucially relevant price variation within city neighborhoods is averaged out. Moreover, not knowing consumers' purchased items limits the explanatory contributions of price data. Lastly, additional work might incorporate psychological perceptions of stress and time pressures to distinguish the direct and indirect effects of commuting time. This is essential for interpretation because otherwise the extent to which perceptions and stress are driving results cannot be determined. Resolving these issues offers opportunities for future research.

[29] For example, research could examine whether adolescent processed-foods intake is related to long commute and labor hours of their parents. In empirical research on neighborhood effects, limiting the sample to youths is a commonly used technique in avoiding self-selection (e.g., Ihlanfeldt and Sjoquist 1990); however, this technique is biased if children and parents share unobserved, confounding characteristics.

Empirical Tables

Unless otherwise noted, all regressions include labor market participation time, age, gender, race, ethnicity, employment information, disability status, school enrollment, marital status and children information, education, household income, smoker status, severe weather indicator, CBSA dummy variables, and ATUS diary date information as controls. Standard errors are clustered by CBSA and are presented in parentheses.

Table 1: Summary Statistics (n=46,496)[30]

Variable	Mean	Std. Dev.	Min	Max
Age	43.12	13.10	18	70
Male	0.431	0.495	0	1
Hispanic	0.150	0.357	0	1
Black	0.123	0.328	0	1
Asian	0.035	0.184	0	1
Non-Hispanic, Other Race	0.017	0.131	0	1
Self-Employed	0.076	0.264	0	1
Works for Hourly Wages	0.333	0.471	0	1
White Collar worker	0.329	0.470	0	1
Blue Collar worker	0.124	0.330	0	1
Service worker	0.273	0.446	0	1
School Enrollment	0.079	0.270	0	1
Disabled	0.043	0.203	0	1
Household Income Midpoint ($ Thousands)	65.38	51.80	2.5	225
Single	0.224	0.417	0	1
Married, Spouse Absent	0.013	0.112	0	1
Widowed	0.034	0.181	0	1
Separated/Divorced	0.166	0.372	0	1
Number of Children	0.984	1.163	0	11
Young Child (age 0-1) Present	0.100	0.300	0	1
High School Graduate	0.242	0.428	0	1
Some College	0.284	0.451	0	1
College Graduate	0.232	0.422	0	1
Grad School or Professional Degree	0.133	0.339	0	1
Smoker	0.016	0.124	0	1
Significant Metropolitan Rain or Snowfall	0.106	0.307	0	1
Non-grocery Purchase Indicator	0.128	0.334	0	1
Fatal Traffic Accident Indicator (Morning)	0.001	0.034	0	1
Fatal Traffic Accident Indicator (Evening)	0.003	0.052	0	1
Exercise Time (Minutes)	16.64	54.53	0	1,073

[30] Other control variables are day of week, month, year, holiday indicators, and area (CBSA) dummy variables. The ATUS is oversampled for weekends–Saturdays and Sundays jointly comprise approximately half of the sample.

Table 1: Summary Statistics (n=46,496)[30]

Variable	Mean	Std. Dev.	Min	Max
Food Preparation Time (Minutes)	27.61	44.26	0	975
Eating Time (Minutes)	68.02	51.09	0	735
Sleeping Time (Minutes)	520.66	131.32	0	1,436
Socializing Time (Minutes)	47.48	89.76	0	1,123
Television Time (Minutes)	155.09	160.06	0	1,348
Labor Time (Minutes)	166.25	238.29	0	1,310
Commuting Time (Minutes)	19.11	37.78	0	630
Commuting Time, Active Mode (Minutes)	0.87	6.89	0	280
Commuting Time, Engaged Mode (Minutes)	15.93	32.75	0	540
Commuting Time, Passive Mode (Minutes)	2.31	15.67	0	585
MET Minutes (Exercise)	80.78	272.90	0	5,215.50
MET Minutes (Non-Exercise Leisure)	1,714.82	520.02	177.4	4,859.10

Data from the American Time Use Survey (2003-2008) and the National Climactic Data Center. MET minutes constructed using data taken from Tudor-Locke et al. (2009).

Table 2: Summary Statistics–Eating and Health Module Variables (2006-2007)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Income Within 185% of Poverty Line	13,460	0.265	0.441	0	1
Body Mass Index (Adjusted)	12,528	28.23	6.066	14.41	65.10
Obesity Status (Adjusted)	12,528	0.316	0.465	0	1
Secondary Eating Minutes	13,639	22.34	81.47	0	1,200
Primary Eating Episodes	13.827	1.9790	0.9469	0	4
Secondary Eating Episodes	13.827	0.8067	0.8990	0	4
Primarily Meal Preparer	13,667	0.612	0.487	0	1
Shares Meal Preparation Duties	13,667	0.120	0.325	0	1

Data from the American Time Use Survey Eating and Health Module (2006-2007).

Table 3: Average Activity Time Means (in Minutes) By Illustrative Commute Time Groups				
	Worked at Home (No Commute)	"Average" Commuter (40-60 Minutes)	Extreme Commuter (180+ Minutes)	ANOVA F-Statistic
Exercise	12.98	10.46	4.76	9.43***
Food Preparation	18.45	17.18	11.39	8.41***
Primary Eating	68.65	61.25	61.73	16.21***
Sleep	471.25	463.10	426.60	27.25***
Socializing	24.74	23.85	20.50	0.87
Television	90.13	99.36	77.48	11.95***
Observations	1,446	4,347	323	

"Worked at Home" groups respondents who did not commute but worked at home at least four hours. "ANOVA F-Statistic" reports Analysis of Variance F-Statistics under the null hypothesis that means are equal across groups.
Asterisks denote statistical significance [*** p<0.01]. Data from the American Time Use Survey (2003-2008).

Table 4: OLS Results for Activity Times (n = 46,496)

	Dependent Variables: Activity Time in Minutes					
	Exercise	Food Preparation	Eating	Sleeping	Socializing	Television
Commute Time (Minutes)	-0.0257*** (0.0060)	-0.0387*** (0.0050)	0.0076 (0.0070)	-0.2205*** (0.0160)	-0.0226** (0.0100)	-0.1740*** (0.0150)
Labor Time (Minutes)	-0.0271*** (0.0010)	-0.0232*** (0.0010)	-0.0220*** (0.0020)	-0.1536*** (0.0030)	-0.0567*** (0.0020)	-0.1381*** (0.0040)
Age	-0.5547*** (0.1260)	1.6635*** (0.1300)	-0.5475*** (0.1240)	-3.1918*** (0.3860)	-1.5336*** (0.2610)	-0.1163 (0.4190)
Age^2	0.0041*** (0.0010)	-0.0170*** (0.0010)	0.0088*** (0.0010)	0.0214*** (0.0040)	0.0126*** (0.0030)	0.0111** (0.0050)
Male	12.2848*** (0.6890)	-16.8017*** (0.6130)	4.1860*** (0.5570)	2.4730* (1.3710)	-4.5310*** (1.0450)	51.0610*** (1.6940)
Hispanic	-2.3720*** (0.8280)	7.6251*** (0.8710)	-0.7156 (1.4360)	16.8834*** (1.9270)	3.8454** (1.5300)	2.485 (4.6650)
Black	-4.9263*** (0.7430)	3.9350*** (0.6390)	-16.8082*** (0.6240)	11.0417*** (1.9820)	3.9695** (1.7200)	28.2361*** (3.4750)
Asian	-4.8435*** (1.0220)	12.3125*** (1.4660)	9.9855*** (1.3800)	17.8703*** (2.9330)	-3.4692* (2.0640)	-0.8161 (3.0270)
Non-Hispanic, Other Race	1.3439 (3.4280)	1.7309 (1.5500)	0.7819 (1.7020)	1.3094 (4.4180)	-2.0313 (2.7810)	0.7785 (6.3880)
Self-Employed	1.6346 (1.2120)	-0.0034 (0.6270)	0.7238 (1.0970)	2.1778 (2.1320)	2.0886 (1.4380)	-9.0407*** (2.3200)
Works for Hourly Wages	-1.0026 (0.6920)	-1.4050*** (0.4550)	-1.8503*** (0.6080)	2.7801** (1.3330)	0.3012 (1.0280)	3.9100** (1.6240)
White Collar worker	1.3887 (0.8940)	-7.0586*** (0.7010)	2.7404*** (0.9210)	14.8422*** (1.5770)	-0.6163 (1.2640)	-11.6527*** (2.1680)
Blue Collar worker	-0.9465 (1.2930)	-6.6715*** (0.9640)	4.6991*** (1.2400)	16.6469*** (2.2530)	0.1791 (1.7910)	-18.1460*** (3.1740)
Service worker	1.7063* (0.9720)	-7.0864*** (0.7390)	1.35 (0.8840)	20.0790*** (1.9660)	-2.6555* (1.4450)	-12.7241*** (2.2220)
School Enrollment	-0.9677 (1.0540)	-4.9830*** (0.6760)	-1.7042* (0.9080)	-20.7803*** (2.6760)	-2.7348* (1.6430)	-33.4248*** (2.2160)
Disabled	-8.6417*** (1.0940)	-9.2730*** (1.1940)	-6.0213*** (1.2590)	30.7295*** (4.3150)	1.0758 (2.5020)	69.7298*** (5.7460)
Household Income (in $ks)	0.0710*** (0.0080)	-0.0089** (0.0040)	0.0374*** (0.0050)	-0.0888*** (0.0130)	0.0168* (0.0090)	-0.1806*** (0.0150)
Single	2.3614*** (0.7520)	-6.1668*** (0.5840)	-4.6024*** (0.6380)	6.8266*** (1.7710)	-0.3996 (1.2490)	16.0302*** (2.0630)
Married, Spouse Absent	2.4569 (1.7520)	0.0618 (1.7500)	-5.2722*** (1.5160)	6.7443 (5.9040)	3.3567 (3.9400)	-3.6228 (6.0960)
Widowed	1.9603** (0.9120)	-5.8838*** (1.2930)	-6.4460*** (1.3060)	3.2753 (3.5750)	5.0779** (2.4360)	-0.6607 (4.6520)

Table 4: OLS Results for Activity Times (n = 46,496)

	Dependent Variables: Activity Time in Minutes					
	Exercise	Food Preparation	Eating	Sleeping	Socializing	Television
Separated or Divorced	2.6445*** (0.6570)	-5.0291*** (0.7120)	-6.9567*** (0.6920)	4.1531** (1.9470)	0.2781 (1.3590)	10.1553*** (2.2830)
Number of Children	-0.7378*** (0.2570)	3.5512*** (0.2250)	-1.2501*** (0.2640)	-5.0852*** (0.5230)	-3.0065*** (0.4240)	-10.1547*** (0.6010)
Young Child Present	-6.4676*** (0.7540)	2.2595*** (0.7440)	0.6244 (0.6980)	-10.6983*** (2.1080)	-1.8844 (1.3920)	-5.0417** (2.1700)
High School Graduate	-1.0228 (0.9370)	-2.7000*** (0.7620)	4.0020*** (0.7160)	-21.4594*** (2.5790)	-1.4082 (1.6940)	-12.4314*** (3.4660)
Some College	-1.5221 (0.9670)	-3.6797*** (0.9160)	7.5828*** (0.7960)	-29.3408*** (2.4890)	-1.7445 (1.7730)	-31.0068*** (3.6340)
College Graduate	1.231 (1.0780)	-5.0573*** (1.0540)	11.9487*** (0.8430)	-32.0637*** (2.6280)	-3.6742** (1.8650)	-49.3530*** (3.5510)
Graduate Degree	4.4331*** (1.3040)	-5.2758*** (0.9830)	14.4119*** (1.1100)	-29.1659*** (3.0330)	-3.5866** (1.7140)	-65.1591*** (4.1320)
Smoker	-5.0229*** (1.4880)	-0.7144 (1.3160)	-1.4432 (1.7280)	-13.1448** (5.2180)	1.6682 (2.8830)	3.7077 (4.8240)
Severe Weather	-2.8140*** (0.6590)	0.6454 (0.6200)	-0.0144 (0.8410)	3.1568* (1.8020)	-0.271 (1.3470)	9.5579*** (2.3750)
Holiday	-1.6165 (2.1010)	11.7112*** (2.0570)	3.3901 (2.1080)	15.9200*** (4.7800)	53.7693*** (5.0500)	12.4844** (6.3080)
Monday	4.0198*** (1.0580)	1.1172 (0.8060)	-4.1574*** (0.7790)	-33.3019*** (2.0350)	-10.6499*** (1.3100)	-12.1419*** (2.8100)
Tuesday	4.4084*** (1.1460)	2.7620*** (0.8500)	-3.7367*** (0.8990)	-34.5360*** (2.1600)	-10.2718*** (1.3060)	-11.6165*** (3.0330)
Wednesday	3.8272*** (0.8420)	1.6753** (0.7630)	-3.7715*** (0.8960)	-36.2531*** (2.1130)	-11.0732*** (1.3010)	-11.4378*** (2.7270)
Thursday	4.1525*** (1.0240)	1.1205 (0.7680)	-2.4762*** (0.8880)	-37.1132*** (2.3090)	-9.6581*** (1.4890)	-13.8165*** (2.8520)
Friday	4.0535*** (1.0700)	-3.9810*** (0.7830)	1.231 (1.0370)	-52.6190*** (2.5060)	1.2955 (1.4770)	-10.9438*** (2.7750)
Saturday	4.0834*** (0.9190)	-4.2823*** (0.6210)	2.0672*** (0.7870)	-35.1950*** (1.9060)	5.3835*** (1.3530)	-12.0868*** (2.1750)
Constant	16.3516*** (3.0770)	4.2693* (2.3940)	79.349*** (2.8140)	700.4933*** (8.5160)	109.1534*** (5.7390)	192.0845*** (8.5730)
R-squared	0.049	0.128	0.069	0.188	0.062	0.198

Controls also include CBSA and diary day month and year information. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 5: Commute Time Coefficients (OLS) Disaggregated by Travel Mode (n=46,496)

	Dependent Variables: Activity Time in Minutes					
	Exercise	Food Preparation	Eating	Sleeping	Socializing	Television
Active Commute (Minutes)	-0.0256 (0.0160)	0.0215 (0.0180)	0.0052 (0.0210)	-0.2503*** (0.0770)	-0.0659* (0.0350)	-0.3233*** (0.0630)
Engaged Commute (Minutes)	-0.0279*** (0.0070)	-0.0430*** (0.0050)	-0.0003 (0.0080)	-0.2245*** (0.0170)	0.0004 (0.0090)	-0.1738*** (0.0160)
Passive Commute (Minutes)	-0.0199** (0.0090)	-0.0444*** (0.0110)	0.0292** (0.0150)	-0.2010*** (0.0240)	-0.0714*** (0.0170)	-0.1320*** (0.0290)

Dependent variables are given in the column headers (activity times in minutes); selected independent variables are detailed by rows (commuting time in minutes using active, engaged, and passive modes).
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 6: Censored Regression Marginal Effects Results (n = 46,496)

	Dependent Variables: Activity Time in Minutes (left-censored at 0)							
	Exercise		Food Preparation		Eating		Sleeping	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Commute Time (Minutes)	-0.0294*** (0.0074)	-	-0.0295*** (0.0048)	-	0.0090 (0.0070)	-	-0.2203*** (0.0157)	-
Active Commute (Minutes)	-	-0.0023 (0.0328)	-	0.0269* (0.0146)	-	0.0088 (0.0164)	-	-0.2502*** (0.0768)
Engaged Commute (Minutes)	-	-0.0286*** (0.0091)	-	-0.0322*** (0.0051)	-	0.0010 (0.0063)	-	-0.2243*** (0.0169)
Passive Commute (Minutes)	-	-0.0393*** (0.0146)	-	-0.0389*** (0.0109)	-	0.0229** (0.0110)	-	-0.2008*** (0.0239)
Labor Time (Minutes)	-0.0231*** (0.0018)	-0.0232*** (0.0018)	-0.0147*** (0.0008)	-0.0146*** (0.0008)	-0.0203*** (0.0016)	-0.0158*** (0.0013)	-0.1536*** (0.0032)	-0.1533*** (0.0032)

Dependent variables are given in the column headers (activity times in minutes, left-censored at 0); selected independent variables are detailed by rows (commuting time and labor time in minutes); marginal effects are calculated as the change in activity time conditional on being uncensored.
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 7:	Commute Time Coefficients (OLS) within Subsamples				
	Dependent Variables: Activity Time in Minutes				
Subsample	Subsample Size	Exercise	Food Preparation	Eating	Sleeping
Male	20,021	-0.0345***	-0.0202***	0.0139	-0.2087***
		(0.0020)	(0.0050)	(0.0090)	(0.0230)
Female	26,475	-0.0145**	-0.0483***	-0.0035	-0.2486***
		(0.0060)	(0.0080)	(0.0120)	(0.0250)
Ages 18-34	13,249	-0.0371***	-0.0303***	-0.0059	-0.2466***
		(0.0084)	(0.0080)	(0.0143)	(0.0324)
Ages 35-49	18,201	-0.0233***	-0.0367***	0.0120	-0.1829***
		(0.0081)	(0.0076)	(0.0093)	(0.0197)
Ages 50-70	15,046	-0.0191*	-0.0449***	0.0092	0.2439***
		(0.0104)	(0.0086)	(0.0146)	(0.0309)
White	31,368	-0.0362***	-0.0404***	0.0020	-0.1940***
		(0.0060)	(0.0050)	(0.0090)	(0.0200)
Nonwhite	15,128	-0.0104	-0.0302***	0.0134	-0.2455***
		(0.0080)	(0.0110)	(0.0110)	(0.0320)
Has Children	24,347	-0.0281***	-0.0336***	0.0042	-0.1724***
		(0.0070)	(0.0070)	(0.0080)	(0.0200)
Commuters	14,491	-0.0324***	-0.0369***	-0.0097	-0.2790***
		(0.0050)	(0.0050)	(0.0090)	(0.0190)
Non Errands	6,839	-0.0349***	-0.0139	-0.0307***	-0.2420***
		(0.0080)	(0.0100)	(0.0110)	(0.0290)
White Collar Occupations	15,306	-0.0336***	-0.0491***	-0.0097	-0.2083***
		(0.0080)	(0.0060)	(0.0110)	(0.0210)
Service Workers	12,704	-0.0186**	-0.0330***	0.0227**	-0.2476***
		(0.0009)	(0.0090)	(0.0110)	(0.0280)
Obese	3,964	0.0098	-0.0736***	0.0592**	-0.3145***
		(0.0260)	(0.0140)	(0.0270)	(0.0610)
Non-obese	8,564	-0.0318***	-0.0395***	-0.0090	-0.2171***
		(0.0110)	(0.0107)	(0.0190)	(0.0370)
Richest 10%	6,908	-0.0262*	-0.0557***	-0.0185	-0.1501***
		(0.0130)	(0.0070)	(0.0140)	(0.0310)
Under 185% of Poverty Line	3,572	-0.0132	-0.0192	-0.0009	-0.1619**
		(0.0170)	(0.0220)	(0.0290)	(0.0810)
Sprawl Index Bottom Quartile	8,768	-0.0009	-0.0434***	0.0182	-0.2552***
		(0.0140)	(0.0150)	(0.0170)	(0.0270)
Sprawl Index Top Quartile	6,967	-0.0299**	-0.0380***	0.0150	-0.1949***
		(0.0120)	(0.0110)	(0.0140)	(0.0380)

Dependent variables are given in the column headers (activity times in minutes); rows list sample stratification; the first column details the sample size; and cells afterwards display the coefficient for commute time form.
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, weather data from the National Climactic Data Center, and urban sprawl data from Smart Growth America. Obesity status is corrected for self-reporting using NHANES-derived algorithms.

Table 8: Instrumental Variable Analyses (Commuters Only; n=12,019)

First Stage Results

	Dependent Variable: Commute Time (Minutes)
Incidence of Fatal Accident (Morning Commute)	27.2066*** (7.9913)
Incidence of Fatal Accident (Evening Commute)	14.8523*** (3.5569)
Joint F-test statistic for Contribution to the Model	10.96*** {p-value < 0.0000}

Second Stage Results

	Dependent Variables: Activity Time in Minutes			
	Exercise	Food Preparation	Eating	Sleeping
Commute Time (Minutes) [OLS]	-0.0289*** (0.0067)	-0.0494*** (0.0054)	-0.0036 (0.0095)	-0.3128*** (0.0229)
Commute Time (Minutes) [IV]	-0.0313 (0.0776)	-0.0561 (0.1017)	0.0376 (0.1211)	-0.7499** (0.3225)
J-Hansen Test	0.9188 {0.3378}	1.7548 {0.1853}	4.9670** {0.0258}	0.4172 {0.5183}
Durbin-Wu-Hausman Test	0.0009 {0.9756}	0.0041 {0.9486}	0.1151 {0.7347}	2.3119 {0.1294}

All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Instrument Joint Significance, J-Hansen, and Durbin-Wu-Hausman test p-values are in braces. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, weather data from the National Climactic Data Center, and fatal traffic accident data from the Federal Highway Administration.

Table 9:	Instrumental Variable Analyses (Commuters in Largest Cities; n=4,283)			
	First Stage Results			
	Dependent Variable: Commute Time (Minutes)			
Incidence of Fatal Accident (Morning or Evening Commute)	17.0119*** (5.0147)			
Joint F-test statistic for Contribution to the Model	11.51*** {p-value < 0.0044}			
	Second Stage Results			
	Dependent Variables: Activity Time in Minutes			
	Exercise	Food Preparation	Eating	Sleeping
Commute Time (Minutes) [OLS]	-0.0316*** (0.0105)	-0.0473*** (0.0083)	-0.0057 (0.0132)	-0.3170*** (0.0386)
Commute Time (Minutes) [IV]	-0.1457** (0.0597)	-0.0884 (0.1364)	0.2445 (0.1727)	-1.3720** (0.3225)
Durbin-Wu-Hausman Test	6.0794*** {0.0272}	0.0795 {0.7821}	2.1663 {0.1632}	8.2345*** {0.0124}

All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Instrument Joint Significance, J-Hansen, and Durbin-Wu-Hausman test p-values are in braces. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, weather data from the National Climactic Data Center, and fatal traffic accident data from the Federal Highway Administration.

Table 10: MET Minutes Analysis (n=46,496)				
	Dependent Variable: MET Minutes			
	MET Minutes: Exercise Activities Only			MET Minutes: Non-Exercise Leisure
	Excluding Control Time	Including Control Time	Including Control Time	Including Control Time
Commute Time (Minutes)	-0.1466*** (0.0248)	-0.0240*** (0.0081)	-	-
Active Commute (Minutes)	-	-	0.0315 (0.0345)	0.7022*** (0.1132)
Engaged Commute (Minutes)	-	-	-0.0161* (0.0095)	0.5623*** (0.0371)
Passive Commute (Minutes)	-	-	-0.0607*** (0.0159)	0.5401*** (0.0480)
Labor Time (Minutes)	-0.1307*** (0.0070)	-0.0011 (0.0018)	-0.0016 (0.0018)	0.2800*** (0.0243)
Exercise Time (Minutes)	-	4.7766*** (0.0381)	4.7766*** (0.0381)	-
Non-Exercise Leisure Time: (Minutes)	-	-	-	1.8605*** (0.0252)

Dependent variables are given in the column headers (MET minutes are calculated as the product of activity MET-intensity level minutes involved in the activity, aggregated for exercise and non-exercise leisure activities, respectively); selected independent variables are detailed by rows (commuting time, labor time, exercise time, and non-excise leisure times in minutes).
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey; MET scores from Tudor-Locke et al. (2009); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 11: EH Module (2006-2007) - Eating Behaviors Extension

	OLS	Negative Binomial Regression (Coefficients)	
Dependent Variable	Secondary Eating (Minutes)	Primary Eating Episodes	Secondary Eating Episodes
Commute Time (Hours)	-1.3112 (1.3554)	-0.0014 (0.0085)	0.0121 (0.0156)
Labor Time (Hours)	0.4601 (0.2985)	0.0028* (0.0016)	0.0043 (0.0029)
Observations	13,639	13,827	13,827

Probit Regression Marginal Effects
Likelihood of Non-grocery Food Purchases

	Pooled Sample	Primary Meal Preparers Only	Share Meal Preparation Duties	No Meal Preparation Duties
Commute Time (Hours)	0.0236*** (0.0053)	0.0290*** (0.0089)	-0.0111 (0.0179)	0.0336*** (0.0084)
Labor Time (Hours)	-0.0029*** (0.0009)	-0.0023 (0.0014)	-0.0004 (0.0031)	-0.0058*** (0.0021)
Observations	13,639	8,014	1,233	3,072

Dependent variables are secondary eating time (in minutes), counts of primary and secondary eating episodes, and an indicator equal to one for reporting positive time purchasing non-grocery food items; selected independent variables are detailed by rows (commuting time and labor time, scaled to hours). Collinearity within areas results in some observations being dropped.
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008) and Eating and Health Module (2006-2007); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 12: Tests for Intertemporal Substitution of Activities during Non-Work Days (n=46,496)

	Dependent Variables: Activity Time in Minutes					
	Exercise	Food Preparation	Eating	Sleeping	Socializing	Television
Not Employed (α_1^k)	10.7384*** (0.8679)	17.7068*** (0.7007)	6.9991*** (0.8180)	64.3724*** (1.5457)	30.0878*** (1.2719)	81.3370*** (2.1917)
Employed, No Labor (α_2^k)	11.5409*** (0.6969)	9.6876*** (0.4555)	10.2592*** (0.6928)	90.3886*** (1.4751)	33.6174*** (1.0954)	71.6613*** (1.8571)
$[\alpha_2^k - \alpha_1^k]$	0.8024 (0.8857)	-8.0193*** (0.7170)	3.2602*** (0.8545)	26.0162*** (1.5992)	3.5296*** (1.2753)	-9.6757*** (2.1698)

Dependent variables are given in the column headers (activity times in minutes); Coefficients for indicator variables α_1^k(having no job) and α_1^k (employed but not working on the diary day) are displayed. All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, and weather data from the National Climactic Data Center.

Table 13: Reduced Form Commute-Obesity Model (Commuters Ages 21-65; n=2,852)				
	Probit Marginal Effects Dependent Variable = Obesity Status	Probit Marginal Effects Dependent Variable = Obesity Status	Ordinary Least Squares Dependent Variable = BMI	Ordinary Least Squares Dependent Variable = BMI
	w/o Time Use	w/ Time Use	w/o Time Use	w/ Time Use
Commute Time (Hours)	-	0.0216* (0.0131)	-	0.2951 (0.1809)
Labor Time (Hours)	-	0.0040 (0.0044)	-	0.0252 (0.0491)
White Collar worker	0.0205 (0.0252)	0.0194 (0.0251)	0.3753 (0.3053)	0.3601 (0.3034)
Blue Collar worker	-0.0446 (0.0277)	-0.0460 (0.0275)	-0.5034 (0.3574)	-0.5287 (0.3583)
Sprawl Index	-0.0021*** (0.0005)	-0.0021*** (0.0005)	-0.0113* (0.0060)	-0.0465*** (0.0009)

The dependent variables are given in the column headers (body mass index (BMI) calculated as kg/m^{2}and an indicator for obesity status equal to one if BMI is equal to or greater than thirty); selected independent variables are detailed by rows (commuting time and labor time in hours; occupational class indicators (the reference group is service workers) and the Smart Growth American urban sprawl index (greater index values indicate areas of more sprawl). The sample is limited to those aged twenty-one and over that commuted during the diary day.
All standard control variables are included. Robust standard errors are in parentheses, clustered by CBSA. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Primary Data from the American Time Use Survey (2003-2008); geographic information from the Current Population Survey, weather data from the National Climactic Data Center, and urban sprawl data from Smart Growth America. BMI and Obesity are corrected for self-reporting using NHANES-derived algorithms.

ESSAY II: ASSOCIATIONS WITH URBAN SPRAWL, FOOD INSECURITY, AND THE JOINT INSECURITY-OBESITY PARADOX

Motivation

A developing literature seeks to resolve the "paradox" of obesity and food insecurity coexisting within the same household (Dinour, Bergen, and Yeh 2007). The paradox's most popular explanation is that low cost, energy-dense food, which is linked to obesity (Drewnowski 2004), is favored by the most severely financially-constrained households, whom are also the likeliest to be food insecure (Dietz 1995; Basiotis and Lino 2003; Adams, Grummer-Stawn, and Chavez 2003; and Drewnoski and Specter 2004). This seeming discrepancy is noted both in academia but also within the popular press where it is argued that obesity and insecurity are often "flip sides" of the same malnutrition determinant, occurring where nutritious foods are unavailable or unaffordable (Berg 2008), a characteristic of the surrounding built environment.

A separate literature associates built environment features with poor nutritional outcomes. In particular, recent studies empirically link obesity to urban sprawl, beginning with Ewing, Schmid, Killingsworth, Zlot, and Raudenbush (2003). Built environment characteristics are also associated with other chronic nutritional afflictions such as atherosclerosis (Morland, Wing, and Diez Rouz 2002) and diabetes (Horowitz, Colson, Herbert, and Lancaster 2004). Many of the hypothesized pathways involve healthy food inaccessibility caused by urban sprawl, and given theories related the paradoxical joint outcomes to inaccessibility, an exploration of the relationship between the built environment and food insecurity is a natural extension.

This essay investigates the relationship between food insecurity and one feature of the built environment, urban sprawl, with an emphasis on joint obese/food insecure outcomes. Broad geographical trends in food insecurity are already apparent: the U.S. Department of

Agriculture reports that the prevalence of food insecurity is greater in rural areas and metropolitan principal cities than non-principal cities and that prevalence is greater in the South than the Northeast or Midwest Census regions (Nord, Andrews, and Carlson 2008). The built environment can vary greatly within such broad geographical classes, and urban sprawl–here referring to decentralized, poorly connected urban form–is a finer dimension to investigate.

There are several reasons why food insecurity might be positively associated with urban sprawl where the built environment itself is a causal factor in nutrition outcomes: (1) sprawl might create “food deserts” and inhibit access to healthy foods (Larson and Gilliland 2008), (2) sprawl may lead to poorer local employment opportunities limiting resources (Kain 1968), and (3) noting the obesity/insecurity paradox’s empirical connection to food stamp programs (Townsend, Peerson, Love, Achterberg, and Murphy 2001), food stamp participation could vary spatially if enrollment knowledge diffuses slowly in less dense areas where social networks are not robust, indirectly affecting paradoxical outcomes–existing research identifies network effects on welfare program participation (Bertrand, Luttmer, and Mullainathan 2000), and theories since Jacobs (1961) have emphasized the urban form’s contribution to social capital development. Alternatively, an identified relationship between sprawl and food insecurity might be non-causal–impoverished families might self-select and cluster into areas of greater sprawl, also producing a positive association.

Data Description

Cross-sectional data are drawn from the Behavioral Risk Factor Surveillance System (BRFSS) 1996-1999. The BRFSS is an individual-level survey of the United States adult population conducted annually by the U.S. Centers for Disease control in conjunction with state health agencies. During the period of 1996 through 1999 the BRFSS Social Context Module, which contains information on household food security, was conducted in a subsample of states: Maryland, Ohio, Pennsylvania, and Virginia were surveyed in 1996; Kansas, Louisiana, Maryland, South Carolina, and Virginia in 1997; Missouri and Virginia in 1998; and Louisiana, New York, and Texas in 1999.

Following previous studies (VanEenwky and Sabel 2003; Laraia, Siega-Riz, and Everson 2004), food insecurity is defined as having answered “yes” to the module question, “In the past 30 days, have you been concerned about having enough food for you or your family?” Obesity is defined as having a body mass index–calculated as weight (kg) divided by height (m) squared–equal to or greater than thirty. Self-reported height and weight are adjusted using algorithms derived from regressing actual height and weight on reported height and weight from National Health and Nutritional Examination Survey data–corrections only exist for adults ages twenty-one and older, and younger respondents are dropped. A third category, “joint outcomes”, indentifies “paradoxical” occurrences of obese individuals who also report recent household food insecurity.

Each respondent’s geographical locations are matched to Smart Growth America’s corresponding county- and metropolitan-level urban sprawl indexes, which were used in the original sprawl-obesity study (Ewing, Schmid, Killingsworth, Zlot, and Raudenbush 2003). The sprawl indexes are constructed from Census 2000 data and do not precisely match the Social Context Module samples’ years. However, because urban form changes slowly over time, the indexes should adequately describe the degree of sprawl of a few years prior. Each index is constructed so that sprawl averages 100 nationally, but within the limited geography of the Social Context Module, the median county sprawl is 131.71 and the median metropolitan sprawl is 109.25. Importantly, the sprawl indexes are constructed such that *lower* index values indicate areas of *greater* sprawl. Therefore, on average, the Social Context Module sample resides in areas less sprawled than the national average.

The county index is a composite of residential density and street connectivity measures, and the metropolitan index additionally includes measures of land use mix and the degree of metropolitan centeredness (a measure of the extent to which there is a local focal point of centered activity). Smart Growth America also publishes the factor index values for the four metropolitan sprawl components: connectivity, centeredness, land use mix, and density. Factor indexes are also matched to respondents' metropolitan areas. The component indexes are constructed so that *lower* values indicate *greater* degrees of sprawl–opposite of the aggregated sprawl index. An analysis using the factors allows a more nuanced understanding of the mechanisms relating sprawl to each outcome.

Street connectivity is particularly of interest because the measure conceptualizes of "access". The connectivity factor is derived from Census TIGER files detailing block size. Connectivity is less where average block lengths are greater and greater where there are a higher percentage of blocks less than 0.01 square miles. A result indicating that the likelihood of joint outcomes is greater in areas of poorer street connectivity is consistent with theories relating hunger and obesity to the inaccessibility of healthy foods.

There are tradeoffs to using each index–the county index measures a finer, more precise, geographical area and is thus likely a more relevant representation of respondents' local environment. Additionally, there is greater variation of sprawl across counties: county level standard deviation in the sprawl index is 55.33 while the metropolitan level standard deviation is 29.75. The metropolitan sprawl index encompasses slightly more observations (1,199) but more importantly includes two additional dimensions of sprawl not captured by the county index. Both measures are used for completeness.

I pool together BRFSS respondents who also completed the Social Context Module and for whom either metropolitan area or county of residence is identifiable for years 1996, 1997, 1998, and 1999. The final samples consist of 13,152 full observations using the metropolitan sprawl index and 11,953 observations using the county sprawl index. Demographic variable information taken from the BRFSS to use as controls are age, gender, race and Hispanic status, marital status, number of children, employment status, education, income, and year and state dummies. Table 1 presents full explanatory variable summary statistics.

I display sample percentages by outcome in Table 2. Incidence of food insecurity in the BRFSS sample is 6.7%, whereas the Department of Agriculture found the national insecurity rate to be above ten percent for the same sample period. Of those indicating recent household food insecurity, 26.7% of the BRFSS sample are obese while only 2.9% are underweight (i.e., with a body mass index less than 18.5). Paradoxical instances of obese respondents reporting food insecurity are infrequent overall, comprising only 1.64% of the sample.

Empirical Analysis

Table 3 displays probit regression marginal effects for the sprawl indexes across obesity, food insecurity, and joint obesity/insecurity outcomes. Control variables marginal effects are unreported for brevity. Obesity and food insecurity outcomes include intersection with each other–that is, an obese individual also reporting food insecurity is include in all three categories. Regressions are clustered by county where the county sprawl index is used and by metropolitan area where the metropolitan sprawl index is used. The regressions are also weighted using final survey weights. All sprawl index scores are divided by 100 to manageably scale marginal effects.

Contrary to expectations, the evidence suggests a *negative* relationship between urban sprawl and food insecurity, net of individual characteristics. Larger values of the sprawl index–again, areas of lesser urban sprawl–are associated with a greater likelihood of reporting food insecurity. Conversely, individuals in areas with greater sprawl are less likely to have reported a concern about obtaining sufficient food. Using the linear specifications, the likelihood of food insecurity rises 1.9 percentage points over the full range of the county sprawl index and 2.3 percentage points over the range of the metropolitan index. In the county sprawl regressions, sprawl without the quadratic is significant only at the 10% level, and when the quadratic is added both terms are jointly insignificant. In the metropolitan sprawl regressions, all terms are significant at the 5% level. It appears that the relationship between food insecurity and sprawl may take place at the metropolitan level, as evidenced by the stronger relationship of that index with insecurity.

This negative correlation contrasts the previously documented (and here also replicated) positive relationship between sprawl and obesity. It indicates that in less sprawled areas, obesity is less common and hunger anxiety is more common. The association between sprawl and insecurity is modest relative to between sprawl and obesity: the likelihood of obesity falls by 10.7 percentage points over the full range of county sprawl and by 0.03 percentage points over the range of metropolitan sprawl.

There is also significant evidence of a relationship between county-measured urban sprawl and the likelihood of joint obesity-food insecurity outcomes {p-value = 0.0061}, suggesting that the "paradox" may relate in some way to the built environment. Although highly significant, the magnitude of the effect is modest: the likelihood of joint outcomes increases 0.08 percentage points from the most sprawled areas until the effect peaks at the index value of 2.04, from where the likelihood of joint outcomes begins to decline again. In comparison, unreported control variables suggest the likelihood of joint outcomes increase 0.16 percentage points for each child and 4.05 for those with a less-than-high-school education.

The value for which the likelihood of joint outcomes peaks is 2.04, which *only* the New York City county sprawl index values exceed. New York City may be an outlier in this analysis either due to the extremity of its counties' index values or because there is something uniquely anti-hunger about the city, such as food pantry programs on a scale impractical for smaller cities. If the New York counties are omitted from the analysis, the negative association between sprawl and joint outcome likelihood persists for the quadratic model {p-value = 0.0927} and the linear marginal effect additionally becomes significant [t-value = 2.07].

The negative association with sprawl would seemingly exclude healthy foods inaccessibility as an explanation for paradoxical outcomes. To more deeply investigate the mechanisms that might be driving the relationships between sprawl and insecurity, the disaggregated metropolitan sprawl factors values are utilized. The probit regressions for each outcome are recalculated using the four factor indexes substituted for the metropolitan index. The marginal effects of sprawl's components are displayed in Table 4.

Of the four factors, only street connectivity and residential density are significantly related to food insecurity. The association with the connectivity index is negative and association with the density index is positive, which suggests that insecurity is more likely in denser areas and is less likely in areas of greater street connectivity. Even though the metropolitan sprawl index is overall more significant in explaining insecurity, the two factors particular to that index–centeredness and mixed use–are insignificant.

That insecurity is less likely in better connected areas supports the hypothesis that inaccessibility produces hunger. However, the association between paradoxical outcomes and the street connectivity index is positive, indicating that there is a greater likelihood of joint outcomes in areas of better developed street connectivity. This evidence is inconsistent with poor accessibility as a determinant of the joint obesity-insecurity paradox, because instead the likelihood of paradoxical outcomes is more likely in areas of greater accessibility.

The minimal criteria for identifying built environmental factors leading to joint outcomes is that the factor marginal effects should have consistent signs and significance across obesity, food insecurity, and joint outcomes. Consistent signs across outcomes would indicate that the factors relationship with obesity and insecurity reinforce each other. Centeredness is the only outcome for which marginal effect signs are consistent (negative) across outcomes, although the factor is insignificant with respect to insecurity.

Lastly, a quaternary outcome variable, where individuals are categorized as neither obese nor food insecure, obese-only, insecure-only, and both obese and insecure, is employed to run multinomial probit regressions using both county and metropolitan sprawl indexes. The New York metropolitan area and associated counties are omitted as outliers. Marginal effects for sprawl are displayed in Table 5.

The multinomial probit results generally replicate the univariate probit regressions results. The county sprawl index is positively related to the likelihood of joint outcomes [t = 2.24] and the metropolitan sprawl index is positively associated with the likelihood of reporting food insecurity. All other marginal effects are insignificant, but the effect of the sprawl indexes on the likelihood of obesity is consistently negative and is consistently positive with respect to both the likelihood of food insecurity and joint outcomes.

Discussion

In that obesity, a disease of overconsumption, is positively associated with sprawl and that food insecurity is a concern about underconsumption, it may be unsurprising that insecurity is more likely on the opposing extreme of sprawl's spectrum. However, there are probably very different mechanisms affecting both outcomes. Few of the theories linking sprawl and obesity are also applicable to food insecurity. The association between sprawl and obesity is most often explained through hypotheses that suburbs' sedentary, car-centric lifestyle result in insufficient physical activity, which are wholly irrelevant to insecurity.

Inaccessibility to healthy foods is the most developed spatial theory which connects the paradox of obesity and food insecurity, and it is not supported by the data. Univariate probit results suggest that more developed street connectivity, representing greater accessibility, is associated with an increased likelihood of reporting joint outcomes. The results do show, however, that food insecurity is more likely in areas of poorer connectivity. Future urban hunger research could more fully focus on accessibility as a determinant and in particular seek to better quantitatively describe the food environment–for example, by measuring households' proximity to grocery and non-grocery food establishments–at preferably a finer scale than the county-level.

There is a relevant theory which may explain sprawl's opposing associations with obesity and food insecurity. Plantinga and Bernell (2005), seeking to explain the relationship between sprawl and obesity, derive a theoretical residential location model with the primary result that cheaper housing on the suburban fringe frees financial resources and induces higher consumption of food, leading to obesity. The logical converse is that more expensive housing in the inner cities constrains finances available to purchase food and raises hunger anxiety, which is consistent with the results of this research. Because housing prices correlate with sprawl, their omission may introduce systematic bias into the results. Yet, the incidence of food insecurity is also high in rural areas, where housing is cheapest, indicating that there are multiple mechanisms affecting food insecurity outcomes. If possible, future spatial research should also include measures of housing prices, which were unavailable in the BRFSS sample.

Lastly, sprawl is endogenous and causal inferences are premature. The obesity-sprawl association is already highly criticized for failing to account for self-selection–in fact, panel data suggest that the relationship between sprawl and obesity is wholly due to selection into sprawled neighborhoods by the obese and is not the result of a causal relationship of sprawl on obesity (Eid, Overman, Puga, and Turner 2008). Future research exploring the relationship between sprawl and food insecurity should also use longitudinal data, if available. Randomized experimental design evidence–the Moving to Opportunity program–observed that food insecurity incidence was 20% lower in the target group: low-income families given vouchers to low-poverty neighborhoods (Orr, Feins, and Jacob 2003). The difference was insignificant, though the sample size was such that a 30-40% difference was necessary to observe a significant difference.

Conclusion

This essay tests for and is the first to identify a relationship between food insecurity and the urban sprawl; specifically, it identifies a negative correlation between sprawl and the likelihood of food insecurity. The results extend a developing literature connecting the surrounding built environment to residents' nutritional outcomes and chronic diseases such as obesity. Additionally, the essay identifies that the likelihood of "paradoxical" joint obesity-insecurity outcomes is also negatively related to sprawl. Moreover, the evidence indicates that joint outcomes are more likely in areas of better accessibility, indicating that the paradox is unlikely caused by healthy food inaccessibility, as some theories propose.

In America, diseases of consumption such as obesity, diabetes, and atherosclerosis tend to overshadow hunger as an issue, yet millions of Americans continue to experience periods of food insecurity. The determinants of insecurity are important to understand, particularly during a period of poor economic conditions, which may worsen food insecurity incidence. Understanding the patterns of *where* insecurity is more likely to occur may help to more efficiently ameliorate conditions.

Finally, this study has several limitations. First, the cross-section nature of the data restricts the causality argument because it does not rule out self-selection. However, food insecure families are a particularly financially constrained and immobile group, meaning self-selection may not be as present as in other contexts. Second, the data are approximately ten years old, and may be outdated. In 2009 the BRFSS again began addressing food insecurity by asking, "How often in the past 12 months would you say you were worried or stressed about having enough money to buy nutritious meals?"–which directly addresses *healthy* food intake–and the 2010 Census will provide updated measures of sprawl, so a more current analysis will soon be possible. Third, although insecurity is commonly used to measure hunger, is it important to recognize the distinction between food *insecurity* (concern over having enough food) from food *insufficiency* (literally not having enough to eat), the latter of which may be more strongly related to inaccessibility. Researchers might consider using more objective nutritional measures as alternative outcomes. Addressing these issues offers opportunities for future research.

Empirical Tables

Table 1: Summary Statistics (Explanatory Variables)

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Age	15,116	44.79	15.87	21	99
Male	15,116	0.500	0.500	0	1
White	15,116	0.735	0.441	0	1
Black	15,116	0.163	0.369	0	1
Other	15,116	0.040	0.197	0	1
Hispanic	15,116	0.062	0.240	0	1
Married	15,116	0.611	0.488	0	1
Divorced/Separated	15,116	0.155	0.362	0	1
Widowed	15,116	0.065	0.247	0	1
Number of Children	15,116	0.776	1.126	0	11
Employed	15,116	0.710	0.454	0	1
Income $10-15K	15,116	0.043	0.204	0	1
Income $15-20K	15,116	0.081	0.273	0	1
Income $20-25K	15,116	0.092	0.289	0	1
Income $25-35K	15,116	0.170	0.376	0	1
Income $35-50K	15,116	0.205	0.403	0	1
Income $50-75K	15,116	0.189	0.392	0	1
Income Over $75K	15,116	0.176	0.381	0	1
Less than High School	15,116	0.091	0.287	0	1
High School Graduate	15,116	0.308	0.462	0	1
Some College	15,116	0.265	0.441	0	1
College Graduate	15,116	0.336	0.473	0	1
1997 BRFSS	15,116	0.197	0.398	0	1
1998 BRFSS	15,116	0.130	0.336	0	1
1999 BRFSS	15,116	0.275	0.447	0	1
County Sprawl Index	11,953	1.317	0.553	0.750	3.521
Metropolitan Sprawl Index	13,152	1.093	0.298	0.586	1.778
Connectivity (Metro Sprawl)	13,152	1.053	0.282	0.372	1.549
Centeredness (Metro Sprawl)	13,152	1.078	0.201	0.739	1.473
Mixed Use (Metro Sprawl)	13,152	0.980	0.199	0.504	1.334
Density (Metro Sprawl)	13,152	1.171	0.501	0.719	2.425

Data from the Behavioral Risk Factor Surveillance System and Social Context Module (1996-1999) and Smart Growth America.

Table 2: Categorical Outcome Percentages [n = 15,116]

	Food Secure	Food Insecure	
Not Obese	73.84%	5.05%	78.88%
Obese	19.48%	1.64%	21.12%
	93.31%	6.69%	

Data from the Behavioral Risk Factor Surveillance System and Social Context Module (1996-1999).

Table 3: Probit Regressions' Marginal Effects of Sprawl Indexes

	Dependent Variable: Obesity Status		Dependent Variable: Food Insecure Status		Dependent Variable: Joint Outcomes Status	
County Level Sprawl Index Sample (n = 11,953)						
Sprawl	-0.0293	0.0995**	0.0070*	0.0168	0.0007	0.0192***
	[-1.57]	[2.07]	[1.95]	[1.35]	[0.26]	[2.88]
$Sprawl^2$	-	-0.0323	-	-0.0024	-	-0.0047***
		[-3.23]		[-0.88]		[-3.16]
χ^2 Joint Sig.	-	33.79***	-	4.56	-	10.20***
{p-value}		{0.0000}		{0.1022}		{0.0061}
Evaluation at Mean Sprawl	-0.039	0.075	0.009	0.018	0.001	0.017
Change over Full Range of Sprawl	-0.081	-0.107	0.019	0.018	0.002	-0.002
Metropolitan Level Sprawl Index Sample (n = 13,152)						
Sprawl	-0.0161	0.1881	0.0196***	-0.1995***	0.0039	-0.0151
	[-1.32]	[1.32]	[2.95]	[-3.00]	[1.27]	[-0.62]
$Sprawl^2$	-	-0.0808	-	0.0862***	-	0.0075
		[-1.48]		[3.32]		[0.76]
χ^2 Joint Sig.	-	7.38***	-	42.11***	-	1.88
{p-value}		{0.0250}		{0.0000}		{0.3903}
Evaluation at Mean Sprawl	-0.018	0.109	0.021	-0.115	0.004	-0.008
Change over Full Range of Sprawl	-0.019	-0.003	0.023	0.005	0.005	0.003

All standard control variables are included. T-statistics are in brackets. Smaller values of the sprawl indexes indicate areas of greater sprawl. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the Behavioral Risk Factor Surveillance System and Social Context Module (1996-1999) and Smart Growth America.

Table 4: Component Analysis of Metropolitan Sprawl (n = 13,152)

Sprawl Component	Dependent Variable: Obesity Status	Dependent Variable: Food Insecure Status	Dependent Variable: Joint Outcomes Status
Connectivity	0.0891***	-0.0241***	0.0072**
	[3.22]	[-4.58]	[2.39]
Centeredness	-0.0846**	-0.0149	-0.0104*
	[-2.58]	[-0.94]	[-1.77]
Mixed Use	0.0372	-0.0149	-0.0013
	[1.54]	[-1.50]	[-0.31]
Density	-0.0692***	0.0393***	0.0005
	[-3.39]	[6.32]	[0.16]

All standard control variables are included. T-statistics are in brackets. Larger values of sprawl component indexes indicate areas where the components' aspects are greater. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the Behavioral Risk Factor Surveillance System and Social Context Module (1996-1999) and Smart Growth America.

Table 5: Multinomial Probit Regressions' Marginal Effects of Sprawl Indexes

	Dependent Variable: Obese Only	Dependent Variable: Food Insecure Only	Dependent Variable: Both Obese and Food Insecure
County Level Sprawl Index Sample (n=11,538)			
Sprawl	-0.0033	0.0044	0.0045**
	[-0.21]	[0.92]	[2.24]
Evaluation at Mean Sprawl	-0.004	0.006	0.006
Change over Full Range of Sprawl	-0.009	0.012	0.013
Metropolitan Level Sprawl Index Sample (n=12,411)			
Sprawl	-0.0191	0.0144**	0.0046
	[-1.39]	[2.10]	[1.51]
Evaluation at Mean Sprawl	-0.021	0.016	0.005
Change over Full Range of Sprawl	-0.023	0.017	0.006

All standard control variables are included. T-statistics are in brackets. Smaller values of the sprawl indexes indicate areas of greater sprawl. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. New York City counties and metropolitan areas are omitted from this analysis as outliers. Data from the Behavioral Risk Factor Surveillance System and Social Context Module (1996-1999) and Smart Growth America.

ESSAY III: THE DETERMINANTS OF THE DECISION TO WALK OR CYCLE TO SCHOOL AND THE DECISION'S ASSOCIATION WITH WEEKLY EXERCISE LEVELS

Motivation

Children are getting fatter. Incidence of obesity among children aged 6-11 rose from 6.5% to 17.0% from 1980-2006 and among adolescents aged 12-19 prevalence increased from 5.0% to 17.6% in the same period (Ogden et al. 2008).[31] Overweight children are more likely to have higher blood pressure, higher cholesterol, and type 2 diabetes mellitus (Freedman et al. 2007). Obesity is also associated with severe–though often less tangible–psychosocial distress outcomes such as depression, fewer and more isolated friendships, and being subjected to teasing (Daniels et al. 2005). Addressing childhood obesity is crucial since youths' obese status is more likely to continue into adulthood (Serdula et al. 1993; Dietz 1994; and Whitaker et al. 1997).

Obesity arises from an energy imbalance–when more calories enter the body through nutritional intake than exit through caloric expenditure. Accordingly, interventions attempting to combat obesity generally seek to increase healthy diets and exercise levels. Because students spend upwards of half their waking day involved in school activities (Koplan et al. 2005), school settings are an often used locus for these interventions. School-based programs have sought to improve cafeteria meal nutrition (Luepker et al. 1996), induce purchases of fruits and vegetables via vending machine pricing (French et al. 1997), and increase exposure to physical education (Sallis et al. 1995). Schools have also experimented with adopting interdisciplinary curricula which broadly introduces healthy lifestyle education specifically targeting obesity (Gortmaker et al. 1999).

[31] Presently, children are defined as obese if their body mass index (BMI)–calculated as weight in kilograms divided by height in meters squared–is at or above the 95th percentile of other children their age and gender, based on the year 2000 Centers for Disease Control growth charts. Children are defined as overweight if they are between the 85th and 95th percentiles for their age and gender.

Walking or cycling to school provides some exercise for students. Active travel is not only healthy in itself–it can contribute upwards of twenty-four minutes to students' total daily physical activity (Sirard et al. 2005)–but moreover some research suggests that walking to school is associated with increased activeness throughout the day (Alexander et al. 2005 and Cooper et al. 2005); that is, students who walk or cycle to school engage in more physical activity during non-travel times in addition to the exercise which is also achieved via transit to school. Advocates of healthy travel to school often cite these findings when arguing that promoting active travel options to school will generate an "inertia effect" in student activeness. The claim is that were students to utilize active travel options to school there will be broader spillovers into non-travel times and activities, increasing physical activity and ultimately healthiness.

The characteristics of the surrounding environment in which a student resides often influence the school transit mode decision. Parents' principal concerns are often the distance of between home and school and the safety of the neighborhood. The National Center for Safe Routes to School issued results from a 2004 survey of 1,588 adults indicating respondents' identification with environmental barriers with walking to school, including distance to school (61.5% identified), traffic-related danger (30.4% identified), and danger from crime (11.7% identified).

Recognizing environmental barriers as impediments to active travel to school, Safe Routes to School programs (SRTS) have developed in numerous communities. The National Center for Safe Routes to School's Talking Point Bulletin[32] states that the "programs are sustained efforts by parents, schools, community leaders and local, state, and federal governments to improve the health and well-being of children by enabling and encouraging them to walk and bicycle to school…SRTS programs examine conditions around schools and conduct

[32] See http://www.saferoutesinfo.org/resources/collateral/srts_talkingpoints.doc.

projects and activities that improve safety and reduce traffic and air pollution in the vicinity of schools. As a result, these programs make bicycling and walking to school a safer and more appealing transportation choice thus encouraging a healthy and active lifestyle from an early age."

This essay seeks to identify the determinants of the decision[33] to walk or cycle to school the decision's subsequent impact on overall activity levels. We utilize data which samples students from urban school districts, which is a highly relevant population given that obesity disproportionately affects individuals from poorer communities (Molarius et al. 2000) and groups of low socioeconomic status (Zhang and Wang 2004). We identify several discernable factors influencing the decision to actively travel to school–in particular, that the distance between students' homes and their schools is most strongly correlated with the decision. However, we find no evidence that walking or cycling to school increases students' weekly quantity of exercise, in contrast to prior results. This suggests that SRTS programs may be ineffective towards improving youth health outcomes, at least in certain settings, and that within these settings, efforts to combat obesity would be more efficiently directed elsewhere.

Literature Review

Over a thirty-year period, statistics reported by the U.S. Department of Transportation indicate a sharp decrease in the number of children who walk or cycle to school, from 42% in 1969 to 13% in 2001.[34] Public health officials concerned with childhood obesity often associate decreases in active travel with environmental factors such as urban sprawl, especially given recent evidence linking sprawl and overall walking time (Ewing et al 2003). Student travel mode

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[33] "The decision" of student transit mode presumably results from a negotiation between student and parent, with the decision likely being made almost exclusively by parents of younger age children and then shifting towards the student at increased ages. Given that the decision is shared, we consider both student and parent factors in analysis.
[34] Source: 2001 National Transportation Survey.

is perceived as a viable channel by which to increase health outcomes and behaviors–many opportunities exist for policy interventions to influence student travel modes because various policies–including student busing or school location decisions–so greatly influence transportation mode choice (Strum 2005).

Within the literature, the most consistent determinant of whether a student walks or cycles to school is the distance between that student's home and school (Martin and Carlson 2005; Cohen et al. 2006; McMillan et al. 2006; Schlossberg et al. 2006; Timperio et al. 2006; Martin et al. 2007; McMillan 2007; and McDonald 2008). The surrounding urban form is also significant, independent of distance–children living in walkable neighborhoods are more likely to walk to school (Kerr et al. 2006), where "walkability" is defined as accessibility to nearby neighborhood amenities such as shops. Additionally, research identifies correlations between active travel and other facets of walkability, for example such as sidewalk systems (Boarnet et al. 2005). Parental attitudes are also important–children are less likely to walk or bike whose parents are concerned about traffic danger and neighborhood safety (Kerr et al. 2006) and children are more likely to walk or bike whose parents feel physical activity is important or who walk regularly (Kerr et al. 2006; McMillan et al. 2006; and McMillan 2007).

Several studies find that children who walk to school have overall higher physical activity levels relative to those who do not and that those who walk have a higher levels of moderate-to-vigorous activity (Alexander et al. 2005 and Saksvig et al. 2007). Such research is often cited by proponents of SRTS programs and those advocating for increased active travel to school. Although active travel is seemingly associated with higher activity levels, findings which relate transit mode and health outcomes are at present inconclusive–commuting mode variations are related with contemporaneous body mass differences in males but not females, and moreover, commuting mode fails to explain adolescents' body mass changes over time (Rosenberg et al. 2006).

As with the decision to actively travel to school, environmental factors also influence how much physical activity children receive. Children are more active in areas where recreational infrastructure–the availability of parks or play spaces–is more developed (Sallis et al. 1993; Zakarian et al. 1994; Gomez et al. 2004; Cohen et al. 2006) and also where transportation infrastructure–the presence of sidewalks or walkability measures such as street connectivity and mixed land use zoning–is more developed (Jago et al. 2005; Frank et al. 2007).[35] Parental perceptions on safety concerning crime and traffic are seemingly as important for children's health outcomes as the physical environment's actual characteristics–children are more likely to be overweight if their parents *perceive* their neighborhood to be unsafe (Lumeng et al. 2006; Gable et al. 2007).

Empirical Estimation

We estimate two models in a system which links active travel and healthy behaviors: Model 1 identifies the determinants of the likelihood a student walks or cycles to school and Model 2 identifies the factors affecting the number of children's exercise sessions.

$$\Pr(Active\ Travel)_i = \alpha_0 + \boldsymbol{\alpha^1 Travel\ Factors_i} + \boldsymbol{\alpha^c Controls_i} + \varepsilon_i \qquad \text{Model 1}$$

$$Exercise\ Count_i = \beta_0 + \boldsymbol{\beta^1 Exercise\ Factors_i} + \boldsymbol{\beta^c Controls_i} + \epsilon_i \qquad \text{Model 2}$$

[35] Given that research links walking and cycling to school with increased physical activities–which are both influenced by environmental factors–the exact relationships between environment, active travel, and physical activity are not clear. That is, it is uncertain whether transportation infrastructure increases active travel which in turn increases physical activity, or whether transportation infrastructure itself might directly increase physical activity.

The equations state that the probability a student walks or cycles is determined by a set of factors exclusive to the transit mode decision, that the count of exercise sessions is determined by a set of factors exclusive to the exercise level decision–including whether or not the student utilizes active modes of transit–and that both decisions share a set of common control factors. Model 1 is estimated using Logistic regressions. Model 2 is estimated using Ordinary Least Squares, Poisson regression, and Negative Binomial regression. Lastly, as an additional contribution to the literature, a final two-step procedure combines the two models by using the predicted values of Model 1 as covariates in Model 2.

Self-selection bias is the primary confounder in typical built environment studies–unobservable individual preferences (such as for residential location and health) may jointly determine the type of neighborhood individuals choose to live in and also their health outcomes, biasing estimates. Children are an ideal sample for built environment studies because they do not choose their residential locations–this is instead chosen by their parents or guardians–and so unobserved preferences cannot influence estimates. For this reason, economists have used samples of teenagers in studies investigating access to labor market opportunities (Ihlanfeldt and Sjoquist 1990).

Admittedly, a set of potential biases still arise because students' and parents' preferences are unobserved. A student with sedentary inclinations might neither actively travel to school nor engage in (much) exercise. In this situation, the student's unobserved preferences for health will bias the result that active (vehicular) travel to school increases (decreases) actively levels.

Data

The Robert Wood Johnson Foundations implemented the Urban Health Initiative to improve health and safety outcomes in economically disadvantaged cities. Beginning in 1996, coalitions in five distressed cities–Baltimore, Detroit, Philadelphia, Oakland, and Richmond–were funded for eight years with approximately one million dollars per city each year to improve health and safety indicators (none of which was obesity). For purposes of evaluation, researchers designed the Survey of Adults and Youth (SAY), a three-wave cross-sectional survey collected by telephone. We utilize data from the third wave of the survey (SAY III), collected in fall 2004 through spring 2005. The survey collected information on parents, children, schools, and the community. The SAY III data is particularly useful because both students' homes and schools are GIS-encoded, allowing a precise calculation of the distance between home and school.

The variable *distcalc* is the "as-the-crow-flies" straight-line distance in miles between the students' homes' and schools' GIS coordinates.[36] Some *distcalc* values exceeded 100 miles, which are certainly outliers. We omitted any observation for which *distcalc* exceeds 20 miles, or the top 1.14% (27 observations).

The two outcomes of interest are whether students walk or cycle to school and the amount of (non-travel) exercise students receive. A dichotomous variable indicates active travel: students that usually walk or bike to school are coded with a "1", all other modes (public transportation, school bus, or car) receive a "0". The weekly count of exercise sessions is captured by the self-reported answer to the survey item, "About how many times a week do you exercise or play sports?"

Concerns about safety due to crime and traffic are identified in the literature as barriers to active travel and exercise. We include a variable indicating whether a student's parent or guardian considers crime to be a "big problem" in their neighborhood. Unfortunately, there is no

[36] Recognizing the measurement error inherent with straight-line distance, we painstaking acquired driving distance via-streets using Google Maps <maps.google.com>. However, the straight-line distance was consistently found to better predict the transit mode. Likely, the Google Maps calculated-distances themselves suffered from measurement problems. In particular, often several travel options were offered–each with varying distances–and it was impossible to know student' actual chosen routes to school (and corresponding distances).

corresponding survey item indicating concern about traffic. With the GIS-encoded records, it is conceivable that future research would devise away to match student-to-school routes to objective traffic measures, such as speed of cars, average traffic flow, and number of accidents–especially incidents involving pedestrians and cyclists.

Additionally, we include a dummy indicating whether or not the child is overweight (which indicates health preferences) and whether or not the child attends private school (for which public school buses may not service). Because rides to school often are commonly provided by students' own parents, we include the amount of allowance (if any) the child receives, the frequency of family dinners, and the number of hours of time with parents, which are collectively intended to proxy the degree of parental involvement with the student. To consider family structure, we include the number of children in the household and whether or not the parents are married. We include dummy variables indicating whether or not the student participates in a sport before school, a sport after school, or a non-sport afterschool activity at least one day during the week–students carrying athletic gear or musical instruments may be less able or willing or actively travel to school. An activity occurring prior to school might also necessitate receiving a ride in the morning, because before-school sports participation may require a prohibitively early departure as active travel is a slower mode than vehicular. For this reason, we also include the frequency of breakfasts eaten at home, another morning activity which potentially constrains time. To capture other aspects of students' schedules and lifestyles in explaining the weekly exercise count, we include hours of recreational time–watching TV, using the internet, or playing video games–and hours of other sedentary time–hours per week the student doing homework or reading. We also indicate whether the student has a job and if they participate in physical education class at school.

As standard control information we include race and Hispanic status, gender, logged family income, either city or zip code of residence fixed effects, and students' age. In addition to age as a continuous variable, we code an indicator equal to one for students aged sixteen and greater, the minimum age for restricted-use driver's licenses.[37] This indicator represents both the ability to drive and additionally the possibility of any social stigma associated with walking or biking to school by students who could otherwise be driving.

Descriptive Statistics

Table 1 presents descriptive statistics for the sample. Almost 20% of the students are overweight–the prevalence of obesity in this urban sample is slightly higher than the national average. Students in the sample have a mean (median) average of 3.95 (4.0) exercise sessions per week. The average distance between students' homes and schools is 3.05 miles and median is 2.08 miles. Lastly, approximately 19.7% of students reported walking or cycling to get to school. In this sample active commuting essentially refers to walking, as only four students reported cycling as a transit mode. More students actively travel in this sample than the national average, but of course the SAY III data is drawn from major urban areas which are less sprawled than most suburban areas.

Comparison of Means by Travel Mode

Table 2 presents sample means and proportions disaggregated by active and inactive travel modes to compare across groups. The first column presents means for students who use vehicular transit modes and the second column presents means for students who walk or cycle to school. The third column displays t-statistics for comparison of means tests between the two

[37] "Restricted-use licenses" could mean that youths are prohibited from driving other youths or may be restricted to certain hours of the day, but license-holders would at least be eligible to drive themselves to school.

groups under the null hypothesis is that the difference between the first and second columns is equal to zero. The tests conservatively assume unequal variances.

The most apparent difference (with the largest t-statistic on that table) between vehicular and active mode students is that the average distance between home and school is much greater on the whole for students using vehicular means than active modes. There is also significant evidence that larger percentages of students use vehicular modes who attend private school, have married parents, and who are old enough to drive. The average student age and household income are higher among students using vehicular modes. Students who walk or cycle to school eat breakfast at home fewer times weekly, are from homes with more children, and spend fewer hours doing homework or reading. On the whole, larger percentages of students use active modes in Oakland and Philadelphia while in Richmond–the least dense city sampled–more students use vehicular modes. Lastly, there is no statistical difference in overweight status by mode [t-statistic = 1.30] (although the percentage point estimate is about 3.2 points higher for vehicular mode users than active mode users).

Results and Discussion

Walking to School

Table 3 presents the estimation of Model 1; all results are in marginal effect format. The first column of Table 3 reports logistic regression results estimating the probability of actively traveling to school using the city fixed effects. The second column reruns the regression using residential zip code fixed effects in lieu of city indicators. Recognizing variation of numerous neighborhood characteristics within cities, zip code fixed effects acknowledge this heterogeneity at a finer level. The zip-code regression has 70 fewer observations because certain zip codes are perfectly correlated with the decision to walk or bicycle to school. Therefore, these zip codes and corresponding observations are omitted. Lastly, the third column of Table 3 is exclusively drawn from the sample of 131 households containing two students who both responded to the survey, which allows a consideration of a student's place in the birth order. Unfortunately, beyond this it is not possible to perform a within home analysis–transit mode variation only occurs within 13 households, which is an insufficient sample size. All results are reported in marginal effect form. Both the distance between school and home and family income were logged to incorporate nonlinearities in the relationships.

Replicating existing results, the marginal effects on (logged) distance between students' home and school is highly significant. In full sample results, an increase of one logged mile in distance between home and school is associated with between an 11.4 and 13.3 percentage point decrease in the likelihood of actively traveling to school. This finding again confirms that the distance between home and school is primary barrier in the decision to actively travel to school. In the two-student-household sample, the marginal effect is diminished so that an additional logged mile is associated with only a 6.0 percentage point reduction in the likelihood of walking or cycling to school.[38] Unlike previous findings, student concerns about crime were not found to significantly explain the transit mode decision.

Attending private school is negatively associated with walking or cycling to school. Each additional hour the student spends with their parent(s) is associated with about a 1.0 percentage point decrease in the likelihood of walking or cycling to school, which is consistent with a "doting" or parental involvement hypothesis. Each additional breakfast at home is associated with a 0.8 point decrease in the likelihood of walking or biking to school. It is uncertain whether

[38] However, it is likely that the two-student sample–only about 15% of the full sample–is too small to produce reliable results. Only logged home-to-school distance, private school attendance, and (weakly) Hispanic ethnicity have associated significant marginal effects. The data are not able to demonstrate any significant birth order effects. Additionally, two-child households may have inherent yet unobservable characteristics which produce non-generalizeable results.

this is also due to parental involvement, or that eating breakfast imposes a time constraint necessitating vehicular travel to school, or conversely that vehicular travel to school frees up time with which the student may be able to eat breakfast.[39] Lastly, there is a strong driving-age effect: students sixteen or older are 6.3-6.8 percentage points less likely to walk or bicycle to school relative to students under the legal driving age.

In terms of race and ethnicity, only Hispanic status is (negatively) significant; moreover, Hispanics are only shown to be less likely to actively travel to school in city fixed-effect model while the ethnic disparity is erased using zip code fixed effects. Males are 3.0-3.2 percentage points more likely to walk or bicycle to school than females. Older children are more likely to actively travel–until 16 years of age–and students from wealthier families are less likely. Finally, as suggested by the summary statistics, students in dense cities–Oakland and Philadelphia–are more likely to actively travel relative to Baltimore; students in Richmond–a much more sprawled city–are more likely to utilize a vehicular means.

Weekly Exercise Sessions

Table 4 displays estimates from regressions modeling weekly exercise sessions. Ordinary least squares coefficients are in the first column, and marginal effects from Poisson and Negative Binomial regressions–which are more appropriate given the non-negative integer structure of the dependent variable–are in the second and third columns, respectively. The marginal effects on the primary variable of interest–whether a student walks or bicycles to school–are statistically insignificant across all three models. Moreover the signs are negative–suggesting active travel decreases exercise levels–in contrast to previous research indicating that

[39] An interesting future study might more definitively assess whether or not there is a trade-off between active-travel to school, determine which way causality runs, and estimate net health impacts.

walking or bicycling to school increases activity levels. Therefore, SAY III data cannot replicate the finding that active transit to school increases students' activity levels.

However, the data are almost exclusively drawn from heavily urban settings, and this finding may indicate that the relationship between active travel and increased exercise levels does not hold true in all types of environments. One explanation may be that in urban settings there are fewer safe recreational areas such as parks to pursue exercise and play sports, or that there are more severe barriers to exercise (such as traffic or crime), which might affect the decision to walk or cycle. Alarmingly, 35.6% of students reported that crime is a big problem in their neighborhoods, yet this factor was found to affect neither active travel nor weekly exercise. For weekly exercise, however, the marginal effects are all negative, and it is conceivable that crime is strongly correlated with unobserved factors in the sample, including the heavily urban context of the sample. Ultimately, it may be that policy makers must consider the broader urban environment if they seek to increase active traveling for the purpose of increasing students' activeness. Additionally, even where Safe Routes to School programs may not achieve general increased activeness, walking and cycling are themselves forms of exercise, and may produce some health benefits.

Unexpectedly, students that have a job report more weekly exercise sessions. This is surprising since employment presumably constrains students' time. While this may be true, it may also be that employment creates its own inertia for activity. Alternatively, having a job may increase the demand for off-hours recreation, for example to counter monotonous employment tasks. This latter hypothesis is further supported by the finding that an additional hour of sedentary activities–doing homework or reading–is (weakly) associated with increased weekly exercise sessions.

The marginal effects on physical activities–participating in an after-school sport and attending a PE class–are both significantly positive. It may be that after-school sports and PE classes create activeness inertia, but active travel to school does not. Unfortunately, it is impossible to rule out whether respondents in this dataset count time involved with such activities towards their weekly tally of exercise. Future evaluators should design surveys to distinguish these possibilities by requiring that all activities are better labeled and distinct.

In terms of control variables, being a male is associated with about 0.88 additional weekly exercise sessions, replicating a gender effect previously identified (Sallis et al. 2000). An additional year in age is associated with slightly decreased activity counts–0.08 fewer sessions for an additional year of age, also identified by previous research (Pate et al. 2002), which cumulates to almost a full count over the distribution. Finally, the only discernable city effect is apparent for Oakland–residing in that city is associated with an additional 0.4 exercise sessions per week, relative to baseline.

Two-Step Procedure

Table 5 presents estimates for the coefficient on walking or cycling to school using the two step procedure. The ordinary least squares predicted values–whether the student walks or cycles to school–from Model 1 are used as independent variables in Model 2. Identification is enabled since distance from home to school, allowance, and private school attendance are unique to the active travel equation, and having a job, attending physical education class, time watching TV, using the internet, and playing video games and time spent reading or doing homework are unique to the weekly exercise count equation. We run the procedure twice, using both city and zip code fixed-effects, respectively. Both times, the coefficient on active travel is significantly *negative*, in contrast to previous results, suggesting active travel is associated with fewer weaker exercise sessions. The city effects estimate suggests that walking or cycling to school reduces a student's weekly exercise sessions by 0.67 sessions. The magnitude of this trade-off increases when zip codes are used: walking or cycling to school is associated with 0.83 fewer counts of exercise.

Why might active travel decrease exercise levels? One possibility is that students substitute non-travel exercise for exercise achieved via transit. A more interesting question is why students in SAY III dataset exercise less when they walk or cycle whereas active travel is associated with higher activity levels for samples from other studies reviewed above. Future research should first attempt to replicate this finding–perhaps attempting first in urban populations–and then try to determine the source of the discrepancy between the SAY III students and those in previous studies.

Conclusion and Extensions

This research identifies several determinants of students' decision to walk or cycle to school using a sample of students primarily in urban settings. We reaffirm that the distance between students' homes and schools is a primary barrier to walking or cycling to school. Unlike previous results, we are unable to demonstrate that that walking or cycling to school increases the general activeness of students. When activity levels are modeled in a two step procedure, walking or cycling is associated with decreased weekly exercise sessions. However, walking and cycling are themselves forms exercise, and even if they reduce non-travel exercise sessions it is uncertain what the net benefit to health might be.

Future work should exploit the geocoding within the SAY III to more fully quantitatively construct students' surrounding built environment. Other measures of walkability (whether sidewalks are available), public transportation options, and finer descriptions of crime and traffic in the neighborhood could be used to explain the decision to walk or cycle to school. Additionally, the number of times of weekly exercise activities could also be explained by accessibility to parks and other recreational areas, as inaccessibility to such areas are commonly cited as a pathway by which the built environment leads to poor health outcomes (Plantiga and Bernell 2007). Because the sample represents an urban environment, the inferences based on these data may not be generalizable, since barriers to outdoors physical activity may more prevalent even if these factors were observed.

Using (self-reported) weekly exercise counts is an imperfect measure of students' exercise quantities. More precise measures of quantity such as hours or minutes is preferable, and gauges of exercise quality–such as the intensity of the activity for a given hour–would provide further descriptive power. Alternatively, student health outcomes–which are the ultimate concern–could be evaluated, completely bypassing the exercise channels. Schools could be randomly assigned treatment interventions seeking to improve active travel, such as providing additional traffic or safety guards, sidewalk improvements, crosswalk and signage improvements, and bike racks. Evaluators could then monitor changes in objective student health measures.

Ultimately, the increase in adolescent obesity rates is very real. Yet the epidemic is arguably highly preventable relative to other public health crises. Our research suggests that encouraging active travel to school may be an inefficient or ineffective means combat adolescent obesity, and certainly in urban populations which are disproportionately affected by obesity. First, the evidence supporting active travel for health is dubious: our findings indicate active travel does not increase general activeness and our research has found no difference in health behaviors of students who walk to school. Second, it is questionable whether students' increased energy expenditures of active travel justify the cost of Safe Routes to School programs, especially since caloric expenditure improvements can be quickly negated through poor food choices. Perhaps other, more holistic approaches would be more effective.

Empirical Tables

Table 1: Summary Statistics (n=1,578)

Variable	Mean Average	Standard Deviation	Minimum	Maximum
Weekly Times Exercising	3.9525	2.4163	0	14
Student Walks or Bikes to School	0.1965	0.3974	0	1
Distance Between Home and School (miles)	3.0510	3.0299	0.005	19.739
Crime in Neighborhood a Big Problem	0.3555	0.4788	0	1
Student Overweight	0.1996	0.3998	0	1
Attends Private School	0.2174	0.4126	0	1
Student Has Job	0.2915	0.4546	0	1
Allowance Amount	12.3327	25.7259	0	150
Frequency of Family Dinners	4.8688	2.4762	0	7
Frequency of Breakfast at Home	2.4303	2.1516	0	5
Participates in Sport After School	0.3042	0.4602	0	1
Participates in Sport Before School	0.0722	0.2590	0	1
Participates in Non-Sport After School	0.3815	0.4859	0	1
Attends Physical Education Class	0.5558	0.4970	0	1
Sedentary Time (Hours)	3.1347	2.9409	0	20
Recreational Time (Hours)	4.5984	4.5289	0	30
Time with Parent (Hours)	1.8516	1.8350	0	10
Parents Married	0.5387	0.4987	0	1
Number of Kids in Household	2.4740	1.4600	1	10
Old Enough to Drive (Age 16+)	0.3112	0.4631	0	1
Two-student Home: Older Child	0.4828	0.5001	0	1
Two-student Home: Equal Age (in Years)	0.1031	0.3043	0	1
White	0.2870	0.4525	0	1
Black	0.5894	0.4921	0	1
Hispanic	0.0767	0.2662	0	1
Male	0.4968	0.5001	0	1
Age	14.1755	2.2028	10	18
Family Income	40.9126	22.4616	10	70
Baltimore	0.2142	0.4104	0	1
Detroit	0.1914	0.3935	0	1
Oakland	0.1984	0.3989	0	1
Philadelphia	0.2237	0.4169	0	1
Richmond	0.1724	0.3778	0	1

The sample size is 1,578 with the exception of “Two-student Home: Older Child” and “Two-student Home: Equal Age (in Years)” which are drawn from a subsample of two-student homes and have 232 observations. Data from the third wave of the Survey of Adults and Youth.

Table 2: Comparison of Sample Means by Transit Mode Choice			
Variable	Vehicular Mode	Active Mode	Significance
Weekly Times Exercising	3.961	3.919	0.27
Student Walks or Bikes to School	0.0%	100.0%	-
Distance Between Home and School (miles)	3.492	1.246	15.54***
Crime in Neighborhood a Big Problem	34.8%	38.7%	-1.28
Student Overweight	20.6%	17.4%	1.30
Attends Private School	24.3%	11.3%	6.00***
Student Has Job	29.4%	28.1%	0.47
Allowance Amount	12.823	10.329	1.70*
Frequency of Family Dinners	4.875	4.843	0.22
Frequency of Breakfast at Home	2.492	2.177	2.29**
Participates in Sport After School	30.8%	29.0%	0.59
Participates in Sport Before School	6.7%	9.0%	-1.27
Participates in Non-Sport After School	38.6%	36.1%	0.822
Attends Physical Education Class	54.8%	58.7%	-1.25
Sedentary Time (Hours)	3.268	2.588	4.79***
Recreational Time (Hours)	4.682	4.258	1.82*
Time with Parent (Hours)	0.888	0.861	1.22
Parents Married	55.2%	48.4%	2.15**
Number of Kids in Household	2.413	2.723	-3.10***
Old Enough to Drive (Age 16+)	33.0%	23.2%	3.58***
Two-student Home: Older Child	50.0%	42.4%	1.54
White	28.5%	29.4%	-0.28
Black	59.7%	55.8%	1.24
Hispanic	7.4%	8.7%	-0.73
Male	48.7%	53.9%	-1.65
Age	14.243	13.900	2.49**
Family Income	42.141	35.887	4.37***
Baltimore	22.2%	18.1%	1.68*
Detroit	19.3%	18.4%	0.38
Oakland	18.8%	24.2%	-2.03**
Philadelphia	19.8%	32.9%	-4.52***
Richmond	19.9%	6.5%	7.49***

T-statistics are comparison of means test under the null hypothesis that mean(*Vehicular Mode*)-mean(*Active Mode*) equals zero. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the third wave of the Survey of Adults and Youth.

Table 3: Determinants of the Decision to Walk or Cycle to School			
Dependent Variable–Student Walks or Cycles to School			
Variable	(1) City	(2) Zip Code	(3) Two-Student Home
ln(*distcalc*)	-0.1333***	-0.1136***	-0.0599**
	(0.010)	(0.010)	(0.026)
Parental Perception of	0.0099	0.0161	0.0162
Crime in Neighborhood	(0.0161)	(0.0156)	(0.0287)
Overweight	-0.0102	-0.0152	-0.0175
	(0.017)	(0.015)	(0.015)
Attends Private School	-0.0636***	-0.0614***	-0.0418**
	(0.016)	(0.014)	(0.021)
Allowance Amount	-0.0004	-0.0003	0.0002
	(0.000)	(0.000)	(0.000)
Frequency of Family	-0.0052*	-0.0040	-0.0049
Dinners	(0.003)	(0.003)	(0.004)
Time with Parent	-0.0099**	-0.0091**	-0.0098
(Hours)	(0.004)	(0.004)	(0.007)
Number of Kids in	0.0091*	0.0100**	-
Household	(0.005)	(0.005)	
Participates in Sport	0.0009	-0.0070	0.0284
After School	(0.016)	(0.014)	(0.029)
Participates in Sport	0.0310	0.0397	-0.0170
Before School	(0.033)	(0.033)	(0.015)
Participates in Other	0.0035	0.0054	-0.0253
After School Activity	(0.015)	(0.014)	(0.019)
Parents Married	-0.0255	-0.0284*	0.0268
	(0.017)	(0.016)	(0.019)
Frequency of Breakfast	-0.0082**	-0.0082**	-0.0055
	(0.004)	(0.003)	(0.005)
Old Enough to Drive	-0.0676***	-0.0627***	-0.0087
(Age 16+)	(0.020)	(0.018)	(0.023)
White	0.0087	0.0016	0.0386
	(0.034)	(0.032)	(0.055)
Black	-0.0206	-0.0268	0.0559
	(0.032)	(0.032)	(0.060)
Hispanic	-0.0634***	-0.0312	-0.0305*
	(0.019)	(0.027)	(0.017)
Male	0.0303**	0.0316**	-0.0031
	(0.015)	(0.014)	(0.016)
Age	0.0163***	0.0127**	-0.0053
	(0.005)	(0.005)	(0.007)
ln(Family Income)	-0.0342***	-0.0351***	-0.0230
	(0.013)	(0.012)	(0.018)
Detroit	0.0249	-	0.0529
	(0.026)		(0.070)

Table 3: Determinants of the Decision to Walk or Cycle to School

Dependent Variable–Student Walks or Cycles to School			
Variable	(1) City	(2) Zip Code	(3) Two-Student Home
Oakland	0.0806**	-	0.1497
	(0.034)		(0.113)
Philadelphia	0.1189***	-	0.0785
	(0.033)		(0.071)
Richmond	-0.0524***	-	-0.0196
	(0.019)		(0.020)
Older Child (of Two Students)	-	-	0.0471
			(0.032)
Equal Age in Years (of Two Students)	-	-	0.0397
			(0.057)
Zip Code Fixed Effects	No	Yes	No
Psuedo-R2 of Logit Regression	0.3399	0.3943	0.5988
Observations	1,578	1,508	232

All results are in marginal effect form evaluated at the mean. The third column, “Two-Student Home”, includes household fixed effects. Standard errors are in parentheses. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the third wave of the Survey of Adults and Youth.

Table 4: Determinants of the Number of Weekly Exercise Sessions			
Dependent Variable–Number of Weekly Exercise Sessions			
Variables	(1) OLS	(2) Poisson	(3) Negative Binomial
Walks or Bikes to School	-0.1104	-0.1046	-0.1127
	(0.151)	(0.127)	(0.151)
Crime in Neighborhood	-0.0766	-0.0738	-0.0677
	(0.1308)	(0.1115)	(0.1330)
Overweight	0.0686	0.0708	0.0672
	(0.146)	(0.126)	(0.150)
Student Has Job	0.3584***	0.3349***	0.3487**
	(0.131)	(0.114)	(0.137)
Frequency of Family Dinners	0.0558**	0.0595***	0.0604**
	(0.025)	(0.022)	(0.026)
Sedentary Time (Hours)	0.0528*	0.0477**	0.0499*
	(0.028)	(0.024)	(0.029)
Recreational Time (Hours)	-0.0123	-0.0122	-0.0137
	(0.018)	(0.015)	(0.018)
Time with Parent (Hours)	0.0009	0.0003	0.0011
	(0.041)	(0.035)	(0.042)
Number of Kids in Household	-0.0269	-0.0263	-0.0276
	(0.041)	(0.036)	(0.043)
Participates in Sport After School	0.8604***	0.8420***	0.8659***
	(0.131)	(0.116)	(0.141)
Participates in Sport Before School	0.5229**	0.4567**	0.4697*
	(0.229)	(0.194)	(0.240)
Participates in Other After School Activity	-0.1464	-0.1432	-0.1452
	(0.122)	(0.103)	(0.124)
Attends PE Class	0.4048***	0.4043***	0.4168***
	(0.128)	(0.109)	(0.130)
Parents Married	-0.2204	-0.2207*	-0.2180
	(0.137)	(0.117)	(0.140)
Frequency of Breakfast	0.0128	0.0145	0.0141
	(0.029)	(0.025)	(0.030)
White	0.3097	0.3044	0.3218
	(0.294)	(0.261)	(0.312)
Black	0.1499	0.1327	0.1333
	(0.283)	(0.242)	(0.288)
Hispanic	0.3378	0.3397	0.3549
	(0.341)	(0.310)	(0.373)
Male	0.8801***	0.8701***	0.8868***
	(0.120)	(0.103)	(0.123)
Age	-0.0792***	-0.0744***	-0.0797***
	(0.030)	(0.025)	(0.030)
ln(Family Income)	0.0372	0.0279	0.0252
	(0.107)	(0.091)	(0.109)

Table 4: Determinants of the Number of Weekly Exercise Sessions

Dependent Variable–Number of Weekly Exercise Sessions			
Variables	(1) OLS	(2) Poisson	(3) Negative Binomial
Detroit	0.1297	0.1266	0.1399
	(0.187)	(0.166)	(0.198)
Oakland	0.4442**	0.4199**	0.4171**
	(0.193)	(0.173)	(0.207)
Philadelphia	0.0949	0.0940	0.0980
	(0.178)	(0.156)	(0.186)
Richmond	0.0886	0.0931	0.0974
	(0.190)	(0.168)	(0.199)
Constant	3.3609***		
	(0.701)		
Observations	1,578	1,578	1,578
R-squared	0.119		

All results are in marginal effect form evaluated at the mean. Standard errors are in parentheses. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the third wave of the Survey of Adults and Youth.

Table 5: Two-Step Analysis–Predicted Transit Mode Influence on the Quantity of Exercise

Dependent Variable–Number of Weekly Exercise Sessions		
	City Fixed-Effects	Zip Code Fixed-Effects
Walks or Bikes to School	-0.6685**	-0.8256**
	(0.303)	(0.326)
Zip Codes	No	Yes
Observations	1,578	1,578

All control variables are included. Standard errors are in parentheses. Asterisks denote statistical significance [*** p<0.01, ** p<0.05, * p<0.1]. Data from the third wave of the Survey of Adults and Youth.

ESSAY IV: CONCLUDING REMARKS

Americans should be alarmed at the sharp rise in the obesity rate over the past thirty years. The incidences of "diseases of lifestyle" such as diabetes or arthrosclerosis are similarly increasing. The costs of these afflictions are measurable in years of quality life or burden on the tax system. The annual cost of obesity alone is in the billions and current public finances schemes are alleged to be unsustainable following projections of medical expenditures in coming decades. There will be increasing pressure to curb costs, and the first objective should be substantially reducing incidence of preventable disease.

The cause of the epidemic is complex and manifold, but consistent evidence–here as well in a proliferating body of evidence–suggests that place matters: net of individual characteristics, the surrounding characteristics of individuals' residential environments significantly impacts health outcomes. The research investigating relationships between health and place is predominately undertaken from a public health perspective, yet economics can also offer a fresh perspective to the literature. The preceding chapters present numerous examples of correlations between the built environment and individuals' health-related behaviors and outcomes using standard economic theories and analytical techniques.

Given that the U.S. population is highly urbanized, it is highly relevant to understand how environmental context interacts with the spread of diet and lifestyle choices believed to promote obesity. The term "built environment" is used throughout the preceding chapters in a purposefully vague sense. In this dissertation, it signifies a catch-all for non-natural, artificially-constructed environmental features. The essays herein commonly focus on both traffic infrastructure and residential location in relations to place of employment, sites foods are purchased, and schools. Given that the urban environment is planned and mutable, it is highly beneficial to identify factors which lead to unintentional health consequences for the ultimate goal of ameliorating urban health.

Admittedly, it is difficult to ascertain the precise mechanisms linking environment and health–perhaps too little is fully understood to advance assuredly effective policy recommendations–so it must be emphasized these results are preliminary. Taking the first essay's commuting opportunity cost as example, an expensive effort to shorten commutes might increase television watching disproportionate to exercise–perhaps with unhealthy snacking accompanying the television watching–offsetting favorable health gains. Health officials often recommend increasing disadvantaged populations' access to nutritious food items; yet, most typical supermarkets stock highly processed foods as well as fresh produce, and consumers accustomed to less healthy fare might merely sort to the snack aisles, representing a failure of any costly incentives enacted to lure a grocery to a food desert. Environmental factors certainly matter, but the problem is much more holistic: inputs to health (time, healthy foods, and recreational opportunities) must be available to individuals willing, able, and sufficiently knowledgeable to make healthy choices.

Given the large body of correlational studies connecting urban sprawl to obesity, the first essays proposes and tests the hypothesis that lengthier commutes limit the leisure time available as inputs to health production. Longer commutes are associated with less time exercising, preparing food, and sleeping in particular. For a given period of exercise, individuals with longer commutes engage in less-intensive exercise activities. In addition to spending less time preparing food for meals, individuals with longer commutes are more likely to purchase prepared meals. Fatal traffic accidents, which create congestion shocks, are used as instrumental variables and trade-off estimates increase for exercise and sleeping–the relatively more time-intensive activities. The second essay identifies an overall negative association between an individual's likelihood of food insecurity and the degree of urban sprawl in an area. Individuals are less likely to report food insecurity where streets are better connected, though they are more likely to "paradoxically" report being both obese and food insecure in better connected areas. In that local amenities are more accessible where streets are better connected, this results rejects claims that obesity and food insecurity jointly arise from poor access to healthy food items–joint outcomes are in fact more likely where access is greater. The third essay identifies determinants of travel mode choice to school for a predominantly urban student population, and then investigates what impact modal choice has on student activeness. In contrast to claims by active travel advocates, there was no evidence that walking or cycling to school increases student activeness. Moreover, a similar null result was found in the first essay–there is no evidence that walking or cycling to work affects commuters' exercise behaviors. Certainly, active travel should be encouraged by virtue of the direct exercise benefits provided, but beyond this the two essays fail to substantiate claims of any active travel spillover into leisure time.

Methodologically, future researchers should particularly exploit natural experiments whenever possible. The treatment in neighborhood effect studies (which encompasses built environment research) is residential location, which is very much not randomly assigned. Outside of randomized voucher experiments, claiming a causal argument is dubious. Fortunately, the factors of interest are never location *per se* but rather attributes of a particular neighborhood, all of which may be subject to shocks observable as natural experiments. The first essay exemplifies this strategy: the essay explores an untested path–lengthy time devoted to commuting–to relate how sprawl might increase obesity prevalence. Unobservable preferences influence location (and by extension commuting time) in the long-run which creates self-selection bias. However, short run commute trip times are affected by congestion levels. Fatal traffic accidents, a primary source of traffic congestion, are employed as instrumental variables to further causal arguments and significant differences in estimates are detected.

Lastly, a large body of unexplored research potential exists in explaining the development of the built environment in a particular locale. The essays contain numerous caveats about the ability to draw causal arguments from neighborhood effect studies in part because the built environment is inherently artificial; it is an endogenous, economic outcome by agents on both sides of "supply and demand". It is surprising that economists have yet to offer contributions to this field: long-standing theories in urban economics, environmental economics, and local public finance theory seek to explain precisely the determinants relevant for urban form development. For example, both residential and firm location decisional theory, the spatial mismatch hypothesis, and local public good provision theory all touch on pertinent issues. The connection between the built environment and obesity–and health more broadly–will likely remain an active research field. Clearly, economic theory can meaningfully contribute to a subject dominated by public health researchers. Shared expertise will ultimately contribute to a deeper and fuller understanding of the complex phenomena at play.

APPENDIX

Construction of Time Use Variables

"Exercise" is the aggregate minutes spent in ATUS activities t130101 through t139999; the activities are aerobics, baseball, basketball, biking, billiards, boating, bowling, climbing, dancing, equestrian sports, fencing, fishing, football, golfing, gymnastics, hiking, hockey, hunting, martial arts, racquet sports, rodeo events, rollerblading, rugby, running, skiing/ice skating, snowboarding, soccer, softball, cardiovascular equipment, vehicle touring/racing, volleyball, walking, water sports, weightlifting, working out (unspecified), wrestling, yoga, and a miscellaneous category.

"Food Preparation" is minutes spent in food and drink preparation and presentation, t020101 + t020102.

"Eating" is t110101, secondary eating minutes taken from the variable ertseat in the Eating and Health Module. A variable summarizing secondary drinking (ertsdrk) is ignored.

"Sleeping" is t010101, only. Sleeplessness and time in a state of insomnia (t010102) is included with t010101 in other studies because it shows intent to sleep; however, we exclude insomnia because stress caused by commuting might alter the ratio of t010101 and t010102, with likely health consequences. Moreover, when t010101 and t010102 are combined, coefficients on commuting (and labor time) are essentially the same.

"Television" is minutes spent watching television (t120303) and "Socializing" is minutes spent socializing and both communicating with others and talking with family and friends on the telephone (t120101 + t160101 + t160102).

"Labor Time" is total minutes spent working at main and other jobs (if applicable); t050101 + t050102. Labor time at home and at other non-working sites is included.

Measuring commuting is not straightforward in the ATUS, as explained in detail by Brown and Borisova (2007). "Travel related to working", t180501,[40] accurately measures commute times for respondents traveling directly between home and work, only and underestimates commute time for respondents making other-purposed stops on the journey between home and work–those "trip-chaining". In this essay, commute time is all travel time between leaving home and arriving at work (and vice versa). "Travel time" is only time which the respondent was traveling, and non-travel time spent on errand stops is excluded. Travel time excludes traveling as entertainment (t181205) and accidents (t189999). Single job respondents are limited to two trips, even if they report multiple trips between home and work. In these instances only the first and last trips are counted. Respondents with second jobs are allowed an additional trip–all travel between their first and second jobs. For an eligible commute, the place of employment must be different than the respondent's residential location; those working at home have commutes of zero, even if coded otherwise (e.g., walking to a home office). Any travel time related to work (t180501) is also excluded if the respondent does not visit an actual place of employment that day. Active and sedentary commute portions are defined by which mode the travel took place: the commute time is classified as "active" if the respondent was walking or bicycling ("tewhere" equal to "14" or "17"), "engaged" if the respondent was operating an automobile (("tewhere" equal to "12"), and "passive" if the respondent was a passenger in a car, bus, subway, train, boat, ferry, airplane, or other mode of transportation. A number of travel "modes" are also classified as places, such as the respondent's home or workplace, for a very small fraction of trip portions (under 3%). Brown and Borisova (2007)

[40] In the individual year ATUS files, the first two digits of travel codes are "17" for 2003-04 and "18" for 2005-07; in the multiple year file all travel begins with "18".

write that this travel could represent time spent waiting for mode changes such as at a bus stop with brief walks, and we choose to classify all place-based travel as "active".

The control variable "Smoker" if defined as equal to one if the respondent indicated any time participating in use of tobacco (or marijuana) products (t120302 greater than zero).

The dichotomous variable indicating the respondent reported positive time purchasing non-grocery food items is constructed as equal to one if t070103 is greater than zero.

MET intensity values are available online at http://riskfactor.cancer.gov/tools/atus-met/. MET intensities are constructed as constants regardless of individual characteristics such as age or gender, with the exception of labor activities, which vary by CPS occupation code (22-classification scheme), and travel activities, which vary by travel mode, neither of which are used to calculate leisure MET minutes.

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