# Sleep and Fatal Vehicle Crashes: Evidence from Sunset Time in the United States

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**Abstract**

Adequate sleep is critical for overall healthy functioning. Insufficient sleep has been linked to a decline in attention and cognitive function, which poses a potential risk for vehicle crashes. This paper aims to study the impact of sleep on fatal vehicle crashes. For the short-term analysis, I explored the variation in sunset times throughout the year in a specific location. By using sunset time as an instrument, I found that a one-hour delay in sunset leads to a decrease of approximately 48 minutes in monthly sleep duration. Additionally, a one-hour increase in monthly sleep leads to about a 2.4% reduction in fatalities. For the long-term analysis, I employed two different approaches. First, I utilized the geographical variation in sunset time across counties within a time zone. However, the results from this approach were not statistically significant. Second, I applied spatial regression discontinuity, focusing on the timing of sunset at a time-zone boundary. From 2004 to 2013, I found that employed individuals sleep less on the later sunset side of the time zone border. However, from 2014 to 2019, they actually sleep more on the later sunset side. Interestingly, traffic fatalities were lower on the late sunset side from 2004 to 2013 but higher from 2014 to 2019.

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# 1 Introduction

Sleep is crucial for both human health and productivity, but its importance remains largely understudied in the fields of health and labor economics. Insufficient sleep is associated with fatigue-related accidents and injuries (Dinges, 1995; Lockley et al., 2007; Barnes and Wagner, 2009), attention, cognitive ability, coordination, motor skills, and processing speed (Dinges and Powell, 1985; Drummond et al., 2005; Banks and Dinges, 2007; Lim and Dinges, 2010), as well as productivity and psychological well-being (Bessone et al., 2021). However, identifying variations in sleep patterns that are both explainable and not strongly correlated with significant lifestyle choices poses a challenge. Measuring sleep outcomes is further complicated by the frequent delay, cumulative nature, and the challenge of quantification in large datasets. Therefore, by utilizing plausibly exogenous variations in sleep patterns, I aim to assess the potential impact of sleep-related cognitive outcomes on an immediate and measurable outcome: fatal vehicle crashes.

The timing of sunset and sunrise changes throughout the year in a specific location, as well as across different locations within a time zone. However, despite this natural variation, our work schedules and school start times often remain inflexible. These rigid school and work hours force individuals to wake up at the same early hour, preventing them from adjusting for this time difference by sleeping in later. This forced synchronization can negatively impact our circadian rhythms, ultimately affecting the duration and quality of our sleep. Consequently, this phenomenon produces both seasonal or short-term effects within a given year and long-term geographical effects across locations within a time zone.

I aim to address the following question: What are the short-run and long-run effects of sleep duration on fatal vehicle crashes in the United States? To answer this question, I utilize three different strategies to isolate the various factors that contribute to differences in sleep patterns caused by astronomical and time-keeping sources. These strategies consist of two instrumental variable (IV) approaches and a spatial regression discontinuity design (RDD).

For the instrumental variable (IV) approach, I exploit two different sources of identifying variation in sleep duration. Variation in sunset time throughout the year in one location isolates a short-term, seasonal variation in sleep duration, while geographic variation in sunset time across counties within the same time zone isolates long-term sleep differences across different areas. In the short term, there is variation in sunset time within a county throughout the year. For example, a later sunset in the summer could lead to a shorter sleep duration. In the long term, there are differences in sunset time among various counties in a time zone. For instance, the sunset is later for locations further west than for locations further east, and people in the western part of the time zone would sleep less.

The regression discontinuity design (RDD) strategy exploits the sharp discontinuity in sunset time across time zone borders. There is a distinct discontinuity in sunset time around the border, with sunset occurring approximately one hour later for counties situated on the right side of the time zone boundary compared to those on the left. For both strategies, I use sleep data from the American Time Use Survey (ATUS) and vehicle fatality data from the Fatality Analysis Reporting System (FARS).

Both the IV and RDD yield interesting first-stage results. The delay in sunset time can potentially disrupt the production of melatonin, consequently pushing sleep schedules to a later time. Using the seasonal, short-run IV method, I discovered that a one-hour delay in sunset results in a decrease of approximately 48 minutes in monthly sleep duration. According to related research, a one-hour delay in sunset time within a particular location is associated with a reduction in nighttime sleep by approximately 20 minutes per week (Gibson and Shrader, 2018). On the other hand, employing the geographical, long-run IV method, I observed a reduction of around 21 minutes in monthly sleep duration for every one-hour delay in sunset, but it is not statistically significant. The RDD results, nonetheless, reveal a noteworthy caveat. One-hour delay in sunset results in a decrease of approximately 10 minutes in average sleep duration. Earlier research conducted by Giuntella and Mazzonna (2019) concentrated on the time frame spanning from 2003 to 2013 and identified that employed individuals tend to sleep less when residing on the later sunset side of the time zone border. When I replicate this analysis using the same dataset and period, my findings align closely with theirs. However, an intriguing twist emerges when I extend the analysis to encompass data collected from 2014 to 2019. During this later period, I observe a contrary trend, wherein employed individuals actually tend to sleep more if they reside on the later sunset side of the time zone border.

Using the seasonal, short-term IV approach, I found that a one-hour increase in monthly sleep leads to a decrease of about 0.035 fatal crashes per 100 million VMT. Scaling this to deaths per town of 10,000 people or a city of 1M people per year, it is equivalent to a 2.4% reduction in fatalities in the short run. Related research has shown that the transition into Daylight Saving Time (DST) during the spring season leads to a significant 5.6% increase in fatal crashes, and this effect remains consistent for a period of six days following the transition (Smith, 2016). This result implies that if sleep increased by an average of one hour per day, then the fatality rate would decrease by $0.035 \times 30.437$, which is approximately one fatal crash per 100 million VMT. Using the across time-zone, long-term IV approach, I find that more sleep would lead to a reduction in fatalities, but it is not statistically significant. Using the RDD methodology, my research indicates that from 2004 to 2013, regions with later sunsets experienced a decrease in traffic fatalities. However, an unexpected shift occurred in the dataset from 2014 to 2019, where areas with later sunsets now show an increased rate of traffic fatalities. While both the first stage impact of the later sunset on sleep and the subsequent effect on traffic fatalities change direction, the fundamental association remains consistent: increased sleep is associated with a higher number of fatal vehicle crashes.

This paper contributes to three strands of literature in economics. First, it contributes to the lab studies of sleep in medical research by using observational data to study the causal impact of sleep on fatalities, providing understanding in real-world situations. There is a plethora of research on lab studies in sleep, which shows that sleep deprivation has a negative impact on attention, cognitive ability, coordination, motor skills, and processing speed (Dinges and Powell, 1985; Drummond et al., 2005; Banks and Dinges, 2007; Lim and Dinges, 2010). Second, this paper contributes to the recent literature focusing on the impact of sleep on productivity and health by examining both the short-run and long-run effects directly from sleep data on fatalities using the IV and RDD approaches. Previous research has found associations between sleep and various outcomes, including fatal vehicle crashes (Smith, 2016), wages (Gibson and Shrader, 2018), productivity and psychological well-being (Bessone et al., 2021), functioning of financial markets (Kamstra et al., 2000), hospital admissions (Jin and Ziebarth, 2020), cognitive skills and depression symptoms (Giuntella et al., 2017), and health outcomes (Giuntella and Mazzonna, 2019). Third, this paper contributes to the research that estimates the effects of school start times on academic achievement (Dills and Hernandez-Julian, 2008; Carrell et al., 2011; Edwards, 2012; Heissel et al., 2017; Avery et al., 2019) by providing additional causal evidence to assist policy makers in making decisions regarding school start times.

The rest of this paper proceeds as follows. Section 2 reviews the literature encompassing sleep studies in the medical fields and empirical evidence of sleep in Economics. Section 3 describes the data used in this paper. Section 4 illustrates the identification strategy and the empirical methods. Section 5 reports the main results, and Section 6 discusses the robustness checks. Section 7 concludes and discusses paths for future research.

# 2 Literature Review

## 2.1 Lab Studies of Sleep in Medical Research

There exists a plethora of research on lab studies in sleep, which shows that sleep deprivation has a negative impact on attention, memory, and mood. For example, Banks and Dinges (2007) reviewed recent experiments on chronic sleep restriction and found that restricting sleep can result in attention lapses, slowed working memory, reduced processing speed, depression, and preservative thinking. They also suggest that long-term sleep deprivation leads to unhealthy physiological results.

Besides chronic sleep restriction, Lim and Dinges (2010) reviewed studies on the impact of short-term sleep deprivation on cognition. They found that simple attention is strongly affected by short-term sleep deficit. The authors believe that sleep deprivation can pose significant safety risks, and implementing countermeasures targeting simple attention would be the most effective way to prevent accidents in industries.

One example of measuring simple attention is the laboratory study of the Psychomotor Vigilance Test (PVT) (Dinges and Powell, 1985). The PVT was initially invented in 1985 to measure sustained attention and has since become the most widely used test in studies of sleep and circadian rhythm research. Numerous studies have demonstrated that the PVT is a highly sensitive indicator of sleep deprivation.

A laboratory study conducted by Drummond et al. (2005) investigated the neural basis of PVT and found that optimal performance is dependent on the brain region responsible for these functions after a normal night of sleep. On the other hand, poor performance following sleep deprivation activates the brain's "default mode." This finding supports previous studies suggesting that sleep has an impact on attention.

This paper contributes to this literature by utilizing observational data to examine the causal impact of sleep on fatalities, providing insights into real-world situations.

## 2.2 Empirical Evidence on Sleep in Economics

Despite the extensive body of medical research highlighting the hazards of sleep deprivation, economists have only recently begun to explore the economic implications of insufficient sleep through empirical analysis. This paper aims to contribute to the emerging field of research on the consequences of sleep deprivation within the economic literature.

### 2.2.1 Productivity and Health

First, this paper is linked to the literature of estimating the impact of sleep on productivity and health (Kamstra et al., 2000). In a recent study, Smith (2016) uses regression discontinuity (RD) and day-of-year fixed effects (FE) model to study the short-run effects of Daylight Saving Time (DST) on fatal crashes and provides evidence of 5.6% increase in fatalities for six days after the spring transition of DST. He decomposes the aggregate effect of DST into an ambient light and sleep mechanism and finds that sleep deprivation is the channel that results in more fatal crashes while changing ambient light merely reallocates fatalities within a day. In addition, he discovers that losing an hour of sleep raises the risk of being in a drowsiness-related fatal crash by 46%.

I differentiate from Smith (2016), as rather than studying the short-run effects of DST on national fatalities using RD and FE models and analyzing sleep mechanism indirectly without using any sleep data or measurements, I examine both the short-run and long-run effect directly from sleep data on county-level fatal crashes using the IV and RDD approach.

The results would help us to form a better policy solution such as whether to keep DST and end clock changes. The benefits of the DST include decreased crime (Doleac and Sanders, 2015) and cost of the DST would be related to sleep loss with transitions. A better solution would keep the benefits of DST while diminishing the costs of the transition. For example, on March 15, 2022, the U.S. Senate passed the Sunshine Protection

Act of 2021, which would keep a permanent DST and end clock changes, but this Act has not made it to the U.S. House for discussion. In addition, the results could contribute to constructing social schedules such as work schedules and school start times in ways that promote sleeping, which is related to health and productivity.

This paper is also linked to Gibson and Shrader (2018), who use IV specification to study the impact of sunset variation within a location over time and sunset variation within a time-zone on wages and find that a one hour increase in weekly sleep results in 1.1% increases in wages in the short run and 5% in the long run. I employ a similar econometric approach to examine the effects of monthly sleep on fatal vehicle crashes at the county level, both in the short run and long run. Additionally, I incorporate the RDD method to estimate the long run effects.

A recent field experiment by Bessone et al. (2021) shows that a randomized three-week treatment to improve sleep in Chennai, India, increases sleep time by 27 minutes at night, which has no significant impact on cognition, productivity, or well-being. However, short naps in the afternoon help to improve the productivity, psychological well-being, and cognition. Instead of using field experiment, I am using non-experimental data to examine the impact of sleep.

Furthermore, Jin and Ziebarth (2020) study the hospital admissions impact of DST. Using an event study method, they find that the hospitalization rates decrease after the transition into standard time by adjusting the time back by one hour during fall and this effect continues for four days after the fall transition. My paper differs by using IV and RDD instead of event study method to estimate the short-run causal impact of sleep on traffic crashes.

In addition, Giuntella et al. (2017) uses IV method to analyze the causal impact of sleep deprivation on cognition and depression of older workers in urban China. They use sunset time as instrument and find that a later sunset time decreases sleep time and an increase in sleep duration could improve cognition and reduce depression. I am using the similar strategy of IV, but I am focusing on the short-run effects of sunset variation in the United States instead of the long-run impacts in urban China.

Another paper by Giuntella and Mazzonna (2019) uses spatial regression discontinuity design (RDD) to examine the health and income effects due to the discontinuity in sunset time at a time-zone boundary in the U.S. and find that an extra hour in sunset time leads to an average of 19 minutes decrease in sleep duration. In addition, they find the insufficient sleep is associated with negative health outcomes such as obesity, diabetes, cardiovascular diseases, and breast cancer. Rather than analyzing the long-term effects of exposure of light in the evening on health outcomes, I aim to measure both the short-run and long-run effects of sunset timing on fatalities. This paper confirms that sleep deprivation could affect the productivity and health of people through increasing the risk in fatal vehicle crashes.

#### 2.2.2 Academic Achievement

Second, this paper is related to the research that estimate the effects of school start times and sleep on academic achievements (Dills and Hernandez-Julian, 2008; Edwards, 2012). Researchers find that starting school later has a significant positive impact on academic scores for students and sleep is one of the mechanisms that could explain this impact. For example, Carrell et al. (2011) use the policy adjustments in the daily timetable at the US Air Force Academy as well as randomized allocation of freshman students to courses and conclude that starting school 50 minutes later has substantial constructive effect on test scores, corresponding to a one-standard-deviation increase in teacher quality.

In addition, a related work by Heissel et al. (2017) uses students moving across time zone border in Florida as instrument for hours of sunlight and finds that changing school start time one hour later relative to sunrise improves academic performance for adolescents in math and reading. The results are in line with sleep researchers' findings, which shows that later start times are beneficial for adolescent learning. However, it is not clear if sleep has a direct causal impact on the academic scores.

A field experiment by Avery et al. (2019) studies the effect of increased sleep on health and academic outcomes using commitment devices and monetary incentives. They find that the subjects in the treatment group are more likely to increase sleep duration and the treatment has positive but small impact on health and academic outcomes. This paper contributes to this literature by analyzing the direct causal impact of sleep on fatal vehicle crashes using non-experimental data to provide insights in the real-world scenarios.

# 3 Data

## 3.1 Individual Sleep Duration (ATUS)

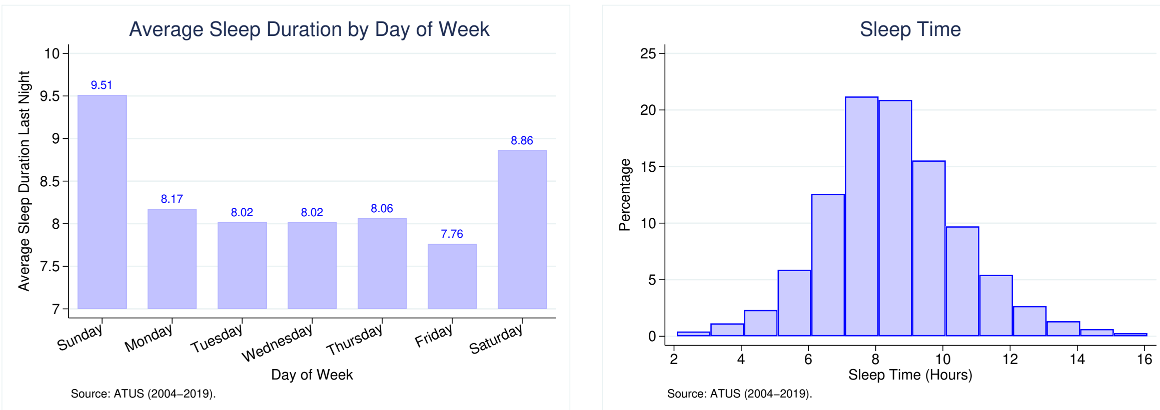



Figure 1: Sleep Duration

This graph shows the average sleep duration by day of week and distribution of sleep duration from ATUS (2004-2019).

The individual sleep duration comes from the American Time Use Survey (ATUS) sponsored by the U.S. Bureau of Labor Statistics (BLS) and conducted by the U.S. Census Bureau since 2003. ATUS is the first continuous survey on time use in the United States. Individuals are randomly selected from the households that just finished the eight-month interview for the Current Population Survey (CPS) and the interviews for ATUS are conducted between two and five months after the last CPS interview. The goal of ATUS is to understand how people allocate their time.

The time diary of the ATUS is conducted through computer-assisted telephone interviews. The respondent is asked to recall the time spend in each activity from 4:00 am on the previous day to 4:00am on the interview day. This method allows the time diaries to be summed to 24 hours to minimize possible biases. For each activity, the ATUS gathers either the ending time or the duration of the activity and the interviewer collects the answers verbatim, which are coded later (Hamermesh et al., 2005).

The diary measures of sleep in ATUS are usually higher than other sleep durations measured in the stylized questions, such as Behavioral Risk Factor Surveillance System (BRFSS), by about 1.7 hours. The average sleep duration in ATUS is about 8.7 hours per night while the average sleep duration in BRFSS is about 7 hours (Kaplan et al., 2020). The explanation is that the diary measures tend to include napping, dozing, falling asleep, and waking up (Basner et al., 2007).

I will use the county level sleep data and the county information is only available after 2004. To analyze the impact of sleep before COVID-19 pandemic, I include the sleep data from 2004 to 2019. There are 210,586 observations from 2003 to 2020. In the analysis, I include only the individuals in the labor force, which is from the ATUS-CPS (2003-2020). The CPS does not include county information for individuals who live in counties with less than 100,000 residents, so I could only match 38.5% of the sample. Therefore, the results from ATUS are more representative for counties that are more urban.

I then limit the analysis for individuals with age between 18 to 55 to avoid the issues of retirement and high-school age workers. I also restrict the sample for people who sleep between 2 to 16 hours per night. People who sleep less than 2 hours account for less than 1% of the whole sample. After the limitations, the sample includes 53,552 observations and 49,671 were employed, which accounts for 92.8% of the sample.

In the analysis, I include the socio-demographic variables, such as age, race, sex, education, marital status, nativity status, and number of children. I also include the geographic characteristic, such as latitude and indicators for large counties and costal counties. Figure 1 depicts the distribution of the sleep duration and shows that people tend to sleep more during weekends. Table 1 shows the summary statistics for the analysis after I combine the data from ATUS and FARS. The average sleep duration in my sample is 8.61 hours.

Using the interview date and the location (latitude and longitude), I could determine the daily sunset time for everyone in the sample from 2004 to 2019 as well as the average sunset time in the related county in 2012. I used the R studio package "suncalc" to calculate the sunset time. The calculations in this package are based on the formulas in Astronomy Answers about position of the sun and the planets. I checked the sunset time, which is similar as the sunset time calculated using the National Oceanic and Atmospheric Administration (NOAA) Sunrise/Sunset and Solar Position Calculators.

Table 1: Summary Statistics

| | Mean | S.D. | Min | Max | Obs. |
|---|---|---|---|---|---|
| ***FARS*** | | | | | |
| Crashes per 100 Million Miles | 1.72 | 0.98 | 0.10 | 5.62 | 36296 |
| ***ATUS*** | | | | | |
| Sleep Duration (Hours) | 8.61 | 2.05 | 2.08 | 15.93 | 36296 |
| **Socio-demographic Variables** | | | | | |
| Age | 38.75 | 9.71 | 18.00 | 55.00 | 36296 |
| White | 0.78 | 0.42 | 0.00 | 1.00 | 36296 |
| Black | 0.14 | 0.35 | 0.00 | 1.00 | 36296 |
| Female | 0.51 | 0.50 | 0.00 | 1.00 | 36296 |
| High School | 0.48 | 0.50 | 0.00 | 1.00 | 36296 |
| College | 0.44 | 0.50 | 0.00 | 1.00 | 36296 |
| Married | 0.54 | 0.50 | 0.00 | 1.00 | 36296 |
| Nativity Status | 0.77 | 0.42 | 0.00 | 1.00 | 36296 |
| Number of Children | 1.09 | 1.15 | 0.00 | 10.00 | 36296 |
| **Geographic Variables** | | | | | |
| Latitude | 37.25 | 5.05 | 25.61 | 48.84 | 36296 |
| Longitude | -92.45 | 17.65 | -123.03 | -68.67 | 36296 |
| Large County | 0.68 | 0.47 | 0.00 | 1.00 | 36296 |
| Coastal County | 0.41 | 0.49 | 0.00 | 1.00 | 36296 |
| **Interview Characteristics** | | | | | |
| Holiday | 0.02 | 0.13 | 0.00 | 1.00 | 36296 |
| Weekend | 0.51 | 0.50 | 0.00 | 1.00 | 36296 |

**Note:** Data are from ATUS (2004-2019) and FARS (2004-2019). Latitude and longitude are from US Census Bureau. The sample is restricted to people who are in the labor force and aged between 18 and 55. The crashes data from FARS are matched to the ATUS at county-year-month level.

## 3.2 Fatal Vehicle Crashes (FARS)

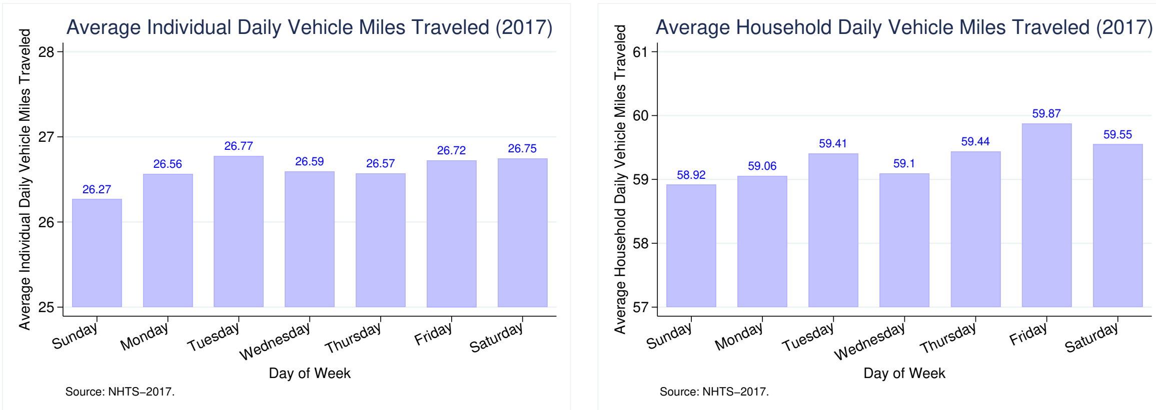



Figure 2: Average Daily Vehicle Miles Traveled

The graph shows the average individual and household daily vehicle miles traveled by day of week from NHTS (2017).

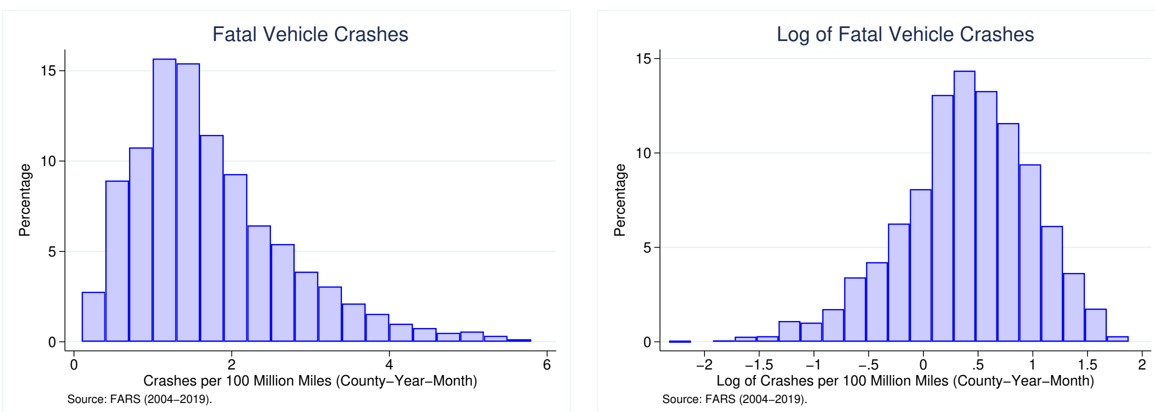



Figure 3: Fatal Vehicle Crashes

The graph shows the distribution of fatal vehicle crashes per 100 million VMT. The right panel shows the distribution after taking natural log of the crashes. Calculated from FARS (2004-2019) and BTS (2017).

The fatal vehicle crash data are obtained from the Fatality Analysis Reporting System (FARS), developed by the National Center of Statistics and Analysis (NCSA) of the National Highway Traffic and Safety Administration (NHTSA). FARS encompasses fatal vehicle crash data from all 50 states in the United States since 1975. To be included in

FARS, a crash must involve a motor vehicle traveling on a public trafficway and must result in the death of at least one motorist or non-motorist within 30 days of the crash.

FARS includes the exact time and location of the accident, as well as the road type, light condition, and weather. I will be using the data from 2004 to 2019, which includes 539,052 observations. There are about 33,690 fatal crashes every year and about 92 fatal crashes per day for the entire United States. Fatal crashes are more likely to happen from 4pm to midnight and on the weekends.

The non-fatal crashes data are not available for the whole nation since many states do not maintain a standard database for the non-fatal vehicle crashes. For fatal crashes data, NHTSA cooperates with each state government to collect the fatal crashes in a standard format. Analyzing only the fatal vehicle crashes creates a lower bound on the impact of sleep on all types of vehicle crashes.

The fatal vehicle crashes in each county are normalized by the vehicle miles traveled (VMT) in each county. The VMT data are from the Bureau of Transportation Statistics (BTS), part of U.S. Department of Transportation. BTS provides average weekday household VMT by census tract for 2009 and 2017. I used the 2017 data and convert the VMT from the tract level to county level. BTS uses the data from 2017 National Household Transportation Survey (NHTS), sponsored by Federal Highway Administration (FHWA), and the 2012-2016 American Community Survey (ACS) 5-year estimate. I used the household numbers in each county to calculate the daily VMT in 2017, and then I normalize the crash counts for each county by the VMT in 2017 to get the crashes per 100 million VMT.

Figure 2 shows the average individual and household daily VMT by day of week from NHTS (2017). The average individual daily VMT is about 26 miles and the average household daily VMT is about 59 miles. Figure 3 graphs the distribution of fatal vehicle crashes per 100 million VMT at county-year-month level. The left panel implies that the mean crashes happen in a county at a given year and month is about 1.7. The distribution is skewed towards the right in the left panel and it is closer to normal after taking natural log of the crashes per 100 million VMT in the right panel.

# 4 Empirical Methods

## 4.1 Identification Strategy 1: Sunset Time as Instrument (IV)

This study aims to discover the causal impact of sleep durations on fatal vehicle crashes. One problem is that there may exist omitted variables bias, which indicates there are variables that are correlates with both sleep duration and crashes. Another concern is the reverse causality, which refers to the situation that the fatal vehicle crashes could affect sleep duration. Therefore, I use the IV strategy to measure the causal relationship between sleep and crashes. Specifically, my identification strategy relies on both the sunset variation across year in one location for short term estimate as well as the locational variation in sunset time across the United States for long run effects.

My strategy is the same as what Gibson and Shrader (2018) utilize to explore the causal influence of sleep duration on wages in the United States, and it is also linked to the regression discontinuity method used to estimate the sleep difference across time-zone border on health outcomes (Giuntella and Mazzonna, 2019). I will first introduce the background of the relationship between sunset and sleep and then I will discuss each the short-run and long-run specification separately.

### 4.1.1 Relationship between Sunset and Sleep

The timing and duration of sleep are strongly associated with the rising and setting of sun. This biological relationship between sleep and daylight provides the reasoning for why selecting sunset as instrument for sleep. Roenneberg et al. (2007) show that light is the strongest signal from the environment for human biological clock and find that sun time, rather than social time, has the primary influence on the synchronization of human circadian rhythm. The circadian system is a strong force that synchronize with environmental stimuli. Nearly every living creature has an internal clock that is set to the Earth's 24-hour rotational timetable. This internal circadian rhythm helps the body to anticipate the external environment, such as when the sun will rise and set, as well as the optimal times to sleep, wake, eat, and exercise. Individuals who do not sleep at their ideal circadian timing or who are sleep deprived compared to intrinsic sleep need are facing more negative health outcomes (Ashbrook et al., 2020). Due to the circadian rhythm, the variation in daylight could affect sleep habits.

Location and seasonal variation in sunset time could all cause a change in sleep patterns. Researchers find that individuals living in a location with later sunset time tend to sleep later (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019). The sunlight changes across year also affect the sleep patterns (Hubert et al., 1998). Latitude and longitude could both influence the sunset and sunrise time. For example, Campante and Yanagizawa-Drott (2015) use the interaction of latitude and the rotation of lunar calendar to identify the causal relationship between the length of Ramadan fasting and the economic growth in Muslim countries. In addition, Brockmann et al. (2017) explore the associations between sleep duration and latitude in Chile and find that people sleep longer with increasing latitude. Furthermore, Friborg et al. (2012) analyze the associations between seasonal variations in day length and sleep comparing Ghana and Norway and find that lack of daylight was related to change of sleep patterns. The change in sleep pattern could affect the sleep duration due to work and school scheduling.

Rigid work and school schedule could disrupt human circadian rhythms and cause health and productivity issues. In the recent economic literature, the distribution of time among market work, home production work, leisure, and rest has been a major topic (Becker, 1965; Gronau, 1977; Aguiar and Hurst, 2007; Guryan et al., 2008; Aguiar et al., 2013; Carneiro et al., 2015; Bastian and Lochner, 2020). The allocation of time could depend on the working and school schedules, and the social times are usually synchronized for optimal welfare (Weiss, 1996; Hamermesh et al., 2008). If people could wake up late to compensate sleep late, then the sleep duration would be the same. However, workers and students have the forced synchronization of work and school scheduling, thus later sunset and bedtime would shorten sleep duration in the short and long term. A decrease in sleep duration could disrupt human circadian rhythms, which could post negative effects on health and productivity (Cappuccio et al., 2010).

### 4.1.2 Daily Sunset Time Variation for Short-Run Analysis

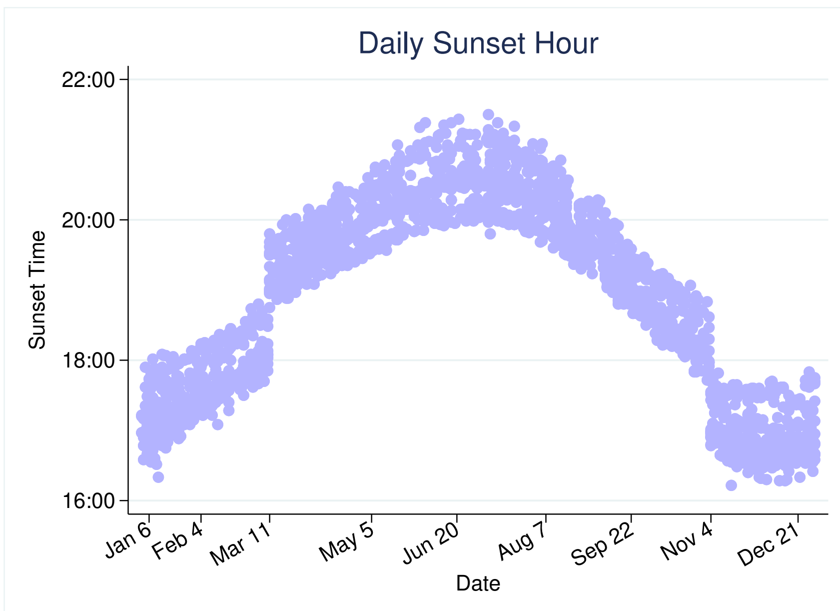



Figure 4: Daily Sunset Hour - Short Run Analysis

This graph depicts the daily sunset hours for counties sampled by ATUS in the continental United States in 2012. The y-axis shows the sunset hour in 24 hour time. For example, 16:00 is the same as 4:00pm. Mar 11 is when the DST starts and Nov 4 is when the DST ends in 2012. Jun 20 is the summer solstice and Dec 21 is the winter solstice. The setup of this graph is similar to Gibson and Shrader (2018).

In the short run, I will use the daily sunset variation in one location across the year as the instrument. Figure 4 shows that the sunset time is like a cosine wave over a year. The latitude of the location determines the amplitude of the wave, and the longitude variation within a time zone defines the average sunset time, which is used to estimate the long-run effects. The substantial spring and fall leaps generated by DST is another characteristic of the sunset time. There is a regular seasonal pattern, and the sunset time is generally late during summer and early during winter. The later sunset time in the summer could result in shorter sleep duration, which could impact the attention and disrupt circadian rhythm.

In terms of the instrument validity, the first requirement is the instrument of sleep must be strongly correlated with sleep. The F test for the first stage is 11.94 for unconditional model and 10.93 for conditional model, which are both greater than 10. This suggest that this instrument has a strong first stage. The second requirement is that the instrument of sleep cannot be correlated with the error term in the equation of interest. If the instrument meets this requirement, then this instrument satisfy the exclusion restriction. The exclusion restriction validity requires that other crashes determinants do not correlate with daily sunset time in a location. Since sunset time follows a predictable seasonal pattern, the major challenge to this assumption is seasonally varying crash determinants.

One potential concern of the identification strategy is that sunset time varies seasonally, so does sunrise time and daylight duration. Medical research show that the length of daylight has a positive effect on mood as the sunlight could help the body to produce vitamin D, which could affect mood and depression (Murase et al., 1995; Lambert et al., 2002; Kjærgaard et al., 2012; Friborg et al., 2012). Furthermore, exposure to more light in the evening could provide incentive to exercise more (Wolff and Makino, 2012). If daylight influences both crashes and sleep through mood or another channel, the short-run results could be misleading. To address the seasonality issue, I include the controls for seasonality, such as year-month fixed effects and I got the similar results. I assume that the crash determinants such as the mood due to seasonality do not correlate with the sunset time.

Other confounding factors may include icy road in winter and drinking behaviors etc.

Those unobserved confounding factors could be correlated with sunset time as well as the crashes. Including the time fixed effects could alleviate the concern of different road conditions in various seasons. Adding the county fixed effects could address the issue that the north and south locations would have different road conditions during winters. I use sunset time instead of sunrise time because the rigid work and school schedules would affect the wake up time, and the sunset time may have a larger impact on the sleep duration for employed people.

### 4.1.3 Average Sunset Time Variation for Long-Run Analysis

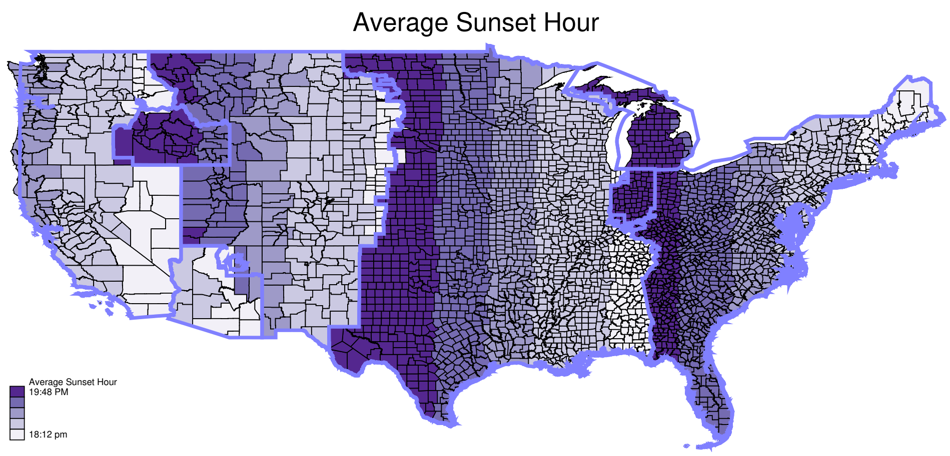



Figure 5: Average Sunset Hour - Long Run Analysis

This graph shows the average sunset hours for all counties in the continental United States in 2012. I used sunset time package “suncalc” from R studio to calculate the average sunset time. I separated counties into 5 quintile based on the average sunset time in 2012. Darker color implies later sunset. The time zone border lines are in blue. The setup of this graph is similar to Gibson and Shrader (2018) and Giuntella and Mazzonna (2019).

In the long run, I will use the average sunset variation across locations as instrument. Figure 5 depicts the average sunset time for the continental United States in 2012. The eastern part gets darker late in a time zone, which indicate that the people who live in eastern areas are more likely to go to bed later and sleep less. Within a U.S. time zone, the largest variance in sunset time is around 1 hour. The average sunset time is constant regardless of latitude. Since all counties in the continental U.S. have almost the same average annual daylight, this is not a confounding factor in the long-run study.

Time and scheduling were not consistent across the United States until the development of the railroad traffic after the Civil War. America's railroads started the first U.S. time zones on November 18, 1883, known as Standard Railroad Time. Later in 1918, the Standard Time Act established the current four continental U.S. time zones including Eastern, Central, Mountain, and Pacific. Since then, the time zones have been in effect, with only minor adjustments at the margins. Currently, 12 of the 48 continental states are in more than one time zone (Bartky, 1989; Hamermesh et al., 2008).

The purpose of the invention of DST was to save energy during times of war. In 1918, the United States established a formal DST schedule, but it was overturned when World War I ended due to its inconvenient nature. In 1966, President Johnson signed the current U.S. DST scheme into law. Each state can surpass the law by enacting its own legislation. In 2007, the DST time was extended by four weeks. Except for Arizona and Hawaii, most states in the United States implement DST, and Indiana began to adopt DST in 2006 (Kamstra et al., 2000).

State and local government could require the Department of Transportation (DOT) to change time zones (Valpando, 2013). This alteration of time zone borders suggest that time zone is not set randomly. Counties have changed in both westward and eastward directions, and it is more common to switch to the east side, which has later sunset. Since the position of the border is not exogenous, comparing nearby counties on the opposite sides of the border could lead to biased results under regression discontinuity design. In addition, I could exclude counties that do not adopt DST to avoid possible endogeneity issue.

As for instrument validity, I first check if the average sunset instrument is strongly correlated with sleep. The F test for the first stage is 0.02 for unconditional model and 0.01 for conditional model and this suggest that this instrument is a weak instrument. Possible confounding factors include sorting and coastal distance, which could possibly correlates with the sunset instrument and the determinants that affect the crashes. Individuals could sort on the eastern of western side of a time zone border, which suggest that there is correlation between average sunset time and population density. In addition, the average sunset time could correlate with coastal distance since sunset time is related to longitude. Coastal distance could affect the risk of vehicle crashes because individuals report better overall health and mental health when they live close to the seaside (White et al., 2013).

## 4.2 Identification Strategy 2: Discontinuity in Sunset Time at Timezone Border (RDD)

The RDD strategy exploits the sharp discontinuity in sunset time across time zone borders. Figure 6 shows there is a distinct discontinuity in sunset time around the border, with sunset occurring approximately one hour later for counties situated on the west side of the time zone boundary compared to those on the east side. Figure 7 illustrates the process of determining the distance of counties to the nearest time zone border within a 400-mile radius using QGIS. Initially, I isolated the time zone borders between each time zone by employing the "split features" function. Subsequently, I utilized the "shortest line" function between the centroids of each county and the time zone borders.

In the RDD framework, it is essential to assume that there are no disparities in observable or unobservable attributes that could introduce confounding effects into the outcomes. Unlike a conventional regression discontinuity design, it is not possible to directly compare individuals living on opposite sides of the time zone boundary because they would be residing at different latitudes. To enable the comparison of individuals residing in neighboring counties, this analysis includes a set of geographic reference variables and utilizes linear controls for latitude.

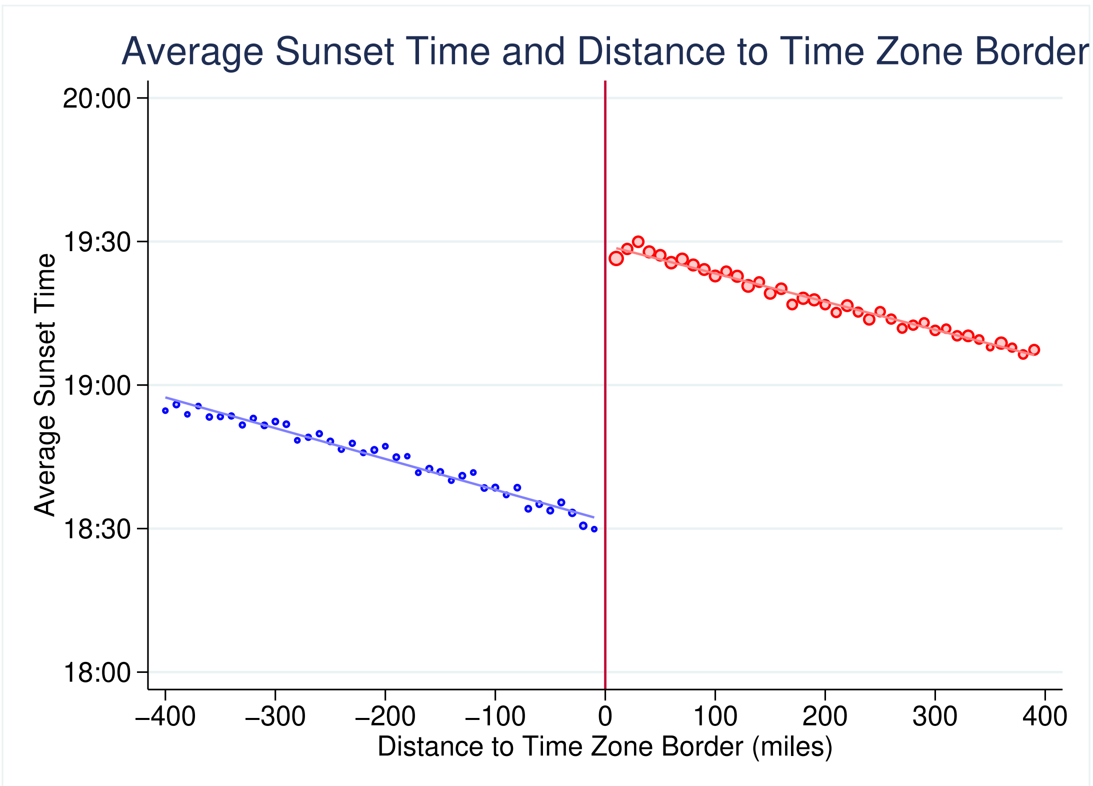



Figure 6: Sunset and Distance to Time Zone Border for Unemployed

This graph shows the discontinuity in sunset time over distance to time zone borders. The distance are calculated using QGIS. I used sunset time package "suncalc" from R studio to calculate the average sunset time. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

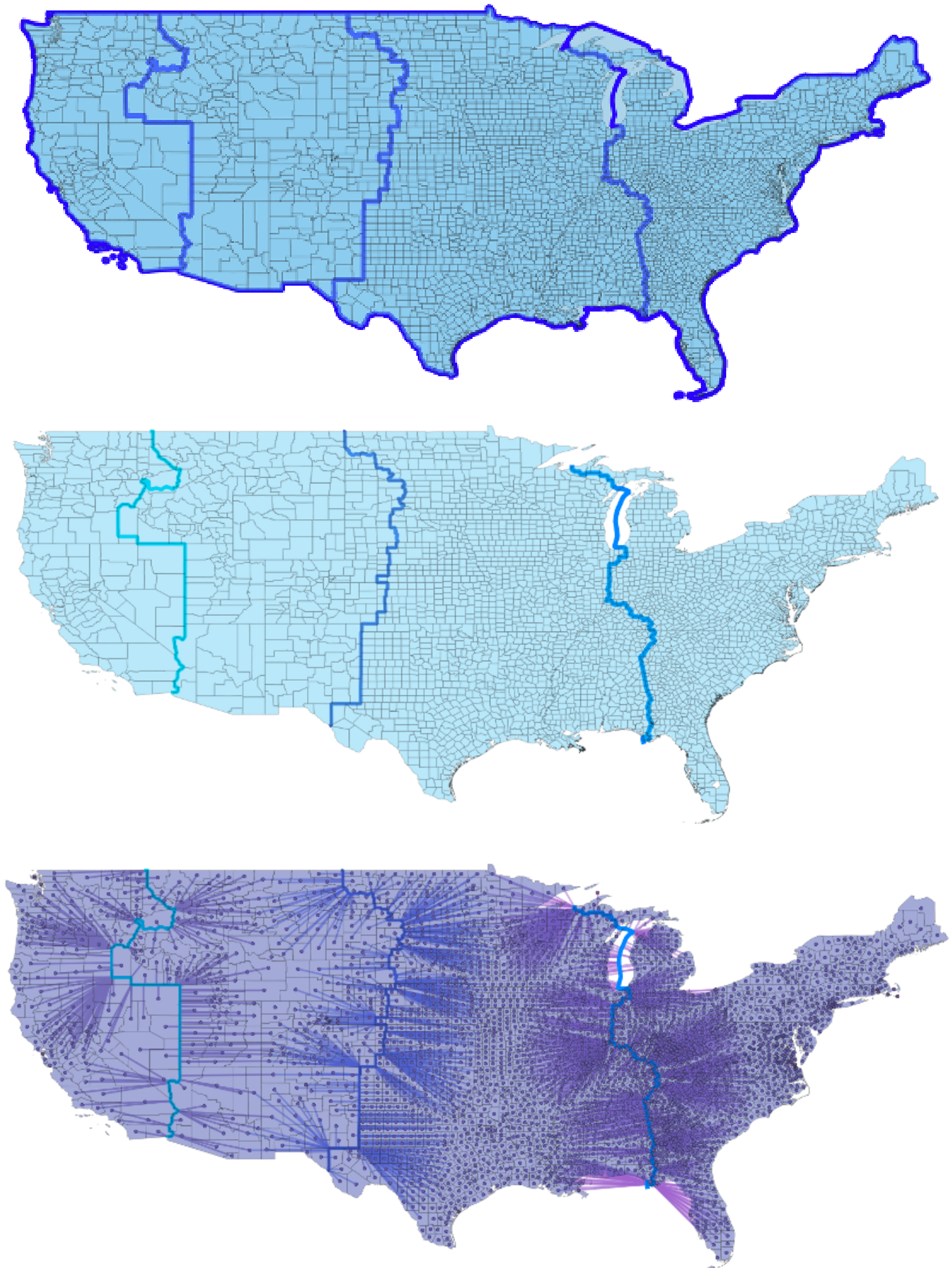


Figure 7: Graph of distance of counties to the nearest time zone border within 400 miles using QGIS.

This graph illustrates the process of determining the distance of counties to the nearest time zone border within a 400-mile radius using QGIS. Initially, I isolated the time zone borders between each time zone by employing the "split features" function. Subsequently, I utilized the "shortest line" function between the centroids of each county and the time zone borders.

## 4.3 Estimation Equations

## 4.4 IV Strategy

First, I use the instrumental variable method. To estimate the short-run effect of sleep, I will first use the monthly changes in sunset within a county as the first instrument. I estimate the following short-run first stage,

$$Sleep_{ijt} = \alpha_1 Sunset_{jt} + X'_{ijt}\delta_1 + \gamma_{1,j} + \eta_{1,ijt} \tag{1}$$

short-run second stage,

$$Crash_{jt} = \alpha_2 \hat{Sleep}_{ijt} + X'_{it}\delta_2 + \gamma_{2,j} + \eta_{2,ijt} \tag{2}$$

and reduced form,

$$Crash_{jt} = \alpha_3 Sunset_{jt} + X'_{it}\delta_3 + \gamma_{3,j} + \eta_{3,ijt} \tag{3}$$

where $Sleep_{ijt}$ is the monthly sleep duration for individual $i$ in county $j$ for date $t$, $Sunset_{jt}$ is the sunset time on that date in that county, $\gamma_{1,j}$ includes county fixed effects, $X_{it}$ is a vector controls including socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). $Crash_{jt}$ is the fatal crashes per 100 million VMT for the county $j$ at county-year-month level. $\eta_{k,jm}$ is the error term for k $\in \{1, 2, 3\}$.

The second instrument is the annual average sunset, which captures the geographical differences in sunset time across counties in the United States. I estimate the following long-run first stage,

$$Sleep_j = \delta_1 Sunset_j + X_j' \beta_1 + \epsilon_{1,j} \tag{4}$$

short-run second stage,

$$Crash_j = \delta_2 \hat{Sleep}_j + X_j' \beta_2 + \epsilon_{2,j} \tag{5}$$

and reduced form,

$$Crash_j = \delta_3 Sunset_j + X_j' \beta_3 + \epsilon_{3,j} \tag{6}$$

where $Sleep_j$ is average monthly sleep duration in location $j$, $Sunset_j$ is the average sunset time in that location, $X_j$ is a vector controls including county-level socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude and indicators for large counties and coastal counties), and interview characteristics (indicators for holiday and weekend). $Crash_j$ is the average fatal crashes per 100 million VMT at county-month level. $\epsilon_{k,j}$ is an error term for k $\in \{1, 2, 3\}$.

## 4.5 RDD Strategy

$$Sleep_{ijt} = \beta_0 + \beta_1 LS_j + \beta_2 f(D_j) + \beta_3 f(D_j) * LS_j + X_{ijt}' \beta_4 + u_{ijt} \tag{7}$$

where $Sleep_{ijt}$ is the daily sleep duration for individual $i$ in county $j$ for date $t$, $LS_j$ is indicator for the county located on the late sunset side of a time zone border, $D_j$ is the distance to the time zone border or the "running variable," $X_{ijt}$ is a vector controls including individual socio-demographics characteristics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude and indicators for large counties and coastal counties), and interview characteristics (indicators for holiday and weekend).

$$Crash_j = \beta_0 + \beta_1 LS_j + \beta_2 f(D_j) + \beta_3 f(D_j) * LS_j + X_j' \beta_4 + u_j \tag{8}$$

where $Crash_j$ is the average fatal crashes per 100 million VMT at county-month level., $LS_j$ is indicator for the county located on the late sunset side of a time zone border, $D_j$ is the distance to the time zone border or the "running variable," $X_j$ is a vector controls including county-level socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude and indicators for large counties and coastal counties), and interview characteristics (indicators for holiday and weekend).

# 5 Results

## 5.1 IV Strategy

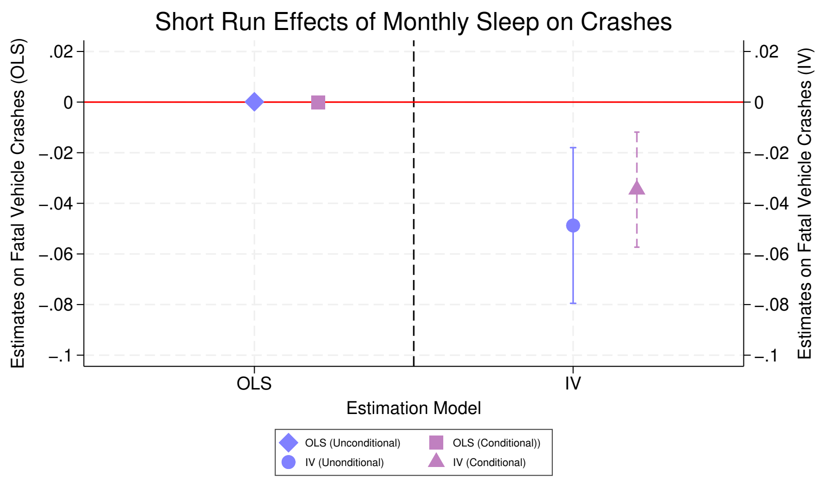
Table 11 shows the results of the short run effects of sunset and sleep. The first and second column suggest that there is no major impact of average monthly sleep on crashes in terms of statistical significance and magnitude under ordinary linear regression (OLS) model. The third and fourth column show the results for Equation (1), which implies that one hour late in sunset will lead to about 48 minutes decrease in monthly sleep or 1.6 minutes reduction in daily sleep duration. The magnitude is about the same after adding controls and fixed effects.

In column (6), the estimates for Equation (2) indicate that one hour augment in monthly sleep leads to 0.035 reduction in fatal crashes per 100 millions VMT at county-year-month level, equivalent to a 2.4% reduction in fatalities in the short run. The result implies that if average sleep increased by one hour, then the fatality will decrease by $0.035 \times 30.437$, which is about one fatal crash per 100 million VMT. This suggests that a one-hour increase in daily sleep leads to a decrease of about one fatal crashes per 100 million VMT as shown from column (6) in Table 3.

One fatal crash per 100 million VMT means that if you drive 100 miles every day, then you may encounter a fatal crash every 2,739 years. Alternatively scaled, an extra hour of daily sleep reduces 1 fatal crashes in 2,724 years if drive 100 miles per day. The seventh and eighth column show that the sunset hour has positive and significant impact on fatalities for Equation (3).

Figure 8 shows the same results for Table 11 and Table 3. In each panel, the left y-axis denotes the scale for OLS results and the right y-axis depicts the scale for IV estimates. The top panel indicates that one hour increase in monthly sleep causes 0.035 reduction in fatalities under IV (conditional model). The bottom panel suggests that additional one hour of sleep reduces fatalities by 2.4% under IV (conditional model). As a comparison, the OLS estimates are close to zero in both panels.

As for the long run results, Table 4 and Table 5 show that there is no significant impact of sleep on fatalities for Equation (4) to (6). One exception is that the sunset time has positive and significant impact on crashes in column (7) under the unconditional model, which is in line with the short-run results, suggesting that a later sunset time increases fatalities.



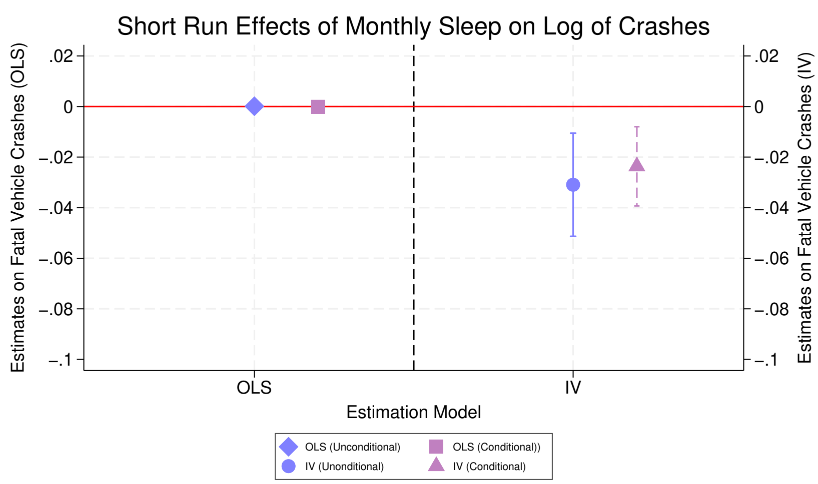




Figure 8: Short Run Effects of Monthly Sleep on Crashes

This graph shows estimates of the short run effects of monthly sleep on crashes using OLS and IV. The error bars are at 95% confidence intervals for the mean. Sleep denotes monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children) and geographic characteristics (latitude, longitude, and dummy for large counties).

Table 2: Short Run Effects of Sunset and Sleep

| | OLS | | IV(First-Stage) | | IV(Second-Stage) | | Reduced-Form | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Crashes | Crashes | Sleep | Sleep | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | 0.000 | -0.000 | | | -0.049*** | -0.035*** | | |
| | (0.00) | (0.00) | | | (0.02) | (0.01) | | |
| Sunset Hour | | | -0.815*** | -0.778*** | | | 0.040*** | 0.027*** |
| | | | (0.24) | (0.22) | | | (0.01) | (0.01) |
| Mean | 1.81 | 1.81 | 261.28 | 261.28 | 1.81 | 1.81 | 1.81 | 1.81 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| County FEs | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 |
| F test | | | 11.99 | 12.55 | | | | |

**Notes:** Sleep and sunset time are measured in hours by state-county level. The dependent variable of sleep is monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 3: Short Run Effects of Sunset and Sleep (Log of Crashes)

| | OLS | | IV(First-Stage) | | IV(Second-Stage) | | Reduced-Form | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Crashes | Crashes | Sleep | Sleep | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | 0.000 | -0.000 | | | -0.031*** | -0.024*** | | |
| | (0.00) | (0.00) | | | (0.01) | (0.01) | | |
| Sunset Hour | | | -0.815*** | -0.778*** | | | 0.025*** | 0.019*** |
| | | | (0.24) | (0.22) | | | (0.00) | (0.00) |
| Mean | 0.41 | 0.41 | 261.28 | 261.28 | 0.41 | 0.41 | 0.41 | 0.41 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| County FEs | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 | 36296 |
| F test | | | 11.99 | 12.55 | | | | |

**Notes:** Sleep and sunset time are measured in hours at county level. Sleep denotes monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 4: Long Run Effect of Sunset on Sleep and Fatal Crashes

| | OLS | | IV(First-Stage) | | IV(Second-Stage) | | Reduced-Form | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Crashes | Crashes | Sleep | Sleep | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | 0.00 | -0.00 | | | -0.39 | 2.24 | | |
| | (0.00) | (0.00) | | | (2.81) | (248.84) | | |
| Sunset Hour | | | -0.35 | -0.02 | | | 0.14* | -0.05 |
| | | | (2.51) | (2.50) | | | (0.07) | (0.06) |
| Mean | 1.99 | 1.99 | 261.39 | 261.39 | 1.99 | 1.99 | 1.99 | 1.99 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| County FEs | No | No | No | No | No | No | No | No |
| Observations | 396 | 396 | 396 | 396 | 396 | 396 | 396 | 396 |
| F test | | | 0.02 | 0.00 | | | | |

**Notes:** Sleep and sunset time are measured in hours by county level. The dependent variable of sleep is monthly average sleep hours in a county. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude and indicators for large counties and coastal counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 5: Long Run Effect of Sunset on Sleep and Log of Fatal Crashes

| | OLS | | IV(First-Stage) | | IV(Second-Stage) | | Reduced-Form | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Crashes | Crashes | Sleep | Sleep | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | 0.00 | -0.00 | | | -0.27 | 0.71 | | |
| | (0.00) | (0.00) | | | (1.90) | (78.43) | | |
| Sunset Hour | | | -0.35 | -0.02 | | | 0.09** | -0.02 |
| | | | (2.51) | (2.50) | | | (0.04) | (0.03) |
| Mean | 0.52 | 0.52 | 261.39 | 261.39 | 0.52 | 0.52 | 0.52 | 0.52 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| County FEs | No | No | No | No | No | No | No | No |
| Observations | 396 | 396 | 396 | 396 | 396 | 396 | 396 | 396 |
| F test | | | 0.02 | 0.00 | | | | |

**Notes:** Sleep and sunset time are measured in hours by county level. The dependent variable of sleep is monthly average sleep hours in a county. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude and indicators for large counties and coastal counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01.

## 5.2 RDD Strategy

The first stage results of RDD reveal a noteworthy caveat. Earlier research conducted by Giuntella and Mazzonna (2019) focused on the time frame from 2003 to 2013 and found that employed individuals tend to sleep less when residing on the later sunset side of the time zone border. When I replicate this analysis using the same dataset and period from 2004 to 2013, my findings closely align with theirs. The reason to use 2004-2019 instead of 2003-2019 is that the county information is not available in 2003. However, an intriguing twist emerges when I extend the analysis to include data collected from 2014 to 2019. During this later period, I observe a contrary trend, wherein employed individuals actually tend to sleep more if they reside on the later sunset side of the time zone border.

Moving on to the second stage results, my research indicates that from 2004 to 2013, regions with later sunsets experienced a decrease in traffic fatalities. However, an unexpected shift occurred in the dataset from 2014 to 2019, where areas with later sunsets now show an increased rate of traffic fatalities. While both the first stage impact of the later sunset on sleep and the subsequent effect on traffic fatalities change direction, the fundamental association remains consistent: increased sleep is associated with a higher number of fatal vehicle crashes.

Figure 9 illustrates the discontinuity in sleep and crash rates in relation to the distance from the time zone border. The first row indicates that individuals located on the right side of the time zone border have similar sleep and fatality rates compared to those on the left side. The second row demonstrates that people living on the side of the time zone border with later sunsets experience less sleep and fewer crashes. Conversely, the third row shows that individuals on the later sunset side have more sleep and higher fatality rates.

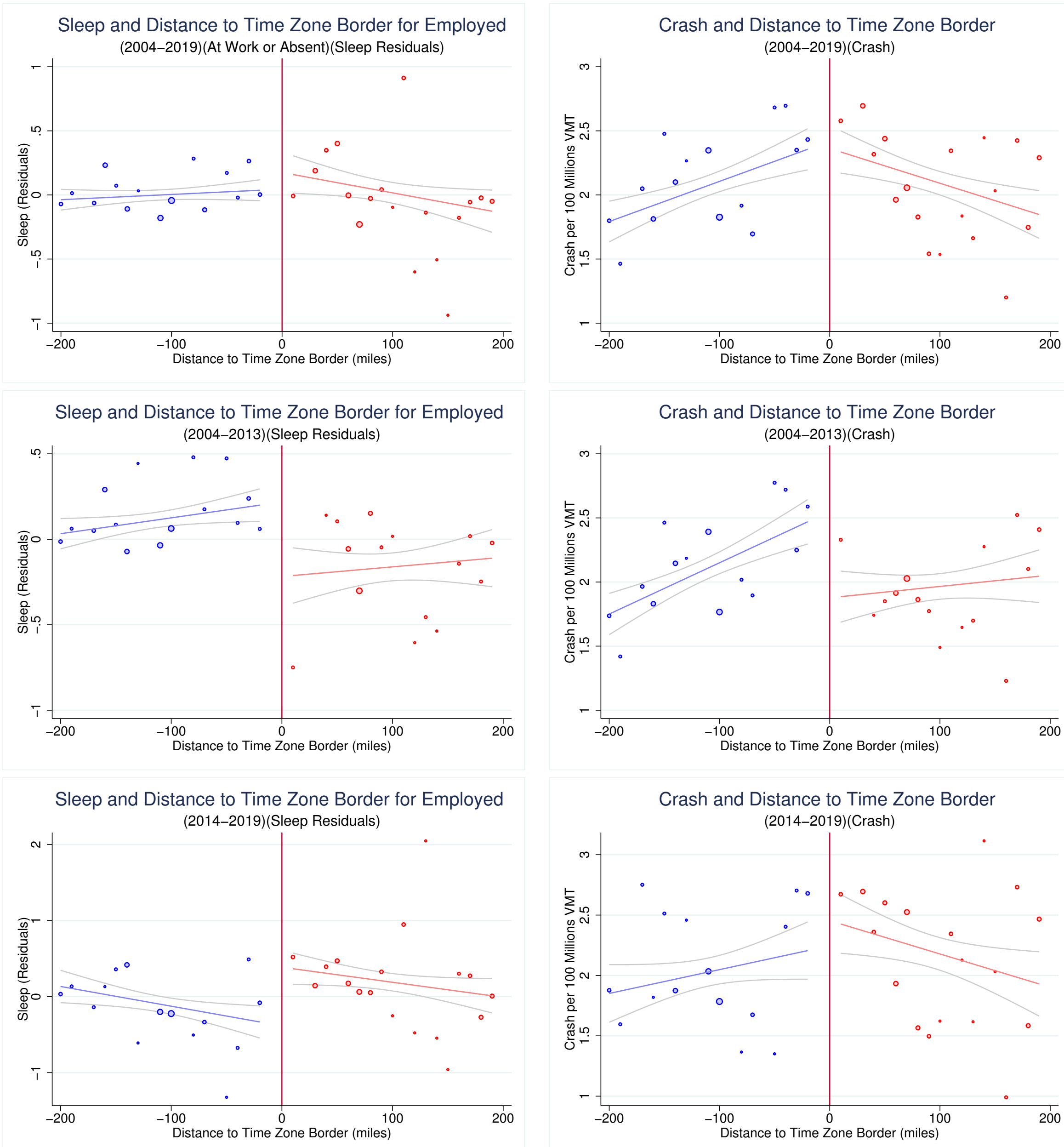



Figure 9: Sleep and Crash Discontinuity

The figure illustrates the discontinuity in sleep and crashes in relation to the distance from the time zone border. Data are from ATUS and FARS (2004-2019). Each point represents the the mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties). The right figure shows the discontinuity in crash and distance to time zone border. Each point represents the mean residuals (10 miles average) of the crash per 100 millions VMT on a set of geographical controls (a linear control for latitude and dummy for large counties). The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

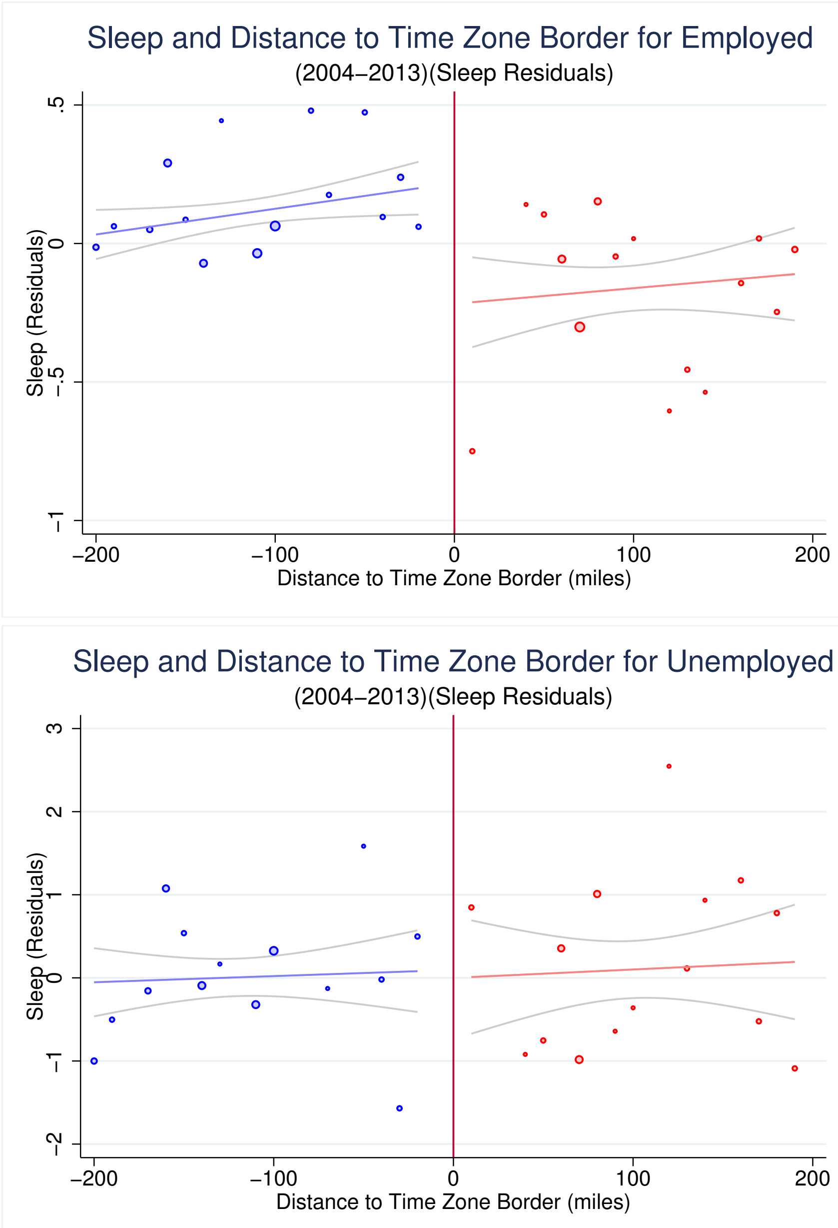
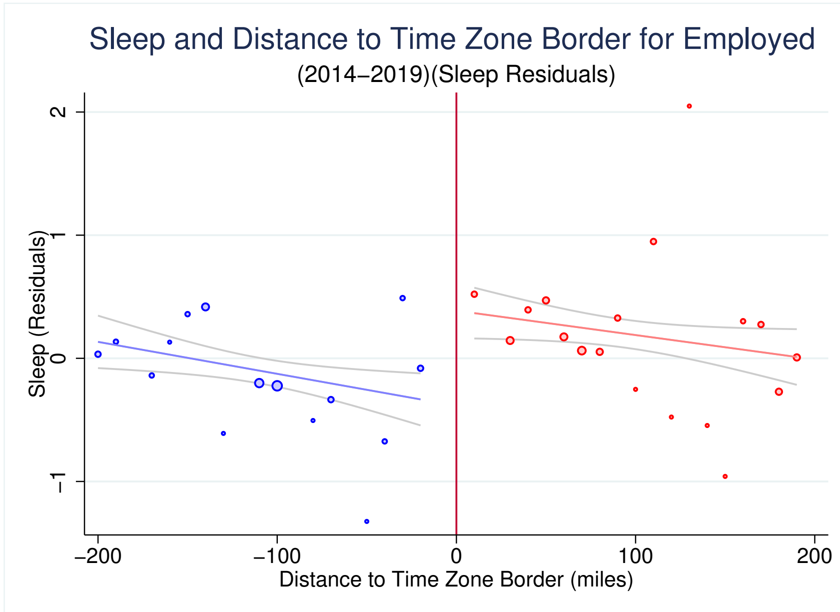



Figure 10: Sleep and Distance to Time Zone Border for Employed

This figure show the discontinuity in sleep and distance to time zone border for employed and unemployed individuals. Data are from ATUS (2004-2013). Each point represents the the mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.



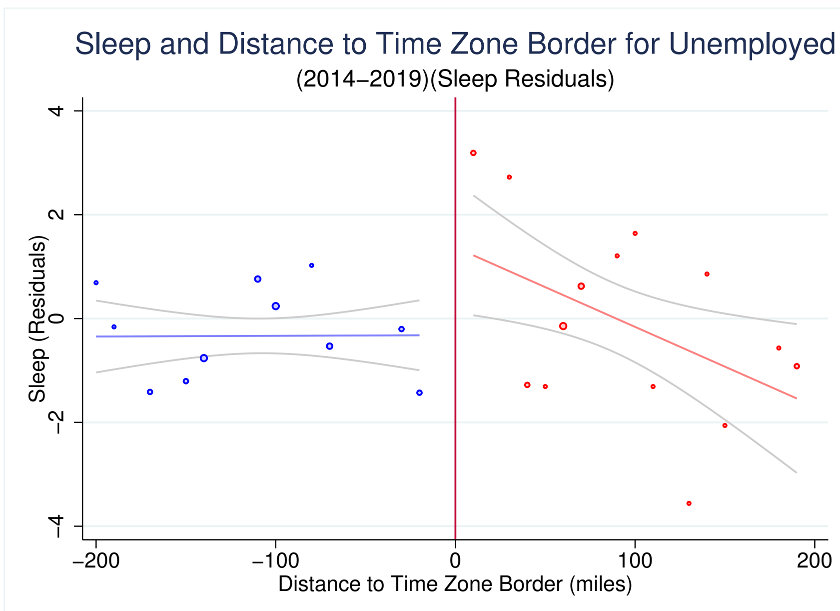




Figure 11: Sleep and Distance to Time Zone Border for Employed

This figure show the discontinuity in sleep and distance to time zone border for employed and unemployed individuals. Data are from ATUS (2014-2019). Each point represents the the mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

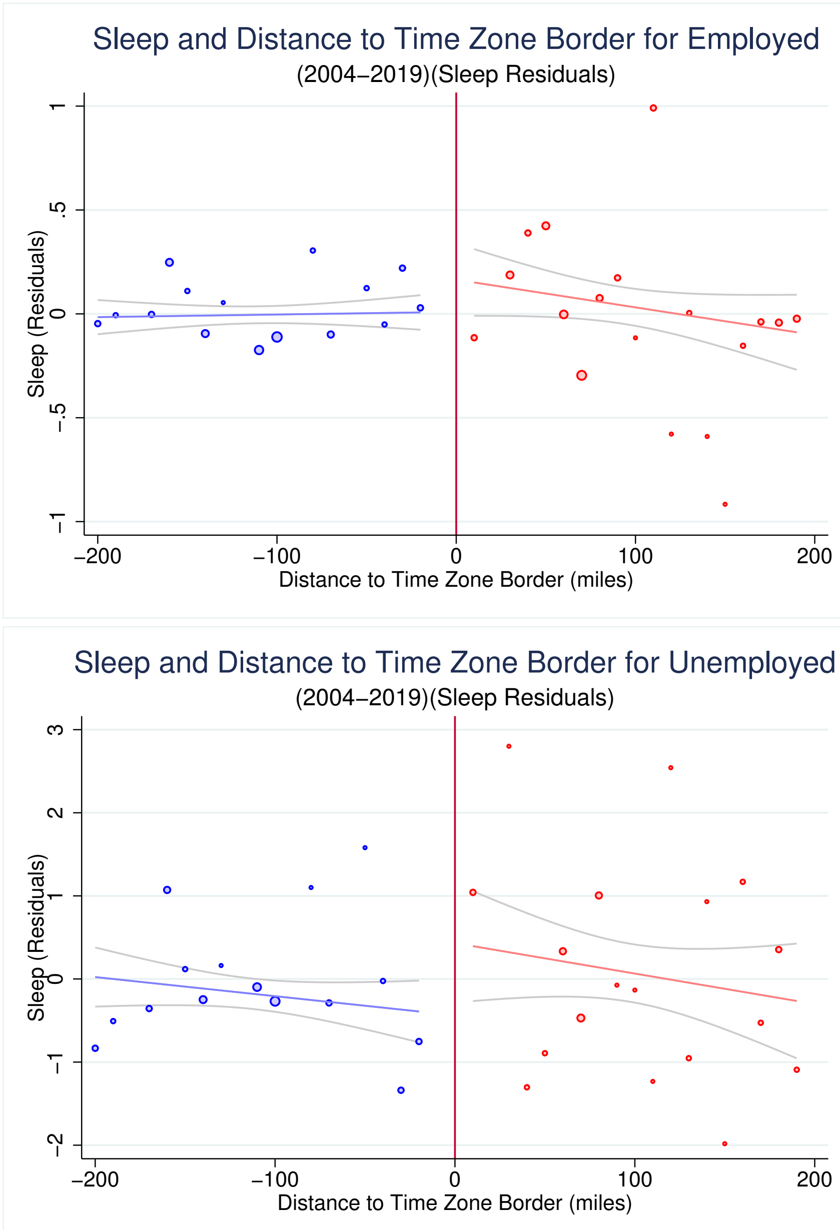



Figure 12: Sleep and Distance to Time Zone Border for Employed

This figure show the discontinuity in sleep and distance to time zone border for employed and unemployed individuals. Data are from ATUS (2004-2019). Each point represents the the mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

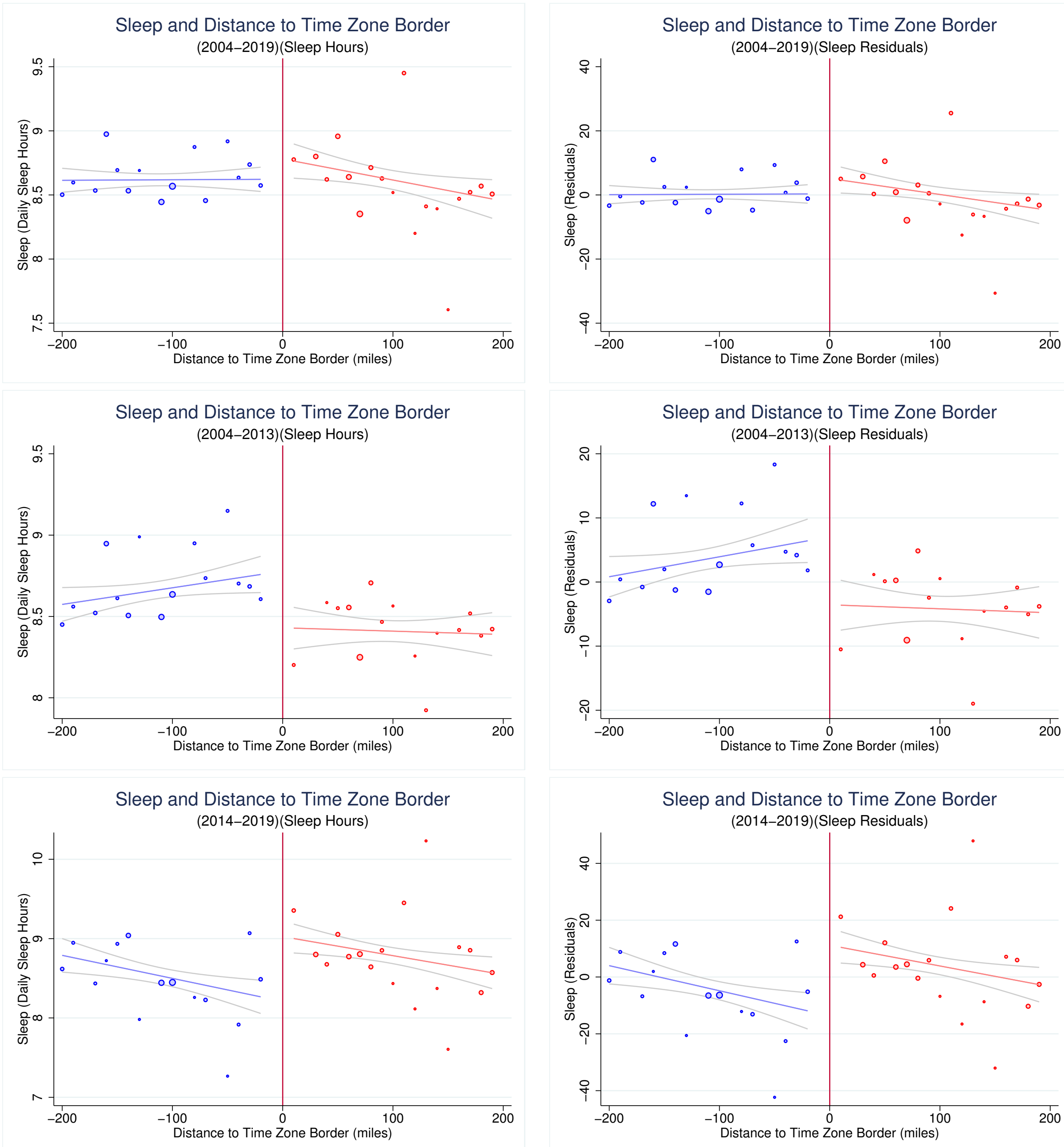



Figure 13: Sleep and Distance to Time Zone Border

This figure show the discontinuity in sleep and distance to time zone border. Data are from ATUS (2004-2019). Each point represents the mean daily sleep hour on the left panel and mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

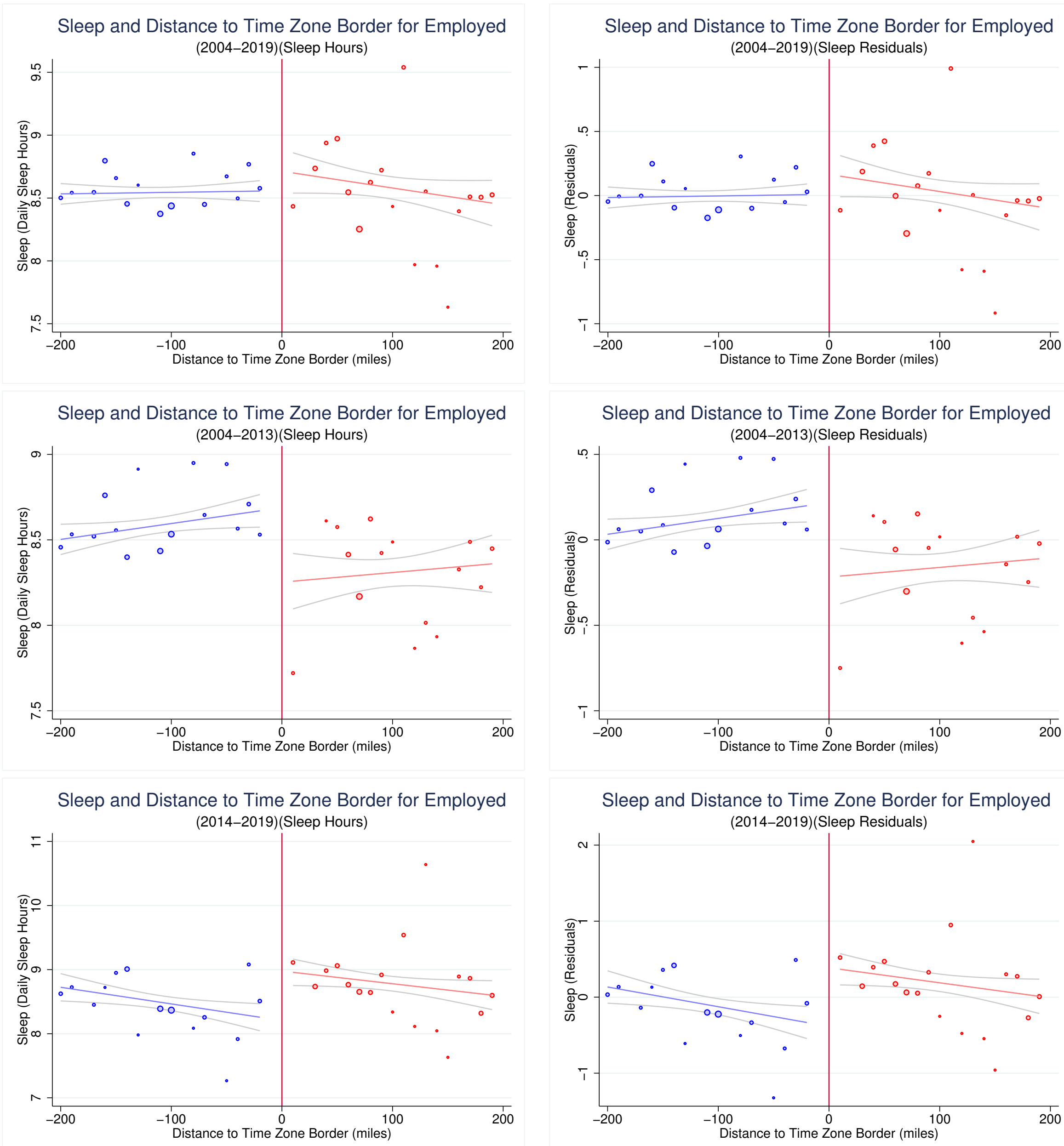



Figure 14: Sleep and Distance to Time Zone Border for Employed

This figure show the discontinuity in sleep and distance to time zone border for employed individuals. Data are from ATUS (2004-2019). Each point represents the mean daily sleep hour on the left panel and mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

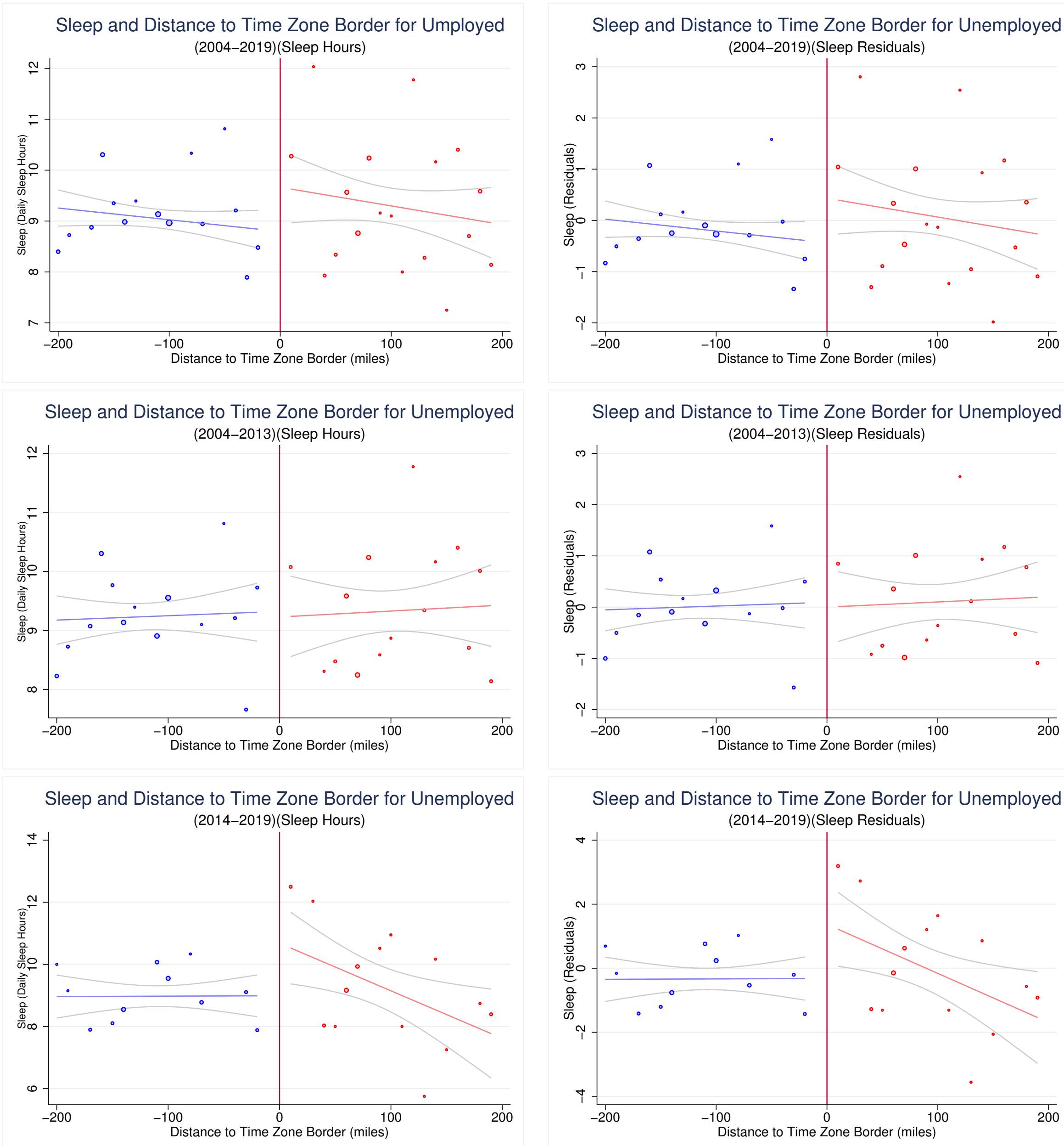



Figure 15: Sleep and Distance to Time Zone Border for Unemployed

This figure show the discontinuity in sleep and distance to time zone border for unemployed individuals. Data are from ATUS (2004-2019). Each point represents the mean daily sleep hour on the left panel and mean residuals (10 miles average) of sleep on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

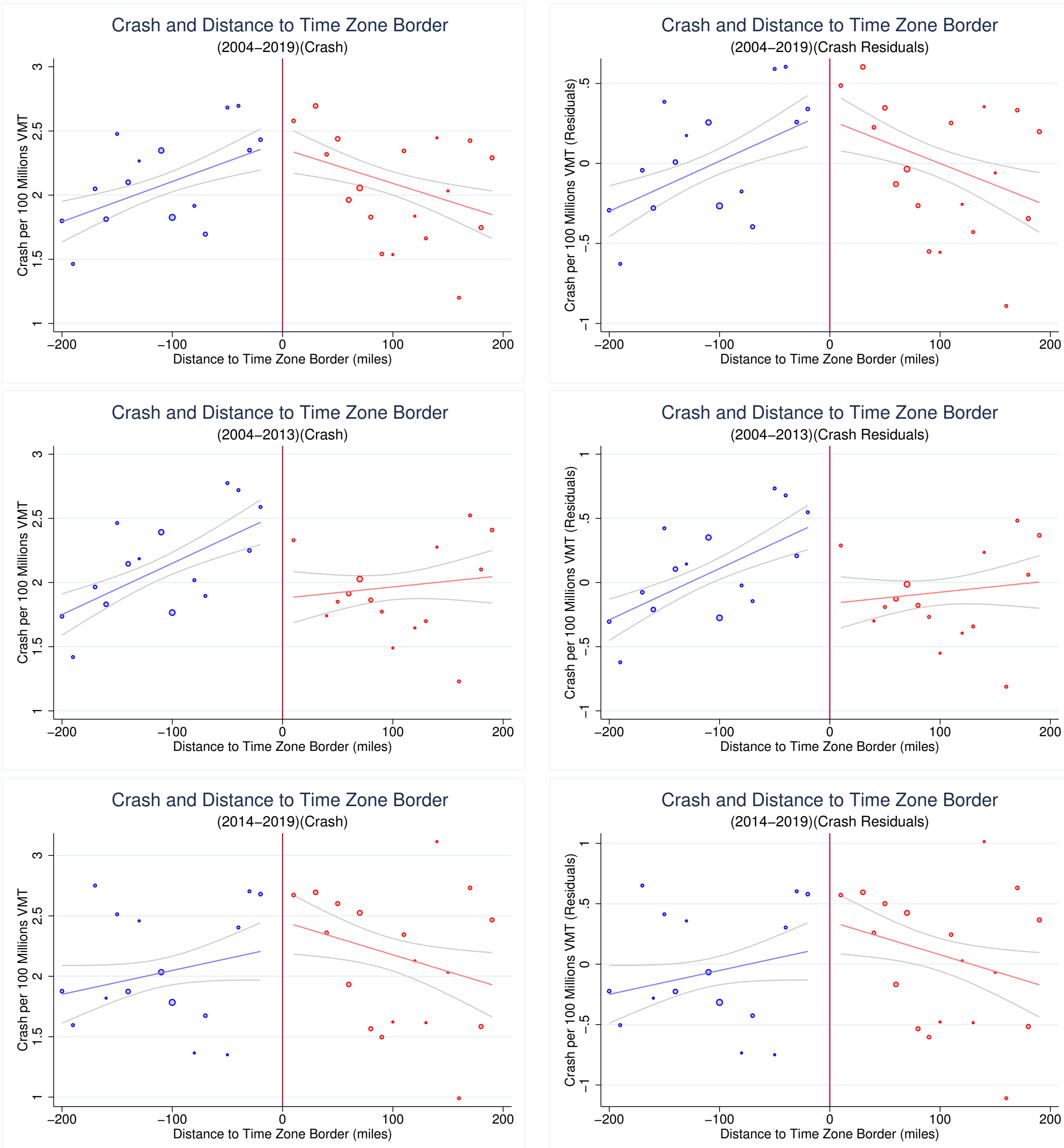



Figure 16: Crash and Distance to Time Zone Border

This figure show the discontinuity in crash and distance to time zone border. Data are from ATUS (2004-2019). Each point represents the mean crash per 100 millions VMT on left panel and mean residuals (10 miles average) of the crash per 100 millions VMT on a set of geographical controls (a linear control for latitude and dummy for large counties) on the right panel. The scatterplot is weighted by the number of observations in distance group. The distance group is calculated using the cut command in Stata.

Table 6: Baseline Estimates: Effects of Locating on the Late Sunset Side on Sleep for Employed (2004-2019)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep $\geq 8hrs$ |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | -0.162* | 0.034 | -0.161 | -0.067 | 0.219*** | -0.095 | -0.021 |
| | (0.10) | (0.08) | (0.12) | (0.14) | (0.07) | (0.15) | (0.02) |
| Mean | 8.53 | 8.53 | 8.53 | 8.56 | 8.56 | 8.56 | 0.62 |
| Controls | No | Yes | Yes | No | Yes | Yes | Yes |
| State FEs | No | No | Yes | No | No | Yes | No |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 | 250 |
| Observations | 11910 | 11910 | 11910 | 3706 | 3706 | 3706 | 11910 |

**Notes:** Data are from ATUS (2004-2019). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 7: Baseline Estimates: Effects of Locating on the Late Sunset Side on Sleep for Employed (2004-2013)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep $\geq 8hrs$ |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | -0.443*** | -0.273*** | -0.229 | -0.363* | -0.066 | -0.356** | -0.077** |
| | (0.10) | (0.10) | (0.15) | (0.19) | (0.10) | (0.17) | (0.03) |
| Mean | 8.49 | 8.49 | 8.49 | 8.53 | 8.53 | 8.53 | 0.61 |
| Controls | No | Yes | Yes | No | Yes | Yes | Yes |
| State FEs | No | No | Yes | No | No | Yes | No |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 | 250 |
| Observations | 8305 | 8305 | 8305 | 2598 | 2598 | 2598 | 8305 |

**Notes:** Data are from ATUS (2004-2019). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 8: Baseline Estimates: Effects of Locating on the Late Sunset Side on Sleep for Employed (2014-2019)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep Hours | Sleep $\geq 8hrs$ |
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | 0.385** | 0.657*** | 0.023 | 0.405* | 0.597*** | 0.404 | 0.090** |
| | (0.19) | (0.14) | (0.19) | (0.21) | (0.19) | (0.26) | (0.04) |
| Mean | 8.63 | 8.63 | 8.63 | 8.64 | 8.64 | 8.64 | 0.65 |
| Controls | No | Yes | Yes | No | Yes | Yes | Yes |
| State FEs | No | No | Yes | No | No | Yes | No |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 | 250 |
| Observations | 3605 | 3605 | 3605 | 1108 | 1108 | 1108 | 3605 |

**Notes:** Data are from ATUS (2004-2019). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 9: Effects of Locating on the Late Sunset Side on Fatal Crashes for Employed (2004-2019)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Crashes | Crashes | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | -0.611** | -0.772*** | -0.650* | 0.207 | 0.192 | -0.385 |
| | (0.29) | (0.26) | (0.34) | (0.31) | (0.23) | (0.41) |
| Mean | 8.57 | 8.57 | 8.57 | 8.57 | 8.57 | 8.57 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| County FEs | No | No | Yes | No | No | Yes |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 |
| Observations | 25873 | 25873 | 25873 | 6724 | 6724 | 6724 |

**Notes:** Data are from FARS and ATUS (2004-2019). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 10: Effects of Locating on the Late Sunset Side on Fatal Crashes for Employed (2004-2013)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Crashes | Crashes | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | -0.763** | -0.902*** | -0.720** | 0.095 | 0.123 | -0.411 |
| | (0.34) | (0.30) | (0.35) | (0.28) | (0.24) | (0.43) |
| Mean | 8.53 | 8.53 | 8.53 | 8.53 | 8.53 | 8.53 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| County FEs | No | No | Yes | No | No | Yes |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 |
| Observations | 18819 | 18819 | 18819 | 4854 | 4854 | 4854 |

**Notes:** Data are from FARS and ATUS (2004-2013). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 11: Effects of Locating on the Late Sunset Side on Fatal Crashes for Employed (2014-2019)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Crashes | Crashes | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se | b/se |
| Late Sunset Side=1 | -0.304 | -0.494* | -0.459 | 0.307 | 0.170 | -1.073** |
| | (0.29) | (0.27) | (0.38) | (0.41) | (0.31) | (0.47) |
| Mean | 8.66 | 8.66 | 8.66 | 8.66 | 8.66 | 8.66 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| County FEs | No | No | Yes | No | No | Yes |
| Bandwidth (miles) | 250 | 250 | 250 | 100 | 100 | 100 |
| Observations | 7054 | 7054 | 7054 | 1870 | 1870 | 1870 |

**Notes:** Data are from FARS and ATUS (2014-2019). Estimates include the distance to the time-zone boundary and the interaction with the late sunset border, socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). Significance levels: * 0.10, ** 0.05, *** 0.01.

# 6 Robustness Check

Confounding factors such as weather and road condition may be correlated with both sunset hour and crashes, so I control for seasonality by adding the time fixed effects. For instance, the road could be icy in the north regions during winters, which poses higher risk on fatal vehicle crashes. Table 12 include year, year-month, and county-month fixed effects and the results all show the similar estimates as Table 11. The impact of sleep on crashes range from -0.049 to -0.034, which indicates that additional sleep has short run negative impact on fatalities. For example, column (3) to (5) implies that one extra hour in monthly sleep causes 0.035 reduction in fatal crashes per 100 millions VMT.

Road type could affect fatal vehicle crashes since the speed is different on various roads. Table 13 illustrates the short run effects of sleep on fatal vehicle crashes by types of roads, such as highway, county road, and local street. The road type is available in FARS since 1987 and I categorize the road as highway if the road is interstate, U.S. highway, or state highway. In addition, I classify the road as local street if the road is township, municipality, or frontage road. The results show that the impact of sleep on fatalities is higher for highway than the other types of roads and the effect is about half of the estimate for all roads. Specifically, column (2) indicates that one hour additional monthly sleep results in 0.019 reduction in fatalities on highway. It is equivalent to 0.57 decrease in fatal vehicle crashes per 100 million VMT if increase daily sleep by one hour.

Light could play a crucial role in fatal vehicle crashes as more ambient light could create a safer driving environment. If the sunset is late for one hour, then additional light during evening should reduce the risk of crashes. Similarly, decreasing one hour light from morning would increase the risk of fatalities. To test this hypothesis, I will decompose the crashes into morning crashes (two hours more of less from the local average sunrise time), evening crashes (two hours more or less from the local average sunset time), least light impacted daytime crashes (the remaining hours), and night time crashes following the similar setup from Smith (2016).

Table 14 shows the short run effects of sunset on fatal crashes by light condition. If the sunset hour is one-hour late, then there would be less crashes in the evening and more crashes in the morning. Counterintuitively, both column (2) and (3) suggest the fatalities decrease for both morning and evening. However, the deduction in the evening crashes is 4.5 times larger than that in the morning crashes. Column (4) indicates that one hour late in sunset could result in 0.018 more fatal crash per 100 million VMT.

Table 15 provides the short run effect of sleep on fatalities by light condition. Column (2) and (3) suggest that there are more crashes during the morning and evening if sleep more. One possible explanation is that the sunset hour is early in the county where individual sleep more, and this would increase the ambient light in the morning and reduce light in the evening. Intuitively, the morning crashes would reduce and the evening crashes would increase. Although both the morning and evening crashes augment from column (2) and (3), there are more crashes in the evening than morning. Column (4) suggests that increasing daily sleep by one hour could lead to about 0.6 reduction in fatal crash per 100 million VMT, which is about 60% of the estimate from column (1). The result indicates that increasing sleep could reduce crashes during the least light impacted time of the day.

Table 12: Short Run IV Estimates of the Effects of Sleep on Fatal Crashes (Control for Seasonality)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Crashes | Crashes | Crashes | Crashes | Crashes |
| | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | -0.049*** | -0.035*** | -0.036*** | -0.034*** | -0.034*** |
| | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) |
| Mean | 1.81 | 1.81 | 1.81 | 1.81 | 1.81 |
| Controls | No | Yes | Yes | Yes | Yes |
| County FEs | No | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No |
| Year-Month FE | No | No | No | Yes | No |
| County-Month FE | No | No | No | No | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 | 36296 |

**Note:** Sleep and sunset time are measured in hours at county-year-month level. The dependent variable of sleep is monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per one billion vehicle miles traveled at state-county-month level. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). Seasonality are captured by adding time fixed effects. The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01

Table 13: Short Run Effects of Sleep on Fatal Vehicle Crashes by Types of Roads

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Crashes (All Roads) | Crashes (Highway) | Crashes (County Road) | Crashes (Local Street) |
| | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | -0.034*** | -0.019*** | -0.007** | -0.009* |
| | (0.01) | (0.01) | (0.00) | (0.01) |
| Mean | 1.81 | 0.93 | 0.32 | 0.48 |
| Controls | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 |

**Notes:** Sleep is measured in hours at county-year-month level. The dependent variable of sleep is monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level by different types of roads. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). F test on the excluded instrument. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 14: Short Run Effects of Sunset on Fatal Vehicle Crashes by Light Condition

| | (1) Crashes (All Hours) b/se | (2) Crashes (Morning) b/se | (3) Crashes (Evening) b/se | (4) Crashes (Daytime) b/se | (5) Crashes (Nighttime) b/se |
|---|---|---|---|---|---|
| Sunset Hour | 0.027*** | -0.006*** | -0.027*** | 0.018*** | 0.012*** |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Mean | 1.81 | 0.23 | 0.40 | 0.55 | 0.34 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 | 36296 |

**Notes:** Sleep is measured in hours at county-year-month level. The dependent variable of sleep is monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level by different types of roads. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and indicator for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses).“Morning” is defined as +/- two hours from the average sunrise time in that county. “Evening” is defined as +/- two hours from the average sunset time in that county. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 15: Short Run Effects of Sleep on Fatal Vehicle Crashes by Light Condition

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Crashes (All Hours) | Crashes (Morning) | Crashes (Evening) | Crashes (Daytime) | Crashes (Nighttime) |
| | b/se | b/se | b/se | b/se | b/se |
| Average Monthly Sleep | -0.034*** | 0.008** | 0.035*** | -0.022*** | -0.015*** |
| | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) |
| Mean | 1.81 | 0.23 | 0.40 | 0.55 | 0.34 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| County FEs | Yes | Yes | Yes | Yes | Yes |
| Observations | 36296 | 36296 | 36296 | 36296 | 36296 |

**Notes:** Sleep is measured in hours at county-year-month level. The dependent variable of sleep is monthly average sleep hours. The dependent variable of crashes refers to fatal crashes per 100 millions VMT at county-year-month level by different types of roads. Controls include socio-demographics (age, race, sex, education, marital status, nativity status, and number of children), geographic characteristics (latitude, longitude, and dummy for large counties), and interview characteristics (indicators for holiday and weekend). The standard errors are robust to heteroscedasticity and clustered at state-county level (reported in parentheses). "Morning" is defined as +/- two hours from the average sunrise time in that county. "Evening" is defined as +/- two hours from the average sunset time in that county. Significance levels: * 0.10, ** 0.05, *** 0.01.

# 7 Conclusion

Sleep deprivation is known to have negative effects on daytime alertness and attention, potentially increasing the risk of fatal vehicle crashes. While laboratory studies in the medical field have established a link between sleep deprivation and adverse health outcomes, there is limited understanding of the causal impact of sleep and the consequences of sleep deprivation in real-world situations.

This paper aims to investigate the causal impact of sleep on fatal vehicle crashes in the United States, utilizing IV and RDD methods, as well as data from the ATUS and FARS. By employing a seasonal, short-run IV approach, the study reveals that a one-hour delay in sunset results in a decrease of approximately 48 minutes in monthly sleep duration. Furthermore, a one-hour increase in monthly sleep is associated with a 2.4% reduction in fatalities. However, when employing a geographical, long-run IV method, statistically significant results were not obtained. In the RDD analysis, it was observed that from 2004 to 2013, employed individuals slept less on the side of the time zone border with a later sunset. Surprisingly, from 2014 to 2019, they actually slept more on the later sunset side. Interestingly, traffic fatalities were lower on the side with a late sunset from 2004 to 2013, but higher from 2014 to 2019.

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