Health and Environmental Implications of Americans' Time Use Responses to External Stimuli: Essays on Air-Quality Alerts and Daylight Savings Time

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Dedication

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Chapter 1:
Introduction

Many environmental policies have clear public health impacts and are designed to improve health outcomes either by reducing the environmental health risks individuals encounter in their daily lives, or by encouraging more healthy lifestyles. One way of testing the effectiveness of these policies is to examine the behavioral changes they induce. In this dissertation, I use the American Time Use Survey (ATUS) to estimate behavioral responses to several environmental policies by examining how individuals shift the amount of time they spend in various activities during the day.

The ATUS is a nationally representative, federally administered survey on time use in the United States. The survey collects information on all activities performed by respondents during a designated 24-hour period. It was first administered in 2003 and has continued throughout every year since, allowing me to collect responses for an 8-year period, 2003-2010. Because each respondent provides detailed information on his/her activities during the designated 24-hour period, I am able to determine how much time each person spends in various morning, afternoon and, evening activities that may be affected by the policies of interest.

Although the ATUS has been in existence for 9 years, it has been under utilized in the economic literature. Researchers have traditionally focused primarily on the budget constraint faced by individuals and households, ignoring the time constraint. Examining how time use is affected by exogenous policy changes has the potential to shed light on many economic questions. For example, the literature has found that as gas prices increase consumption decreases, however; at a very inelastic rate. Analysis of time-use data could add to these findings by examining what behaviors are most affected. Do the higher prices cause individuals to carpool or take public transit to work, or do they contribute to fewer recreational excursions? Do the higher prices make commutes longer or shorter? Does this affect the amount of time spent working during the day? Time use data sets such as the ATUS can be used to lend insights to many of the behavioral questions we are concerned about in economics.

This dissertation consists of three essays that use the ATUS to examine individual responses to different environmental policies with a particular focus on the behavioral responses that may affect health. In the first essay, I investigate whether individuals respond to publicly provided information on air quality by reducing their vigorous outdoor activities, and thus minimizing their exposure to dangerous concentrations of pollutants. In the second essay, I estimate behavioral responses to Daylight Savings Time (DST) by examining how individuals shift the amount of time they spend in activities that may affect residential energy use. Finally, in the third essay I investigate how DST affects the time individuals spend in exercise and other aerobic activities to determine if it can be used as a low cost policy to promote public health.

Despite considerable improvements in air quality over the past few decades, there is still concern that the health risks from air pollution are too high. This has lead the EPA and others to push for even stricter emissions and ambient air-quality standards. However, there are concerns that the marginal benefits of additional abatement regulations no longer exceed their increasing marginal costs and that alternative approaches are needed to reduce the health risks from air pollution. Essay 1 investigates the effectiveness of one alternative policy – demand-side episodic programs that attempt to reduce exposure on high-pollution days by increasing averting behavior. If effective, these policies offer a lower cost alternative to tighter standards and other supply side policies. Specifically, I study whether individuals respond to daily information provided on air-quality levels, and whether they respond particularly to air quality alerts issued during periods of high pollution. While controlling for individual responses to actual air quality index levels, my results show that individuals engage in averting behavior on alert days by reducing the time they spend in vigorous outdoor activities by 18 percent or 21 minutes on average.

With few exceptions, previous DST studies have relied on simulation models to estimate and extrapolate energy savings under different policy programs. Although these studies have found a range of energy savings, Kellogg and Wolf (2007) found that the most sophisticated simulation model available in the literature significantly overstated electricity savings when it was applied to Australian data. This suggests that individuals are not operating completely off the clock (as assumed in previous DST studies), but instead that the time of sunrise and sunset affects their daily behaviors. Essay 2 uses the ATUS to estimate behavioral responses to DST by examining how individuals shift the amount of time they spend sleeping, awake at home, and awake away from home during the day for a time period immediately surrounding a change in the DST regime. Aggregating activities into these three broad categories allows for a simple and clear analysis of how changes in time use due to DST may affect residential energy consumption.

Sunrise occurs one hour later in the morning due to DST, meaning that mornings are darker and cooler than they would be on ST. During the cooler months in the spring and fall especially, this may cause individuals to use more lighting and heating electricity regardless of behavioral/time-use adjustments. Similarly, DST causes the late afternoons and early evenings to be warmer and brighter. This should reduce lighting electricity, but likely lead to increased air conditioning use, making the overall impact on afternoon and evening energy consumption ambiguous. Most simulation models suggest that afternoon energy savings do result from DST, and those savings more than offset the increased use in the morning, making DST an energy-reducing policy. However, one cannot accurately draw such conclusions without information on how behaviors change on DST. My results suggest that the DST time shift has the largest impact in the spring, and that individuals are getting up earlier in the morning and spending the additional time at home. This would use additional energy beyond what traditional simulation models predict. Additionally, there is also evidence that individuals are spending less time at home in the evenings, which may reduce energy consumption.

Several states have recently discussed legislation to either observe standard time year around or DST year around. These new proposals are interesting because they mark a clear shift in the motivation for DST away from residential energy conservation. Proposals now cite other economic and social costs of DST, whereas the literature to date has focused primarily on energy effects. To address the need for additional research into the other possible behavioral impacts of DST, Essay 3 uses ATUS data to investigate how DST affects the time individuals spend in exercise and other aerobic activities. For example, an additional hour of after-work daylight can be used for biking, jogging, playing golf or tennis, walking, or other aerobic activities. If DST leads to increases in physical activity, there may be a public health argument for adopting year long DST or even double DST. In its 2011 Annual Report on Health Statistics, the Center for Disease Control (CDC) found that only 20 percent of adult Americans meet the federal Physical Activity Guidelines. Given these disappointing numbers and America's obesity problem, DST may prove to be a low cost policy tool to improve health outcomes. In fact, my results suggest that adding an additional hour of evening daylight in the spring results in an additional 16 minutes of exercise on average.

In all three essays of this dissertation, the previous literature was narrow in scope, focusing on small geographic regions, and used incomplete outcome measures. Thus, each essay makes a unique contribution to the literature by using a nationally representative data set over a long period of time with detailed data on time use. The results from all three essays also have important policy implications that are discussed further in their respective conclusions.

Chapter 2:

Responses to Air Quality Alerts: Do Americans Spend Less Time Outdoors?

2.1 Introduction

Despite considerable improvements in air quality over the past few decades, there is still concern that the health risks from air pollution are too high. This has motived the Environmental Protection Agency (EPA) to push for even stricter emissions and ambient air-quality standards, but these proposals have been widely contested (Broder 2010). The EPA estimates that the Clean Air Act costs over 50 billion dollars a year in direct costs alone, and some economists have put the annual costs at over 100 billion dollars.[1] As in the general textbook example, even tighter standards are likely to deliver incremental improvements only at increasing costs because the marginal cost of air pollution abatement is upward sloping (Pindyck and Rubinfield 2001; and Santerre and Nuen 2006). This has led policy makers and researchers to consider alternative approaches to reduce the health risks from air pollution.

Air pollution levels can vary dramatically from day to day based on predictable weather variables such as sunlight and temperature, and low pollution levels do not impose serious acute health risks (Committee of the Environmental and Occupational Health Assembly of the American Thoracic Society 1996). Thus, episodic policies aimed at reducing exposure on peak pollution days could be cost effective relative to policies aimed at reducing pollution exposure across all days. These approaches may include efforts to reduce the supply of pollution on those days expected to yield high-pollution levels, such as reducing manufacturing or discouraging vehicle use. Alternatively, policy can also reduce exposure by increasing averting behavior among individuals. In other words, damages associated with pollution exposure can be mitigated by reducing the demand for high air quality, which may be less costly than supply-side approaches. For instance, a given level of reduced exposure may

[1] In its first prospective study of the CAA, the EPA estimated that direct costs for the regulations would be $45 billion in 2010. Later, in its Second Prospective study the estimates for 2010 rose to $57 billion. Meanwhile, other economists generated their own estimates including Lutter and Belzer (2000) whose conservative results put 2010 costs at $100 billion. (In all cases, estimates are in 2010 dollars.)

be achievable at lower cost by asking certain groups to avoid outdoor activity on bad air days rather than mandating pollution abatement technologies that reduce air pollution below acceptable levels on low air pollution days. This idea motivates a two-part approach to reducing health risks from pollution whereby emissions and ambient air-quality standards are used to reduce pollution to a level where concentrations are within healthy ranges on most days, and episodic programs are used to reduce exposure on days when pollution is predicted to reach unhealthy levels.

This paper investigates the feasibility of such an approach by examining whether individuals respond to publicly provided information on air quality by reducing their vigorous outdoor activities (VOA), and thus minimizing their exposure to dangerous concentrations of pollutants on high-pollution days. Specifically, I study whether individuals respond to daily information provided on air-quality levels, and whether they respond specifically to air quality alerts issued during periods of high pollution.

Many jurisdictions have implemented demand-side policies intended to induce averting behavior from individuals by informing them about health risks from pollution and providing real-time information about air quality and warnings on low-air-quality days. The San Joaquin Valley Air Pollution Control District operates a "Air Alert program" in California's Central Valley that issues Air Alerts on days when air quality is forecast to be unhealthy. In fact, over 50 cities in California alone operate air alert programs (Airnow 2011). These health information campaigns are driven by the belief that individuals may engage in too little health-risk averting behavior because they are uninformed about the presence and/or the magnitude of the risks they face. By providing agents with consistent and reliable information about these risks, policymakers believe they can induce welfare-enhancing averting behavior.

However, the effectiveness of these programs depends on the behavioral response of individuals who may ignore information and disregard warnings, or who may overreact and forgo productive activity, including beneficial exercise. In fact, research shows that consumers often do not correctly estimate health risks and have a tendency to overestimate worst-case outcomes (Viscusi 1990, 1997). Thus, whether air-quality alerts improve the level of risk-averting behavior among individuals and improve health outcomes is an empirical question that rests on measuring the behavioral response of individuals to information-provision campaigns.

A number of studies have evaluated the impacts of health information campaigns including air-quality alert programs, finding in most cases that individuals do respond to alerts by engaging in averting behaviors. However, a concern with most prior air-quality alert studies is that they examine small population sub-groups, predominantly in Southern California, and measure averting behavior by examining attendance at outdoor facilities rather than studying activities such as outdoor exercise and outdoor work that are most likely to cause health complications due to air pollution (Zivin and Neidell 2009, and Neidell 2009).

To overcome the limitations of previous research, I use The American Time Use Survey (ATUS), a nationally representative survey, which contains information on all outdoor activities of respondents. These data, along with information on all alert days, offers the opportunity to systematically study averting behavior on a national scale and draw conclusions about consumers' reactions to information provided on air quality – both alerts and daily air quality index (AQI) information. Additionally, the ATUS data allows me to study all vigorous outdoor activities (VOAs) rather than a single specific activity like attendance at an outdoor facility. Thus my analysis is more consistent with the policy goals of alert programs and will allow for more conclusive results.

This paper also contributes to the literature by exploring not only the overall effects of air-quality alerts, but also intra-day and inter-day substitution effects. These effects can be important from an overall health perspective because, ideally, reductions in VOAs in response to episodic poor air quality would be replaced by increased activity, either on nearby days or during low-pollution times during an alert day, such as the morning hours. Alternatively, outdoor VOAs could also be replaced with indoor VOAs. Finally, the ATUS data also allows averting behaviors to be correlated with detailed household demographic data, in order to determine whether responses vary across different population subgroups. This is particularly relevant when examining air quality because high pollution levels are most dangerous for young children and seniors

This paper proceeds in section 2 with a review of existing literature on responses to health-risk information. Section 3 provides background information on air-pollution regulations and air-quality alert programs. Section 4 describes the data used in this analysis, and section 5 discusses the econometric models used to estimate the level of response to air-quality information. The results are presented in section 6, and section 7 summarizes the main findings and draws conclusions about the effectiveness of episodic pollution information policies.

2.2 Literature Review

The fact that air pollution has serious, immediate and long-term impacts on health is well established in the epidemiology literature. Numerous studies have shown that exposure to pollutants such as airborne particulate matter and ozone is associated with an increase in mortality and hospital admissions due to respiratory and cardiovascular disease. A detailed summary of this literature can be found in Brunekreef and Holgate (2002) and EPA (2006).

Because, improvements in human health are the primary benefit associated with cleaner air, economists have begun measuring the economic or social costs associate with high pollution concentrations and the effectiveness of pollution abatement policies and regulations. Key papers in this literature include Chay and Greenstone (2003) and Currie and Neidell (2005). Both studies investigated how pollution affected infant mortality rates, and found that a reduction in both suspended particulates and carbon monoxide resulted in a reduction in the infant mortality rate. A large literature has followed from these papers,[2] and more recent studies have investigated how pollution affects other outcomes such as absences in elementary and middle schools (Currie et al., 2009).

Most relevant to this paper is the literature on air-quality alert programs. Alerts warn residents that the air quality outside is unsafe and that outdoor activities should be reduced, but additionally, a number of regions across the country operate voluntary episodic pollution-control programs that appeal to motorists to reduce car trips on smoggy days. Several studies have examined this latter policy goal including Cummings and Walker (2000), Scheffler (2003), Welch et al. (2005), and Cutter and Neidell (2009), but the results are inconclusive. For example, Welch et al. used hourly Chicago Transit Authority train ridership data to examine the smog alert program in Chicago, but found that alerts did not have a significant overall effect. Cutter and Niedell (2009), on the other hand find a 2.5- 3.5 percent reduction in traffic volumes due to alerts in the San Francisco bay area.

This paper focuses specifically on the health risk avoidance behavior of consumers in response to air-quality alerts. Evidence of averting behavior related to air pollution was first noted in the epidemiological studies measuring the health effects from exposure to ozone and other ground-level pollutants. Krupnick, Harrington, and Ostro (1990) estimated a model that allowed ozone to affect ill individuals differently than healthy individuals and found that ozone was negatively correlated with additional illness, a result consistent with the idea that those individuals at risk of health complications due to pollution engage in averting behavior.

Several studies have attempted to measure the response to both poor air-quality

[2]For example, Lleras-Muney (2005), Mansfield et al. (2006), Beatty and Shimshack (2007), Neidell (2004) and (2009), Neidell and Moretti (2011).

days and to alerts. Bresnahan, Dickie, and Gerking (1997) used stated preference methods to investigate whether or not individuals varied outdoor activities in response to air-quality alerts, finding that those who experienced smog-related symptoms spent significantly less time outdoors when ozone concentrations exceeded the national standard. Later, Neidell (2009) used data on attendance at two outdoor facilities in the Los Angeles area to measure pollution-avoidance behavior. He found that attendance dropped as much as 15 percent on air-quality alert days. Using the same data, Zivin and Neidell (2009) showed that responses to alerts dropped on the second consecutive alert day and disappeared completely on the third day.

These previous studies on responses to air-quality alerts suggest that these programs do induce pollution-averting behavior, but the studies are limited in scope. Zivin and Neidell (2009) and Neidell (2009) measured avoidance behavior by changes in attendance at both the Los Angeles Zoo and Botanical Gardens and the Griffith Park Observatory, although neither facility is particularly associated with an outdoor activity. Additionally, daily visitors at the zoo are likely to be predominantly tourists (vacationers) who have less flexibility in their schedules, and therefore are less responsive to air-quality alerts than the general population.

This chapter uses the American Time Use Survey (ATUS), a nationally representative data set that contains information on all activities. These data, along with information on all alert days, offer the opportunity to study averting behavior on a national scale and draw general conclusions about consumers' reactions to information provided on air quality – both alerts and daily AQI measures. The health risks associated with high levels of air pollution are largest for young children and the elderly, and in this study I use individual level data with detailed demographic variables allowing me to investigate whether or not averting responses to poor air quality differ between these target groups and groups who are at less risk.

2.3 Background

Epidemiological studies show that exposure to common air contaminants like ozone and particulate matter can aggravate asthma and chronic lung diseases such as emphysema and bronchitis. It can also cause scarring of the lung tissue and permanently reduce lung functions (especially in small children). Although sensitive populations (elderly, children under 14, pregnant women, and individuals with heart or lung disease) are the most susceptible to the risks from of pollution, healthy individuals can also experience respiratory irritation and difficulty breathing when pollution levels are sufficiently high. In fact, these health effects can appear quickly after minimal exposure time (U.S. EPA 2006), and thus the EPA mandates that communities with populations in excess of 350,000 report daily pollution levels.[3] Specifically, these areas are required to report the Air Quality Index (AQI) daily to the general public via either the local media (newspapers, radio, television), a recorded telephone message, or a publicly accessible Internet site. The reports must include the reporting area, the reporting period, the critical pollutant, the AQI, and the category descriptor.

The AQI is an index running from 0 to 500 developed by the EPA for reporting daily air quality. Raw measures of ground-level ozone, particle pollution, carbon monoxide, and sulfur dioxide are used to calculate AQI values for each pollutant using standard formulas developed by EPA. Then the highest of these AQI values is reported as the AQI value for that day. Higher AQI values are associated with greater levels of air pollution and more serious health risks. Specifically, when AQI exceeds 100 the air is unhealthy for sensitive groups (young children and the elderly), and when it is above 150 everyone may experience adverse health effects.

Additionally, the CAA requires the EPA to set National Ambient Air Quality Standards for six common air pollutants - particle pollution, ground-level ozone, car-

[3]Part 58.50 of Title 40 of the U.S. Code of Federal Regulations - AMBIENT AIR QUALITY SURVEILLANCE, Air Quality Index Reporting states that Metropolitan Statistical Areas (MSAs) with a population of more than 350,000 are required to report the AQI daily to the general public.

bon monoxide, sulfur oxides, nitrogen oxides, and lead. The first two ("criteria" air pollutants) present the most widespread health threats, and thus the EPA regulates them by developing human health-based and/or environmentally-based criteria (science-based guidelines) for setting permissible levels. In fact, according to EPA data, ground-level ozone is the pollutant responsible for the majority of alert days, which is likely because it forms easily in hot summer weather, especially in urban areas. Ozone is not emitted directly into the air, but rather is created by a chemical reaction between oxides of nitrogen (NOx) and volatile organic compounds (VOC) in the presence of sunlight. VOC come from gasoline, paint fumes, charcoal lighter fluid and consumer products; whereas NOx is emitted from cars, power plants, industrial boilers, refineries, chemical plants, and other gas-powered equipment.

Many areas of the United States remain in non-attainment of the ground-level ozone standard. In fact, almost half of the 675 counties monitoring ozone are currently in violation (Broder, 2010). In an effort to reduce ozone and minimize health risks, many cities across the country operate air alert programs established to warn residents when levels of air pollution reach unhealthy levels – usually when the Air Quality Index (AQI) exceeds either 100 or 150. These alert programs are intended to serve both demand- and suply-side purposes. They warn residents that the air quality outside is unsafe and that outdoor activities should be reduced, and they appeal to motorists to reduce car trips and encourage residents to avoid wood burning and other polluting activities.

The EPA has established a set of guidelines based off of AQI measures for recommending precautions individuals to take to protecting them from dangerous levels of pollution. For example, when AQI levels are between 100 and 150, people with lung disease, children, older adults, and people who are active outdoors should "reduce prolonged or heavy outdoor exertion." Similarly, when AQI levels are between 150 and 200, the EPA recommends that the previously mentioned groups avoid "outdoor exertion", while everyone else should limit these activities (EPA 2009).

2.4 Data

My data allows for the first nation-wide empirical assessment of individuals' responses to air quality information and to air quality alerts. I combine five data sets to aggregate information on daily activities, pollution levels, surface weather, and air quality alert days. First I used responses from the ATUS, a nationally-representative, federally-administered survey on time use in the United States, to collect information on outdoor activities during a designated 24-hour period. The ATUS was first administered in 2003 and has continued throughout every year since, allowing me to collect responses for an 8-year period, 2003-2010. Each ATUS respondent is selected randomly from the Current Population Survey (CPS), a monthly survey of households conducted by the Census Bureau for the Bureau of Labor Statistics, and asked to provide detailed information on his/her activities during a designated 24-hour period.

Using the ATUS-X Extract Builder, I created a variable that included all activities that might be considered vigorous outdoor activities (VOAs). Examples of such activities include biking, golfing, playing basketball, working in the yard, running, and working. Many of these activities can be performed inside or outside, and the distinction is essential for this paper. Thus only minutes spent doing these activities "outdoors away from the respondent's home" or "in the respondent's home yard" were included.

To analyze if respondents shift the timing of VOAs in response to pollution, I divided each day into four six-hour periods (12am-6am, 6am-12pm, 12pm-6pm, and 6pm-12am) and created a time-use variable for each one. For example, one such variable measures the time spent in VOAs between 12am and 6am. Summary statistics for these variables and other demographic variables measured in the ATUS are provided in Table 2.

A significant number of the ATUS responses had missing information for the respondent's geographic location. These data are necessary in order to match the responses to appropriate pollution and weather data, so I used data from the CPS for the corresponding years and matched respondents to their final interviews. These interviews occurred 2-5 months prior to the ATUS survey and contained more complete geographic information including the respondent's core based statistical area (CBSA). After matching the two data sets and dropping all responses for which a valid CBSA could not be identified, 84,977 responses spanning 8 years (See Table 1 for frequencies) and 296 CBSAs remained. The CBSA covering New York, Northern New Jersey and Long Island was home to the most respondents - 6,748, and Los Angeles-Long Beach-Riverside was second with 3,813 respondents. All CBSA's had at least 5 responses.

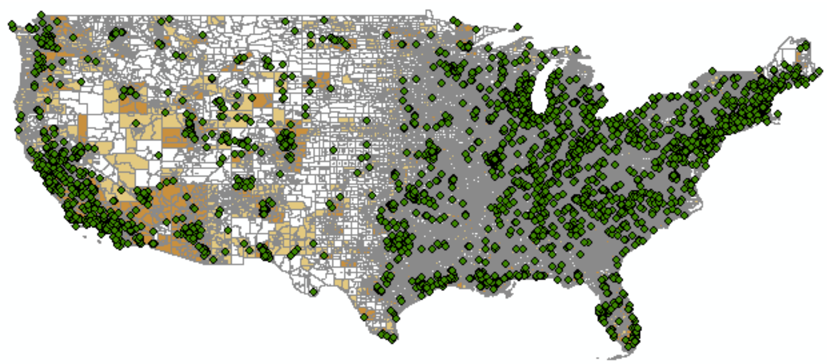
Table 2.1: ATUS Data Frequencies

Year of Interview	Frequency	Percent	Cumulative
2003	11,938	14.05	14.05
2004	10,028	11.80	25.85
2005	10,176	11.98	37.82
2006	10,564	12.43	50.26
2007	10,105	11.89	62.15
2008	10,854	12.77	74.92
2009	10,736	12.63	87.55
2010	10,576	12.45	100
Total	84,977	100	

Particle pollution and ground-level ozone offer the most widespread health threats and are thus the key pollutants to control for in the analysis. Data for ozone, was obtained from the EPA Technology Transfer Network Air Quality System (AQS). Each file contained hourly ambient air pollution data collected by EPA, state, local, and tribal air pollution control agencies from thousands of monitoring stations in the

US. Ozone levels are commonly reported in the form of rolling 8-hour averages. Thus, I calculated 8-hr averages from the data and kept the highest average for each day. I also obtained an extraction (from AQS) with longitude and latitude coordinates for all of the sites monitoring ozone with an EPA-approved method. Figure 1 shows the monitoring site locations. Geographic Information Systems (GIS) software allowed stations to be matched to CBSAs, and thus the pollution data to be merged with the ATUS data. Not all stations had data for every day between 2003 and 2010, so it was necessary to match each ATUS response to pollution data from the closest station to the center of the respondent's CBSA that had data on that day.

Figure 1: Ozone Monitoring Sites



Historical daily surface weather data for the United States during 2003-2010 from the National Climatic Data Center's (NCDC) Climate Data Online database were used to provide daily measures of mean temperature, mean dew point, mean sea level pressure, mean station pressure, mean visibility, mean wind speed, maximum sustained wind speed, maximum wind gust, maximum temperature, minimum temperature, and total precipitation (rain and/or melted snow) for over 2000 stations in the US. Each station's latitude and longitude coordinates were used to determine which station was located closest (measured as the crow flies) to the center of each

CBSA, allowing the data for those stations to be merged with the ATUS data and the pollution data.

Lastly, the EPA provided a list of all air quality alert days from 2004-2010. The list contains information on the location of the alert, the pollutant causing the alert, and the forecast for the day's AQI. This list identified 5,863 unique alert days across 160 CBSAs. After matching these data with ATUS responses (using CBSA identifiers), the data set contained 1,931 ATUS responses on alert days in 85 CBSAs. Additionally, the data set contains 2,114 ATUS responses on days after an alert.

Table 2 below shows the summary statistics for the final data set after all the components were merged together.[4]

[4]The data summary statistics are consistent with the US population according to both the 2000 and 2010 Census. For example, in 2000 12.3 percent of the US population was reported to be black, while 3.6% were reported Asian. These statistics were similar in the 2010 census. Additionally, the male-female breakdown is similar, with 6 percent more females in the final data than the census.

Table 1.2: Data Summary Statistics

Variable	# Obs.	Mean	Std. Dev.	Min	Max
Total VOAs	84,977	23.78	72.05	0.00	1060
VOAs 12am - 6am (min)	84,977	0.29	4.71	0.00	240
VOAs 6am - 12pm (min)	84,977	2.51	19.10	0.00	360
VOAs 12pm - 6pm (min)	84,977	11.70	42.25	0.00	360
VOAs 6pm - 12am (min)	84,977	3.00	16.47	0.00	360
AQI	55,187	36.75	16.62	0.51	212.43
Ozone 8 hr average (ppm)	55,187	0.04	0.02	0.00	0.15
Population per square mile (2010)	55,193	822.28	807.27	14.08	2,764
Mean temperature (˚F)	82,405	58.62	17.58	-36.40	104
Mean wind speed (knots)	82,402	6.25	2.95	0.00	26.2
Precipitation (inch)	82,026	0.08	0.24	0.00	5.71
Hours worked last week	84,977	24.51	22.19	0.00	160
Age (yrs)	84,977	45.81	17.44	15	85
Max Temp (˚F)	82,389	65.67	20.57	-4.74	116.35
Min Temp (˚F)	82,389	46.15	19.28	-61.6	104
Dummy Variables	**# Obs.**	**Yes**	**%**	**No**	**%**
VOAs (min)	84,977	17,064	20.08	67,913	79.92
Elderly	84,977	14,037	16.52	70,940	83.48
Holiday	84,977	1,490	1.75	83,487	98.25
Female	84,977	48,002	56.49	36,975	43.51
Kids under 5 yrs	84,977	15,292	18.00	69,685	82.00
Family income greater than $75,000	84,977	23,526	27.69	61,451	72.31
Income $\geq$ 185% of poverty line	84,977	21,187	24.93	63,790	75.07
Full time student	84,974	6,621	7.79	78,353	92.21
Air Quality Alert	84,977	1,931	2.27	83,046	97.73
Air Quality Alert on Previous day	84,977	2,114	2.49	82,863	97.51
Air Quality Alert due to PM 2.5	84,977	277	0.33	84,700	99.67
Black	84,977	10,501	12.36	74,476	87.64
Asian	84,977	2578	3.03	84,839	96.97
Indian	84,977	942	1.11	84,035	98.89
Hispanic	84,977	12,728	14.98	72,249	85.02
Married	84,977	42,144	49.59	42,833	50.41
Pregnant	84,977	308	0.36	84,669	99.64
At least a bachelor's Degree	84,977	27,772	32.68	57,205	67.32
Unemployed	84,977	4,317	5.08	80,660	94.92
Retired	84,977	12,877	15.15	72,100	84.85
Northeast	84,977	17,984	21.16	66,993	78.84
Midwest	84,977	19,050	22.42	65,927	77.58
South	84,977	28098	33.07	56,879	66.93
West	84,977	19,845	23.35	65,132	76.65

2.5 Empirical Methods

In order to investigate whether or not individuals respond to daily information provided on pollution levels, and similarly whether they respond to air quality alerts issued during periods of high pollution concentrations, I exploit the spatial variation in pollution concentrations and the time spent outside on a given day. The EPA warns individuals to reduce exposure on high pollution days by avoiding yard work or other strenuous activities that could increase one's breathing rate. Thus, I specify the number of minutes spent in VOAs as the dependent variable, and seek to examine how VOAs change as a function of air quality, air-quality alerts, weather variables, and demographic variables.

Two different econometric models are used to account for several important aspects of the data. First, nearly 80 percent of the ATUS respondents report zero minutes spent in VOAs on a given day. This means that traditional linear estimation models are inappropriate and regression methods that account for these zeros should be utilized. I estimated a Logit model where the dependent variable is collapsed into a binary variable equal to zero if the respondent reported zero minutes of VOA and equal to 1 if he/she reported any positive number of minutes of VOA. This model estimates whether the probability of engaging in VOAs is affected by the alert status. I also estimated a General Linear Model with a log link (GLM-LL) that accommodates nonnegative skewed outcomes for minutes spent in VOAs (Nichols 2010).

In both the Logit and the GLM-LL regression models, I use a similar set of explanatory variables to control for all air pollution, weather, and demographic factors that may affect the time spent engaging in outdoor activities. Given that newspapers and other media sources usually report air quality in terms of the AQI, I calculated the ozone AQI for each day based upon the maximum eight-hour average ozone concentration. It seems unlikely that responses to small changes in AQI when air quality is good (AQI below 50) are symmetric with responses when AQI exceeds 100, so I flexibly model AQI by including a series of indicator variables for 25 degree AQI bins, with the highest bin for days over 200 points.

Alert status is a dummy variable set equal one to if there is an air-quality alert for a CBSA-day combination. Year, month, and day-of-week dummy variables, are also included, as well as a dummy variable indicating whether or not the day was a designated holiday. To control for demographic differences that may affect outdoor activities, variables for the ATUS respondent's age, race, income, education, employment status, student status, marital status, and number of children are included. Lastly, I also control for unobserved CBSA-level fixed effects.

In principle, cities issue air-quality alerts when the forecasted air quality index (AQI) exceeds a particular threshold; however, in practice alerts are often issued when adjacent areas expect AQI to exceed 100 even if local AQI forecasts are in the "good" and "moderate" ranges. These alerts are deemed necessary because air pollution travels easily, putting nearby cities at risk. In fact, alerts are frequently issued for days with low AQI forecasts; out of 1,931 total alerts in the data 897 alerts were issued on days when the AQI for the targeted city was below 100. This suggests a randomness to the assignment of alerts in the data, which aides in the identification of responses to alerts versus high AQI levels.

In addition to investigating the total population response to air-quality alerts and AQI levels, we are also interested in how different sub-populations respond. Thus, both the Logit and the GLM-LL were estimated using different subsets of the ATUS population and also with interactions between the alert variable and various demographic variables. More specifically, basic alert response is estimated initially using all of the ATUS responses, and then for just the elderly population who are at greater risk of health complications due to exposure to high levels of pollution. Additionally, low-income and minority households may have less access to conventional information outlets, so a third version of the model was run including interaction terms between alert and demographic indicators for low-income and races other than white. Finally, while the ATUS does not observe the time use of children directly, it does report the amount of time that adults spend caring for children outside. Thus, alert response is estimated for the subset of the population with children under the age of 13 using minutes spent caring for children outdoors as the dependent variable to determine if caregivers are adopting averting behavior to protect this vulnerable population group from exposure to poor air quality.

Pollution concentrations vary over the course of a day, starting out low in the morning and reaching their maximum in the mid to late afternoon. This means that averting behaviors can take multiple forms. First, individuals may substitute morning outdoor activities for afternoon/evening outdoor activities on high-pollution days. Alternatively they may move activities forward or back by a day to avoid being outside on alert days. Individuals may also substitute an increase in indoor exercise for VOAs on days when alerts warn them to avoid outdoor activities. And finally, individuals may forgo outdoor activities altogether on high-pollution days. To measure all four types of averting behavior, I used several versions of VOAs as the dependent variable in each regression discussed below. First, I estimated VOAs for the entire day as the dependent variable. This regression measures overall avoidance behavior. Additionally, each model was also run with VOAs for the morning (6am-12pm) hours of the day, and for the afternoon/evening (12pm-6pm) hours as dependent variables. If individuals engage in intraday substitution of VOAs, we would expect to see alerts positively associated with morning VOAs and negatively associated with afternoon VOAs when pollution levels are greatest. Evidence of this kind of within day substitution would suggest that the regression over the entire day, as well as prior studies that have failed to account for time of day, underestimate the total amount of averting behavior on air-quality alert days. I also test for inter-day substitution of VOAs by estimating a model with dummy variables for alerts on the previous day and alerts issued on the next day. And finally, I used the total number of minutes spent in indoor exercise as the dependent variable to see if they are influenced by alert days. The alert indicator in this model will have a positive coefficient if respondents substituted an increase in indoor exercise for VOAs on air-quality alert days.

2.5.1 Logit Regression Model

One test of the effect alerts have on individuals' outdoor activities is to examined if ATUS respondents were more or less likely to engage in any VOA on alert days. In this model, the dependent variable is binary, taking the value 1 if the ATUS respondent reported spending any time in VOAs and zero otherwise. We are interested in how the probability of VOAs, $P(y = 1|X) = p(X)$, changes on alert days. To do this, I consider a logit fixed effects model with the following underlying latent model:

$$y^*_{ijt} = X_{ijt}\beta + c_j + e_{ijt}$$

$$y_{ijt} = 1 \text{ if } y^*_{ijt} => 0, \text{ and } y_{ijt} = 0 \text{ if } y^*_{ijt} =\leq 0$$

where y^*_{ijt} is a continuous but unobserved measure of VOAs for individual i on date t in CBSA j, X_{ijt} is a vector of explanatory variables, and c_j is a fixed effect that accounts for inter-CBSA intrinsic differences in VOAs and unobserved explanatory variables that are constant over time. Assuming that e_{ijt} has a standard logistic distribution, then,

$$P(y_{ijt} = 1|X_{ijt}, c_j) = \frac{\exp(c_j+X_{ijt}\beta)}{1+\exp(c_j+X_{ijt}\beta)}$$

This model can be estimated using conditional likelihood estimation. The coefficient estimates represent the effect each variable in X_{ijt}, has on the log-odds ratio of y_{ijt}, so the marginal effects are also reported. The marginal effects of most interest are those for the alert dummy variable and the alert interaction terms. A statistically significant negative coefficient for the alert dummy variable indicates that individuals do engage in averting behavior by avoiding outdoor activities. Similarly, if the elderly engage in relatively more averting behavior we would also expect to see a negative coefficient on the interaction of the elderly indicator with the alert status indicator.

2.5.2 GLM-LL Regression

Many ATUS respondents report zero minutes doing VOA during particular days or time periods within a day. This means that VOAs, the dependent variable, is heavily skewed towards zero. Tobit models are commonly used to analyze non-negative, zero-skewed data, because one can set zero as the lower limit. However, the problem is that when this model is estimated, every zero in the data is replaced with an arbitrary small value, a, that is smaller than any other observed value in the data. Then the model takes the logs of the data and uses $ln(a)$ as the lower limit. As Nichols (2010) points out, this approach does not make sense in a setting where zero values represent true outcomes, and are not the results of some rounding or lower detection problem. Additionally, while the value of a is chosen arbitrarily, it can affect estimation results.

At first glance, it might also seem reasonable to run a simple linear regression of ln(y) on X, but this is not the most efficient model. The log-linear model assumes $E[ln(y)|X] = Xb$, which does not make sense when y can be zero. The GLM-LL specification is derived from relaxing the Poisson model's conditional moments assumptions, and assumes $ln(E[y|X]) = Xb$, allowing it to accommodate zero outcomes. Thus, given the limitations of these alternative methods, I estimated minutes spent in VOAs with a GLM-LL estimator.

In a simple Poisson model the density of VOA minutes for individual i on date t , y_{it}, given all explanatory variables, X_{it}, is determined by the conditional mean $\mu(X_{it}) = E(y_{it}|X_{it})$:

$$f(y_{it}|X_{it}) = \exp\left[-\mu(X_{it})\right]\left[\mu(X_{it})\right]^{y_{it}} / y_{it}!$$

where ! denotes factorial. The conditional mean can then be parameterized by $\mu(X_{it}) = exp(X_{it}\beta)$, where β is a vector of parameters to be estimated and X_{it} is the vector of explanatory variables that influence minutes of VOAs. The resulting log likelihood of this model is then:

$$L(\beta) = \sum_i \sum_t (-\log(y_{it}!) - \exp(X_{it}\beta) + y_{it}X_{it}\beta)$$

The Poisson distributional assumption imposes strong restrictions on the conditional moments of y_{it}, namely that $E(y_{it}) = Var(y_{it})$, that are violated in many applications. However, Gourieroux, Monfort and Trognon (1984) showed that the estimated parameters (β) are consistent provided the conditional mean is correctly specified, and the Poisson assumption is needed only for efficiency. In other words, the estimated coefficients are not affected by the validity of the Poisson assumption, but the standard errors are. This realization gave rise to the Poisson quasi-maximum likelihood estimator (QMLE) or the GLM-LL, which I implement by using a Poisson model and estimating the variance-covariance matrix of the estimates (the standard errors are the square root of the diagonal of this matrix) using the Huber/White/Sandwich linearized estimator. This estimator does not assume $E(y_{it}) = Var(y_{it})$, and in fact, it does not even require that $Var(y_{it})$ be constant.

This simple GLM-LL does not account for location-specific unobserved variables that may affect the time an individual spends in VOAs. Even though I have an extensive set of demographic and meteorological controls, I cannot rule out unobserved locational heterogeneity. For example, there may be regional or city-specific attitudes or cultural influences that affect how and when individuals exercise outdoors. To control for locational heterogeneity I follow the work of Hausman, Hall, and Griliches (1984), who developed a fixed effects poisson regression model under full distributional assumptions. The log likelihood function for this fixed effects model is,

$$L(\beta) = \sum_j \sum_t y_{ijt} \log \sum_{t=1}^{T} \exp\left[-(X_{ijt} - X_{ijt})\beta\right]$$

where the $y_{ijt}!$ term is dropped because it does not depend on β, and where j denotes the CBSA for individual i on date t. Similar to the Logit model, the coefficients of most interest are on the alert dummy variable and the alert interaction variables. Again, a negative and significant coefficient for the alert dummy variable indicates that individuals do engage in averting behavior by avoiding vigorous outdoor activities. For alert programs to be effective policy instruments, they need to generate enough averting behavior to improve health outcomes. Thus, in addition to signs, the magnitude of the alert dummy variables and interaction variables are also of interest.

2.6 Results

In what follows, I first analyze whether or not the general public responds to daily information provided about AQI levels, and whether they respond to air-quality alerts. Second, I examine how responses vary across different subsets of the general population defined by age, education, wealth, and race. Finally, I report tests for VOA substitution patterns such as engaging in fewer VOAs and more indoor vigorous actives on alert days.

2.6.1 Main Results for Total Population

Results from estimating the CBSA fixed effects Logit model and GLM-LL on the entire population reveal that on average individuals reduce the time they spend in VOAs by 18 percent on air-quality alert days, and that they are 3 percent less likely to participate in any VOAs on alert days. Results for the alert indicators from both models are reported in column 1 of Tables 2.3 and 2.4, while the the complete estimation results are reported in Tables 2.3A and 2.4A in the appendix. The coefficients on the air-quality alert indicator are negative and significant in both models (at the 99 percent level in the Logit model and at the 90 percent level in the GLM-LL, which suggests that individuals do engage in averting behavior. The coefficients from the Logit regression represent the increase in the predicted log odds of the VOA dummy variable being equal to 1, that is associated with a one-unit change in the independent variable. For example the coefficient on the alert indicator is -0.18 which implies that an alert day reduces the probability that an individual will do any VOAs. From the marginal effect (also reported in Table 2.3, column 1) the probability of doing any VOAs falls by 3 percent on alert days.

Similarly, the coefficient estimates for the GLM-LL regression represent the percent change (in decimal form) in minutes of VOAs resulting from a one-unit change in the independent variable. For example, the coefficient for the alert indicator is 0.176, which indicates an 18 percent reduction in VOAs on air-quality-alert days. The mean number of minutes spent in VOAs among those who did participate in VOAs is 118.4, so on average these individuals reduced VOAs by 21 minutes.

From both Tables 2.3A and 2.4A, we see that the signs of all of the coefficients across the two models are consistent with economic theory. The coefficients for max temperature, precipitation, and wind speed are negative in both equations indicating that higher levels of each cause a drop in VOAs. Similarly, the coefficients for the retired, part-time, and unemployed indicators are positive indicating that individuals with less work responsibilities tend to spend more time doing VOAs. The coefficients for the pregnant and children indicators are both negative indicating less time spent in VOAs.

The base level of AQI in both regressions is 0-50, which is the range in which air quality is considered good. Thus, the coefficients for the AQI bin indicators represent the change in VOAs compared to days with good AQI (between 0 and 50). These AQI coefficients for the GLM-LL estimation are shown graphically in Figure 2 along with their 95 percent confidence intervals. None of the coefficients are significantly different from zero, and there does not appear to be any trend in them to indicate that people respond to AQI level. Similar results were found with the Logit model. Thus, the evidence indicates that the overall population is not adjusting VOA in response to air-quality information.

Table 2.3: Logit Regressions

	(1) Total Pop.	(2) Elderly	(3) Total Pop.	(4) Non-Elderly	(5) Kids <13
Alert	-0.1836***	-0.8649***	0.0139	1.0132***	-0.4953*
	(0.0690)	(0.1631)	(0.1053)	(0.2211)	(0.2699)
	[-0.0284]	[-0.1599]	[0.0021]	[0.1491]	-[0.0182]
Poverty * Alert			0.1068		
			(0.1690)		
			[0.0165]		
Not-white * Alert			-0.4324***		
			(0.1645)		
			[-0.0668]		
College plus *Alert			0.0809		
			(0.1432)		
			[0.0125]		
Elderly * Alert			-0.8761***		
			(0.1914)		
			[-0.1354]		
Alert * Forcast150				1.1407***	
				(0.2294)	
				[0.1679]	

Standard errors in parentheses
n= 54,078; 13,411; 54,078; 15,583
Marginal effects (dy/dx where y= p(VOA)) in brackets
Other covariates can be found in Table 3A in the appendix
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: GLM-LL Regressions

	(1) Total Pop.	(2) Elderly	(3) Total Pop.	(4) Non-Elderly	(5) Kids <13
Alert	-0.1763*	-0.5854**	-0.0591	0.3402	-0.3966
	(0.0932)	(0.3072)	(0.1809)	(0.3342)	(0.467)
Poverty * Alert			-0.1176		
			(0.3361)		
Not-white * Alert			-0.2397		
			(0.3046)		
College plus *Alert			-0.0466		
			(0.2990)		
Elderly * Alert			-0.5201*		
			(0.2885)		
Alert * Forcast150				0.4569	
				(0.3514)	

Robust standard errors in parentheses
n= 54,078; 13,411; 54,078; 15,583
Other covariates can be found in Table 4A in the appendix
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: AQI Bin Coefficients - Total Population

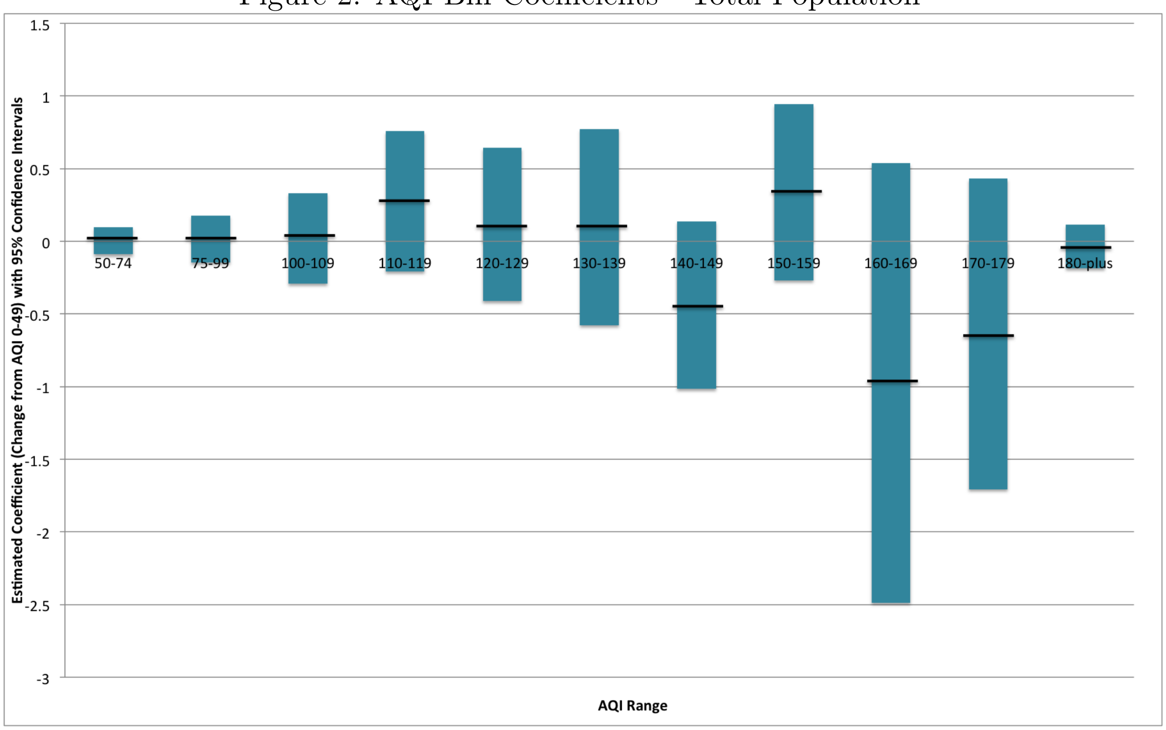
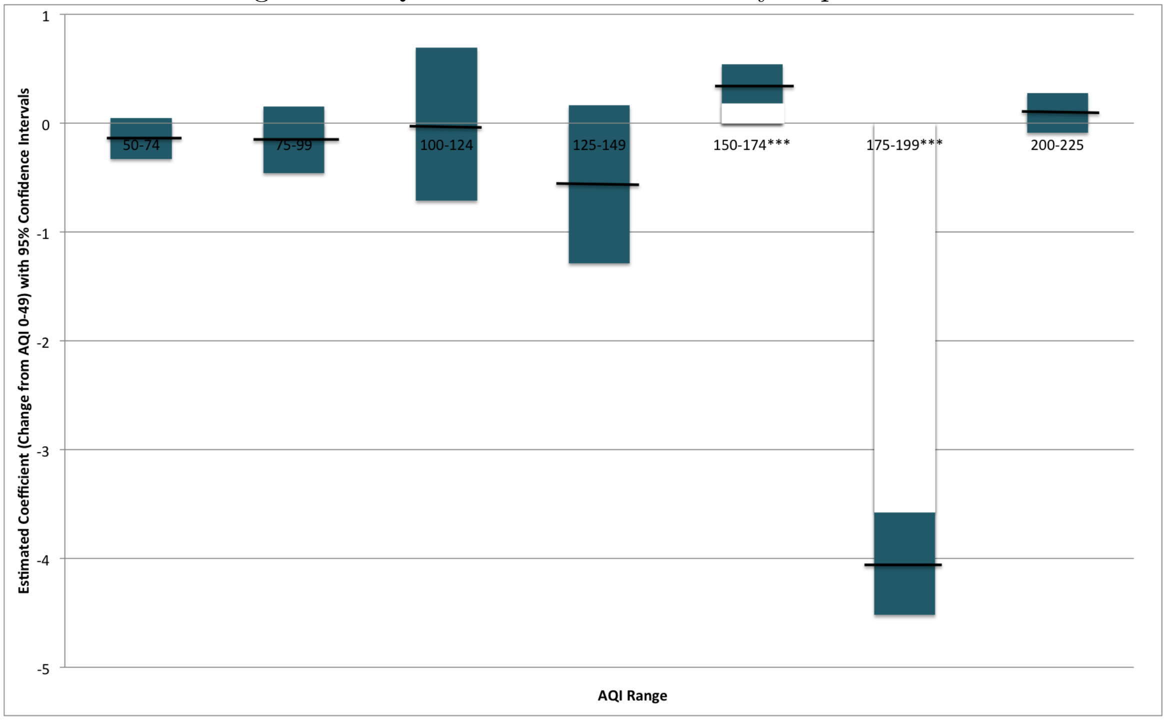


Figure 3: AQI Bin Coefficients - Elderly Population



2.6.2 Results for Population Subgroups

2.6.2.1 Elderly

Because elderly individuals are at greater risks of health complications when pollution levels are high, we are particularly interested in their response to air-quality alerts. The results for the alert variables from estimating the Logit and GLM-LL regressions for just the elderly subset of the population (age ≥ 65) are contained in column 2 of Tables 2.3 and 2.4, while full models for the elderly are reported in the appendix. The air-quality alert indicator is negative and significant in both models. On average elderly individuals reduce time spent in VOAs by 59 percent on air-quality alert days and the probability that they will participate in any VOAs falls by 15 percent. The mean number of minutes spent in VOAs for elderly individuals who do participate in VOAs is 110.8, so on average these individuals reduce VOAs by 65 minutes. As in the estimation for the total population, the covariates for the elderly model are consistent with economic theory; however, the standard errors are larger, likely due to the reduced sample size. Additionally, because of the smaller sample size, several of the AQI bins were combined to avoid collinearity.

The AQI coefficients for the GLM-LL estimation of the elderly population are shown graphically in Figure 3, and indicate that elderly individuals may be responding to AQI levels above 175. The coefficients for AQI levels below 175 vary in sign and are insignificant and small in magnitude. The coefficient on the 175-200 AQI indicator is negative, large, and significant at the 99 percent level which may indicate that elderly individuals respond to information regarding extremely high AQI levels.[5] However, there is no indication that they respond to AQI levels around 100 - the level at which the EPA suggests the elderly limit their outdoor activities.

2.6.2.2 Income, Race, Education

The Logit and GLM-LL models discussed thus far, show that individuals do respond to air-quality alerts and that the elderly, who are most sensitive to poor air quality have a significantly larger response. This is consistent with the goals of the policy, and helps to mitigate concerns about under or over reactions to the alert information. Policymakers may also be concerned about the responses among different demographic groups. For example, alert-day information is commonly distributed via newspapers, emails, and TV, making access to the information potentially more difficult for lower income, minority, and less educated households.

The third version of the Logit and GLM-LL estimates allow air-quality alert responses to be differentiated by income, race, and education. For these models a dummy variable for households with income at or below 185 percent of the federal poverty line was constructed using household size data and annual poverty guidelines from the U.S. Department of Health and Human Services. Approximately one third

[5] The coefficient on the 200 plus AQI indicator is insignificant and positive, which is likely do to the limited number of observations with AQI levels above 200.

of the sample (21,187 households) falls under this low-income threshold. Both the Logit and GLM-LL models were estimated using the entire population and including interaction variables for alert status and poverty status, alert status and race, alert status and education (a variable indicating respondents with a bachelor degree or higher), and alert status and elderly.

The results from this third version of each model are contained in column 3 of Tables 2.3 and 2.4. In both models, the coefficient on the alert and poverty interaction term is not significantly different from zero, providing no indication that lower income households respond differently to alerts than the rest of the population. Similarly, the coefficient on the interaction term between alert and education is not significantly different form zero, indicating that individuals with a college degree do not respond differently to alerts.

There is some weak evidence that the nonwhite population responds more to air-quality alerts. In the Logit model (Table 2.3), the alert and race interaction term is negative and significant. The coefficient on the alert-race interaction term is also negative in the GLM-LL model, but the effect is not statistically significant. The marginal effect for the interaction term in the Logit model implies that the probability of participating in VOAs for non-white individuals falls by 6 percent more than the rest of the population on alert days. state boarders

The results from the third version of each model also show that the elderly and alert interaction term is negative, significant, and large; while the alert indicator itself is not significantly different form zero. From the marginal effects we see that on alert days, the probability of VOAs for elderly individuals falls by 14 percent more than the rest of the population who don't appear to have a significant response. This indicates that not only do the elderly exhibit more averting behavior than the rest of the population, but that their response is driving the significance we found in the general regression for the entire population (column 1). This result raises concerns about the salience of air pollution information to the non-elderly population. Although this population is less susceptible to health complications associated with air pollution exposure than the elderly, there is still plenty of evidence of both acute and long-term risks from exposure to high concentrations of pollution for the general populations (Spix et al. 1998, and EPA 2006).

2.6.2.3 Nonelderly and 150 AQI Alerts

Cities issue air quality alerts when the forecasted AQI in the immediate and/or surrounding area is expected to be above 100; however, AQI in the 100-150 range are only labeled as dangerous for sensitive populations. Alert announcements usually state the forecasted AQI and the sensitive population, thus one possible explanation for the lack of response in the non-elderly population is that these individuals only respond to alerts when the forecasted concentration levels are expected to be dangerous for the entire population (AQI above 150). To test this theory, I estimated both regression models using just the non-elderly population and included an indicator for alert days with AQI forecasts greater than or equal to 150. The results for both alert variables are reported in column 4 of Tables 2.3 and 2.4. In the GLM-LL model both of the alert coefficients are positive and insignificant, providing no evidence that non-elderly individuals alter the amount of time they spend in VOAs on alert days. Similarly, in the logit regression both of the alert coefficients are positive, however in this model they are also significant indicating that non-elderly individuals are more likely to participate in VOAs on alert days. In summary, neither set of results is consistent with averting behavior, further suggesting that only the elderly population responds to air-quality alerts.

2.6.2.4 Respondents with Young Children

Young children are also particularly susceptible to pollution because they take in 20 to 50 percent more air than adults while exercising, and because their lungs are not yet fully developed (Kleinman, 2000). Although the ATUS does not directly measure children's time use, it does measure the amount of time individuals spend outside caring for children. Thus, I estimate whether or not parents or other family members limit the time they spend outside with young children on alert days using only the ATUS respondents with children under the age of 13. The dependent variable in these 2 regressions is thus minutes spent caring for children outdoors, not as VOAs. The results for both models are in column 5 of Tables 3 and 4. The coefficient for the alert variable is negative in both models indicating that individuals spend less time caring for children outdoors on air-quality alert days. In the Logit regression the coefficient is significant at the 90 percent level and indicates that individuals are about 2 percent less likely to spend any time caring for children outdoors on alert days. In the GLM-LL model, the alert coefficient suggests that individuals reduce the amount of time spent caring for children outdoors by 40 percent on alert days, however it is only significant at the 67 percent level.

2.6.3 Results for VOA Substitution

The results indicate that individuals, the elderly in particular, engage in averting behavior in response to air-quality alerts, however they provide no indication of when during the day the averting behavior happens, and whether or not individuals make up the averted VOAs by substituting to times within the day or across days where AQI readings are better. For example, pollution concentrations usually reach their peak in the mid to late afternoon, making 12pm - 6pm the highest risk period of the day for VOAs. This provides an opportunity for individuals to substitute morning VOAs for afternoon VOAs to avoid pollution health risks. If this kind of intra-day substitution of VOAs does in fact occur, than the full-day estimates for this study and all of its predecessors clearly under estimate the total averting response to air-quality alerts.

Table 2.5 shows estimation results for the alert variables from the GLM-LL model for different segments of the day (the full model is reported in Table 2.5A in the appendix). Column 1 reports results from the estimation of air-quality-alert responses between 12pm and 6pm. The alert variable is negative and significant at the 95 percent level, indicating that individuals reduce the time they spend in VOAs in the afternoon on alert days. The magnitude of the coefficient implies a 31 percent reduction in VOAs, which constitutes 18 minutes on average for those individuals who do engage in VOAS. Similarly, column 2 shows that individuals spend 79 percent fewer minutes in VOAs between 6am and 12pm on alert days. With an average of 12 minutes in VOAs during this period, this implies a 10-minute reduction. Both the morning and the afternoon models find positive and significant averting behavior, which is not consistent with intra-day substitution - especially considering the larger relative magnitude of the morning response. These results also mitigate concerns of bias in the overall estimates from Tables 3 and 4 due to substitution.

Table 2.5: GLM-LL Regressions for Intra-Day VOA Substitution

	(1) 12pm - 6pm (1)	(2) 6am - 12pm (2)	(3) Indoor Exercise (3)
Alert	-0.3070**	-0.7940**	-0.1147
	(0.1290)	(0.3448)	(0.3045)

Robust standard errors in parentheses
n=52,256; 52,256; 50,357
Other covariates can be found in Table 5A in the appendix
*** p<0.01, ** p<0.05, * p<0.1

I also tested for inter-day VOA substitution by estimating the GLM-LL model with additional variables indicating if an alert was called on the day prior, the day after, or the day before the day prior. I also included interaction variables for contemporaneous and lagged alerts to control for the fact that consecutive days may have had air-quality alerts. The results from these regressions are shown in columns 1-3 of Table 2.6. The results in column 1 reveal that an alert issued on the previous day has a negative and significant affect on VOAs, indicating that individuals do not shift VOAs from alert days to the next day. Rather, it appears that they extrapolate forward the poor air quality on a given day by also reducing VOAs on the day immediately following an alert.

Additionally, neither the coefficient on the alert variable nor the coefficient on the contemporaneous alerts term is statistically significant, suggesting that, when alerts are issued on two consecutive days, the response on the 2nd day is driven by the extrapolated effect of the alert on the previous day as opposed to that of the current alert. However, because the coefficient on the term for the previous day's alert is negative and significant the overall effect for the second day is similar to the general effect we measured in Table 2.4.[6] Similarly, in column 2 we see that an alert issued on the next day has no significant affect on VOAs, suggesting that individuals do not predict alerts and shift VOAs forward from alert days to the day before. Given the that individuals don't appear to make up VOAs on days immediately before or after alerts, I also looked into the effect of alerts issued 2 days prior. In column 3 we see that none of the alert terms are significant, however the coefficient on the indicator for an alert issued two days prior is positive and significant at the 80 percent level which provides some evidence that individuals may make up some of the averted VOAs two days later. In other word, the results indicate that individual reduce VOAs on the day of an alerts as well as on the following day, but that they engage in more VOAs on the second following day.

[6]This later result is not consistent with Zivin and Neidell (2009)

Table 2.6: GLM-LL Regressions for Inter-Day VOA Substitution

	(1) Alert Prev Day	(2) Alert Next Day	(3) Alert 2 Prev Days
Alert	-0.1529	-0.2551**	-0.1561
	(0.1364)	(0.1057)	(0.1337)
Alert Prev	-0.2845*		-0.1538
	(0.1460)		(0.1670)
Alert 2 days Prev			0.2562
			(0.1707)
Alert*Alert Prev	0.1887		0.1633
	(0.2318)		(0.1998)
Alert*Alert 2 Prev			0.2165
			(0.3434)
Alert*Alert Prev.*Alert 2 Prev			-0.2013
			(0.4205)
Alert Prev.*Alert 2 Prev			-0.4466
			(0.3665)
Alert Next		-0.0047	
		(0.1881)	
Alert*Alert Next		0.1438	
		(0.2313)	

Robust standard errors in parentheses
n=54,078; 54,078; 54,078
Other covariates can be found in Table 6A in the appendix
*** p<0.01, ** p<0.05, * p<0.1

Finally, I use the total number of minutes spent in indoor exercise as the dependent variable in the GLM-LL to see if they are impacted on alert days, and thus, whether individuals substitute between indoor exercise and outdoor exercise on alert days. The results are reported in column 3 of Table 2.5, and reveal no significant change in indoor activities on alert days, suggesting that individuals do not make-up forgone outdoor VOAs with indoor exercise.

Essentially, although we find evidence of averting behavior by ATUS respondents, we do not find any clear evidence of substitution of VOA within the day or across days. Nor is there evidence of substitution of indoor exercise for VOAs. This suggests that air-quality alert programs lead to reductions in overall physical activity, which may be a concern given the country's battle against rising levels of obesity and other lifestyle-related diseases. Additionally, the failure to makeup missed VOAs exacerbates the welfare losses that would be associated with any over-reactions to alert days.

2.7 Conclusions

Several previous studies have examined the effectiveness air-quality alert programs, finding evidence that individuals do respond to alerts by engaging in averting behaviors (Zivin and Neidell 2009, and Neidell 2009). However, these studies examined small localized regions (predominantly in Southern California) and measured averting behavior by attendance at outdoor facilities rather than vigorous outdoor activities that are most likely to cause health complications due to air pollution. This is the first analysis of air-quality alert programs that uses a nationally representative data set over a long time period containing detailed information on individuals' outdoor activities. My results show that on average individuals engage in averting behavior on alert days by reducing the time they spend in vigorous outdoor activities by 18 percent, or 21 minutes.

This analysis is also the first to use a full set of demographic variables, and allow averting behaviors to vary across different subsets of the population. These differing responses then help reveal any potential over or under responders. Consistent with the policy's goals, I find that averting behavior is greater amongst the more sensitive populations. Elderly individuals are estimated to respond to air-quality alerts by spending 59 percent less time in vigorous outdoor activities, which represents a 65 minute reduction. However, the results also indicate that the response from the elderly population drives the significant results found for the general populations, and that non-elderly individuals do not respond to alerts even when forecasted AQI levels are dangerous for everyone, i.e., AQI above 150. Additionally, although other heath-information campaign analyses suggest that response levels vary according to socioeconomic variables such as income and race, I find no evidence that either of these variables negatively effect air-quality alert response levels.

This analysis is also the first to examine comprehensively whether and how individuals substitute for reduced VOAs on alert days. From a public health perspective, individuals ideally would make-up postponed activities at a time/place where pollution levels were safe. This could be accomplished by shifting the activities either indoors, forward to the next non-alert day, backward to the previous non-alert day, or earlier in the day when pollution levels are lower. I tested for all four of these forms of substitution, but found no evidence that forgone activities were being made-up. Although averting behavior in response to air-quality alerts is a positive result regarding public health, there are unquestionably negative health affects associated with a 17 percent overall reduction in vigorous activities – especially in light of a growing obesity problem – suggesting that this issue needs further investigation.

In summary, the results from this paper suggest that air-quality alert programs do reduce exposure to pollution for the elderly and children, but that non-elderly adults do not respond to the information. In other words, pollution information does not appear to be salient to younger adults, which is an issue that needs to be addressed before alert programs can be fully effective policy tools.

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Chapter 3:

Behavioral Responses to Daylight Savings Time

3.1 Introduction

Since its initial adoption, Daylight Savings Time (DST) has been promoted as a tool to conserve energy, particularly by reducing the demand for electric lighting (Aries and Newsham 2007). The program, however, has always been controversial in the US, which may stem in part from the conflicting conclusions found in the literature investigating the effects of DST. The majority of the research has focused on energy consumption changes due to DST, but the results vary greatly, with some studies finding reductions in overall electricity use between 0.5 and 3.5 percent (Ebersole et al., 1974), and others concluding that there are no reductions in energy use (Kellogg and Wolf, 2007) or perhaps even increases in use. As frustration over energy prices and concerns about the environmental impact of energy consumption continue to grow, the effectiveness of DST programs has become a central issue in many states and countries around the world (Miga, 2012). Policymakers seek ways to induce conservation, but the DST literature fails to provide reliable answers about the true responses to scheduled time shifts.

With few exceptions, previous DST studies have relied on simulation models to estimate and extrapolate energy savings under different policy programs. Although these studies have found a range of positive energy saving, Kellogg and Wolf (2007) found that the most sophisticated simulation model available in the literature significantly overstated electricity savings when it was applied to Australian data. This result casts serious doubt on the reliability of previous estimates of DST savings.

In the last few years, a few studies have used data from quasi experiments to empirically test the effects of DST (Kellogg and Wolf, 2007; Kotchen and Grant, 2011). These studies found that DST actually increased energy use. The disagreements within the literature suggest the need for continued research. In fact, the discrepancy in the existing literature between the earlier simulation studies and more recent empirical studies is cited by critics of DST, who claim that the shift in time twice a year causes far more confusion and social disruption than energy savings (Lynch, 2012).

The concerns over the true energy costs or savings of DST are also reflected in the refusal of some states (Arizona and Hawaii) to participate in DST. Several other states including Colorado, Florida, Montana, and Nevadan have recently discussed legislation to either observe standard time year around (i.e. not participate in DST) or DST year around.

This paper sheds light on why the simulation models may be incorrectly estimating the energy impacts of DST by investigating how individuals adjust behaviors in response to DST. For example, the spring DST shift causes sunrise to occur an hour later in the morning and sunset to occur an hour latter in the evening. Simulation models assume that individuals perform the same activities at the same time regardless of the daylight and temperature; however, the shift in daylight from the morning to the evening may cause individuals to rearrange or adjust their daily activities.

I use the American Time Use Survey (ATUS) to estimate behavioral responses to DST by examining how individuals shift the amount of time they spend sleeping, awake at home, and awake away from home during the day. In other words, I test whether individuals are operating completely "off the clock" (as assumed in many previous DST studies), or whether the time of sunrise and sunset affects their daily behaviors.

The majority of the literature supporting DST policies is also regarded as outdated. Basic patterns of energy use have changed considerably in the past two decades, as have energy efficiency technologies. By 2012, traditional incandescent light bulbs were being replaced by more efficient alternatives such as compact flourescent lights and LED lamps. This means that residential lighting no longer requires as much energy as it did when DST was first investigated and adopted in the U.S. (Vestel, 2009). There has also been a significant increase in the rate of adoption of residential air conditioning in the past several decades,[7] which may cause an increase in energy use in evening hours that offsets any reductions generated by less artificial lighting.

The more recent empirical studies that suggest DST may actually result in an increase in energy use are very limited in scope. Kellogg and Wolff (2008) investigated how electricity consumption in Australia was affected by the DST extension surrounding the 2000 Olympic games, and Kotchen and Grant (2011) looked at how energy consumption was affected by changes to DST in Indiana. DST is a national policy, and both of these studies seem too narrow in scope to provide clear answers regarding DST's energy effects. Importantly, the sun rises and sets at vary different times in the southern and northern states and temperatures very significantly. Thus, just because fall DST caused increased morning energy usage in Indiana, does not imply that it will have the same effect in all the states across the country.

By determining the underlying behavioral responses to DST, this paper tests assumptions made in the previous simulation models that may have led to overly optimistic estimates of energy savings. Because the ATUS is a nationally representative data set that contains information on all activities of respondents, I can systematically study behavioral responses on a national scale and draw conclusions about individuals' reactions to time shifts – both shifting time forward by an hour in the spring, and shifting it back again in the fall.

Results of this analysis suggest that the DST time shift has the largest impact in the spring and that individuals respond by waking up earlier in the morning and spending the additional time at home. There is also evidence that individuals are spending less time at home in the evenings. These results suggest that the extra daylight in the evening after switching to DST creates the opportunity to undertake outdoor evening activities that were otherwise not possible, and that individuals are

[7]In 1965, just 10 percent of U.S. homes had air conditioners, according to the Carrier Corporation. By 2007, however, the number was 86 percent.

scheduling household chores and activities in the morning that they would normally do in the evening in order to free up additional time. This shift towards morning chores was not anticipated in simulation studies and provides important insight into the discrepancies between the predicted energy savings and realized savings. Additionally, the results provide insights into other important impacts associated with DST, such as reduced time sleeping and additional time spent in evening activities. This will aid policy makers in optimizing DST policies to best achieve desired social and environmental goals.

This chapter proceeds in section 2 with a review of existing literature on DST. Section 3 provides background information on DST programs and recent policy changes and proposals. Section 4 describes the data used in this analysis, and section 5 discusses the econometric models used to estimate the behavioral response to DST. The results are presented in section 6, and section 7 summarizes the main findings and draws conclusions about the behavioral responses to DST and the effectiveness of different policy proposals.

3.2 Literature Review

The primary goal of DST has always been to reduce the demand for energy – especially for residential lighting. Thus, researchers have attempted to determine the impacts of various DST regimens on energy consumption. The vast majority of these studies develop models to predict lighting use under DST and then implement simulation methods to predict total energy savings. Predictions vary widely, ranging from energy reductions as great as 9 percent attributable to DST to the suggestion of increased energy use, or energy penalties under DST. A detailed summary of this literature can be found in Aries and Newsham (2007). In one of the more recent studies, the California Energy Commission (Kendel et al. 2001) used data from the then-current

DST system to forecast energy use under a program that extended DST to the entire year. The study predicted that such a change would result in a 0.6 percent reduction in electricity consumption, as well as an overall reduction in electricity prices.

The DST literature contains relatively few studies that expost evaluate the effects and behavioral responses to the time changes. Perhaps the most well-known of these studies is one conducted by the U.S. Department of Transportation (DOT 1975) fulfilling the requirements of the Emergency Daylight Saving Time Energy Conservation Act of 1973. Using data from the two years of yearlong DST following the 1973 oil embargo, the study concluded that average hourly electricity load rates fell by 1 percent as a result of DST. However, the National Bureau of Standards (Filliben 1976) later reviewed and evaluated the study, concluding that the energy savings were uncertain and statistically insignificant.

More recently, several studies have used changes in DST policies and quasi experiments to empirically test the impacts of DST. First, the Department of Energy (Belzer et al. 2008) used regression models of daily and hourly electricity consumption from a sample of utilities located across the United States to assess the effects of the 2007 DST extension. Researchers used a difference-in-difference approach that compared data from 2006 (before the extension) to data from 2007 (after the extension) and controlled for variables other than DST that might affect energy consumption, including heating and cooling degree days, day of week, and holiday status. They found that the total electricity savings of Extended Daylight Saving Time (EDST) were about 0.5 percent per day of the extension. The savings usually occurred in the late afternoon and evening with small increases in usage occurring during the early mornings. The results also suggested that the energy savings were not consistent across geographical regions. The reduction in energy use was smaller in southern states, which may be due to greater air conditioning use in the warmer afternoons and evenings.

Later, Kellogg and Wolff (2008) used data from a quasi-experiment that occurred in Australia when DST was extended to accommodate the 2000 Olympic games. The extension was not implemented in all states, and thus the authors were also able to use a difference-in-difference model by comparing panel data on half-hourly electricity consumption from a state that experienced the extension with one that did not. The results indicated that the extension failed to reduce energy consumption, and although the estimates are not statistically significant they suggested an overall increase in use.

Most recently, Kotchen and Grant (2011) exploited a natural experiment that occurred in Indiana because of the Energy Policy Act of 2005, to provide empirical estimates of DST effects on electricity consumption in the United States. Prior to the 2005 law, the majority of Indiana counties did not observe DST, allowing the authors to compare micro-data on households' electricity demand before and after 2007 to estimate the effects of DST. Their results show that DST actually increased residential electricity demand in Indiana by about 1 percent per year or $9 million. The authors further show that the increase in demand varies across season with the greatest increase occurring in the fall.

Clearly the DST literature has failed to come to a consensus on the effects of moving clocks forward in the spring and back in the fall. The most sophisticated simulation models spanning the last several decades all conclude that DST will lead to reductions in energy use. In contrast, however, the most recent empirical studies suggest otherwise. In this paper I try to reconcile these two subsets of the literature. By examining how individuals alter their behaviors in response to DST, I can determine which assumptions from the simulation models are inaccurate and lead to over estimates of DST energy savings. These results can be used to produce more accurate simulation models for assessing future DST proposals.

3.3 History of DST

DST was first introduced in the United States on March 19, 1918 with the Standard Time Act. This legislation mimicked policies that were already used in several European countries to conserve fuel during World War I. The practice however was very unpopular and the national law was abolished shortly after the war. In the time between the first and second world wars, the choice to participate in DST was left to local governments, and its adoption varied across cities and states. In 1942 President Franklin Roosevelt reintroduced national DST, but extended the time change to cover the entire year, calling it "War Time". Again, following the war in 1945, DST policy returned to local control and remained that way till 1966.

During the early 1960s, many industries complained about the inconveniences caused by DST policies that varied across cities and states. Not only did adoption rates vary, but so did the beginning and ending dates of DST. The inconsistency was particularly hard for the transportation industry. Conducting business across state boSenator Brophyrders was very difficult and many people began lobbying for a national law regulating DST. This resulted in the Uniform Time Act of 1966, which mandated that clocks be advanced one hour beginning at 2:00 a.m. on the last Sunday in April and turned back one hour at 2:00 a.m. on the last Sunday in October. States were allowed to exempt themselves from DST as long as the entire state did so. Additionally, states that were in two different time zones were allowed to exempt one times zone without the other. This provision applied to multiple states, and both Michigan and Indiana for example, housed some counties that did observe DST while others did not. For example, Indiana falls in both the Central and Eastern Time zones.

The Department of Transportation (DOT) is charged with enforcing and evaluating DST. This has included amongst other things, evaluating proposals to extend DST. It was through this evaluation process that Congress decided to change the effective dates of DST in 1986 with the goal of reducing energy use. Beginning in 1987, DST started on the first Sunday in April and remained in effect till the last Sunday in October. Then, after another review process by the DOT, Congress passed the Energy Policy Act of 2005, which extended DST for another four weeks each year again in hopes of reducing energy demand. As of 2006, DST starts on the second Sunday of March and ends on the first Sunday of November.

Today, all states and territories except Arizona, Hawaii, American Samoa, Puerto Rico, and the Virgin Islands observe DST; however, the policy still remains controversial. Several states have recently discussed legislation to either observe standard time year around or DST year around. In its 2011 session, the Colorado legislature voted on bills for both moves. In the spring, a bill introduced by Senator Brophy that would have put Colorado on yearlong DST gained initial support, but was later rejected by the Senate Appropriations Committee. Nevada has similarly debated both legislation moving to yearlong DST and legislation moving to yearlong Standard Time. Meanwhile, Florida, Montana, and Alaska have all discussed moving to yearlong Standard Time and thereby abolishing DST.

DST programs also vary across Europe and the rest of world, further complicating the time changes. For example, in the spring the U.S., England, and Australia all begin DST at a different time in a three-week span.

3.4 Data

To measure how individuals responded to the change in sunlight that is caused by the DST shift, I combine data on daily activities, DST status, and surface weather conditions. First, I use the ATUS, a nationally representative, federally administered survey on time use in the United States. The survey collects information on all activities performed by respondents during a designated 24-hour period. It was first administered in 2003, allowing evaluation of responses for an eight-year period from 2003-2011. Because each respondent provides detailed information on his/her activities during the designated 24-hour period, I was able to determine how much time each person spent in various morning and evening/afternoon activities that may be affected by DST and may impact residential energy demand, the outcome variable analyzed in previous DST studies.

Using the ATUS-X Extract Builder, I created three, mutually exclusive variables measuring the time spent in, sleep, activities at home, and activities away from home. Aggregating activities into these three broad categories allows for a simple and clear analysis of how changes in time use may effect residential energy consumption. For example, if individuals sleep less in the morning when DST is in effect, they will likely begin using lighting and heating earlier. Thus, energy demand in the morning may rise. This effect would be further supported if individuals also spent more time in home-based activities in the morning. Essentially all ATUS activities were divided into one of the three categories.

DST affects the amount of daylight in the morning and evening, thus this analysis focuses on how the amount of time spent in each of the three activities varies during those two periods of the day. Data from the Astronomical Applications Department of the U.S. Naval Observatory reveals that sunrise occurs between 5am and 8am in the U.S., and sunset occurs between 3pm and 8pm. Thus, for each ATUS respondents, I measure the amount of time he/she reports doing each of the three activities between the hours of 5am and 9am, and 3pm and 8pm. Initial analysis showed similar behavioral shifts between the hours of 3-5pm and 5-8pm. It seems reasonable to assume that behaviors shift between late afternoon and evening, and thus, in the evening I aggregated the data into two blocks. Summary statistics for the 3 variables and the three time periods are provided in Table 2 below.

A significant number of the ATUS responses had missing information for the respondent's geographic location, which is necessary in order to match the responses to appropriate weather data and DST policy, so I used data from the CPS for the corresponding years and matched respondents to their final interviews. These interviews occurred 2-5 months prior to the ATUS survey and contained more complete geographic information including the respondent's core based statistical area (CBSA). After matching the two data sets and dropping all responses for which a valid CBSA could not be identified, 84,977 responses spanning 8 years (See Table 3.1 for frequencies) and 296 CBSAs remained. The CBSA covering New York, Northern New Jersey and Long Island was home to the most respondents - 6,748, and Los Angeles-Long Beach-Riverside was second with 3,813 respondents. All CBSA's had at least 5 responses.

Table 3.1: ATUS Data Frequencies

Year of Interview	Frequency	Percent	Cumulative
2003	11,938	14.05	14.05
2004	10,028	11.80	25.85
2005	10,176	11.98	37.82
2006	10,564	12.43	50.26
2007	10,105	11.89	62.15
2008	10,854	12.77	74.92
2009	10,736	12.63	87.55
2010	10,576	12.45	100
Total	84,977	100	

To determine when respondents were on DST when completing the ATUS I used information on the start and end dates for DST for each year, 2003 - 2010. DST was extended beginning in 2007 and thus the data set contains information on 4 years prior to the policy change and 4 years after.

In addition to sunrise and sunset times, surface weather conditions may also influence the amount of time respondents spend sleeping, at home, and away from home. To control for these effects, I use historical daily surface weather data for the United States from the National Climatic Data Center's (NCDC) Climate Data

Online database. The data contain daily measures of mean temperature, mean wind speed, maximum temperature, minimum temperature, and total precipitation (rain and/or melted snow) for over 2000 stations in the US. Each station's latitude and longitude coordinates were used to determine which station was located closest (measured as the crow flies) to the center of each CBSA, allowing the data for those stations to be merged with the ATUS. Table 3.2 below shows the summary statistics for the final data set.

Table 3.2: Data Summary Statistics

Variable	# Obs.	Mean	Std. Dev.	Min	Max
Sleep	88,477	525.42	136.0921	0	1436
Sleep 5am - 9am (min)	88,477	130.20	79.62	0	240
Home 5am - 9am	88,477	43.60	55.23	0	240
Home 3pm - 5pm	88,477	47.67	49.93	0	120
Home 5pm - 8pm	88,477	99.23	71.58	0	180
Away 5am - 9am	88,477	28.86	53.85	0	240
Away 3pm - 5pm	88,477	32.30	46.11	0	180
Away 5pm - 8pm	88,477	29.26	50.85	0	240
Mean temperature (°F)	82,405	58.62	17.58	-36.40	104
Mean wind speed (knots)	82,402	14.85	36.12	0.00	504
Precipitation (inch)	84,977	0.56	0.50	0.00	1
Age (yrs)	84,977	45.81	17.44	15	85
Max Temp (°F)	82,389	65.67	20.57	-54.4	131.5
Min Temp (°F)	82,389	46.15	19.28	-61.6	104
Latitude	55,900	37.50	4.94	19.42	48.54
Dummy Variables	# Obs.	Yes	No		
Female	84,977	48,002	36,975		
Kids under 5 yrs	84,977	15,292	69,685		
Full time student	84,974	6,621	78,353		
Black	84,977	10,501	74,476		
Asian	84,977	138	84,839		
Indian	84,977	942	84,035		
Hispanic	84,977	12,728	72,249		
Married	84,977	42,144	42,833		
At least a bachelor's Degree	84,977	27,772	57,205		
Graduate degree	84,977	10,216	74,761		
Unemployed	84,977	4,317	80,660		
Retired	84,977	12,877	72,100		
PST	88,477	15,231	73,246		
MST	88,477	53,17	83,160		
CST	88,477	22,953	65,524		
EST	88,477	44,727	43,750		

3.5 Empirical Methods

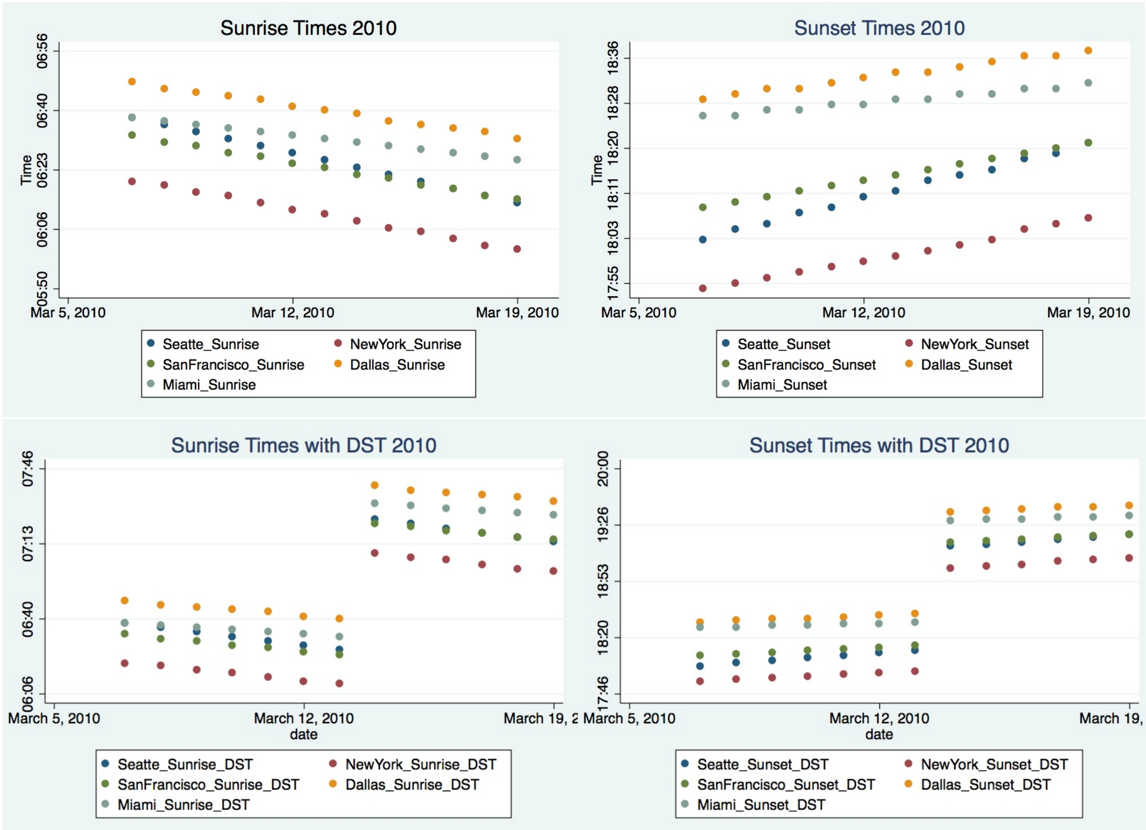
In order to investigate how individuals change their behavior in response to DST, I focus on those activities that will most directly affect residential energy demand.

DST changes the amount of sunlight in the mornings and the evenings, and thus is most likely to affect activities performed at those times. Thus, the empirical methods presented below are used to estimate weather individuals shift the amount of time they spend sleeping, at home, and away from home in the mornings and late afternoons/evenings.

3.5.1 Regression Discontinuity Design

Since DST takes effect in the US on a precise day and time each year, I can identify the effect of the time change using a regression discontinuity design (RDD). Sunrise and sunset times change by 0-3 minutes per day, meaning that days just before the sharp, 1-hour shift forward in time that occurs each spring (or the 1-hour shift backward that occurs in the fall) are otherwise similar. See Figure 4 for a graphical representation of sunrise and sunset time around the springtime DST shift. Weather variables are also similar for days on either side of the DST transition. This allows me to use days just prior to the time change as counterfactuals for days just after, and any difference in activities at the threshold can be attributed to DST.

Figure 4: Sunrise and Sunset Times Spring 2010



The identifying assumption with this RDD model is that in the absence of DST, the activity variables (sleep, home, and away) vary continuously with the forcing variable, the date. This means that, for example, time spent sleeping in the morning evolves smoothly with the date and that any discrete changes in the variable can be attributed to DST. Importantly, this assumption doesn't imply that sleep cannot vary as the sunrise/sunset times change naturally; it simply requires that such activities move smoothly across the DST transition.

In 2001, Hahn et al. discussed many of the identification and estimation issues surrounding RDD estimation and related it to the treatment effects literature. They suggested estimating RDD equations using non-parametric procedures that do not assume underlying linearity. Kernel regressions are a leading non-parametric approach because they are fundamentally a local method, which pairs well with most RDD studies. The problem however, is that they perform poorly at cutoff points, which is precisely what an RDD equations is trying to estimate.

In fact, Imbens and Lemieux (2008) show that there is systematic bias in kernel regression estimates of the treatment effect. The bias arises because, when using a finite sample, a researcher must choose a bandwidth around the cutoff point that is large enough to contain sufficient observations to get a reasonable amount of precision in the estimated average values of the dependent variable. In other words, the researcher faces a tradeoff between bias and precision when using kernel regressions to estimate RDD models. Choosing a larger bandwidth yields more precise estimates, but could also potentially bias the estimates.

To avoid the bias of kernel regressions and consistently estimate the treatment effect, I follow Hahn et al. (2001) who suggest running local linear regressions. This approach requires estimating a standard regression within small bins on both sides of the cutoff point, which will provide consistent estimates of the treatment effect at the cutoff. In fact, the most direct way of estimating the treatment effect is to run a pooled regression over the cutoff and allow for the functional form to vary on either side by including interaction terms between the treatment variable, a dummy variable D indicating DST ($D = 1$ if response was effected by DST and $D = 0$ otherwise), and the forcing variable, Date = Z. An advantage of this method is that it provides a direct estimate of the treatment effect along with standard errors. The estimation equation is:

$$Y_i = \alpha_i + \tau \cdot D_i + \beta_1 \cdot z_i + \beta_2 \cdot D_i \cdot z_i + \gamma \cdot X_i + e_i$$

Where Y_i represents the minutes of time spent in a given activity (sleep, home, away), z_i measures the days from the DST transition (z – DST_date), and X_i is a matrix of demographic, household, and weather covariates such as age, employment status, presence of young children, and max temperature. I estimate the RDD equations over a range of 6 days (excluding weekends) on each side of the DST transition based on the estimated optimal bandwidth for a sharp design as given by Imbens and Kalyanaraman (2009).[8] I also include a dummy variable for those responses that are affected by the 2006 policy changes that extended DST by three weeks in the summer and one week in the fall. These covariates are included in the regressions to increase the precision of the RDD estimator and to capture variation in activity patterns. For example, morning sleep patterns likely vary significantly by age and employment status. As suggested by Lee (2009), I enter the covariates directly into the regression equations as suggested in the equation above; however, all equations were also estimated by "residualizing" the dependent variable. For this diagnostic check, a prediction of Y based on the baseline covariates X is subtracted from Y, and then RD regression is run using the residuals as the dependent variable. The sign and the significance of the treatment effect was robust to the method used for covariates.

The amount of time that individuals spend in different activities can vary significantly from weekdays to weekends, and thus DST may have differing effects. To control for this issue, I only included weekdays in my RDD analysis. Additionally, the ATUS collects information from employed and unemployed individuals, and the behavioral effects of DST may vary across these population subgroups. My sample is comprised predominantly of employed individuals, and to test whether or not the unemployed were biasing the results, I also estimated the RDD equation over a population of only employed individuals. The results were similar to those estimated using the entire population, thus I report only the full population result here.

[8]Additional bandwidths were tested and are discussed in the robustness section.

3.5.2 Robustness

An alternative method of estimating the behavioral effects of DST would be to take advantage of the policy change that occurred after 2006. For all subsequent years the DST transition occurred 3 weeks earlier in the spring (second Sunday in March) and 1 week later in the fall (first Sunday in November). This means that our data set can be divided into two groups – (1) observations occurring between 2003-2006 and (2) observations occurring between 2007-2010.

For the spring transition we can focus on observations occurring in either the week right before the second Sunday in March or the week right after[9]. By limiting the data set in this way we know that those observations in group 1 (2003-2006) were not exposed to DST in either week and those observations group 2 (2007-2010) were exposed to DST in the second week, but not the first. Thus we can calculate the effect of DST by subtracting the average change in the activity variable, such as sleep, for the first (control) group from the average change for the second (treatment) group. This difference-in-differences (DID) method removes any biases in second period comparisons between the treatment and control group that could be the result of permanent differences between these groups, as well as biases from comparisons over time in the treatment group that could be the result changes in sunrise time.

RDD is generally considered more closely related to random experiments than DID methods, and thus I use DID as a robustness and credibility check for the regression previously discussed (Lee, 2009). For the spring DST transition, the DID regression equation that I estimate is:

$$Y_i = \beta_0 + \beta_1 W_{2i} + \beta_2 T_i + \beta_3 W_{2i} T_i + \gamma \cdot X_i + e_i$$

where Y is the number of minutes spent in the activity of interest, W_2 is a dummy

[9]The spring DST transition was moved head by three weeks, and thus we tested larger date ranges. The signs of the coefficients of interest were robust to all specifications.

variable for the week after the DST transition and measures factors that may cause changes in Y even in the absence of the DST. T is a dummy variable for the treatment group and captures any differences between group 1 and group 2 outside of the DST policy change that may affect Y. Finally, X_i is a matrix of other covariates identical to those used in the RDD regressions. The coefficient of interest is β_3, on the interaction term between W_2 and T. This dummy variable is equal to 1 for all ATUS responses that occurred in the week after the second Sunday in March between 2007 and 2010. The difference-in-differences estimate of the DST treatment affect is then:

$$\beta_3 = \left(\bar{Y}_{T,1} - \bar{Y}_{C,1}\right) - \left(\bar{Y}_{T,,2} - \bar{Y}_{C,2}\right)$$

Similarly, for the fall transition we can narrow the analysis to observations falling in the week on either side of the first Sunday in November. By focusing on these two weeks of observations we know that those observation in group 1 will again act as the control group, because they were not exposed to DST in either week. Similar to the spring transition, the observations in group 2 (2007-2010) will represent the treatment group because they will be exposed to DST in the first week, but not in the second. Thus, the fall differences and differences estimation equation is:

$$Y_i = \beta_0 + \beta_1 W_1 + \beta_2 T + \beta_3 W_1 T + \gamma \cdot X_i + e_1$$

where the only difference from the spring equation is that we are interested in measuring the effect of being in the treatment group and in the earlier week (week 1) because in the fall we transition off of DST. Thus the coefficient of interest, β_3, is on the interaction term between W1 and T.

3.5.3 Placebo

Regression discontinuity designs are often sensitive to the choice of bandwidth or the range of the forcing variable used for the regression. I estimate the equations above using a range of 6 weekdays on each side of the DST transition, which is calculated following the recommendations of Imbens and Kalyanaraman (2009). As a robustness check, I also estimated the equations using a window of 4 weekdays and 12 weekdays.

I also ran standard falsification checks by using the same regressions but substituting arbitrary dates for the DST transition. Specifically, for the years 2003 – 2006 I used the dates of the newest DST policy (2nd Sunday in March and 1st Sunday in November), and for the years 2007 – 2010 I used DST dates from the original policy (1st Sunday in April and last Sunday in October). Under the assumptions of the RDD model one should not find discontinuities in time use at these alternate cutoff dates.

3.6 Results

Based on assumptions used in many previous DST simulation models, we would expect to see little behavioral change by individuals. In other words, if people truly do operate completely off "of the clock" with little regard to daylight, then we would expect that time use would not change when the country switches to DST. The results from the RDD and differences-in-differences estimation of how DST affects time use, however reveal that on average the switch to DST in the spring causes individuals to reduce the time they spend sleeping in the morning and increase the amount of time they spend at home in the morning. Similarly, the results suggest that on average individuals spend less time at home in the evening and more time away in the early afternoon. The results for the fall DST estimation are less significant but also suggest that individuals sleep less and are home more in the morning during DST.

3.6.1 RDD

The discontinuity effects or DST coefficients for the spring RDD equations are reported in Table 3.3, and the complete estimation results are reported in Table 3.3A in the appendix. The RDD coefficients reported are the estimates of the discontinuity or jump (measured in minutes) in the dependent variable that occurs due to the transition to DST in the spring. The first column of the table shows the RDD coefficient for the equation estimating the amount of time spent sleeping in the morning (5am-9am). The negative and statistically significant coefficient suggests that on average individuals sleep 30 minutes less following the spring DST transition. Similarly, the positive and statistically significant coefficient in the second column suggests that on average individuals spend 25 more minutes at home in the morning (5am-9am) following the DST transition. Combined, these results are consistent with recent empirical papers that find that DST leads to increased energy use in the mornings. From Table 3.3, columns 4 and 6 one can also see that, on average, switching to DST causes individuals to spend less time at home in the evening and more time away in the early afternoon.

Several RDD coefficient estimates in Table 3 were not statistically significant, suggesting that there is not a consistent behavioral change in the data. Specifically, the RDD coefficient estimate for column 3 suggests that, on average, individuals spend less time at home in the late afternoon (3pm-5pm), which compliments the significant finding that individuals reduce the amount of time at home in the evening. However, the estimate is only significant at the 84 percent level. Similarly, the RDD coefficient for a discontinuity in time spent away from home in the morning is negative but only significant at the 84 percent level. This negative coefficient suggests that individuals spend less time away from the home in the morning, which is consistent with the significant results that individuals spend more time at home. Finally, the coefficient estimate in column 7 is positive but small and only significant at the 58 percent level, suggesting that DST may not have a strong effect on the amount of time spent away from home between 5 and 9pm.

The discontinuity effects for the fall RDD equations are reported in Table 1.4, and the complete estimation results can be found in Table 3.4A in the appendix. Here, the RDD coefficients reported are the estimates of the discontinuity or jump in the dependent variable that occurs due to the transition back to standard time (ST). Thus we need to be careful when interpreting the signs of the results. For example, the coefficient in column 1 is positive suggesting that individuals sleep more on ST than on DST. This result is consistent with the previous estimate the individuals spend less time sleeping in the morning after DST goes into effect. The results in Table 3.4 are far less significant and much smaller than those in Table 3.3 suggesting that the effects of DST are more pronounced in the spring. Although the coefficients are not statistically significant, their signs are consistent with the results presented in Table 3.3.

3.6.2 Robustness

The DID estimates of the spring DST treatment affect are presented in Table 3.5 in row 3. These coefficients represent the estimated change in minutes spent in the dependent variable as a result of switching to DST. To allow the DST treatment effect to differ between weekday and weekend and between population subgroups I included interaction terms. Row 4 contains the coefficients for the treatment effect interacted with employment status that represents how DST effects differ for employed individuals. Similarly, row 5 contains the coefficients for the treatment effect interacted with weekend, showing how DST effects time use on the weekdays differently than on the weekends. For example, from column 1 we see that on average individuals sleep 21 fewer minutes in the morning as a result of DST. We also see that this effect disappears on the weekends.

Table 3.3: RDD Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	-29.875**	25.401**	-12.487	-34.298**	-16.829	18.668**	8.831
	(14.967)	(11.188)	(8.772)	(13.598)	(12.001)	(9.323)	(10.865)
Observations	1,080	1,080	1,080	1,080	1,080	1,080	1,080
R^2	0.115	0.139	0.228	0.134	0.192	0.228	0.109

Standard errors in parentheses

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

Appendix Table 3.4: RDD Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	15.307	-2.421	1.039	0.294	-1.859	1.544	-0.881
	(15.628)	(11.594)	(9.784)	(15.069)	(12.750)	(10.331)	(11.757)
Observations	940	940	940	940	940	940	940
R^2	0.098	0.178	0.214	0.110	0.213	0.220	0.070

Standard errors in parentheses

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

The remaining results in Table 3.5 are less significant than those in Table 3.3, however we again see consistency in the signs of the DST treatment effect. For example, the results suggest that on average individuals spend less time at home in the mornings and more time at home in the late afternoon and evening. In fact, we see that in column 3 the coefficient on the treatment and employment interaction term is negative and statistically significant, suggesting that, on average, DST results in employed individuals spending less time at home in the late afternoon. This result is consistent with the spring RDD results presented above.

The results for the regressions measuring time away from the home are not statistically significant and thus do not lend support for or against our RDD results.

The difference-in-differences estimates of the fall DST treatment affect are presented in Table 3.6 in row 3, and the complete estimation results can be found in Table 3.6A in the appendix. Similarly to the fall RDD estimates, these results not are not statistically significant, which suggests that the fall DST transition is less pronounced than the spring.

3.6.3 Placebo

Each of the RDD regressions was estimated using alternative ranges for the bandwidth – 4 weekdays and 12 weekdays. The results from the spring RDD estimates are shown in Tables 3.7A, 3.8A, 3.9A, and 3.10A in the appendix. The signs of the estimated discontinuities were consistent across all bandwidth choices; however, the results were less significant in both the robustness estimations. Importantly, the results support our previous findings that individuals sleep less in the morning and spend more time awake at home following the spring DST transition. Thus there is no evidence that the results reported above are driven by the choice of bandwidth.

Standard falsification checks were also estimated using the newest DST policy dates for years 2003-2006, and old DST policy dates for 2007-2010. The results from

Table 3.5: Dif & Dif Results: Spring DST Transition

Variables	(1) sleep5a9a	(2) home5a9a	(3) home3p5p	(4) home5p8p	(5) away5a9a	(6) away3p5p	(7) away5p8p
Week 2	1.301	6.326	11.131**	16.235**	-5.654	-5.759	-8.915*
	(6.955)	(5.124)	(4.501)	(6.535)	(4.654)	(3.826)	(4.601)
Treatment	7.108	2.424	6.576*	5.825	-6.181	-2.999	-6.462
	(6.051)	(4.458)	(3.916)	(5.684)	(4.049)	(3.329)	(4.002)
Week 2*treatment	-20.562*	6.979	-7.519	-11.638	6.892	5.067	6.065
	(10.856)	(7.998)	(7.025)	(10.200)	(7.264)	(5.972)	(7.180)
Week 2*treat*Employed	8.791	-10.273	-9.760*	-5.653	2.654	4.200	4.187
	(8.635)	(6.362)	(5.588)	(8.109)	(5.778)	(4.750)	(5.712)
Week 2*treatment*wknd	20.103**	-14.219**	0.636	1.420	-3.265	-0.584	-0.505
	(8.555)	(6.303)	(5.537)	(8.038)	(5.724)	(4.706)	(5.659)
Observations	1,376	1,376	1,376	1,376	1,376	1,376	1,376
R^2	0.162	0.107	0.140	0.088	0.199	0.201	0.075

Standard errors in parentheses

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

Table 3.6: Dif & Dif Results: Fall DST Transition

Variables	(1) sleep5a9a	(2) home5a9a	(3) home3p5p	(4) home5p8p	(5) away5a9a	(6) away3p5p	(7) away5p8p
Week 1	-3.387	-0.884	-4.089	-7.864*	1.866	3.046	5.255*
	(4.747)	(3.458)	(3.088)	(4.468)	(3.219)	(2.706)	(3.172)
Treatment	-6.167	3.219	-0.145	-2.855	3.926	1.195	1.155
	(5.257)	(3.831)	(3.420)	(4.949)	(3.565)	(2.997)	(3.513)
Week 1*treatment	4.564	2.008	9.148	14.122	-3.493	-8.822*	-11.406*
	(9.143)	(6.661)	(5.948)	(8.605)	(6.200)	(5.212)	(5.933)
Week 1*treat*employ	1.633	0.497	-5.487	-5.455	-2.302	4.991	9.688**
	(7.767)	(5.659)	(5.053)	(7.310)	(5.267)	(4.428)	(4.663)
Week 1*treatment*wknd	-2.174	-1.186	-7.418	2.641	-4.040	3.926	-2.158
	(7.685)	(5.599)	(4.999)	(7.233)	(5.211)	(4.381)	(5.135)
Observations	1,821	1,821	1,821	1,821	1,821	1,821	1,821
R^2	0.188	0.118	0.134	0.084	0.213	0.163	0.048

Standard errors in parentheses

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

the spring and fall estimations are shown in Tables 3.11A and 3.12A. The coefficients on the estimated discontinuities are insignificant for all equations, which is consistent with the assumptions of the RDD model above. These arbitrary dates do not represent a change in DST and thus we did not find a change in time use.

3.7 Discussion & Conclusion

The results presented above provide clear evidence of several significant behavioral changes that occur as a result of DST; however, before we consider how these changes will effect energy demand, we should first set out the shifts in energy use that simulation models predic will result from shifting sunlight forward 1 hour even when individuals operate "off the clock." First, DST causes the sun to rise 1 hour later, meaning that mornings are darker and cooler than they would be on ST. During the cooler months in the spring and fall especially, this may cause individuals to use more lighting and heating electricity regardless of behavioral/time-use adjustments. Similarly, DST will cause the late afternoons and early evenings to be warmer and brighter. This should reduce lighting electricity, but will likely lead to increased air conditioning use, making it hard to establish the true shift in energy afternoon/evening energy demand. Most simulation models suggest that the afternoon energy savings more than offsets the increased use in the morning, making DST an energy-reducing policy. However, one cannot accurately draw such conclusions without information on how behaviors change on DST.

Fortunately, the results from our analysis are informative in this regard. First, we found that individuals sleep less in the morning and spend more time awake at home following the spring DST transition. Using the results from the spring RDD estimation we see that on average individuals sleep for 30 minutes less and spend most of that extra awake time at home. This will encourage additional use of both lighting and heating energy during that time because individuals are spending more time at home. This result is consistent with recent empirical studies that have looked at energy demand in the morning on DST (Kellogg and Wolf 2008). Although additional demand due to darker cooler mornings may have been expected in simulation studies, this additional time of increased use was likely overlooked.

The spring RDD results also suggest that on average DST causes individuals to spend less time at home in the afternoon/evenings. This suggests that residential energy demand decreases while individuals are away from the house. Thus, although DST has mixed effects on energy use when at home, our results seem to suggest that decreases in energy use in the evening may be the result of less time spent at home.

Although these results do not provide clear answers to the effectiveness of DST policies they do provide important insights. They suggest that the DST time shift causes individuals to get up earlier in the morning and spending the additional time at home. There is also evidence that individuals are spending less time at home in the evenings. These results suggest that the extra daylight in the evening after switching to DST creates the opportunity to undertake outdoor evening activities that were otherwise not possible, and that individuals are scheduling household chores and activities in the morning that they would normally do in the evening in order to free up additional time. This shift towards morning chores was not antisipated in simulation studies and provides important insight into the discrepancies between the predicted energy saving and the realized savings.

The shifts in time use during the morning and the afternoon are similar in magnitude, suggesting that afternoon energy savings do not necessarily outweigh the morning increases in demand. In fact, most recent empirical studies suggest DST is energy neutral or perhaps energy taxing. These conclusions are perfectly consistent with the results we have discussed here. If the increase in energy demand in the mornings combined with the increase in time spent at home outweighs savings from spending more time away from home, then DST will cause an increase in overall residential energy demand.

Although this analysis does not provide significant evidence that the effects of the program vary geographically, it seems likely that the behavioral effects we found would change with latitude. Sunrise (and thus DST) varies with latitude and we established that individuals do respond to changes in sunlight. Morning and afternoon temperatures also vary geographically, which would affect heating and air conditioning usage. Thus, future DST studies should investigate how shifts in energy demand during the different parts of the day vary by latitude. It might be that DST is effective as an energy-conservation tool in certain regions and not in others.

In summary, this is the first study to investigate behavioral responses to DST by examining how individuals shift the amount of time they spend in certain activities during the day, and we found several key results. First, on average, individuals sleep 30 minutes less in the mornings following the spring DST transition, and spend 25 more minutes at home. We also found evidence that individuals spend less time at home in the afternoon/evening following the spring transition. The results for the fall transition back to ST were not statistically significant, but the estimated signs remain consistent with the estimates from the spring transition.

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Chapter 4:

Does Daylight Savings Time Lead to More Time Exercising?

4.1 Introduction

According to the Center for Disease Control and Prevention (CDC), the key to achieving and maintaining a healthy weight is "about a lifestyle that includes healthy eating, regular physical activity, and balancing the number of calories you consume with the number of calories your body uses." With this in mind, the government continues to fight aggressively against rising obesity rates - in 2009-2010, more that 35% of Americans were obese (National Center for Health Statistics (NCHS), 2012). Recent calorie posting laws and sugar tax proposals aimed at reducing calories consumed have received considerable attention, however, there is also a strong push to motivate Americans to be more active.

In order to realize the health benefits from exercise, the federal Physical Activity Guidelines recommends that adults engage in at least 150 minutes per week of moderate-intensity or 75 minutes per week of vigorous-intensity aerobic physical activity, and muscle strengthening activities at least twice a week (U.S. Department of and Human Services, 2008). In the 2011 Annual Report on Health Statistics, the CDC found that only 20 percent of adult Americans successfully met both of these guidelines, and that over 50 percent met neither (NCHS, 2012). The National Physical Activity Plan (NPAP) is a comprehensive set of policies, programs, and initiatives aimed at improving these statistics. The plan is the product of collaborative work by hundreds of private and public organizations including the CDC, the United States Department of Agriculture, the American Medical Association, and the YMCA, and promotes ideas such as making sure roadway spending includes money for accommodating bikes and pedestrians, providing tax breaks for building owners or employers who provide amenities in workplaces that support active commuting, and increasing funding and resources for parks, recreation, fitness and sports programs and facilities in areas of high need (Hellmich, 2010). However, many of the policies proposed in the NPAP have the potential to be very costly and some critics question how effective they will be at increasing physical activity. Thus, policymakers are looking for proven-effective ways to encourage physical activities that won't add to existing budget deficits.

A number of studies have investigated individual, social, and environmental correlates of adult and child physical activity, and found that individuals in the south consistently spend more time exercising than their northern counterparts (Barnes and Schoenborn, 2003; Eyler et al., 2002). This result may be due in part to the fact that days are longer in the South during many months of the year. The weather is also warmer in the South, which likely contributes to the higher rates of exercise. Additionally, research has also shown that more Americans workout in the evening than in the morning (BLS). Thus, extending the amount of after-work daylight and thus warmth may in fact improve America's physical activity statistics.

Daylight Savings Time (DST) is a common energy conservation policy used in the United States and countries throughout the world that pushes the clock forward by 1 hour in the spring. In other words, it causes the sun to rise and set 1 hour later, meaning that late afternoons and early evenings are warmer and brighter. This additional hour of after-work daylight can be used for biking, jogging, playing golf or tennis, walking, or other aerobic activities.

In this paper, I investigate how DST impacts the amount of time individuals spend doing physical activity. If DST does indeed lead to increases in physical activity, there may be a public health argument for adopting year-long DST or even double DST. Especially in light of America's growing obesity problem, DST could potentially be an important tool in the fight to get America moving, and may be particularly important for young children who are much less likely than adults, to substitute indoor exercise for outdoor activities when DST is not in effect.

In this study I use data from the American Time Use Survey (ATUS), a nationally representative survey on time use in the United States, to investigate how DST affects the amount of time individuals spend in aerobic physical activities (APAs). Data from both the spring and fall DST transition periods are used to identify changes in exercise due to DST and to test whether behavioral changes are greater in the fall or spring. To my knowledge, the impact of DST on physical activity has not previously been considered in the literature.

Because seasonal variation in temperature, daylight, recreation, and work may confound the effect of DST on exercise, I employ a regression discontinuity design (RDD) by comparing the amount of time spent in exercise activities during days that fall just before and just after the spring and fall DST transitions. Assuming other factors potentially impacting exercise regimens vary smoothly about the administratively determined DST transition dates, the RDD allows that days just prior to DST are reasonable counterfactuals for days just after DST. Additionally, identification of the DST effect on exercise is strengthened by an exogenous change in the dates of DST transitions beginning in 2007. In all subsequent years, the DST transition occurred 3 weeks earlier in the spring (i.e., on the second Sunday in March) and 1 week later in the fall (i.e., the first Sunday in November). Thus, across years, I observe days of the year that are both treated as DST and not treated as DST. The administrative change in DST thus provides exogenous variation in treatment status, as in a controlled field experiment, that permits identification of the DST effect on exercise in a difference-in-differences (DID) setting.

Results from estimating the RDD and DID Poisson models reveal that on average individuals spend 15 more minutes in APAs per day after the spring DST transition, and that individuals are 2.5 times more likely to engage in any APAs. This suggests that additional after-work daylight does promote physical activity. The results also reveal that the fall transition back to standard time (ST) does not significantly affect physical activity.

This chapter proceeds in section 2 with a review of existing literature on DST.

Section 3 provides a brief background on DST programs and the growing obesity problem in the U.S. Section 4 describes the data used in this analysis, and section 5 discusses the econometric models used to estimate the response to DST. The results are presented in section 6, and section 7 summarizes the main findings and draws conclusions about the effect DST has on exercise habits and how the results might influence policy.

4.2 Literature Review

Previous research related to DST has primarily focused on the impacts of various DST regimens on energy consumption. Early studies developed simulation models to predict energy consumption and results suggested that DST would reduce usage by as much as 9 percent. Aries, and Newsham (2007) provide a detailed summary of this literature. More recently, several studies have used changes in the DST policies and quasi experiments to empirically test the impacts of DST. The results from these studies contradict their predecessors and suggest that DST may actually result in increased energy use, at least in some geographical areas.

Kellogg and Wolff (2007) used Australian panel data on half- hourly electricity consumption from when DST was extended to accommodate the 2000 Olympic games. The extension was not implemented in all states, allowing the authors to employ a difference-in-difference model, and their estimates suggest that the extension failed to reduce energy consumption, and perhaps caused an overall increase in use. Later, Kotchen and Grant (2011) exploited a natural experiment that occurred in Indiana after the Energy Policy Act of 2005, and their results indicate that DST increased residential electricity demand in Indiana by about 1 percent per year or $9 million.

Researchers have also investigated the non-energy related effects of DST. For example, shifting clocks forward by an hour in the spring results in less daylight during morning commutes, which researchers have hypothesized might lead to more traffic accidents or more deaths for pedestrians. The additional light in the evenings may alternatively keep pedestrians safe in the evenings. DST also results in the loss of an hour of sleep in the spring, which might have health related effects and lead to higher rates of heart attack and suicide in the days immediately following. Alternatively, the lost hour of sleep may cause drivers to be less attentive in the days following the DST transition resulting in more traffic accidents. Studies investigating these possibilities as well as others, have failed to determine any significant and consistent effects of DST. For a more complete review of this literature see Aries and Newsham (2007).

To the best of my knowledge, this is the first study that investigates how DST affects individuals' exercise habits; however, the epidemiology literature has studied individual and social correlates of adult and child physical activity. For example, Cunningham and Michael (2004) find that neighborhood safety, footpath safety, access to convenient facilities, enjoyable scenery, low perceived crime rates, and low traffic density where most commonly associated with higher rates of physical activity. Humpel et al. (2002) and Bauman and Bull (2007) provide reviews of this literature. Interestingly, weather is not consistently correlated with physical activity, although surveys indicate that individuals engage in more exercise during the spring and summer than during the fall and winter (Gallup, 2011). If the link between daylight, weather and physical activity can be made, it would offer policy options to get Americans moving that don't require the expensive infrastructure investments such as footpaths and other facilities suggested in the previous studies.

4.3 Background

4.3.1 History of Daylight Savings Time in the United States[10]

DST was first introduced in the United States on March 19, 1918 with the Standard Time Act. This legislation mimicked policies that were already being use in several European countries to conserve fuel during World War I. The practice however was very unpopular and the national law was abolished shortly following the war. In the time between World Wars I and II, the choice to participate in DST was left to local governments, and its adoption varied across cities and states. In 1942 President Franklin Roosevelt reintroduced the practice of DST, but extended the time change to cover the entire year calling it "War Time". Again, following the war in 1945, DST returned to a local policy and remained that way untill 1966.

During the early 1960s, many industries began complaining about the inconveniences caused by DST policies that varied across cities and states. Not only did adoption rates vary, but so did the beginning and ending dates of DST. The inconsistency was particularly hard for the transportation industry. Conducting business across state boarders was very difficult and many people began lobbying for a national law regulating DST. This resulted in the Uniform Time Act of 1966, which mandated that clocks be advanced one hour beginning at 2:00 a.m. on the last Sunday in April and turned back one hour at 2:00 a.m. on the last Sunday in October. States were allowed to exempt themselves from DST as long as the entire state did so. Additionally, states that were in two different time zones were allowed to exempt one time zone without the other. This later law applied to multiple states, and both Michigan and Indiana for example, housed some counties that did observe DST while others did not. Indiana falls in both the Central and Eastern Time zones. The official dividing line between the two time zones has progressively shifted west over time and now

[10]Discussion similar to section 3.3.

only 12 counties still observe central time. Until 2007, with the exception of these 12 counties, Indiana did not observe DST.

The Department of Transportation (DOT) is officially in charge of enforcing and evaluating DST. This has included evaluating proposals to extend DST. It was through this evaluation process that Congress decided to change the effective dates of DST in 1986 with the goal of reducing energy use. Beginning in 1987, DST started on the first Sunday in April and remained in effect till the last Sunday in October. Then, after another review process by the DOT, Congress passed the Energy Policy Act of 2005, which extended DST for another four weeks each year again in hopes of reducing energy demand. As of 2006, DST starts on the second Sunday of March and ends on the first Sunday of November.

Today, all states and territories except Arizona, Hawaii, American Samoa, Puerto Rico, and the Virgin Islands observe DST. However, several states have recently discussed legislation to either observe standard time or DST all year long. In its 2011 session, the Colorado legislature voted on bills for both moves. In the spring, senator Brophy's bill, that would have put Colorado on yearlong DST, gained initial support but was later rejected by the Senate Appropriations Committee. Nevada has similarly debated both legislation moving to yearlong DST and legislation moving to yearlong Standard Time. Proponents of year-around DST in both states thought that the additional daylight would lead to more out-of-the-house activities, which would bolster the economy. The new legislation proposals are interesting because they mark a clear shift in the motivation for DST away from residential energy conservation. Proposals now cite other economic and social costs of DST; however, the studies to date have focused on energy effects. Clearly, additional research is needed into the other possible impacts of DST such as the effect it has on time spent in exercise and physical activities.

4.3.2 Exercise and Healthy Lifestyle Policies in the United States

The link between exercise and healthy weight is well established, and according to the President's Council on Physical Fitness and Sports, exercise is associated with the loss of body fat in both obese and normal weight persons. In fact, the council recommends that an exercise program be a component of all individuals' lives regardless of weight. Additionally, the federal Physical Activity Guidelines suggest that adults engage in at least 150 minutes per week of moderate-intensity or 75 minutes per week of vigorous-intensity aerobic physical activity, and muscle strengthening activities at least twice a week. In the 2011 Annual Report on Health Statistics, the CDC found that only 20 percent of adult Americans successfully met both of these guidelines, and that over 50 percent met neither (NCHS 2012).

In light of the health benefits and the federal government's recommendations, interest for environmental and policy strategies to promote physical activity has grown in communities around the country. These strategies often include providing access to facilities and programs not currently available, and supporting social environments that favor these activities. Examples include walking and biking trails, funding for public facilities, zoning and land use that facilitate activity in neighborhoods, mall walking programs, and building construction that encourages physical activity. These types of policies are particularly appealing because they offer community-wide solutions that are accessible to everyone and promote health to all subsets of the population.

Despite the growing interest and popularity of these sorts of strategies to promote physical activity, the current economic conditions have made finding funding very difficult. Thus, DST could potentially be an important and low cost method of promoting exercise amongst Americans. The ATUS data reveals that most Americans exercise in the evening (BLS). In fact, from our data set we know that the mean number of minutes spent in APAs during the hours of 4pm and 8pm (16 minutes) is

4.5 times larger than the mean number of minutes spent in APAs during the hours of 6am and 10am. Thus, the additional hour of daylight in the evening that results from DST may be influential in creating more opportunities for physical activities. It may be particularly important for young children who are less likely to engage in physical activity after sunset.

4.4 Data

To measure whether or not individuals respond to the shift in sunlight from the morning to evening that is caused by DST, I combine data on daily exercise/aerobic activities, daylight savings status, and surface weather conditions. The American Time Use Survey (ATUS), a nationally representative, federally administered survey on time use in the United States, provides a detailed record of respondents' time use over 24 hours. The survey was first administered in 2003 and responses have been consistently collected since. Thus, this analysis contains information from 8 years, 2003-2010. Each respondent provides detailed information on how he/she spent time over a 24 hour period, allowing for a detailed accounting of time spent in aerobic physical activities (APAs).

Using the ATUS-X Extract Builder, I created a variable that included all APAs and summed the amount of time each respondent spent in any of the activities over a 24-hour period. Examples of summed activities include biking, golfing, playing basketball, working in the yard, and running.

The ATUS not only allows one to measure the total number of minutes spent in APAs during a day, but also allows for summations over subsets of the day. Thus, I can also analyze whether or not increases in APAs are occurring during the increased evening daylight. Data from the Astronomical Applications Department of the U.S. Naval Observatory reveals that sunset occurs between 4pm and 8pm during the times when DST is implemented or removed. Thus, for each ATUS respondent, I measure the amount of time he/she reports doing APAs during the entire day and between the hours of 4pm and 8pm.

The ATUS data is matched with weather information at the smallest geographical level possible, the core based statistical area (CBSA). However, a significant number of the ATUS responses had missing information for the respondent's CBSA. Fortunately, all ATUS respondents previously participated in the Consumer Population Survey (CPS), and I was able to use data from the corresponding years and match respondents to their final CPS interviews. These interviews occurred 2-5 months prior to the ATUS survey and contained more complete geographic information including CBSAs for most respondents. After matching the ATUS and the CPS data sets and dropping all responses for which a valid CBSA could not be identified, 88,477 responses spanning 8 years (See Table 4.1 for frequencies) and 296 CBSAs remained. The CBSA with the most responses, 6,748, covers New York, Northern New Jersey and Long Island, while the CBSA covering Los Angeles-Long Beach-Riverside was second with 3,813 respondents. Finally, all CBSA's had at least 5 responses.

Table 4.1: ATUS Data Frequencies

Year of Interview	Frequency	Percent	Cumulative
2003	11,938	14.05	14.05
2004	10,028	11.80	25.85
2005	10,176	11.98	37.82
2006	10,564	12.43	50.26
2007	10,105	11.89	62.15
2008	10,854	12.77	74.92
2009	10,736	12.63	87.55
2010	10,576	12.45	100
Total	84,977	100	

To correctly identify the effects of DST on APAs, it was crucial to identify whether or not respondents were affected by DST when completing the ATUS. To do this, I used information on the start and end dates for DST for each year, 2003 – 2010. This information is shown in Table 1; beginning in 2007, DST was extended by three weeks in the spring and one week in the fall. Thus, the data set contains information on four years prior to the policy change and four years after.

Surface weather conditions may also influence the amount of time respondents spend exercising. Thus, it is important to control for these variables when determining the effects of DST. This analysis uses historical daily surface weather data for the United States from 2003-2010 from the National Climatic Data Center's (NCDC) Climate Data Online database. The data contain daily measures of mean temperature, mean wind speed, maximum temperature, minimum temperature, and total precipitation (rain and/or melted snow) for over 2000 stations in the US. Each station's latitude and longitude coordinates were used to determine which station was located closest (measured as the crow flies) to the center of each CBSA, allowing the data for those stations to be merged with the ATUS. Table 4.2 below shows the summary statistics for the final data set.

Table 4.2: Data Summary Statistics

Variable	# Obs.	Mean	Std. Dev.	Min	Max
APAs (min)	88,477	17.61	55.38	0	1073
APAs 4pm - 8pm (min)	88,477	15.84	51.59	0	953
Mean temperature (°F)	82,405	58.62	17.58	-36.40	104
Mean wind speed (knots)	82,402	14.85	36.12	0.00	504
Precipitation (inch)	84,977	0.56	0.50	0.00	1
Age (yrs)	84,977	45.81	17.44	15	85
Max Temp (°F)	82,389	65.67	20.57	-54.4	131.5
Min Temp (°F)	82,389	46.15	19.28	-61.6	104
Latitude	55,900	37.50	4.94	19.42	48.54
Dummy Variables	# Obs.	Yes	No		
Female	84,977	48,002	36,975		
Kids under 5 yrs	84,977	15,292	69,685		
Full time student	84,974	6,621	78,353		
Black	84,977	10,501	74,476		
Asian	84,977	138	84,839		
Indian	84,977	942	84,035		
Hispanic	84,977	12,728	72,249		
Married	84,977	42,144	42,833		
At least a bachelor's Degree	84,977	27,772	57,205		
Graduate degree	84,977	10,216	74,761		
Unemployed	84,977	4,317	80,660		
Retired	84,977	12,877	72,100		
Pacific Standard Time (PST)	88,477	15,231	73,246		
Mountain Standard Time (MST)	88,477	53,17	83,160		
Central Standard Time (CST)	88,477	22,953	65,524		
Eastern Standard Time (EST)	88,477	44,727	43,750		

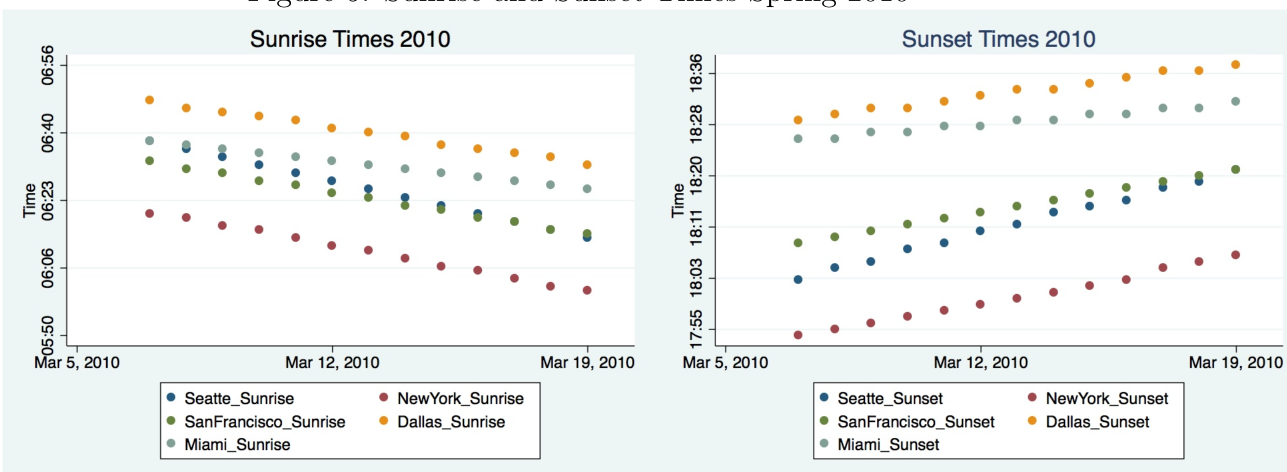
4.5 Empirical Methods

4.5.1 Regression Discontinuity Design

Since DST takes effect in the US on a precise day and time each year, I can identify how the time change affects exercise using regression discontinuity design (RDD). Sunrise and sunset times change by 0-3 minutes per day, meaning that days just before the sharp, 1-hour shift forward in time that occurs each spring (or the 1-

hour shift backward that occurs in the fall) are otherwise similar. See Figure 5 for a graphical representation of sunrise and sunset time around the spring DST shift. Weather variables such as temperature, wind, and precipitation are also similar for days on either side of the DST transition. This allows me to use days just prior to the time change as counterfactuals for days just after, and any difference in exercise activities at the threshold can be attributed to DST.[11]

Figure 5: Sunrise and Sunset Times Spring 2010



The identifying assumption with this RDD model is that in the absence of DST, the amount of time spent in APAs varies continuously with the forcing variable, the date. This means that, time spent in APAs evolves smoothly with the date and that any discrete changes in the variable can be attributed to DST. Importantly, this assumption doesn't imply that sleep cannot vary as the sunrise/sunset times change naturally or as temperatures shift naturally; it simply requires that such activities move smoothly across the DST transition.

As discussed in Hahn et al. (2001) and Imbens and Lemieux (2008) many researchers recommend estimating RDD equations using non-parametric procedures that do not assume underlying linearity. Although kernel regressions are a leading non-parametric approach because they are fundamentally a local method, they per-

[11]For further discussion of RDD methods for analyzing the effects of DST using ATUS data see section 3.5.

form poorly at cutoff points, such as those RDD equations estimate. In fact, Imbens and Lemieux (2008) show that there is systematic bias in kernel regression estimates of the treatment effect, that arises because the researcher must choose a bandwidth around the cutoff point that is large enough to contain enough observations to get a reasonable amount of precision in the estimated average values of the dependent variable. This creates a tradeoff between bias and precision, where choosing a larger bandwidth yields more precise estimates, but could also potentially bias the estimates.

To avoid the bias of kernel regressions and consistently estimate the treatment effect, I follow Hahn et al. (2001) who suggest running locally linear regressions. This approach requires estimating a standard regression within small bins on both sides of the cutoff point, which will provide consistent estimates of the treatment effect at the cutoff. In fact, the most direct way of estimating the treatment effect is to run a pooled regression over the cutoff and allow for the functional form to vary on either side by including interaction terms between the treatment, DST $= D$, and the forcing variable, Date $= Z$. An advantage of this method is that it provides a direct estimate of the treatment effect along with standard errors. The estimation equation is:

$$Y_i = \alpha_i + \tau \cdot D_i + \beta_1 \cdot z_i + \beta_2 \cdot D_i \cdot z_i + \gamma \cdot X_i + e_i$$

Were Y_i represents the minutes of time spent in APAs, z_i measures the days from the DST transition ($z -$ DST_date), and X_i is a matrix of demographic, household, and weather covariates such as age, employment status, presence of young children, and max temperature. I estimate the RDD equations over a range of 5 days (excluding weekends) on each side of the DST transition based on the estimated optimal bandwidth for a sharp design as given by Imbens and Kalyanaraman (2009).[12] I also include a dummy variable for those responses that are affected by the 2006 policy

[12] Additional bandwidths were tested and are discussed in the robustness section.

changes that extended DST by three weeks in the summer and one week in the fall. These covariates are included in the regressions to increase the precision of the RDD estimator and to capture variation in activity patterns. For example, time spent exercising will likely vary by age, employment status, and temperature. As suggested by Lee (2009), I enter the covariates directly into the regression equations as in the equation above; however, all equations were also estimated by "residualizing" the dependent variable. For this diagnostic check, a prediction of Y based on the baseline covariates X is subtracted from Y, and then RD regression is run using the residuals as the dependent variable. The sign and the significance of the treatment effect proved robust to the method used for covariates.

4.5.2 Difference in Difference

We can also estimate how DST affects APAs by taking advantage of the policy change that occurred after 2006. For all subsequent years the DST transition occurred 3 weeks earlier in the spring (second Sunday in March) and 1 week later in the fall (first Sunday in November). This means that our data set can be divided into two groups – (1) observations occurring between 2003-2006 and (2) observations occurring between 2007-2010.[13]

When analyzing the effect of the spring DST transition we can focus on observations occurring in either the week right before the second Sunday in March or the week right after. Thus limiting the data set such that those observations in group 1 (2003-2006) were not exposed to DST in either week, and those observations in group 2 (2007-2010) were exposed to DST in the second week, but not the first. We can calculate the effect of DST by subtracting the average change in the amount of time spent in APAs, for the first (control) group from the average change for the second (treatment) group. This difference-in-differences (DID) method removes any biases

[13]For further discussion of DID methods for analyzing the effects of DST using ATUS data see section 3.5.2.

in second period comparisons between the treatment and control group that could be the result of permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of changes in sunrise or sunset times.

For the spring DST transition, the basic linear DID regression equation is:

$$Y_i = \beta_0 + \beta_1 W_{2i} + \beta_2 T_i + \beta_3 W_{2i} T_i + \gamma X_i + e_i$$

where Y is the number of minutes spent in APAs, W_2 is a dummy variable for the week after the DST transition and measures factors that may cause changes in Y even in the absence of the DST. T is a dummy variable for the treatment group and captures any differences between group 1 and group 2 outside of the DST policy change that may affect Y. Finally, X_i is a matrix of other covariates identical to those used in the RDD regressions. The coefficient of interest is β_3, on the interaction term between W_2 and T. This dummy variable is equal to 1 for all ATUS responses that occurred in the week after the second Sunday in March between 2007 and 2010. The difference-in-differences estimate of the DST treatment affect is then:

$$\beta_3 = E\left[Y = 1 | W_2 = 1, T = 1, X\right] - E\left[Y = 0 | W_2 = 1, T = 1, X\right]$$

It is necessary to note however, nearly 80 percent of the ATUS respondents report zero minutes spent in APAs on a given day. This means that the traditional linear functional form is not appropriate. Instead, I estimated the difference in difference using a Logit model, where the dependent variable is binary, taking the value 1 if the ATUS respondent reported spending any time in APAs and zero otherwise.[14] With this model we are estimating whether or not DST increases the probability

[14] A Linear Probability Model was also tested, and the results were similar to those of the Logit model.

that individual will engage in any APAs (which is consistent with policy desires to get more Americans to exercise regularly), and thus we are interested in how the probability of APAs, $P(y = 1|X) = p(x)$, changes during DST. For the Logit model, the conditional expectation of APAs is:

$$E\left[Y|W_2, T, X\right] = \Lambda\left(\beta_1 W_{2i} + \beta_2 T_i + \beta_3 W_{2i} T_i + \gamma X_i\right)$$

where $\Lambda\left(\cdot\right)$ is the conditional distribution function of the logistic distribution such that $\Lambda\left(z\right) = \exp(z)/(1 + \exp(z))$. The difference-in-differences estimate of the DST treatment affect with the Logit model is then:

$$\beta_3 = E\left[Y = 1|W_2 = 1, T = 1, X\right] - E\left[Y = 0|W_2 = 1, T = 1, X\right]$$

$$= \Lambda\left(\beta_1 + \beta_2 + \beta_3 + \gamma X_i\right) + \Lambda\left(\beta_1 + \beta_2 + \gamma X_i\right)$$

In other words, the treatment effect is the marginal effect of the coefficient of the interaction term, β_3.

Similarly, to estimate how time spent exercising changes during the fall DST transition we can narrow the analysis to observations falling in the week on either side of the first Sunday in November. Focusing only on these two weeks of observations ensures that those observation in group 1 were not exposed to DST in either week and will again act as the control group. The observations in group 2 (2007-2010) will then represent the treatment group because they will be exposed to DST in the first week, but not in the second. Thus, the fall linear differences and differences estimation equation would be:

$$Y_i = \beta_0 + \beta_1 W_1 + \beta_2 T + \beta_3 W_1 T + \gamma \cdot X_i + e_1$$

where the only difference from the spring equation is that we are interested in measuring the effect of being in the treatment group and in the earlier week (week 1) because in the fall we transition off of DST. Thus the coefficient of interest, β_3, is on the interaction term between W1 and T. The difference-in-differences estimate of the DST treatment affect with the Logit model is then:

$$\beta_3 = E\left[Y = 1 | W_1 = 1, T = 1, X\right] - E\left[Y = 0 | W_1 = 1, T = 1, X\right]$$

$$= \Lambda\left(\beta_1 + \beta_2 + \beta_3 + \gamma X_i\right) + \Lambda\left(\beta_1 + \beta_2 + \gamma X_i\right)$$

4.6 Results

Results from estimating the RDD and DID Poisson models reveal that on average individuals spend 15 more minutes in APAs after the spring DST transition, and that individuals are 2.5 times more likely to engage in APAs. The results also reveal that the fall transition back to standard time (ST) does not significantly affect physical activity.

4.6.1 RDD

The discontinuity effects or DST coefficients for the spring RDD equations are reported in Table 4.3, and the complete estimation results are reported in Table 4.3A in the appendix. The RDD coefficients reported are the estimates of the discontinuity (measured in minutes) in the time spent in APAs that occurs due to the transition to DST in the spring. The first column of the table shows the RDD coefficient for the equation estimating the amount of time spent in APAs over the entire day. The positive and statistically significant coefficient suggests that on average individuals spend 15 more minutes in APAs following the spring DST transition. This result suggests that the additional daylight in the evening does promote more time spent in physical activity. I also estimated how the time spent in APAs during the evening changed as a result of the spring forward in time. The results presented in the second column of table 2 show the RDD coefficient for the equation estimating the amount of time spent in APAs during the hours of 4pm and 8pm. Again, the coefficient is positive and statistically significant, suggesting that on average individual engage in 14 more minutes of APAs following the spring DST transition. These results provide strong evidence that the extra hour of daylight in the spring does in fact lead to more exercise and physical activity.

Table 4.3: RDD Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
DST	15.141*	13.454*
	(8.047)	(7.562)
Observations	956	956
R^2	0.070	0.060

Standard errors in parentheses

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

From Table 3A we see that the signs of all of the coefficients across the two RDD regressions are consistent with economic theory. The coefficients for the dummy variables indicating that the respondent is elderly, married, has children under the age of 13, and is female are negative in both equations indicating that on average these individuals spend less time in APAs. Similarly, the coefficients for the dummy variables indicating an advanced degree and living outside the city are both positive suggesting that these characteristics are associated with more time in APAs. Finally, the coefficient for max temperature is positive indicating that warmer days in the spring cause an increase in APAs.

In the fall, Americans transition back to ST and lose an hour of daylight in the evening. Thus, we would expect to see a drop in exercise when DST ends. The results from the RDD estimation are, however, not significant suggesting that the transition back to ST does not affect exercise. The discontinuity effects for the fall RDD equations are reported in Table 4.4, and the complete estimation results can be found in Table 4.4A in the appendix. Here, the RDD coefficients reported are the estimates of the discontinuity or jump in time spent in APAs that occurs due to the transition back to standard time (ST). Thus we need to be careful when interpreting the signs of the results. For example, a negative and statistically significant coefficient would suggest that individuals exercise more on DST than on ST. The coefficients for both equations – total APAs and APAs between 4pm and 8pm – are very insignificant, suggesting that there is not a consistent behavioral change that is noticeable in the data set.

Table 4.4: RDD Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
DST	12.392	-1.914
	(42.367)	(39.837)
Observations	956	956
R^2	0.068	0.057

Standard errors in parentheses

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

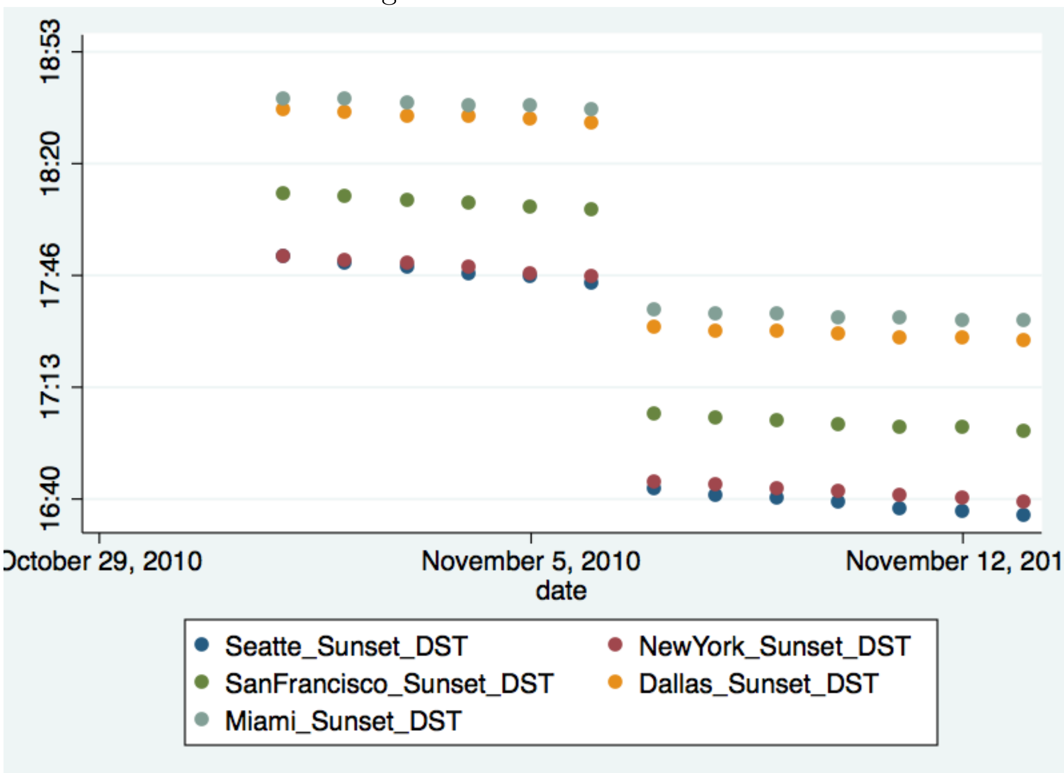
Although the fall RDD coefficient was not significant, we do see in Table 4.4A that the coefficients for the covariates are consistent with those from the spring DST results (Table 4.3A), and thus consistent with economic theory.

The effects of DST may be less noticeable in the fall because the time of sunset in late October/early November is too early. For many locations in the U.S. the sunsets before the workday ends, or before one could reasonably get home and get into physical activities regardless of DST. Figure 6 below show sunset time in 5 U.S. cites for one week on either side of the fall DST transition. For the northern most cities, New York and Seattle, the sun sets by 5:45 even while on DST. If we assume that individuals work till 5pm, then only those residing in the very southern cities could conceivably leave work and transition into APAs before the sun sets. This means that the benefit of DST – the extra evening daylight- will have disappeared prior to the switch back to ST. Given that most Americans exercise in the evenings (BLS, 2010), if after-work daylight is not effected by the fall DST transition, it seems reasonable to expect to see no significant change in minutes spent in APAs.

Additionally, the number of Americans who exercise regularly falls significantly during the colder winter months (Mendes, 2011), which also suggests that the effects of DST may be less noticeable. In New York, the average high in November (when DST ends) is 54 degrees and the average low is 42 degrees (The Weather Chanel). Given that the evenings are getting cooler earlier due to less sun, it seems likely that many individuals will have transitioned into less exercise prior to the end of DST. Similarly, in San Francisco, a more centrally located city in terms of latitude, the average high in November is 63 degrees; however, the chance of precipitation is more than twice as high as in other DST months (The Weather Chanel).

The Fall RDD results do not lend support for year-round DST proposals, but they do suggest that the current dates of DST may not be optimal for encouraging physical activity. In fact, if policy makers were purely interested in exercise, they may want to consider proposals for double DST– or a two-hour shift forward in time during the fall and winter.

Figure 6: Sunset Times Fall 2010



4.6.2 Differences-in-Differences

The DID estimates of the spring DST treatment affect are presented in Table 4.5 in the third row, and the complete estimation results are reported in Table 4.5A in the appendix. The coefficients represent the increase in the predicted log odds of APAs greater than zero associated with DST in the spring. For example the coefficient on the week 2 and treatment interaction term is 0.827, which implies that DST increases the probability that an individual will do any APAs. From the marginal effects that are reported in square brackets, the probability of doing any APAs increases by almost 4 percent after the spring DST transition. Similarly, the coefficient for the week 2 and treatment interaction term in column 2 is positive, suggesting that DST increases the probability that individuals will engage in APAs between the hours of 4pm and 8pm. The coefficient is not significant, but the marginal effects indicate that people are almost 6 percent more likely to engage in evening APAs on DST.

Table 4.5: Logit DID Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Week 2	-0.587	-0.433
	(0.394)	(0.394)
	[0.024]	[0.032]
Treatment	-0.640*	-0.644*
	(0.347)	(0.353)
	[0.029]	[0.052]
Week 2*Treatment	0.827*	0.724
	(0.489)	(0.491)
	[0.037]	[0.058]
Observations	606	606

Standard errors in parentheses

Marginal effects (dy/dx where y= p(VOA)) in brackets

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

From Table 4.5A we see that the signs of all of the covariates are again consistent with economic theory and with the RDD results. The coefficients for the dummy variables indicating that the respondent doesn not have a college degree, has children under the age of 13, and is female are negative in both equations indicating that on average these individuals less are likely to engage in APAs. Similarly, the coefficients for the dummy variables indicating an advanced degree and an income in excess of \$75,000 are both positive suggesting that these characteristics are associated with higher probabilities of APAs. Finally, the coefficient for max temperature is positive indicating that warmer days in the spring increase the likelihood that an individual will engage in APAs.

Similar to the fall RDD estimates, the DID estimates of the fall DST treatment affect are not statistically significant which suggests that there is not a noticeable shift in the probability of engaging in physical activity due to DST ending. The results from the fall DID estimation are presented in Tables 4.6 and 4.6A. Again, the lack of significance is likely due to the earlier sunset times and cooler temperatures in the fall.

Table 4.6: Logit DID Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Week 1	0.737	0.737
	(0.468)	(0.466)
	[0.063]	[0.095]
Treatment	-0.039	-0.099
	(0.269)	(0.272)
	[0.003]	[0.011]
Week 1*Treatment	-0.909	-0.827
	(0.643)	(0.641)
	[0.045]	[0.068]
Observations	606	606

Standard errors in parentheses

Marginal effects (dy/dx where y= p(VOA)) in brackets

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

4.6.3 Robustness

RDD estimates are often sensitive to the choice of bandwidth or the range of the forcing variable used for the regression. The equations above were estimated using a range of 5 weekdays on each side of the DST transition, which is consistent with the recommendations of Imbens and Kalyanaraman (2009). As a robustness check, I also estimated the equations using a window of 4 weekdays and 10 weekdays. The signs of the estimated discontinuities were consistent across all bandwidth choices; however, the results were less significant in the 10-weekday estimations.

As an additional robustness check, standard falsification checks were also estimated using the same regression but substituting arbitrary dates for the DST transition. Specifically, for the years 2003 – 2006 the dates of the newest DST policy (2nd Sunday in March and 1st Sunday in November) were used, and for the years 2007 – 2010 DST dates from the original policy (1st Sunday in April and last Sunday in October) were used. Under the assumptions of the RDD model there should not be discontinuities in time use at these alternate cutoff dates. The results from the spring and fall falsification equations are presented in appendix tables 4.7A and 4.8A respectively. As expected none of the discontinuity coefficients are statistically significant, which provides further support for the positive results estimated above.

4.7 Discussion & Conclusion

Using ATUS data on daily exercise and aerobic activities, I have empirically identified a statistically significant increase in exercise following the Spring DST transition in the U.S. Results suggest that, on average individuals spend a quarter of an hour more in APAs after the spring DST transition, and that the increase occurs in the afternoon/evening hours. Additionally, the results suggest that individuals are 4 percent more likely to participate in any APAs after the transition. In other words, DST seems to promote physical activity, and may, therefore, be a low cost policy option to increase the number of Americans meeting the 2008 federal Physical Activity Guidelines. Current policies depend on public funding for parks, trails, and other infrastructure that is increasingly difficult to come by, making the need for less costly alternatives ever greater.

The results from this analysis also suggest that the fall transition back to ST has little or no effect on exercise habits, which is most likely a result of the earlier sunset times and cooler temperatures in November. For Americans living in the northern part of the country, the sun sets before the workday is over in November regardless of DST, and thus, many have already adjusted/subtracted exercise activities. For everyone else, the combination of cooler temperatures, more precipitation, and darker evening has likely derailed their exercise regimens.

Given that the spring results suggest that additional after-work daylight does promote physical activity, it may be worth considering proposals for double DST in the late fall and winter months. In fact, the results seem to suggest that a policy that uses DST in the spring and summer months and double DST in the fall and winter months would maximize physical activity in those locations where winter temperatures do not prohibit exercise.

This analysis provides the first empirical economic assessment of the effect that DST has on physical activity; however, there are several limitations worth noting. First, the analysis only estimates changes in APAs at the time of DST transition. The data does not allow for identification of DST effects during the months between transition dates because time spent in physical activity is correlated with many other variables. Thus our results are localized estimates of the increase in APAs and should not be interpreted to suggest that DST would lead to the same increase throughout its duration. Additionally, although this analysis suggests that DST may have a beneficial impact of physical activity, the policy likely has other costs and benefits that must be considered when determining an optimal policy.

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Chapter 5:
Conclusions

In this dissertation I have used the American Time Use Survey (ATUS) to empirically investigate the effectiveness of several environmental and health related policies by examining how Americans adjust their daily activities in response to the environment. In each essay the ATUS provided a unique way to measure individuals' response levels by providing detailed accounts of all activities over a 24-hour period. This, coupled with the fact that the ATUS is a nationally representative survey, allows each essay to make an important contribution to the existing literature.

Results from the first essay show that, on average, individuals engage in averting behavior on alert days by reducing the time they spend in vigorous outdoor activities by 18 percent, or 21 minutes. Additionally, because the ATUS collects detailed demographic information, I showed that averting behavior is greater among the more sensitive populations. Elderly individuals are estimated to respond to air-quality alerts by spending 59 percent less time in vigorous outdoor activities. The results also indicate that the response from the elderly population drives the significant results found for the general populations, and that non-elderly individuals do not respond to alerts even when forecasted AQI levels are dangerous for everyone. In other words, these results suggest that pollution information does not appear to be salient to younger adults, undermining the effectiveness of such programs.

The second essay provides the first analysis of behavioral responses to Daylight Savings Time (DST) and finds evidence of several significant changes. First, on average, individuals sleep 30 minutes less in the mornings following the spring DST transition, and spend 25 more minutes at home. This will likely lead to an increase in both lighting and heating energy demand, especially in the cooler, darker spring and fall months. The results also revealed that individuals spend less time at home in the afternoon/evening following the spring transition, which suggests that the afternoon residential energy consumption savings are greater than previously expected. As new DST policies continue to be introduced, these results will aid policy makers in choosing policies that best achieve desired social and environmental goals.

Finally, the third essay empirically identifies a statistically significant increase in exercise following the spring DST transition in the U.S. The analysis suggests that, on average, individuals spend a quarter of an hour more in aerobic physical activities (APAs) after the spring DST transition, and that the increase occurs in the afternoon/evening hours. Additionally, individuals are 4 percent more likely to participate in any APAs after the transition. In other words, the results reveal that DST promotes physical activity, and thus a similar policy may be useful in the fight against Americans' sedentary lifestyles. Current policies depend on public funding for parks, trails, and other infrastructure that is increasingly difficult to come by, making the need for less costly alternatives such as DST ever greater.

In summary, this dissertation successfully illustrates how the ATUS can be used for effective policy research in environmental and health economics. The results presented here constitute only a small subset of the possible applications for the ATUS. Future research may choose to look at other activity measures such as how gas prices affect the amount of time spent driving or the amount of time spent working. It would also be interesting to see if the recent changes in healthcare affect the amount of time that individuals spend caring for elderly relatives.

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Appendix

Table 2.3A: Logit Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
Alert	-0.1836***	-0.8649***	0.0139	1.0132***	-0.4953*
	(0.069)	(0.1631)	(0.1053)	(0.2211)	(0.2699)
	-{0.0284}	-{0.1499}	{0.0021}	{0.1491}	-{0.0182}
Alert * Poverty185			0.1068		
			(0.169)		
			{0.0165}		
Alert * Not-white			-0.4324***		
			(0.1645)		
			-{0.0668}		
Alert * College			0.0809		
			(0.1432)		
			{0.0125}		
alert * Elderly			-0.8761***		
			(0.1914)		
			-{0.1354}		
Alert * Forcast150				1.1407***	
				(0.2294)	
				{0.1679}	
Max Temp	-0.008	-0.099	-0.0076	0.0099	-0.0603
	(0.0454)	(0.0738)	(0.0455)	(0.0514)	(0.1657)
	-{0.0012}	-{0.0172}	-{0.0012}	{0.0015}	-{0.0022}
Max Temp > 90	-0.0741	-0.0671	-0.0723	-0.0735	-0.1726
	(0.0488)	(0.1002)	(0.0489)	(0.0544)	(0.1779)
	-{0.0115}	-{0.0116}	-{0.0112}	-{0.0108}	-{0.0063}
Max Temp < 25	0.2887	-0.3355	0.2991	0.2466	1.6278
	(0.5158)	(0.7595)	(0.516)	(0.5705)	(1.5586)
	{0.0446}	-{0.0582}	{0.0462}	{0.0363}	{0.0598}
Precipitation	-0.0765***	-0.0843*	-0.0798***	-0.0756***	-0.0875
	(0.0261)	(0.0495)	(0.0261)	(0.029)	(0.0797)
	-{0.0118}	-{0.0146}	-{0.0123}	-{0.0111}	-{0.0032}
Precipitation > 0.1	-0.1893***	-0.0578	-0.1868***	-0.2135***	-0.2461**
	(0.037)	(0.0688)	(0.0371)	(0.0414)	(0.1172)
	-{0.0293}	-{0.01}	-{0.0289}	-{0.0314}	-{0.009}
Wind Speed	-0.0100**	-0.0134	-0.0102**	-0.0085	-0.0096
	(0.0047)	(0.0086)	(0.0047)	(0.0053)	(0.0142)
	-{0.0016}	-{0.0023}	-{0.0016}	-{0.0012}	-{0.0004}

Table 2.3A (Cont.): Logit Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
Max Temp 2	0.0003	0.0019	0.0003	-0.0001	0.0032
	(0.0011)	(0.0018)	(0.0011)	(0.0012)	(0.004)
	{0.0001}	{0.0003}	{0.0001}	{0.}	{0.0001}
Max Temp 3	0.	0.	0.	0.	0.
	(0.)	(0.)	(0.)	(0.)	(0.)
	{0.}	{0.}	{0.}	{0.}	{0.}
Max Temp 4	0.	0.	0.	0.	0.
	(0.)	(0.)	(0.)	(0.)	(0.)
	{0.}	{0.}	{0.}	{0.}	{0.}
Kids < 12 yrs	-0.1019***	-0.0197	-0.1006***	-0.0560*	0.0997***
	(0.029)	(0.3498)	(0.029)	(0.0322)	(0.0376)
	-{0.0158}	-{0.0034}	-{0.0155}	-{0.0082}	{0.0037}
Age	0.0379***	0.1511	0.0369***	0.0175**	0.1169
	(0.004)	(0.0975)	(0.004)	(0.0069)	(0.0827)
	{0.0059}	{0.0262}	{0.0057}	{0.0026}	{0.0043}
Income > 75,000	0.2034***	-0.0187	0.1999***	0.2126***	0.3142***
	(0.027)	(0.0727)	(0.0271)	(0.0287)	(0.0804)
	{0.0315}	-{0.0032}	{0.0309}	{0.0313}	{0.0115}
Bachlor Degree Plus	0.1608***	0.1225**	0.1607***	0.1832***	-0.0015***
	(0.0253)	(0.0514)	(0.0256)	(0.028)	(0.0005)
	{0.0249}	{0.0212}	{0.0248}	{0.027}	-{0.0001}
Age 2	-0.0003***	-0.0011*	-0.0002***	0.	-0.1673
	(0.)	(0.0007)	(0.)	(0.0001)	(1.0435)
	{0.}	-{0.0002}	{0.}	{0.}	-{0.0061}
Retired	0.0964**	0.1641**	0.0969**	0.1073	
	(0.0488)	(0.0807)	(0.0489)	(0.0703)	
	{0.0149}	{0.0285}	{0.015}	{0.0158}	
Unemployed	0.2954***	0.3285***	0.2923***	0.2863***	0.6051***
	(0.0311)	(0.1113)	(0.0312)	(0.0328)	(0.0883)
	{0.0457}	{0.057}	{0.0452}	{0.0421}	{0.0222}
Part-time Student	0.1557***	0.3388***	0.1538***	0.1336***	0.6129***
	(0.0366)	(0.107)	(0.0366)	(0.0393)	(0.0987)
	{0.0241}	{0.0587}	{0.0238}	{0.0197}	{0.0225}
Full-time Student	-0.4281***		-0.4238***	-0.4225***	-0.1993
	(0.0821)		(0.0821)	(0.082)	(0.2144)
	-{0.0662}		-{0.0655}	-{0.0622}	-{0.0073}

Table 2.3A (Cont.): Logit Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
Married	0.2233***	0.2281***	0.2228***	0.2037***	-0.1427
	(0.0262)	(0.0461)	(0.0262)	(0.0301)	(0.0917)
	{0.0345}	{0.0395}	{0.0344}	{0.03}	-{0.0052}
Mexican	0.3202***	0.2342	0.3014***	0.3696***	0.0739
	(0.0672)	(0.1492)	(0.0674)	(0.0736)	(0.1802)
	{0.0495}	{0.0406}	{0.0466}	{0.0544}	{0.0027}
Hispanic	-0.5538***	-0.1769	-0.5229***	-0.6126***	-0.1319
	(0.0551)	(0.1095)	(0.0558)	(0.0614)	(0.1512)
	-{0.0856}	-{0.0307}	-{0.0808}	-{0.0902}	-{0.0048}
Black	-0.6926***	-0.5597***	-0.6820***	-0.7574***	-0.2416*
	(0.041)	(0.0748)	(0.0412)	(0.0469)	(0.1448)
	-{0.1071}	-{0.097}	-{0.1054}	-{0.1115}	-{0.0089}
Asian	-0.2998	0.7697	-0.3074	-0.2716	-0.4243
	(0.3194)	(1.299)	(0.3195)	(0.3204)	(1.0284)
	-{0.0464}	{0.1334}	-{0.0475}	-{0.04}	-{0.0156}
Indian	-0.0653	-0.3751	-0.0629***	-0.0788	0.1683
	(0.1014)	(0.2475)	(0.1014)	(0.1092)	(0.3367)
	-{0.0101}	-{0.065}	-{0.0097}	-{0.0116}	{0.0062}
Female	-0.4495***	-0.4353***	-0.4483***	-0.4710***	0.0347
	(0.0228)	(0.0449)	(0.0228)	(0.0255)	(0.0833)
	-{0.0695}	-{0.0755}	-{0.0693}	-{0.0693}	{0.0013}
Pregnant	-0.6554***	0.	-0.6533***	-0.6357**	0.0563
	(0.2513)	(0.)	(0.2513)	(0.2522)	(0.3759)
	-{0.1014}	{0.}	-{0.101}	-{0.0936}	{0.0021}
AQI 50-74	0.0084	-0.0489	0.0085	0.022	0.2276*
	(0.0411)	(0.0922)	(0.0411)	(0.046)	(0.1374)
AQI 75-99	-0.0349	0.0939	-0.0403	-0.0817	-0.1818
	(0.0703)	(0.1622)	(0.0703)	(0.0786)	(0.2846)
AQI 100-109	-0.0533		-(0.0549)		
	(0.162)		(0.162)		
AQI 110-119	0.013		-0.0098		
	(0.2346)		(0.2354)		
AQI 120-129	-0.066		-0.0869		
	(0.3163)		0.3167		
AQI 130-139	-0.3595		-0.3482		
	(0.3352)		(0.3356)		
AQI 140-149	-0.3001		-0.2979		
	(0.5803)		(0.5813)		
AQI 150-159	0.3623		0.3617	0.1285	
	(0.4889)		(0.4889)	(0.5522)	

Table 2.3A (Cont.): Logit Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
AQI 160-169	-0.7295		-0.7208	-0.7478	
	(0.7831)		(0.7834)	(0.7853)	
AQI 170-179	-0.0141		-0.0136	0.1531	
	(0.848)		(0.8482)	(0.8808)	
AQI 180 -plus	0.3686		0.3377	0.5313	
	(0.4227)		(0.4218)	(0.4888)	
AQI 100-124		-0.2867		-0.0407	
		-0.3575		(0.1349)	
AQI 125-149		-0.1424		-0.2248	
		(0.5334)		(0.2818)	
AQI 150-174		0.7668			
		(1.0478)			
AQI 175-199		-0.543			
		(1.1983)			
AQI 200_plus		0.6026			
		(0.8413)			
AQI 100-150					-0.4896
					(0.5988)
AQI 150-plus					0.3682
					(1.0843)

Robust standard errors in parentheses
Marginal effects (dy/dx where y= p(VOA)) in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.4A: GLM-LL Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
Alert	-0.1763*	-0.5854*	-0.0591	0.3402	-0.3966
	(0.0932)	(0.3072)	(0.1809)	(0.3342)	(0.467)
Alert * Poverty185			0.1178		
			(0.3361)		
Alert * Not-white			-0.2399		
			(0.3046)		
Alert * College			-0.0466		
			(0.2985)		
alert * Elderly			-0.5201*		
			(0.2885)		
Alert * Forcast150				0.4569	
				(0.3514)	
Max Temp	-0.0431	-0.1041*	-0.043	-0.0386	0.474
	(0.0588)	(0.0569)	(0.059)	(0.072)	(0.7045)
Max Temp > 90	-0.0565	-0.0814	-0.0565	-0.0413	0.0795
	(0.0642)	(0.0999)	(0.065)	(0.0792)	(0.2664)
Max Temp < 25	-0.1328	-0.7215	-0.1284	-0.2509	2.5233
	(0.6307)	(0.9186)	(0.6315)	(0.7403)	(4.9948)
Precipitation	-0.0650**	-0.082	-0.0664**	-0.0568*	-0.0164
	(0.0304)	(0.0507)	(0.0297)	(0.0317)	(0.1082)
Precipitation > 0.1	-0.2480***	-0.0487	-0.2468***	-0.2938***	-0.3210*
	(0.0449)	(0.063)	(0.0447)	(0.0487)	(0.179)
Wind Speed	-0.0091*	-0.0170*	-0.0091*	-0.0079	0.0066
	(0.0053)	(0.0088)	(0.0053)	(0.0063)	(0.0229)
Max Temp 2	0.0016	0.0023	0.0016	0.0014	-0.0052
	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0153)
Max Temp 3	0.	0.	0.	0.	0.
	(0.)	(0.)	(0.)	(0.)	(0.0001)
Max Temp 4	0.	0.	0.	0.	0.
	(0.)	(0.)	(0.)	(0.)	(0.)
Kids < 12 yrs	-0.0930***	-0.3435	-0.0919***	-0.0725*	
	(0.035)	(0.3586)	(0.0346)	(0.0374)	
Age	0.0454***	0.2627**	0.0448***	0.0369***	0.1136**
	(0.0058)	(0.1056)	(0.0057)	(0.0106)	(0.0576)
Income > 75,000	0.1463***	-0.099	0.1456***	0.1674***	-0.0258
	(0.0342)	(0.0665)	(0.0341)	(0.0359)	(0.1404)
Bachlor Degree Plus	-0.0061	-0.0065	-0.0041	0.005	0.4163***
	(0.0368)	(0.0541)	(0.0342)	(0.0417)	(0.1073)
Age 2	-0.0004***	-0.0019***	-0.0004***	-0.0003**	-0.0016**
	(0.0001)	(0.0007)	(0.0001)	(0.0001)	(0.0007)

Table 2.4A (Cont.): GLM-LL Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
Unemployed	0.2306***	0.1616	0.2297***	0.2312***	0.460***
	(0.0381)	(0.1146)	(0.0396)	(0.0401)	(0.1252)
Part-time Student	0.1103***	0.2614**	0.1094***	0.1024**	0.5877***
	(0.0385)	(0.1095)	(0.0387)	(0.0411)	(0.1289)
Full-time Student	-0.4764***		-0.4745***	-0.4655***	-0.477
	(0.1198)		(0.1197)	(0.1204)	(0.3137)
Pregnant	0.2611***	0.2632***	0.2613***	0.2495***	0.4625
	(0.0312)	(0.0502)	(0.0312)	(0.0324)	(0.38)
Married	0.1934	-0.1132	0.1874	0.2958**	-0.1147
	(0.1468)	(0.1629)	(0.1398)	(0.1426)	(0.1157)
Mexican	-0.4051***	0.0582	-0.3935***	-0.5033***	0.3986
	(0.1415)	(0.1491)	(0.1314)	(0.1366)	(0.3696)
Hispanic	-0.6321***	-0.515***	-0.6264***	-0.687***	-0.1459
	(0.0497)	(0.0807)	(0.0491)	(0.0635)	(0.3031)
Black	-0.1692	1.1083	-0.1708	-0.1461	-0.2842
	(0.3194)	(0.8918)	(0.3185)	(0.3143)	(0.2324)
Asian	0.2192**	-0.3821*	0.2208**	0.2569**	-18.1547***
	(0.111)	(0.2215)	(0.1111)	(0.1255)	(0.4349)
Indian	-0.7095***	-0.6746***	-0.7089***	-0.736***	0.3159
	(0.0304)	(0.0446)	(0.0311)	(0.0369)	(0.4329)
Female	-0.6468*		-0.6475*	-0.6424*	-0.0673
	(0.3435)		(0.3432)	(0.3426)	(0.1048)
AQI 50-74	0.0028	-0.1414	0.0031	0.0385	0.1747
	(0.0476)	(0.0954)	(0.0475)	(0.0506)	(0.1534)
AQI 75-99	0.0161	-0.1534	0.0148	0.0496	-0.5286
	(0.0827)	(0.1555)	(0.0821)	(0.0838)	(0.3533)
AQI 100-109	0.0211		0.0221		-1.043
	(0.1592)		(0.1591)		(0.9244)
AQI 110-119	0.2754		0.2555		-18.0071***
	(0.2461)		(0.2536)		(0.3446)
AQI 120-129	0.1161		0.1057		-18.0274***
	(0.2687)		(0.2679)		(0.5368)
AQI 130-139	0.0986		0.1063		1.1565*
	(0.3444)		(0.3438)		(0.5928)
AQI 140-149	-0.4378		-0.4343		-18.0931***
	(0.2943)		(0.2994)		(0.6316)
AQI 150-159	0.3377		0.3372	0.268	-18.5105***
	(0.309)		(0.3077)	(0.354)	(0.5489)
AQI 160-169	-0.9747		-0.9738	-0.8915	-24.9032***
	(0.7714)		(0.7713)	(0.7804)	(1.2394)

Table 2.4A (Cont.): GLM-LL Regressions

	(1)	(2)	(3)	(4)	(5)
	Total Pop.	Elderly	Total Pop.	Non-Elderly	Kids < 13
AQI 170-179	-0.6372		-0.6356	-0.6295	2.3163***
	(0.545)		(0.5448)	(0.56)	(0.7466)
AQI 180_plus	-0.0344		-0.0431	0.2808***	-18.3294***
	(0.0769)		(0.0785)	(0.0929)	(0.8147)
AQI 100-124		-0.0104		0.0812	
		(0.3587)		(0.1255)	
AQI 125-149		-0.5628		0.1617	
		(0.3698)		(0.2935)	
AQI 150-174		0.3542***			
		(0.0948)			
AQI 175-199		-4.0486***			
		(0.2405)			
aqi200_plus		0.0919			
		(0.093)			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5A: GLM-LL Regressions for Intra-Day VOA Substitution

	(1)	(2)	(3)
	12pm - 6pm	6am - 12pm	Indoor
Alert	-0.3070**	-0.7940**	-0.1147
	(0.129)	(0.3448)	(0.3045)
Max Temp	-0.0274	0.0820	0.0005
	(0.0624)	(0.1588)	(0.0868)
Max Temp > 90	-0.0654	-0.2134	0.3167
	(0.0792)	(0.2676)	(0.3363)
Max Temp < 25	0.3448	-0.2883	2.0605
	(0.7465)	(1.2462)	(1.527)
Precipitation	-0.0784**	0.1299	0.1362*
	(0.0331)	(0.1062)	(0.0781)
Precipitation > 0.1	-0.2249	-0.4557***	-0.0732
	(0.0529)	(0.1548)	(0.1297)
Wind Speed	-0.0139**	0.0150	0.0261
	(0.0064)	(0.014)	(0.0202)
Max Temp 2	0.0018	-0.0029	0.0008
	(0.0016)	(0.0042)	(0.0024)
Max Temp 3	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Max Temp 4	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Kids < 12 yrs	-0.0966**	0.0451	-0.7014
	(0.0385)	(0.0972)	(0.1664)
Age	0.0288***	0.0200*	0.0231*
	(0.0061)	(0.0104)	(0.0126)
Income > 75,000	0.1573***	0.1952**	0.4252***
	(0.0375)	(0.0775)	(0.0953)
Bachlor Degree Plus	-0.0119	0.2064**	
	(0.0389)	(0.0878)	
Age 2	-0.0003***	-0.0002*	-0.0005***
	(0.0001)	(0.0001)	(0.0002)
Retired	0.0531	0.0474	0.4853**
	(0.0654)	(0.1741)	(0.2066)
Unemployed	0.2952***	0.2148	-0.3444***
	(0.0408)	(0.145)	(0.1183)
Part-time Student	0.1722***	0.0726	-0.2567**
	(0.0425)	(0.1298)	(0.1241)
Full-time Student	-0.3553***	-0.7131***	0.5874***
	(0.1167)	(0.2248)	(0.1327)
Pregnant	-0.6340	-2.0482***	-0.7126
	(0.4311)	(0.7761)	(0.5866)

Table 2.5A (Cont): GLM-LL Regressions for Intra-Day VOA Substitution

	(1)	(2)	(3)
	12pm - 6pm	6am - 12pm	Indoor
Married	0.2757***	0.1486**	-0.0956
	(0.0395)	(0.0716)	(0.145)
Mexican	0.1987	0.0930	0.0402
	(0.154)	(0.2461)	(0.3433)
Hispanic	-0.4374***	-0.5931**	-0.3765
	(0.1451)	(0.2316)	(0.3367)
Black	-0.7304***	-0.1499	-0.0364
	(0.063)	(0.0928)	(0.1358)
Asian	-0.0730	-0.5510	-0.727
	(0.3233)	(0.7476)	(0.7192)
Indian	0.1977	0.4771	-0.1819
	(0.125)	(0.2941)	(0.4179)
Female	-0.7073***	-0.6769***	-0.4355***
	(0.0327)	(0.1049)	(0.0705)
aqi50_74	0.0022	0.0140	-0.0093
	(0.054)	(0.1212)	(0.1425)
aqi75_99	-0.0060	0.4327**	-0.3256*
	(0.1071)	(0.1948)	(0.1945)
aqi100_109	-0.0257	0.1339	0.005
	(0.2007)	(0.4592)	(0.399)
aqi110_119	0.1973	0.7334*	0.503
	(0.3517)	(0.3915)	(0.454)
aqi120_129	-0.0913	0.6898	-22.2149***
	(0.4261)	(0.509)	(0.5014)
aqi130_139	0.0365	0.9970**	0.8108
	(0.3774)	(0.478)	(0.5914)
aqi140_149	-1.8340**	-16.8791***	-22.3614***
	(0.8153)	(0.4322)	(0.4294)
aqi150_151	0.2409	1.1200**	-22.3551***
	(0.3544)	(0.4691)	(0.5348)
aqi160_169	-0.4997	-17.2606***	-21.7611***
	(1.1741)	(0.8142)	(0.6631)
aqi170_179	-0.2565	-17.6775***	-21.2488***
	(0.2382)	(0.6434)	(0.7997)
aqi180_plus	0.1218	0.1493	-21.3916***
	(0.0776)	(0.1211)	(0.8175)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6A: GLM-LL Regressions for Intra-Day VOA Substitution

	(1)	(2)	(3)
	Alert Prev. Day	Alert Next Day	Alert 2 Prev Days
Alert	-0.1482	-0.2517**	-0.1561
	(0.1344)	(0.108)	(0.1337)
Alert Previous	-0.2835*		-0.1538
	(0.1462)		(0.167)
Alert 2 days Previous			0.2562
			(0.1707)
Alert*Alert Prev.	0.1843		0.1633
	(0.2316)		(0.1998)
Alert*Alert 2 Prev.			0.2165
			(0.3434)
Alert*Alert Prev.*Alert 2 Prev			-0.2013
			(0.4205)
Alert Prev.*Alert 2 Prev			-0.4466
			(0.3665)
Alert Next		-0.0038	
		(0.1882)	
Alert*Alert Next		0.1439	
		(0.2313)	
Max Temp	-0.0389	-0.0434	-0.0405
	(0.0597)	(0.0589)	(0.0591)
Max Temp > 90	-0.0564	-0.0582	-0.0526
	(0.0651)	(0.0638)	(0.0629.)
Max Temp < 25	-0.1231	-0.1338	-0.1184
	(0.6291)	(0.6301)	(0.6302313)
Precipitation	-0.0640**	-0.0644**	-0.0672**
	(0.0304)	(0.0302)	(0.0293)
Precipitation > 0.1	-0.2475***	-0.2482***	-0.2460***
	(0.0449)	(0.0451)	(0.0444)
Wind Speed	-0.0090*	-0.0090*	-0.0089*
	(0.0053)	(0.0052)	(0.0053)
Max Temp 2	0.0015	0.0016	0.0015
	(0.0015)	(0.0015)	(0.0015)
Max Temp 3	0.0000	0.0000	0.0000
	(0)	(0)	(0)
Max Temp 4	0.0000	0.0000	0.0000
	(0)	(0)	(0)
Kids < 12 yrs	-0.0923***	-0.0930***	-0.091543**
	(0.0351)	(0.0352)	(0.0354)
Age	0.0452***	0.0453***	0.0448***
	(0.0057)	(0.0057)	(0.0057)

Table 2.6A (Cont): GLM-LL Regressions for Intra-Day VOA Substitution

	(1)	(2)	(3)
	Alert Prev. Day	Alert Next Day	Alert 2 Prev Days
Income > 75,000	0.1466***	0.1467***	0.1469***
	(0.0342)	(0.0343)	(0.0344)
Bachlor Degree Plus	-0.0051	-0.0065	-0.0057
	(0.0369)	(0.0366)	(0.0367)
Age 2	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)
Retired	0.1510**	0.1524**	0.1483**
	(0.0596)	(0.0597)	(0.0587)
Unemployed	0.2299***	0.2304***	0.2306***
	(0.0386)	(0.0379)	(0.0386)
Part-time Student	0.1086***	0.1102***	0.1091***
	(0.0385)	(0.0384)	(0.0384)
Full-time Student	-0.4782***	-0.4776***	-0.4776***
	(0.1197)	(0.1191)	(0.1206)
Pregnant	-0.6555*	-0.6468*	-0.6729*
	(0.3432)	(0.3433)	(0.3464)
Married	0.2616***	0.2611***	0.2613***
	(0.0312)	(0.0313)	(0.031)
Mexican	0.1900	0.1937	0.1888
	(0.1448)	(0.1463)	(0.1449)
Hispanic	-0.4029***	-0.4055***	-0.4023***
	(0.1396)	(0.1412)	(0.14)
Black	-0.6314***	-0.6313***	-0.6365***
	(0.0497238)	(0.0499)	(0.0506)
Asian	-0.1742	-0.1680	-0.1718
	(0.3185086)	(0.3184)	(0.319)
Indian	0.2178**	0.2193**	0.2167**
	(0.111)	(0.1108)	(0.1103)
Female	-0.7088***	-0.7097***	-0.7097***
	(0.0306)	(0.0305)	(0.03)
AQI 50-74	0.0024	0.0022	0.0025
	(0.047)	(0.0475)	(0.0472)
AQI 75-99	0.0175	0.0136	0.0199
	(0.0826)	(0.0831)	(0.0826)
AQI 100-124	0.0610	0.0556	0.0551
	(0.128)	(0.1289)	(0.1279)
AQI 125-149	0.0903	0.0916	0.0785
	(0.2391)	(0.2403)	(0.2374)
AQI 150-159	0.3282	0.3356	0.3410
	(0.3111)	(0.3102)	(0.3118)

Table 2.6A (Cont): GLM-LL Regressions for Intra-Day VOA Substitution

	(1)	(2)	(3)
	Alert Prev. Day	Alert Next Day	Alert 2 Prev Days
AQI 160-169	-0.9803	-0.9814	-0.9717
	(0.7738)	(0.7677)	(0.7663)
AQI 170-179	-0.6448	-0.6391	-0.6289
	(0.5448)	(0.5445)	(0.5422)
AQI 180-Plus	-0.0387	-0.0386	-0.0324
	(0.0804)	(0.0815)	(0.0809)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table 3.3A: RDD Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	-29.875**	25.401**	-12.487	-34.298**	-16.829	18.668**	8.831
	(14.967)	(11.188)	(8.772)	(13.598)	(12.001)	(9.323)	(10.865)
Date	3.262	-3.328	2.106	7.052**	4.436*	-3.929**	-2.712
	(3.181)	(2.378)	(1.865)	(2.890)	(2.551)	(1.982)	(2.309)
DST*Date	-1.729	0.490	-1.404	-6.120**	-2.525	3.499*	2.698
	(3.332)	(2.491)	(1.953)	(3.027)	(2.672)	(2.075)	(2.419)
Retired	6.664	0.077	4.282	-11.941	-2.220	-5.399	5.754
	(10.326)	(7.719)	(6.052)	(9.382)	(8.280)	(6.432)	(7.496)
Female	14.487***	2.537	9.586***	14.666***	-23.046***	-6.994**	-6.330*
	(4.532)	(3.388)	(2.656)	(4.118)	(3.634)	(2.823)	(3.290)
Advance degree	-5.589	3.642	-13.139***	-21.230***	-6.316	5.478	13.026**
	(7.557)	(5.649)	(4.429)	(6.866)	(6.060)	(4.707)	(5.486)
Observations	1,080	1,080	1,080	1,080	1,080	1,080	1,080
R^2	0.115	0.139	0.228	0.134	0.192	0.228	0.109

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.3A (Cont): RDD Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Child under 13	-12.055**	16.937***	11.229***	10.359**	-2.224	-4.248	-0.187
	(5.737)	(4.289)	(3.363)	(5.213)	(4.600)	(3.574)	(4.165)
Latitude	0.398	-0.291	-0.249	0.229	-0.338	-0.224	-0.551
	(0.531)	(0.397)	(0.311)	(0.482)	(0.426)	(0.331)	(0.385)
Age	-1.967**	2.327***	0.293	0.278	-0.503	-1.044*	-0.880
	(0.910)	(0.680)	(0.533)	(0.827)	(0.730)	(0.567)	(0.661)
Age*age	0.016	-0.018**	0.001	0.005	0.003	0.009	0.007
	(0.011)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)	(0.008)
Married	-5.949	-1.110	2.594	11.228**	3.164	-1.740	-2.366
	(5.142)	(3.844)	(3.014)	(4.672)	(4.123)	(3.203)	(3.733)
Elderly	-2.295	11.707	5.438	-1.058	-13.891	-8.980	-4.162
	(13.092)	(9.787)	(7.673)	(11.895)	(10.498)	(8.155)	(9.504)
Observations	1,080	1,080	1,080	1,080	1,080	1,080	1,080
R^2	0.115	0.139	0.228	0.134	0.192	0.228	0.109

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.3A (Cont): RDD Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Outside city	-7.584*	0.258	-1.810	-4.559	2.362	0.425	-2.583
	(4.409)	(3.296)	(2.584)	(4.006)	(3.535)	(2.746)	(3.201)
Max temp	0.300	-0.072	-0.218*	-0.410**	-0.160	0.151	0.245*
	(0.193)	(0.144)	(0.113)	(0.175)	(0.155)	(0.120)	(0.140)
MST	-0.846	12.342	-1.031	18.248	-1.342	8.241	6.240
	(12.704)	(9.496)	(7.446)	(11.542)	(10.186)	(7.913)	(9.223)
CST	-2.543	3.717	6.121**	5.521	-0.017	-5.068	-2.308
	(5.080)	(3.797)	(2.977)	(4.615)	(4.073)	(3.164)	(3.688)
PST	-6.656	7.424	4.920	6.577	-3.204	-8.686**	-7.124
	(6.058)	(4.529)	(3.551)	(5.504)	(4.858)	(3.774)	(4.398)
Observations	1,080	1,080	1,080	1,080	1,080	1,080	1,080
R^2	0.115	0.139	0.228	0.134	0.192	0.228	0.109

Standard errors in parentheses

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

Appendix Table 3.3A (Cont): RDD Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
After 2006	7.183	-5.255	0.932	4.434	-0.410	0.547	-3.730
	(4.619)	(3.453)	(2.707)	(4.196)	(3.703)	(2.877)	(3.353)
Tuesday	9.306	-6.561	-1.486	1.919	-0.846	-4.579	-3.039
	(7.054)	(5.273)	(4.134)	(6.408)	(5.656)	(4.394)	(5.121)
Wednesday	-0.074	-12.172**	-6.092	-3.709	5.944	4.299	5.631
	(7.144)	(5.340)	(4.187)	(6.490)	(5.728)	(4.450)	(5.186)
Thursday	-2.716	-0.603	-3.162	-9.194	-1.206	3.614	8.177
	(7.220)	(5.397)	(4.231)	(6.559)	(5.789)	(4.497)	(5.241)
Friday	-2.063	-1.627	-5.175	-15.131**	-5.694	4.878	8.816
	(7.792)	(5.824)	(4.567)	(7.079)	(6.247)	(4.853)	(5.656)
Observations	1,080	1,080	1,080	1,080	1,080	1,080	1,080
R^2	0.115	0.139	0.228	0.134	0.192	0.228	0.109

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.4A: RDD Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	15.307	-2.421	1.039	0.294	-1.859	1.544	-0.881
	(15.628)	(11.594)	(9.784)	(15.069)	(12.750)	(10.331)	(11.757)
Date	2.157	-1.184	1.649*	-0.708	-0.252	-0.698	0.445
	(1.512)	(1.121)	(0.946)	(1.458)	(1.233)	(0.999)	(1.137)
DST*date	-2.736	1.551	-3.436	0.694	1.412	1.270	-1.252
	(3.337)	(2.475)	(2.089)	(3.217)	(2.722)	(2.206)	(2.510)
Retired	31.984***	-18.656**	12.578*	4.762	-4.644	-2.432	5.492
	(10.424)	(7.733)	(6.526)	(10.051)	(8.504)	(6.891)	(7.842)
Female	2.676	11.808***	7.124**	9.131**	-19.304***	-4.883	-3.004
	(4.603)	(3.415)	(2.882)	(4.438)	(3.755)	(3.043)	(3.463)
Advance degree	1.468	-6.444	-3.914	-11.322	-3.437	13.277***	13.921**
	(7.346)	(5.450)	(4.599)	(7.083)	(5.993)	(4.856)	(5.527)
Observations	940	940	940	940	940	940	940
R^2	0.098	0.178	0.214	0.110	0.213	0.220	0.070

Standard errors in parentheses

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

Appendix Table 3.4A (Cont): RDD Results: Fall DST Transition

Variables	(1) sleep5am9am	(2) home5am9am	(3) home3pm5pm	(4) home5p8pm	(5) away5am9am	(6) away3pm5pm	(7) away5pm8pm
Child under 13	-4.097	21.080***	12.899***	13.306**	-12.184**	-9.152**	-1.772
	(5.822)	(4.319)	(3.645)	(5.614)	(4.750)	(3.849)	(4.380)
Latitude	0.318	-0.649	-0.109	0.145	0.573	-0.466	-0.554
	(0.550)	(0.408)	(0.344)	(0.530)	(0.449)	(0.364)	(0.414)
Age	-0.601	1.754***	-0.550	0.141	-1.344*	1.247**	-0.097
	(0.894)	(0.663)	(0.560)	(0.862)	(0.729)	(0.591)	(0.672)
Age*age	-0.000	-0.009	0.010	0.003	0.010	-0.019***	-0.002
	(0.011)	(0.008)	(0.007)	(0.010)	(0.009)	(0.007)	(0.008)
Married	-4.408	8.567**	1.364	7.996	0.608	-1.652	0.564
	(5.136)	(3.810)	(3.216)	(4.952)	(4.190)	(3.395)	(3.864)
Elderly	20.418	4.139	-0.433	3.627	-20.036*	6.162	-6.863
	(13.182)	(9.779)	(8.253)	(12.711)	(10.755)	(8.714)	(9.917)
Observations	940	940	940	940	940	940	940
R^2	0.098	0.178	0.214	0.110	0.213	0.220	0.070

Standard errors in parentheses

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

Appendix Table 3.4A (Cont): RDD Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Outside city	-4.852	1.242	-2.552	-5.327	4.195	1.536	0.799
	(4.592)	(3.407)	(2.875)	(4.428)	(3.747)	(3.036)	(3.455)
Max temp	0.136	-0.266	0.314	-0.683	-0.513	-0.144	-0.028
	(1.759)	(1.305)	(1.101)	(1.696)	(1.435)	(1.162)	(1.323)
MST	8.416	3.716	16.218**	5.885	-7.515	-11.953	-2.099
	(12.293)	(9.120)	(7.696)	(11.853)	(10.029)	(8.127)	(9.248)
CST	3.326	-0.084	-2.850	-15.195***	-0.463	3.404	7.795*
	(5.285)	(3.920)	(3.308)	(5.095)	(4.311)	(3.493)	(3.975)
PST	4.943	1.715	-0.286	-3.494	-2.702	-1.571	-0.663
	(6.146)	(4.559)	(3.848)	(5.926)	(5.014)	(4.063)	(4.623)
Observations	940	940	940	940	940	940	940
R^2	0.098	0.178	0.214	0.110	0.213	0.220	0.070

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.4A (Cont): RDD Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
After 2006	-11.751**	5.235	-2.152	1.872	5.270	2.348	-5.151
	(4.705)	(3.490)	(2.946)	(4.536)	(3.838)	(3.110)	(3.539)
Tuesday	3.683	5.210	8.360*	1.662	-3.189	-6.503	-3.515
	(7.055)	(5.234)	(4.417)	(6.803)	(5.756)	(4.664)	(5.308)
Wednesday	7.426	-1.606	6.574	-3.123	-6.119	-16.497***	-5.997
	(7.277)	(5.399)	(4.556)	(7.017)	(5.937)	(4.811)	(5.475)
Thursday	0.394	5.115	-0.126	-5.725	-5.764	-5.699	0.055
	(8.146)	(6.043)	(5.100)	(7.854)	(6.646)	(5.385)	(6.128)
Friday	2.531	5.098	-2.412	-17.254**	-2.655	-2.645	7.517
	(8.970)	(6.654)	(5.616)	(8.649)	(7.318)	(5.929)	(6.748)
Observations	940	940	940	940	940	940	940
R^2	0.098	0.178	0.214	0.110	0.213	0.220	0.070

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.5A: Dif & Dif Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Week 2	1.342	6.191	6.839	12.614	-11.910	-2.924	-4.273
	(6.953)	(5.131)	(5.881)	(9.259)	(8.095)	(6.182)	(7.381)
Treatment	7.173	2.208	5.526	-2.934	-16.003**	-2.887	-0.848
	(6.048)	(4.463)	(5.161)	(8.125)	(7.104)	(5.425)	(6.477)
Week 2*treatment	-20.509*	6.803	-11.969	-12.223	23.135**	11.755	5.019
	(10.852)	(8.008)	(8.256)	(12.999)	(11.365)	(8.679)	(10.362)
Week 2*treatment*employed	8.650	-9.807	0.768	4.240	-5.438	-8.159	-3.849
	(8.627)	(6.366)	(6.966)	(10.967)	(9.589)	(7.323)	(8.743)
Week 2*treatment*weekend	20.062**	-14.083**					
	(8.552)	(6.311)					
Retired	15.642*	-12.345*	6.045	-7.510	-5.312	-3.149	2.014
	(8.771)	(6.472)	(7.157)	(11.267)	(9.851)	(7.523)	(8.982)
Observations	1,376	1,376	663	663	663	663	663
R^2	0.162	0.104	0.286	0.150	0.198	0.266	0.090

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.5A (Cont): Dif & Dif Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Female	6.347	5.229*	5.435	6.857	-25.145***	-2.001	-2.312
	(4.083)	(3.013)	(3.385)	(5.329)	(4.659)	(3.558)	(4.248)
Advance degree	-1.034	2.822	-7.637	-18.267**	-9.357	-4.028	1.617
	(6.781)	(5.004)	(5.653)	(8.900)	(7.781)	(5.942)	(7.095)
Child under 13	-5.808	12.258***	12.135***	10.198	-2.957	-4.516	-0.756
	(5.132)	(3.787)	(4.252)	(6.695)	(5.853)	(4.470)	(5.337)
Latitude	0.341	-0.120	-0.486	-0.303	-0.743	-0.047	-0.508
	(0.486)	(0.359)	(0.392)	(0.618)	(0.540)	(0.413)	(0.493)
Age	-1.204*	1.069**	-0.539	1.061	-0.400	0.143	-0.861
	(0.665)	(0.491)	(0.556)	(0.876)	(0.766)	(0.585)	(0.698)
Age*age	0.005	-0.002	0.012*	-0.002	-0.001	-0.005	0.006
	(0.007)	(0.005)	(0.006)	(0.010)	(0.008)	(0.006)	(0.008)
Observations	1,376	1,376	663	663	663	663	663
R^2	0.162	0.104	0.286	0.150	0.198	0.266	0.090

Standard errors in parentheses

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

Appendix Table 3.5A (Cont): Dif & Dif Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Married	-11.540**	7.615**	-0.426	9.226	3.837	-1.340	-2.760
	(4.561)	(3.365)	(3.820)	(6.014)	(5.258)	(4.015)	(4.794)
Central city	8.543**	-3.637	0.526	-3.643	-0.363	2.256	2.260
	(4.303)	(3.175)	(3.542)	(5.576)	(4.875)	(3.723)	(4.445)
Max temp	1.009	0.401	-1.097	-1.526	-0.987	1.208	0.158
	(0.948)	(0.699)	(0.836)	(1.316)	(1.151)	(0.879)	(1.049)
Max temp*max temp	-0.007	-0.004	0.008	0.010	0.007	-0.010	-0.000
	(0.008)	(0.006)	(0.007)	(0.011)	(0.010)	(0.007)	(0.009)
PST	-8.579	2.479	3.668	7.729	-1.000	-9.818**	-2.207
	(5.460)	(4.029)	(4.484)	(7.060)	(6.172)	(4.714)	(5.628)
MST	-8.606	3.191	11.620	28.153*	-3.573	2.770	-3.830
	(11.609)	(8.566)	(9.434)	(14.854)	(12.987)	(9.918)	(11.841)
CST	-1.284						
	(4.659)						
Observations	1,376	1,376	663	663	663	663	663
R^2	0.162	0.104	0.286	0.150	0.198	0.266	0.090

Standard errors in parentheses

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

Appendix Table 3.5A (Cont). Dif & Dif Results: Spring DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Tuesday	3.002	-10.746	8.628*	0.416	3.301	-0.497	-1.396
	(9.101)	(6.715)	(5.219)	(8.216)	(7.183)	(5.486)	(6.550)
Wednesday	6.185	-9.817	-1.687	-1.157	2.409	3.448	9.115
	(9.109)	(6.722)	(5.208)	(8.200)	(7.169)	(5.475)	(6.537)
Thursday	1.695	-1.636	12.065**	1.494	4.689	-0.920	10.348
	(8.887)	(6.558)	(5.097)	(8.025)	(7.016)	(5.358)	(6.397)
Friday	5.623	-13.929**	5.633	4.822	3.974	0.887	4.531
	(9.072)	(6.694)	(5.221)	(8.221)	(7.187)	(5.489)	(6.553)
Saturday	51.366***	-0.182					
	(7.919)	(5.844)					
Sunday	45.284***	-8.680					
	(8.109)	(5.984)					
Observations	1,376	1,376	663	663	663	663	663
R^2	0.162	0.104	0.286	0.150	0.198	0.266	0.090

Standard errors in parentheses

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

Appendix Table 3.6A: Dif & Dif Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Week 1	-7.395	-1.457	-4.218	-9.295	7.894	2.586	9.730**
	(6.858)	(5.032)	(4.106)	(6.449)	(5.475)	(4.303)	(4.880)
Treatment	-11.340	0.658	-2.974	-6.200	9.586	7.062	4.216
	(7.395)	(5.426)	(4.427)	(6.954)	(5.904)	(4.640)	(5.262)
Week 1*treatment	12.399	8.640	11.986*	24.405**	-16.949*	-12.870*	-11.384
	(11.627)	(8.532)	(6.961)	(10.933)	(9.283)	(7.295)	(8.273)
Week 1*treat*employ	-1.720	-7.960	-8.738	-18.073*	8.891	5.778	2.425
	(10.788)	(7.917)	(6.459)	(10.145)	(8.613)	(6.769)	(7.676)
Retired	29.872***	-11.862	9.137	-0.014	-8.295	-2.035	5.521
	(10.242)	(7.516)	(6.132)	(9.631)	(8.177)	(6.426)	(7.287)
Observations	882	882	882	882	882	882	882
R^2	0.117	0.166	0.253	0.109	0.223	0.234	0.073

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.6A (Cont): Dif & Dif Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Female	1.417	6.780*	4.842	9.148**	-17.325***	-5.156*	-5.444
	(4.914)	(3.606)	(2.942)	(4.620)	(3.923)	(3.083)	(3.496)
Advance degree	-4.266	-3.429	-7.705*	-12.082*	-0.781	12.079**	9.482*
	(7.784)	(5.712)	(4.660)	(7.320)	(6.215)	(4.884)	(5.539)
Child under 13	-2.767	20.608***	16.741***	4.534	-12.109**	-2.654	7.581*
	(6.273)	(4.603)	(3.755)	(5.899)	(5.008)	(3.936)	(4.463)
Latitude	0.365	-0.836**	-0.176	-0.692	0.257	-0.052	-0.095
	(0.573)	(0.420)	(0.343)	(0.539)	(0.457)	(0.359)	(0.408)
Age	-0.387	1.352**	-0.436	0.612	-0.652	0.702	-0.216
	(0.804)	(0.590)	(0.481)	(0.756)	(0.642)	(0.504)	(0.572)
Age*age	0.003	-0.006	0.010*	-0.000	0.000	-0.011**	-0.001
	(0.009)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)
Observations	882	882	882	882	882	882	882
R^2	0.117	0.166	0.253	0.109	0.223	0.234	0.073

Standard errors in parentheses

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

Appendix Table 3.6A: (Cont). Dif & Dif Results: Fall DST Transition

Variables	(1) sleep5am9am	(2) home5am9am	(3) home3pm5pm	(4) home5p8pm	(5) away5am9am	(6) away3pm5pm	(7) away5pm8pm
Married	-11.132**	10.013**	-2.090	11.269**	2.275	-2.041	-5.033
	(5.476)	(4.019)	(3.279)	(5.149)	(4.372)	(3.436)	(3.897)
Central city	10.989**	-2.910	2.051	0.620	-5.618	-0.843	2.641
	(5.373)	(3.943)	(3.217)	(5.052)	(4.290)	(3.371)	(3.823)
Max temp	2.588	-0.056	0.610	0.028	-2.018	-0.516	-0.968
	(1.681)	(1.234)	(1.006)	(1.581)	(1.342)	(1.055)	(1.196)
Max temp squared	-0.023*	-0.001	-0.005	-0.001	0.017*	0.004	0.007
	(0.013)	(0.010)	(0.008)	(0.012)	(0.010)	(0.008)	(0.009)
PST	6.394	0.102	4.539	-3.011	-5.404	-4.726	-3.953
	(6.433)	(4.721)	(3.851)	(6.049)	(5.136)	(4.036)	(4.577)
MST	26.184	17.711	34.474***	16.145	-21.401	-23.299**	-2.811
	(18.158)	(13.324)	(10.871)	(17.074)	(14.497)	(11.393)	(12.920)
CST	5.221	-2.297	-0.216	-11.047**	-4.015	3.406	6.535*
	(5.536)	(4.062)	(3.314)	(5.206)	(4.420)	(3.473)	(3.939)
Observations	882	882	882	882	882	882	882
R^2	0.117	0.166	0.253	0.109	0.223	0.234	0.073

Standard errors in parentheses

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

Appendix Table 3.6A (Cont): Dif & Dif Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
Tuesday	6.197	-1.513	10.119**	-0.187	-5.928	-6.677	-4.158
	(7.607)	(5.582)	(4.554)	(7.153)	(6.073)	(4.773)	(5.413)
Wednesday	8.154	-5.813	10.313**	-2.904	-4.752	-13.829***	-3.411
	(7.573)	(5.557)	(4.534)	(7.121)	(6.046)	(4.751)	(5.388)
Thursday	5.474	5.407	4.640	-2.257	-8.875	0.236	2.703
	(7.655)	(5.617)	(4.583)	(7.198)	(6.111)	(4.803)	(5.447)
Friday	8.329	-1.116	3.061	-0.742	-2.195	-5.385	0.673
	(7.597)	(5.575)	(4.548)	(7.143)	(6.065)	(4.766)	(5.405)
Observations	882	882	882	882	882	882	882
R^2	0.117	0.166	0.253	0.109	0.223	0.234	0.073

Standard errors in parentheses

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

Table 3.7A: RDD Results: Spring DST Transition (Range 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	-17.735	23.242**	-3.862	-5.618	-9.055	5.760	-11.160
	(13.030)	(9.938)	(7.627)	(11.924)	(10.362)	(8.101)	(9.467)
Observations	956	956	956	956	956	956	956
R^2	0.112	0.132	0.234	0.139	0.181	0.235	0.111

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3.8A: RDD Results: Fall DST Transition (Range 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5p8pm	away5am9am	away3pm5pm	away5pm8pm
DST	16.131	4.998	-8.538	-28.650**	-7.714	-1.432	12.540
	(12.350)	(9.302)	(7.703)	(11.959)	(10.115)	(8.203)	(9.261)
Observations	869	869	869	869	869	869	869
R^2	0.095	0.180	0.223	0.112	0.215	0.218	0.068

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3A: RDD Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4p8p
DST	15.141*	13.454*
	(8.047)	(7.562)
Date	-2.114	-1.419
	(1.572)	(1.478)
DST*Date	0.066	-0.761
	(2.051)	(1.927)
After 2006	-1.076	-0.756
	(2.998)	(2.817)
Retired	-1.705	-0.088
	(6.764)	(6.357)
Female	-10.074***	-8.411***
	(2.967)	(2.788)
Observations	956	956
R^2	0.070	0.060

Standard errors in parentheses

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

Table 3.9A: RDD Results: Spring DST Transition (Range 12)

Variables	(1) sleep5am9am	(2) home5am9am	(3) home3pm5pm	(4) home5pm8pm	(5) away5am9am	(6) away3pm5pm	(7) away5pm8pm
DST	-21.524***	5.200	-4.127	-5.484	8.981	4.244	-1.589
	(7.512)	(5.494)	(4.451)	(6.864)	(5.947)	(4.629)	(5.486)
Observations	1,868	1,868	1,868	1,868	1,868	1,868	1,868
R^2	0.106	0.125	0.222	0.129	0.185	0.231	0.097

Standard errors in parentheses

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

Appendix Table 3.10A: RDD Results: Fall DST Transition (Range 12)

	(1)	(2)	(3)	(4)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5pm8pm
DST	17.768**	1.413	4.227	7.207
	(7.528)	(5.520)	(4.622)	(7.220)
Observations	1,739	1,739	1,739	1,739
R^2	0.091	0.177	0.217	0.094

Standard errors in parentheses

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

Robustness Table 3.11A: RDD Results: Spring DST Transition (Placebo)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5pm8pm	away5am9am	away3pm5pm	away5pm8pm
DST robust	-16.147	6.718	0.152	10.967	6.534	-9.636	-7.641
	(15.478)	(10.665)	(9.097)	(14.138)	(12.053)	(9.439)	(11.266)
Observations	968	968	968	968	968	968	968
R^2	0.097	0.157	0.243	0.141	0.202	0.266	0.104

Standard errors in parentheses

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

Robustness Table 3.12A: RDD Results: Fall DST Transition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	sleep5am9am	home5am9am	home3pm5pm	home5pm8pm	away5am9am	away3pm5pm	away5pm8pm
DST robust	-0.280	-0.415	-13.907	0.563	-4.306	3.727	-0.410
	(15.914)	(11.825)	(10.134)	(15.373)	(13.482)	(10.428)	(11.858)
Observations	905	905	905	905	905	905	905
R^2	0.108	0.203	0.216	0.105	0.220	0.232	0.084

Standard errors in parentheses

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

Table 4.3A (Cont): RDD Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Advance degree	9.361*	9.947**
	(4.997)	(4.696)
Child under 13	-11.167***	-9.611***
	(3.764)	(3.537)
Latitude	0.624*	0.472
	(0.348)	(0.327)
Age	-1.214**	-0.706
	(0.584)	(0.548)
Age*age	0.010	0.006
	(0.007)	(0.007)
Married	-2.190	-0.800
	(3.386)	(3.183)
Elderly	-5.993	-6.975
	(8.522)	(8.009)
Observations	956	956
R^2	0.070	0.060

Standard errors in parentheses

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

Table 4.3A (Cont): RDD Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Outside city	2.046	1.114
	(2.874)	(2.701)
Max temp	0.277**	0.232**
	(0.125)	(0.117)
MST	-3.838	-1.521
	(7.960)	(7.481)
CST	-0.734	-0.471
	(3.318)	(3.118)
PST	4.643	2.658
	(4.001)	(3.760)
Observations	956	956
R^2	0.070	0.060

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.4A: RDD Results: Fall DST Transition

Variables	(1) Total APAs	(2) APAs 4pm8pm
DST	12.392	-1.914
	(42.367)	(39.837)
Date	-0.806	-0.532
	(0.525)	(0.493)
DST*date	0.030	-0.030
	(0.190)	(0.179)
After 2006	-25.134	-17.565
	(16.099)	(15.137)
Retired	-1.934	-0.201
	(6.784)	(6.379)
Female	-10.268***	-8.622***
	(2.966)	(2.788)
Observations	956	956
R^2	0.068	0.057

Standard errors in parentheses

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

Table 4.4A (Cont): RDD Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Advance degree	9.569*	10.227**
	(4.994)	(4.696)
Child under 13	-11.299***	-9.669***
	(3.771)	(3.545)
Latitude	0.560	0.420
	(0.347)	(0.326)
Age	-1.193**	-0.684
	(0.584)	(0.549)
Age*age	0.010	0.006
	(0.007)	(0.007)
Married	-2.277	-0.901
	(3.389)	(3.186)
Elderly	-5.891	-6.852
	(8.530)	(8.020)
Observations	956	956
R^2	0.068	0.057

Standard errors in parentheses

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

Table 4.4A (Cont): RDD Results: Fall DST Transition

	(1)	(2)
Variables	Totals APAs	APAs 4pm8pm
Outside city	2.089	1.148
	(2.878)	(2.706)
Max temp	0.242*	0.202*
	(0.124)	(0.117)
MST	-2.878	-0.718
	(7.965)	(7.490)
CST	-0.761	-0.503
	(3.321)	(3.123)
PST	4.637	2.662
	(4.007)	(3.767)
Observations	956	956
R^2	0.068	0.057

Standard errors in parentheses

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

Table 4.5A: Logit DID Results: Spring DST Transition

Variables	(1) Total APAs	(2) APAs 4pm8pm
Week 2	-0.587	-0.433
	(0.394)	(0.394)
Treatment	-0.640*	-0.644*
	(0.347)	(0.353)
Week 2*treatment	0.827*	0.724
	(0.489)	(0.491)
Retired	-0.659	-0.582
	(0.513)	(0.511)
Female	-0.325	-0.316
	(0.233)	(0.236)
Advance degree	0.618*	0.642*
	(0.351)	(0.350)
Observations	606	606

Standard errors in parentheses

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

Table 4.5A (Cont): Logit DID Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
No college degree	-0.197	-0.230
	(0.267)	(0.270)
Income_a75	0.498*	0.467*
	(0.261)	(0.264)
Child under 13	-0.515*	-0.451
	(0.310)	(0.314)
Latitude	0.078**	0.076**
	(0.038)	(0.039)
Age	-0.069	-0.046
	(0.044)	(0.044)
Age*age	0.001	0.000
	(0.001)	(0.001)
Elderly	0.465	0.416
	(0.667)	(0.663)
Observations	606	606

Standard errors in parentheses

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

Table 4.5A (Cont): Logit DID Results: Spring DST Transition

Variables	(1) Total APAs	(2) APAs 4pm8pm
Married	0.018	0.033
	(0.283)	(0.285)
Outside city	-0.017	0.001
	(0.257)	(0.261)
Small metro	0.450	0.422
	(0.375)	(0.380)
Non metro	-10.478	-11.188
	(666.912)	(972.307)
Non white	0.219	0.326
	(0.285)	(0.285)
Max temp	0.016	0.017
	(0.018)	(0.018)
Observations	606	606

Standard errors in parentheses

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

Table 4.5A (Cont): Logit DID Results: Spring DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Precipitation	-0.437*	-0.360
	(0.260)	(0.261)
Min Temp	-0.012	-0.014
	(0.018)	(0.019)
Tuesday	0.155	0.105
	(0.364)	(0.365)
Wednesday	0.637*	0.444
	(0.353)	(0.357)
Thursday	0.346	0.293
	(0.359)	(0.359)
Friday	-0.520	-0.481
	(0.415)	(0.413)
Observations	606	606

Standard errors in parentheses

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

Table 4.6A: Logit DID Results: Fall DST Transition

Variables	(1) Total APAs	(2) APAs 4pm8pm
Week 1	0.737	0.737
	(0.468)	(0.466)
Treatment	-0.039	-0.099
	(0.269)	(0.272)
Week 1*Treatment	-0.909	-0.827
	(0.643)	(0.641)
Retired	-0.636	-0.580
	(0.506)	(0.505)
Female	-0.315	-0.312
	(0.232)	(0.234)
Advance degree	0.652*	0.679*
	(0.352)	(0.351)
Observations	606	606

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6A: (Cont). Logit DID Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
No college degree	-0.165	-0.196
	(0.265)	(0.268)
Income_a75	0.482*	0.460*
	(0.259)	(0.263)
Child under 13	-0.463	-0.400
	(0.308)	(0.312)
Latitude	0.080**	0.078**
	(0.038)	(0.039)
Age	-0.071	-0.050
	(0.044)	(0.044)
Age*age	0.001	0.000
	(0.001)	(0.001)
Elderly	0.471	0.427
	(0.663)	(0.660)
Observations	606	606
Number of statefip	25	25

Standard errors in parentheses

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

Table 4.6A: (Cont). Logit DID Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Elderly	0.471	0.427
	(0.663)	(0.660)
Married	0.045	0.065
	(0.284)	(0.287)
Outside city	-0.025	-0.015
	(0.258)	(0.262)
Small metro	0.408	0.377
	(0.376)	(0.381)
Non metro	-10.528	-10.474
	(644.460)	(659.397)
Non white	0.241	0.343
	(0.285)	(0.285)
Max temp	0.015	0.016
	(0.018)	(0.018)
Observations	606	606
Number of statefip	25	25

Standard errors in parentheses

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

Table 4.6A (Cont): Logit DID Results: Fall DST Transition

	(1)	(2)
Variables	Total APAs	APAs 4pm8pm
Precipitation	-0.417	-0.368
	(0.264)	(0.266)
Min Temp	-0.007	-0.009
	(0.019)	(0.019)
Tuesday	0.156	0.099
	(0.363)	(0.364)
Wednesday	0.619*	0.416
	(0.350)	(0.355)
Thursday	0.378	0.313
	(0.360)	(0.360)
Friday	-0.516	-0.485
	(0.416)	(0.415)
Observations	606	606

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Table 4.7A: RDD Results: Spring DST Robust Transition

	(1)	(2)
Variables	Total APAs	APAs 4p8p
DST Robust	-5.106	-3.357
	(7.945)	(6.610)
Observations	855	855
R^2	0.031	0.035

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness Table 4.8A: RDD Results: Fall DST Robust Transition

Variables	(1) APAs	(2) APAs 4p8p
DST Robust	4.163	7.612
	(8.273)	(7.783)
Observations	837	837
R^2	0.060	0.055

Standard errors in parentheses

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