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No Rest for the Weary: Commuting, Hours Worked, and Sleep

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Abstract

This paper is the first to combine data from large nationwide surveys to investigate how commuting and work hours affect sleep. I estimate that 11-21% of the marginal unit of time spent working and 22-30% of the marginal unit of time spent commuting replaces sleep. Controlling for these effects, commuting before 5 a.m. and after 9 a.m. each increase the likelihood of short sleep. I also find that time spent commuting and working and the prevalence of these strange commute times each contribute to unintentionally falling asleep at some time during the day, while early commuting in particular increases the likelihood of falling asleep while driving. Little of these effects are explained by reduced time spent sleeping, indicating that there are multiple biological channels through which commuting duration and timing impact road safety. None of these effects appear for non-workers as opposed to the employed, supporting the validity of the results. Overall, most of the effects are stronger for women than for men, though the prevalence of early commutes is particularly associated with less sleep among men.

JEL codes: R41, I15, J16

Keywords: Commuting; Sleep; Time Allocation; Gender

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1 Introduction

What are the relationships between time spent commuting, working, and sleeping? To explore this question, I combine health survey data on sleep behavior with commuting and working data at the county level. The results indicate that longer commutes, longer workweeks, and commutes that begin at more unusual times of the day raise the risk of short sleep and unintentionally falling asleep, and that these effects differ considerably between men and women.

A well-developed medical literature has established that short sleep is associated with long list of health risks, including obesity, diabetes, hypertension, and cardiovascular disease (Buxton and Marcelli 2010). Despite this, the incidence of short sleep among full-time workers in the U.S. has increased over previous decades (Knutson et al. 2006; Luckhaupt et al. 2010). Knutson et al. also find that, after adjusting for socioeconomic factors, there has been no such significant change for those that don't work full-time. Fundamental economic theory states that consumption of sleep, like any other good, should fall as its cost rises. It appears that critical opportunity costs of sleep arise particularly from work and related activities such as commuting.

Based on the American Community Survey (ACS) from 2006 to 2011, over 95% of workers commute in some fashion, and the average commute in the United States is around 25.5 minutes (McKenzie 2014). According to the National Household Travel Survey, commuting accounted for 28% of all vehicle miles traveled in the U.S. in 2009 (Santos et al. 2011). There is evidence that increased commuting has negative consequences for mental health (Turcotte 2011; Roberts et al. 2011) and physical health (Sugiyama et al. 2013; Ding et al. 2014), though how much of this occurs through loss of sleep as opposed to other channels is unclear. Further, these health effects do not necessarily translate into effects on overall well-being (Dickerson et al. 2014).

The relationship between commuting and sleep as competing uses of time is especially important because of the dangers of driving while sleep-deprived. A decrease in driving performance due to a decrease in sleep time has been documented by laboratory experiments (Philip, et al. 2005) and occupational surveys (Scott, et al. 2007). MacLean et al. (2003) provide a review of the literature on sleep deprivation and driving safety. They note that sleepiness may be factor in up to 20% of motor vehicle accidents, and that prolonged wakefulness can have an effect on driving performance comparable to illegal levels of alcohol intoxication.

Independent of the amount of time devoted to sleep, driving ability has been shown to depend on time of day (Williamson et al. 2011). In particular, driving performance is impaired at early morning hours and in the early afternoon (Lenne et al. 1997), and crashes attributed to falling asleep occur primarily during these periods (Pack et al. 1995). Work schedules that move commute times to these periods can therefore be expected to increase the risk of motor vehicle accidents. "Strange hours" of work are especially prevalent in the U.S. relative to other countries, even after controlling for the number of hours worked (Hamermesh and Stancanelli 2014).

I estimate that 11-21% of the marginal unit of time spent working and 22-30% of the marginal unit of time spent commuting replaces sleep. Controlling for these effects, commuting before 5 a.m. and after 9 a.m. each increase the likelihood of short sleep. Further investigation shows that time spent commuting and working and the prevalence of these strange commute times each contribute to unintentionally falling asleep at some time during the day, while early commuting in particular increases the likelihood of falling asleep while driving. Little of these effects are explained by reduced time spent sleeping, indicating that there are multiple channels through which commuting behaviors impact road safety. None of these effects appear for non-workers as opposed to the employed, supporting the validity of the results. Overall, most of the effects are stronger for women than for men, though the prevalence of early commutes is particularly associated with less sleep among men.

2 Previous Literature

Becker (1965) famously developed a theory of time use, with implications for theories of commuting (Nelson 1977) and sleep (Biddle and Hamermesh 1990). Intuitively, an agent maximizes utility under a time constraint, such as 24 hours in a day, in the same way he does under a budget constraint. In fact, these two types of constraints can be represented by one equation as long as the time spent working is a choice variable. Thus, the fundamental economic theory on consumption and income is directly analogous to activity and time endowment. From this point of view, authors have investigated how commuting times affect choices between work and leisure (Ross and Zenou 2008; Van Ommeren and Gutierrez-i-Puigarnau 2011). Whether sleep is considered "leisure" depends on the definition (Aguiar and Hurst 2007), but it nonetheless represents a vital, universal, and extensive use of time.

Among the previous literature, this paper is most similar to Christian (2012), who estimates that 28-35% of additional commuting time would have otherwise been spent sleeping. On the topic of early and late commutes, the most similar work is Basner et al. (2014), who show that starting work or educational training one hour earlier is associated with 20 fewer minutes of sleep. These and other studies of sleep time such as Knutson et al. (2006) and Basner et al. (2007) primarily use the American Time Use Survey (ATUS).[1] Studies of non-market activities such as sleep rely on the level of detail unique to time use surveys such as the ATUS (Aguiar and Hurst 2007). In particular, the ATUS is the largest sample that contains individual-level observations of both sleeping and commuting time. A subsample of the Current Population Survey has participated in the ATUS each year since 2003. Participants are asked to report what they did each minute for 24 hours starting at 4 a.m. of the day prior to the survey. Each activity is recorded in one of 431 categories, including working, traveling to and from work, and sleeping. However, there are multiple difficulties associated with using the ATUS or other time use surveys.

Most importantly, time use surveys have small samples relative to other nationwide sur-

[1]Time use surveys from other nations have been used, but none are as common as the ATUS. For example, Chatzitheochari and Arber (2009) use the 2000 United Kingdom Time Use Survey to examine relationships between working time, shift work, and sleeping time, and Szalontai (2006) uses a time use survey from South Africa to show that sleeping time has an inverse relationship with economic opportunities.

veys, and thus allow only coarse regional distinctions. Aguiar et al. (2013) merge state-level unemployment data with the ATUS to measure how work hours lost during the Great Recession were replaced by a comprehensive list of activities, including sleep. Antillon et al. (2014) focus specifically on the relationship between state unemployment and ATUS-observed sleep time. Brochu et al. (2012) perform a similar analysis with Canadian time use data and unemployment at the province level. Each paper provides evidence that sleep time is countercyclical, but each is restricted by the nature of time use surveys to a highly aggregated regional measure of business cycles. In this paper, I am able to match county-level variables to individually reported sleep durations. While I am interested in commuting and work hours, I am also able to include unemployment rates among other controls at the county level.

A problem with the ATUS specific to the topic of sleep concerns the start and end times of the diary day. Because the time diary begins and ends at 4 a.m., few continuous sleep durations are actually observed.[2] The number of minutes of sleep observed over the diary is usually the sum of time slept since 4 a.m. in the morning and time slept from some bedtime until 4 a.m. the following night. In other words, most diary days are bookended by separate periods of sleep. If individuals have very regular sleep schedules, then this sum is representative of daily sleep time, but this is a strong assumption to make, especially for days around weekends or holidays.

Another issue is that the variables of interest may be endogenous. This is true for commuting variables if those with a weaker preference for sleep or sleep regularity sort into areas or occupations with longer or more irregular commutes. Similarly, light sleepers may disproportionately choose jobs with longer hours. Since preference for sleep cannot be observed in the cross-sectional data, the results may be biased.

Since few other surveys ask about both driving and sleeping time, these issues have remained in the literature. One exception is Ding et al. (2014), who use a health survey conducted in New South Wales, Australia to examine relationships between driving time and

[2]This is identically the case for the time use subsample of the Canadian General Social Survey and the 2000 UK Time Use Survey.

health behaviors, including sleep. Their analysis is limited to a binary variable for insufficient sleep (defined to be fewer than seven hours) and four intervals (0-30 minutes, 31-60 minutes, 61-120 minutes, and 120 minutes or more) for the answer to the question "About how many hours in each 24 hour day do you usually spend driving?" Monaco et al. (2005) use a survey of truck drivers to show that longer hours of driving are associated with decreased sleep time and increased risk of falling asleep while driving. By nature, their sample is restricted to a special case where driving and working are one and the same.

The Behavioral Risk Factor Surveillance System (BRFSS) in the United States offers suitable information on sleep for the general population, but lacks information on commuting and working. This paper introduces the solution of complementing the BRFSS data with county-level data from the ACS. This novel approach provides many advantages over time use data. First, it removes bias due to within-county sorting based on individual preferences. Second, it provides sleep-related outcomes besides time spent sleeping. Third, it allows for county-level controls. Fourth, it provides a larger sample. Aggregation does not introduce any bias to the results, but has the disadvantage of decreased precision. This is counteracted by a larger sample size and does not prevent me from obtaining statistically significant results.

3 Data

3.1 BRFSS individual responses

The BRFSS is an annual nationwide telephone survey overseen by the Centers for Disease Control and Prevention. The BRFSS sleep data come from the optional "inadequate sleep" survey module that was conducted from 2009 to 2012. BRFSS optional modules are sets of questions on specific topics that states (and Washington D.C. and Puerto Rico) may choose to include in their surveys in a given year. Table 1 summarizes regional participation from 2009 to 2012, unlisted states having not participated.[3] No state participated in the module for all four years, and most only participated for one year. New York, California,

[3] Puerto Rico participated in the module in 2012, with 1777 employed respondents, but I chose to exclude them from the sample.

Pennsylvania, Florida, and Texas, and thus some of the longest mean commutes in the U.S., are absent from the sample.

I consider four questions from the sleep module. The first asks "On average, how many hours of sleep do you get in a 24-hour period? Think about the time you actually spend sleeping or napping, not just the amount of sleep you think you should get."[4] The distribution of responses is presented in Figure 1. For this question, the respondent is not instructed to give a whole number of hours, but the survey proctor is instructed to round the response to the nearest hour. Still, reported sleep time compares reasonably with a normal distribution. 36.1% reported sleeping 6 or fewer hours per day, which I define as "short sleep."

Figure 2 presents the distribution of responses to the question "During the past 30 days, for about how many days did you find yourself unintentionally falling asleep during the day?" 71.3% of the responses are zeroes and only 8.8% of responses exceed five days. The lack of variation in positive responses diminishes the potential value of a count model for this variable.

A third question from the module asks "During the past 30 days, have you ever nodded off or fallen asleep, even just for a brief moment, while driving?" 56,962 employed respondents responded either yes or no, with 2,153 of these respondents, or about 3.9%, admitting to falling asleep while driving in the past 30 days.[5] This statistic should be interpreted with caution. Drivers that are judged to have fallen asleep just prior to a crash often deny having done so, and laboratory studies show that most people who fall asleep for no longer than a few minutes honestly fail to acknowledge it (Horne and Reyner 1999). Not only should 3.9% be interpreted as a lower bound, but relatively weak estimated effects on this variable should not be taken as a lack of an effect on road safety, especially with contrasting evidence for unintentionally falling asleep some time during the day.

The last question I consider asks "During the past 30 days, for about how many days have you felt you did not get enough rest or sleep?" Besides being part of the sleep module

[4]This question became a core survey question in 2013. However, 2013 is the first year of the BRFSS for which sub-state geography is not identified for the sake of confidentiality.

[5]This is after removing from the sample the 584 respondents who reported not having a driving license or otherwise not being a driver.

in 2011 and 2012, this question was also part of the core survey in 2008, 2009, and 2010. These three years of the BRFSS offer about ten times the sample size compared to the four years of the sleep module. Responses to this question from employed respondents over the three-year period are presented in Figure 3. 26.8% of respondents reported getting enough sleep every night in the past month. Though in general one could consider a count model for an answer in this format, the strong response bias toward multiples of five days suggests that this would be inappropriate.

The advantage of larger and geographically broader sample size is diminished by the subjective nature of this question. This question relies on the respondent's definition of "enough sleep." Thus, of the four questions described, I consider it to be the least informative about sleep and sleep-related safety.

3.2 ACS county-level variables

The BRFSS does not provide data on commuting. To solve this issue, I use county-level means from the 5-year American Community Survey sample from 2008-2012. Assuming that a day of commuting involves one trip to work and another equally long trip back home, I double the commute time variable to represent daily travel time.

I also obtain county-level population sixteen years and older, population density, labor force participation, and unemployment from the same sample.[6] These county-level controls are a luxury not offered by the ATUS. In addition to mean commuting time, I include mean weekly hours worked and two measures of "strange hours" as variables of interest. For the latter, I use the percentage of commuters that depart home after or at midnight and before 5 a.m., and the percentage that depart after or at 9 a.m. and before midnight. I refer to these two variables as "early commutes" and "late commutes," respectively.

Table 2 summarizes the ACS data separately for the two BRFSS samples for employees and non-workers. The employee and non-worker subsamples are conveniently similar in size. Non-workers tend to live in less populated areas with lower labor force participation

[6]Weekly hours worked are averaged over all workers, non-workers excluded.

and higher unemployment rates, but the differences are small. The sleep module and core sample means are practically the same; though it excludes some of the largest cities in the U.S., the sleep module sample is reasonably representative of the nation.

4 Methodology

4.1 Specifications

I regress the BRFSS sleep question responses on the ACS county-level variables and a set of individual level controls that may influence sleep behavior. Specifically, I include dummy variables for the month of the survey, marital status, education, sex, race, the presence of one, two, or three or more children in the household, and intervals for income and age.

Each of these four variables of interest (commute time, early commutes, late commutes, and hours worked) are expected to negatively affect sleeping time and increase the likelihood and frequency of unintentionally falling asleep. Commuting time and weekly work hours represent opportunity costs of sleep, while strange departure times interfere with the body's circadian rhythm. There is a large medical literature on the biological reasons for sleep difficulty as a result of irregular work hours, such that the existence of "Shift Work Sleep Disorder" is well-established and associated a wide range of associated health risks (Schwartz and Roth 2006).

I restrict the sample to workers that are not self-employed.[7] As a falsification test, I perform the same regressions for the subsample of non-workers. Non-workers in the sample are primarily retirees, but also include those out of work, homemakers, and students.[8] The expectation is that county-level commuting variables have weak, if any, effects on sleep time for non-workers relative to employees.[9]

I report results for employees with and without the inclusion of state fixed effects. Includ-

[7] The self-employed comprise about 8.5% of all respondents for both the three-year core survey sample and the sleep module sample. Self-employment represents a unique situation with regard to commuting and work scheduling. The results are insensitive to including the self-employed in the sample of workers.

[8] The BRFSS only distinguishes between individuals that have been "out of work" for greater than and less than one year, without regard as to whether the individual is unemployed or has exited the labor force.

[9] The effects may conceivably be non-zero due to longer non-commuting travel time because of increased traffic congestion, or because sleep patterns formed while working may persist. Still, the effects for employees should be larger in absolute value.

ing state fixed effects eliminates variation in the variables of interest across states. This is valuable to the extent that state fixed effects are picking up on inter-state differences in sleep preferences, but it is counterproductive to the extent that they are picking up on differences in inter-state means of the variables of interest. Based on this, I tentatively prefer results without state fixed effects, but robustness to their inclusion is a strength.

There is a well-developed literature on the different responses to commute times for men and women (White 1986). Authors have found evidence of sex-specific effects for such variables as labor force participation (Black et al. 2014) and psychological health (Roberts et al. 2011). Recognizing this, I perform the same regressions as described above on male and female subsamples with sex-specific versions of the variables of interest.[10]

4.2 Econometric Concerns

The estimation is vulnerable to bias because individual preferences for sleep are unobservable. A greater preference for sleep is positively correlated with sleep time and negatively correlated with those variables that interfere with sleep, including all of the variables of interest. This will downwardly bias the already negative estimates for sleep time and upwardly bias the already positive estimates related to lack of sleep. The use of county-level rather than individually observed variables reduces this bias, because the county-level variables are unrelated to any choice of workplace location, method of commuting, or any other determinant of the variables of interest at the individual level, except those that involve a change in the county of residence.

The bias is not wholly eliminated because individuals may still sort into counties based on their preferences for sleep. For example, more career-motivated individuals may sort into larger cities (Rosenthal and Strange 2008), and simulataneously be more willing to sacrifice sleep. Alternatively, people who are more vulnerable to sleepiness may locate where they can be safer by spending less time driving. There are many more imaginable examples, but they all share the effect of exaggerating the estimates.

[10]Using sex-specific county means is necessary to avoid bias from aggregation.

The drawback to using county-level means is measurement error. Because this measurement error is not correlated with an individual's actual unobserved commute time, it does not introduce any bias into estimation of the effects of the county-level variables.[11] Only the precision of the estimates suffers, which is remedied by the larger sample size relative to previous studies.

Another concern is that the county-level variables may be highly collinear. To examine this possibility, Table 3 provides correlations between all of the county-level variables, weighted by the number of observations per county in the sleep module sample.[12] More populated counties, as expected, tend to be more population-dense, have longer average commutes, and have a greater percentage of late commutes and a smaller percentage of early commutes. Longer weekly hours are correlated with a larger percentage of early commuters and a smaller percentage of late commuters. The latter correlation of -0.533 is the only one in the table above 0.5 in absolute value, indicating that collinearity among the county-level variables is not a major concern.

5 Results

The remainder of this paper presents and discusses the results. In all tables, standard errors are in parentheses and clustered by county. One, two, and three stars show statistical significance at p-values of .10, .05, and .01, respectively. All logit coefficients are exponentiated for ease of interpretation.

5.1 Sleep Time

Panel A of Table 4 reports OLS estimates with time spent sleeping per 24 hours as the dependent variable.[13] The first column reports these effects for employed people, the second includes state fixed effects, and the last column uses the sample of non-workers instead of

[11]This does cause the estimated effects of the individual-level controls to be biased to the extent that they are correlated with the individual deviations from the county means, but these are not of interest in this paper.

[12]The correlations are similar in the core sample.

[13]Count models (treating the number of sleep hours as discrete) give analogous results. OLS results are preferred for interpretation.

the employed. As expected, none of the estimates for non-workers are statistically significant at conventional levels. This supports the claim that estimates for the employee sample are measuring the actual effects of the variables of interest as opposed to some omitted correlates. With this in hand, I turn to the estimates for the employee sample.

As expected, the estimated coefficients for all variables of interest are negative. Coefficients on daily commute time, percentage of late commutes, and weekly hours are statistically significant at the 1%, 5%, and 10% levels, respectively, and this is robust to the inclusion of state fixed effects. The coefficient on daily commute time of -0.304 implies that 30% of extra time devoted to commuting would have otherwise been devoted to sleep. The results imply an analogous percentage for time devoted to work of about 11%.[14] These percentages are significantly different at the 10% level. However, including state fixed effects doubles the coefficient on work hours and reduces the coefficient on commute time, causing the percentages to be practically equal. This is not enough evidence to infer whether sleep substitution differs for time spent commuting versus working. The inclusion of state fixed effects has otherwise little consequence.

A one percentage point increase in late commutes is associated with 27 fewer seconds of sleep, keeping commuting and working time constant. This implies a disruptive effect of irregular working hours on sleep time as opposed to a time tradeoff. Because this variable cannot distinguish between late morning, afternoon, and evening commuters, it is unclear if the results are being driven by one of these types or a combination. The estimated coefficient for early commuters is negative and larger in absolute value than that for the percentage of late commutes, but it is not statistically significant at conventional levels.

Panel B of Table 4 reports results of logit regressions using a binary sleep time measure as the dependent variable. The dependent variable is equal to one if the reported amount of sleep is less than or equal to six hours. For employees, estimates for all variables of interest are greater than one, as expected, and significant at the 5% level. A one-minute increase in daily commute time increases the likelihood of short sleep by 0.6%. A one-hour increase in

[14] This is the coefficient on working hours per week times the number of days in a week divided by the number of minutes in an hour: $-0.923 * 7/60 \approx -10.8\%$.

mean weekly hours worked increases the likelihood of short sleep by 2.7%. One percentage point increases in early and late commutes are associated with 3.6% and 1.1% increases in the likelihood of short sleep, respectively. Reassuringly, none of the estimates are statistically significant at conventional levels for non-workers.

The estimates for commuting and working time are not significant when state fixed effects are included. However, the estimated effect of early commutes, the only variable of interest that did not show a significant effect on sleep time in Panel A, remains positive and significant with respect to short sleep. Table 4 as a whole thus shows that all four variables of interest play a role in decreasing the amount of sleep Americans consume.

5.2 Falling Asleep

Panel A of Table 5 reports results of logit regressions using a dependent variable equal to one if the respondent reported unintentionally falling asleep in the past 30 days.[15] The first column reports the baseline results for employees and the second, third and fourth columns experiment with additional controls. The last column reports results for non-workers. Commute time, working time, and early commuting all increase the likelihood of unintentionally falling asleep for employed people. These estimates are largely robust to the inclusion of state fixed effects and are not statistically significant at conventional levels for non-workers. Including state fixed effects reduces precision in the estimation for hours worked but does little to affect the point estimate.

In the third and fourth columns, I include the individual's reported sleep time as a control. The fourth column shows that state fixed effects have a similar effect on the estimates with and without the sleep time control. The estimates of the variables of interest are robust to the inclusion of sleep time. This means that, though commuting and working reduce sleep time as evidenced in Table 4, there appear to be one or more other channels through which commuting and working raise the likelihood of unintentionally falling asleep. The simplest

[15] In results unreported, I experimented with a zero-inflated negative binomial model, which supplements the logit model with a count model for the number of days reported. Other than commute time acting through through the count effect rather than the probability of a nonzero response, the results are similar.

explanation is fatigue, such that, among two similar people who sleep the same amount each night, the one who spends more time working and commuting has greater difficulty staying awake.

Panel B of Table 5 reports results of logit regressions using a dependent variable equal to one if the respondent reported falling asleep while driving in the past 30 days. For employees, a one-minute increase in daily commute time is associated with a 1.7% increase in the likelihood of falling asleep while driving. A one percentage point increase in early commutes is associated with a 4.3% increase in the likelihood of falling asleep while driving in the past month. The percentage of late commutes and weekly work hours do not have a statisitically significant effect. Once again, none of the estimates are statistically significant at conventional levels for non-workers.

The result for early commutes is consistent with the previous literature on driving performance by time of day (Pack et al. 1995; Lenne et al. 1997). The result for early commutes is also robust to controlling for sleep time, suggesting that this effect is working through some channel other than simply lack of sleep, such as circadian disturbance. The lack of a result for late commutes is not too surprising given the 15-hour width of the interval.

None of the estimates are significant with the inclusion of state fixed effects. Overall, the results in Panel B are weaker than those in Panel A, owing perhaps to response bias with respect to falling asleep while driving. Though it is less specific, falling asleep some time during the day may be a more reliable indicator of fatigue, which translates to unsafe driving. All together, the results in Table 5 provide evidence that commuting and working times that are longer and especially early in the morning have a negative impact on road safety.

5.3 Not Enough Sleep

Table 6 reports results of logit regressions using a dependent variable equal to one if the respondent reported not getting enough sleep at least once in the past 30 days. Longer commutes and a greater prevalence of late commutes are associated with a higher likelihood of not getting enough sleep some time in the past month. Strangely, longer work hours are associated with a decreased likelihood of not getting enough sleep. The result for late commutes is not robust to the inclusion of state fixed effects. However, these issues are overshadowed by the similarity in the estimates for employees and non-workers. From results not shown, this puzzling result is robust to many specifications.[16] I interpret this as evidence that the question on getting "enough sleep" is too subjective to be a valuable measure of sleep behavior. Consequently, Table 6 allows little inference regarding the relationship between commuting, work hours, and sleep.

5.4 Sex-Specific Results

In Table 7 I divide the sleep module sample by sex and estimate separate effects on males and females. The variables of interest are sex-specific in these regressions. That is, county means are averaged over only workers of the sex to which the sample is restricted.

Longer commute times and especially working hours have a greater marginal effect on women than men. For all four of the dependent variables, the difference in the estimated effect of longer working hours on women is statistically greater than that on men at the 1% level. It appears that women are fully driving the effects of weekly work hours on sleep time and falling asleep. Women also appear to be driving the effect of commute time on unintentionally falling asleep. While the time tradeoff between sleep and commuting for men (-0.17) is statistically significant at the 5% level, it is also statistically smaller than the estimated tradeoff for females (-0.447) at the 10% level.

Early commuting appears to have a larger effect on sleep time for men, while late commuting appears to have a larger effect on sleep time for women.[17] This is consistent with differences in departure times for men and women in the U.S. 2.6% of women in the 2008-2012 ACS had early commutes compared to 5.6% of men, while 25.9% of women had late commutes compared to 22.5% of men. However, for women, the prevalence of early com-

[16]These include restricting the sample to counties below population density percentiles, restricting the sample to states that participated in the sleep module, removing the county-level controls, alternative binary dependent variables such as at least 10 or 30 days of not enough sleep, count models with and without zero-inflation, and interval regression. Results using only the sleep module sample are insignificant at conventional levels for both employees and non-workers.

[17]This interpretation should be taken with some caution, as the early commute estimates are particularly imprecise.

muting has especially strong association with unintentionally falling asleep. Each percentage point increase in the share of female workers that commute before 5 a.m. is associated with a 9.7% increase in the likelihood of falling asleep while driving in the past month, compared to an analogous 3.6% for men, with the difference being significant at the 10% level.

6 Conclusion

This paper presents an array of evidence that commuting and working erode sleep time and an individual's ability to stay awake throughout the day. For each additional minute spent commuting and working, I estimate that 13-18 and 7-13 seconds of sleep are lost, respectively. I also provide evidence that strange commute times are associated with less sleep, and that early commute times in particular are associated with a higher likelihood of falling asleep while driving. Further, I show that these results differ significantly by sex: commuting time, working time, and late commuting have greater marginal effects on women, while early commuting is especially detrimental to men's sleep time and women's ability to stay awake during the day. While I also present estimated effects of the same variables on getting not enough sleep, I find their validity more questionable. The survey question is too subjective be meaningful, despite the tenfold larger sample size. This leaves the BRFSS sleep module as the preferred source of information on sleep behavior in this paper.

Because many of the largest and densest urban areas are absent from the sleep module sample, this analysis is most applicable to areas of low or moderate density. Another reason is that mean commute times in the largest urban areas are curiously stable over time (Gordon et al. 1991). This is an empirical regularity that authors have attempted for decades to explain (Levinson and Kumar 1994; Van Ommeren and Rietveld 2005; Anas 2014). It is not clear how stable urban commute times will be in the future. Using data on a comprehensive set of U.S. Census tracts in 1990 and 2000, Kirby and LeSage (2009) show that the prevalence of long commutes rose between those years, the rise being strongly associated with sex-specific changes in employment and age distribution. Unlike other studies, they observe the entire range of regional densities in the United States. Their results indicate that as demographics change, so will commute times.

Even without a change in commute times, the results suggest that reducing the share of early commutes (starting between midnight and 5 a.m.) would enhance road safety. This is supported by the economics literature on the relationship between mental clarity and time of day (Dickinson and McElroy 2010; Dickinson and Whitehead 2014). The potential benefit is limited by the small share of early commutes as a percentage of all commutes in the U.S. (2.6% for women and 5.6% for men). Further, the burden of risk due to early morning commuting is likely to be predominantly on the part of the commuter himself, as collisions with other vehicles are less likely at those times of the day when there are fewer vehicles on the road. In a free market, this private risk is capitalized into wages and rents, so that an early commuter is no worse off than an otherwise equivalent counterpart.

The negative consequences of a commuter's lack of sleep go beyond the externality imposed on other drivers. These range from effects on productivity, to work safety, to physical, mental, and social health. The results here show that the timing and duration of commuting and working have implications for these various outcomes through tradeoffs in terms of sleep and sleepiness.

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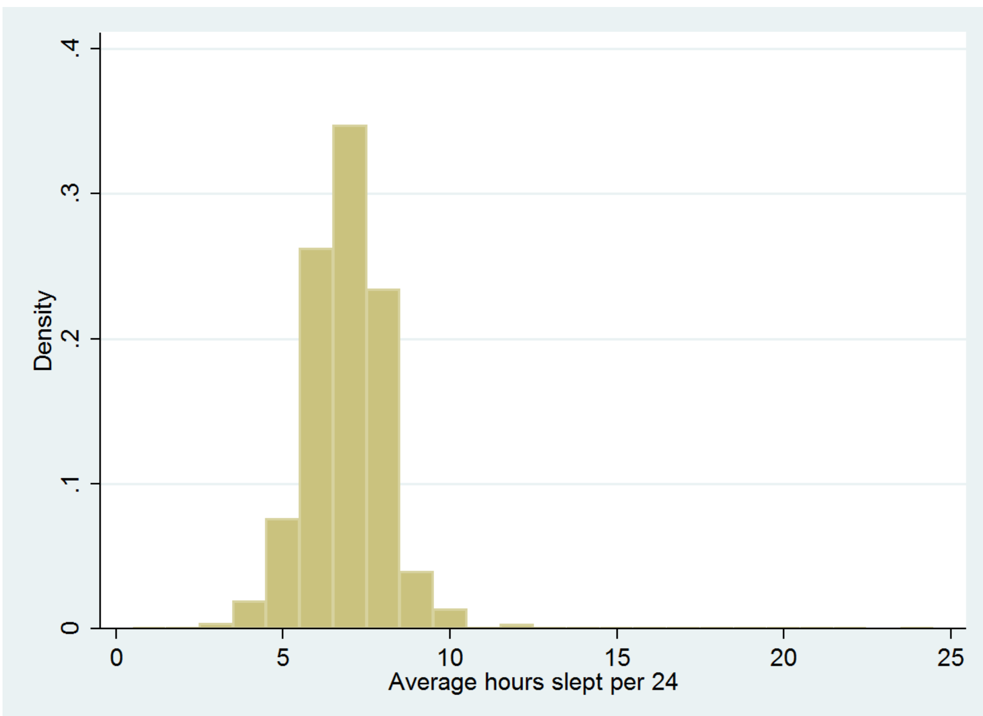

Figure 1: Distribution of responses of employed persons to the survey question "On average, how many hours of sleep do you get in a 24-hour period? Think about the time you actually spend sleeping or napping, not just the amount of sleep you think you should get." N = 56150 respondents, with sample mean and standard deviation of 6.892 and 1.227 hours, respectively.

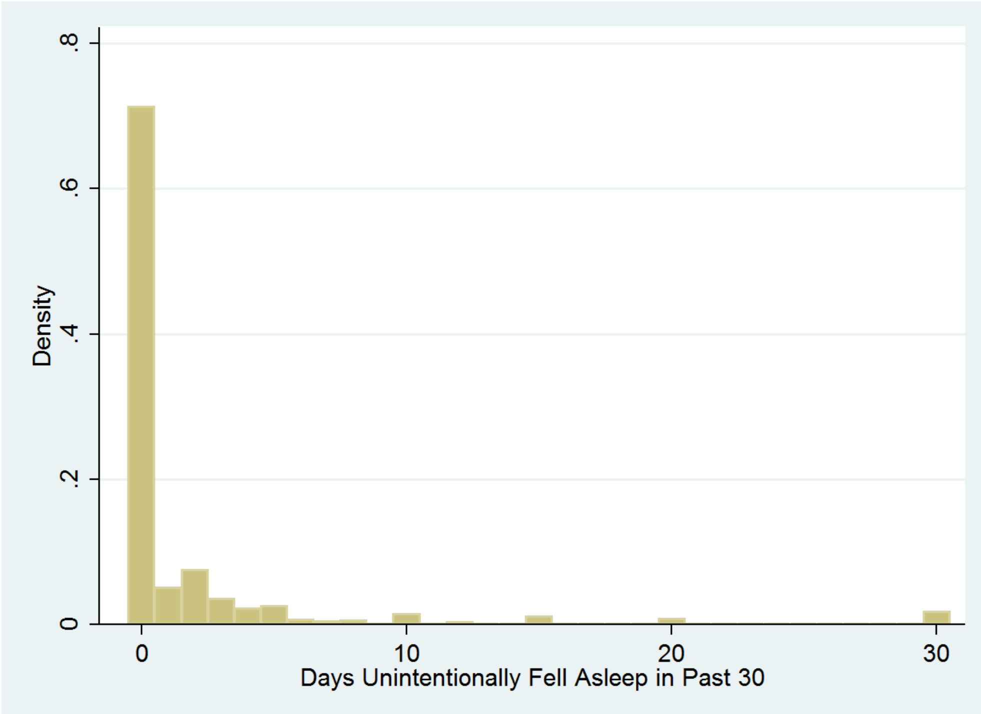

Figure 2: Distribution of responses of employed persons to the survey question "During the past 30 days, for about how many days did you find yourself unintentionally falling asleep during the day?" N = 55557 respondents, with sample mean and standard deviation of 1.787 and 4.996 days, respectively.

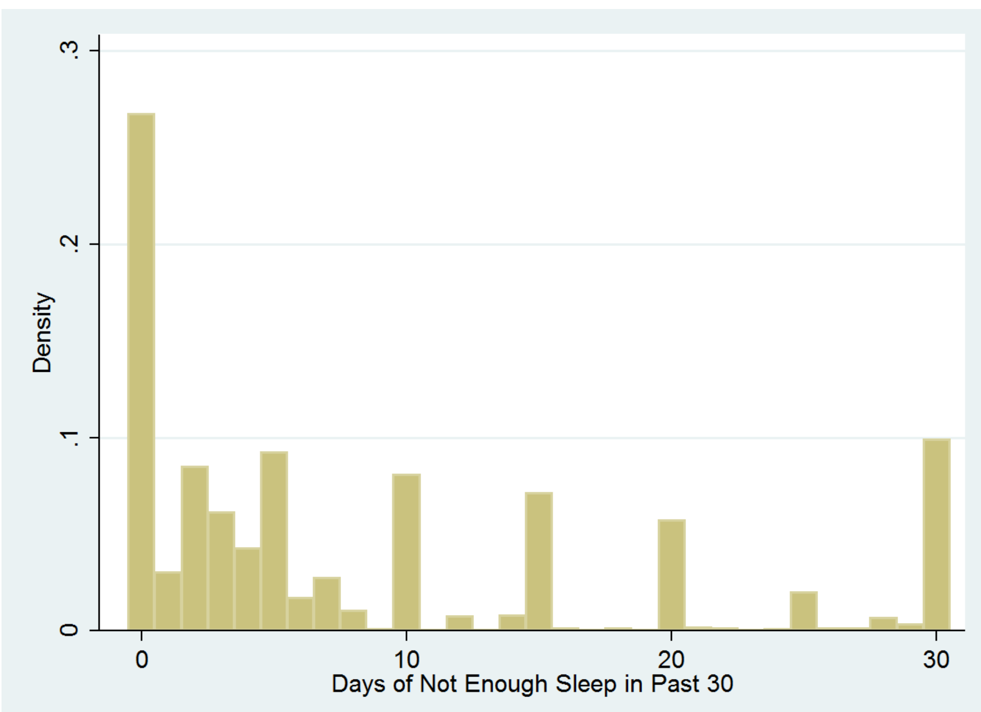

Figure 3: Distribution of responses of employed persons to the survey question "During the past 30 days, for about how many days have you felt you did not get enough rest or sleep?" N = 535219 respondents, with sample mean and standard deviation of 8.612 and 9.836 days, respectively.

Table 1: State Participation in the BRFSS Sleep Module

	Number of Employed Respondents				
State	2009	2010	2011	2012	Total
Alaska	0	0	1623	2105	3728
Arkansas	0	1275	0	0	1275
Connecticut	0	2919	0	0	2919
Delaware	0	1837	0	0	1837
D.C.	0	1728	0	0	1728
Georgia	2360	0	0	0	2360
Hawaii	2735	2605	0	0	5340
Illinois	2462	0	0	0	2462
Kansas	0	0	0	2537	2537
Louisiana	3402	0	0	0	3402
Minnesota	2577	4457	7319	0	14353
Missouri	0	1966	0	0	1966
Nevada	0	1453	0	1732	3185
Oregon	0	1617	0	1685	3302
Tennessee	0	0	1832	0	1832
Wyoming	2507	0	0	0	2507
Total	16043	19857	10774	8059	54733

Number of respondents to the BRFSS sleep module questions that reported being employed for wages at the time of the survey, by state and year. Zero responses reflect years for which states opted not to participate in the sleep module. States not listed did not participate in the module in any of the years. Puerto Rico participated in 2012, but is not included in the analysis.

Table 2: Summary Statistics for County-Level Variables

	Workers		Non-Workers	
	Mean	Std. Dev.	Mean	Std. Dev.
Sleep Module, 2009-2012				
Daily commute time (mins.)	47.21	8.11	46.91	8.09
% Early commuters	4.45	2.21	4.60	2.19
% Late commuters	23.55	3.43	23.61	3.52
Weekly work hours	38.42	1.31	38.39	1.32
Population over age 16	403484.61	589012.90	377421.41	582398.23
Population density (per mile^2)	945.66	1679.34	817.45	1552.24
% Labor force participation	67.08	5.41	65.73	5.72
% Unemployment	8.49	2.39	8.85	2.51
N	47868		47165	
Core Sample, 2008-2010				
Daily commute time (mins)	48.00	9.58	47.77	9.22
% Early commuters	4.30	1.98	4.45	2.02
% Late commuters	23.49	3.51	23.54	3.51
Weekly work hours	38.46	1.25	38.43	1.24
Population over age 16	395640.77	734652.08	391640.39	769228.82
Population density (per mile^2)	943.95	3199.75	848.52	3081.98
% Labor force participation	65.10	6.10	63.80	6.56
% Unemployment	8.78	2.72	9.16	2.81
N	486305		493115	

All variables are from the 2008-2012 American Community Survey. Each county is weighted by the number of corresponding observations in the BRFSS sample.

Table 3: Correlations of County-Level Variables

Variables	Daily Comm. Time	% Early Comm.	% Late Comm.	Work Hours	Pop. Over 16	Unem.	LFP
Daily Commute Time	1.000						
% Early Commuters	0.227	1.000					
% Late Commuters	-0.164	-0.242	1.000				
Weekly Work Hours	0.227	0.274	-0.533	1.000			
Pop. Over16	0.338	-0.109	0.319	-0.027	1.000		
Unemployment	0.201	0.070	0.354	-0.200	0.157	1.000	
LFP	0.022	-0.313	0.152	-0.005	0.225	-0.421	1.000
Pop. Density	0.384	-0.341	0.176	0.122	0.413	0.146	0.201

Each county is weighted by the number of corresponding observations in the BRFSS sleep module sample. Weighting by core sample observations gives similar results.

Table 4: Effects on Sleep Time and Short Sleep

	Employees		Non-Workers
Panel A: OLS Regression			
Dependent Variable: Minutes of Sleep Per Day			
Daily Commute Time	-0.304***	-0.223***	-0.154
	(0.094)	(0.083)	(0.108)
% Early Commuters	-0.756	-0.402	-0.685
	(0.511)	(0.251)	(0.753)
% Late Commuters	-0.457**	-0.491**	0.156
	(0.213)	(0.194)	(0.211)
Weekly Work Hours	-0.923*	-1.809***	0.963
	(0.498)	(0.566)	(0.657)
State FE		✓	
N	47868	47868	47165
Panel B: Logit Regression			
Dependent Variable: 6 or Fewer Hours of Sleep Per Day			
Daily Commute Time	1.006**	1.002	1.004
	(0.003)	(0.002)	(0.003)
% Early Commuters	1.036**	1.028***	1.024
	(0.014)	(0.007)	(0.020)
% Late Commuters	1.011**	1.010*	0.998
	(0.005)	(0.005)	(0.006)
Weekly Work Hours	1.027**	1.025	0.984
	(0.014)	(0.017)	(0.021)
State FE		✓	
N	47868	47868	47165

Sample is pooled over all observations from the BRFSS sleep module from 2009 to 2012. All regressions include individual-level controls for month of the survey, marital status, education, sex, race, the presence of one, two, or three or more children in the household, and intervals for income and age, as well as county-level controls for population, population density, labor force participation, and unemployment. "Employees" were employed for wages and "Non-Workers" were not employed at the time of the survey. Standard errors are clustered by county. Coefficients in Panel B are exponentiated for ease of interpretation.

*: Significant at 10%.

**: Significant at 5%.

***: Significant at 1%.

Table 5: Effects on Falling Asleep During the Day and While Driving

	Employees				Non-Workers
Panel A: Logit Regression					
Dependent Variable: Unintentionally Fell Asleep In Past 30 Days					
Daily Commute Time	1.006***	1.005**	1.005***	1.004**	1.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Early Commuters	1.023**	1.015**	1.020**	1.013**	0.999
	(0.011)	(0.006)	(0.010)	(0.006)	(0.006)
% Late Commuters	1.006	1.013***	1.004	1.011**	1.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Weekly Work Hours	1.031**	1.034*	1.027**	1.027	1.012
	(0.014)	(0.018)	(0.013)	(0.017)	(0.011)
Daily Sleep Time			0.996***	0.996***	
				(0.000)	(0.000)
State FE		✓		✓	
N	47868	47868	47868	47868	47165
Panel B: Logit Regression					
Dependent Variable: Fell Asleep While Driving In Past 30 Days					
Daily Commute Time	1.009*	1.007	1.007	1.006	1.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
% Early Commuters	1.043**	1.017	1.038*	1.013	1.029
	(0.022)	(0.017)	(0.020)	(0.017)	(0.022)
% Late Commuters	0.993	1.005	0.989	1.001	1.009
	(0.011)	(0.013)	(0.011)	(0.013)	(0.017)
Weekly Work Hours	1.003	1.022	0.996	1.011	1.059
	(0.031)	(0.034)	(0.030)	(0.034)	(0.042)
Daily Sleep Time			0.994***	0.994***	
			(0.000)	(0.000)	
State FE		✓		✓	
N	47323	47323	47323	47323	44040

Sample is pooled over all observations from the BRFSS sleep module from 2009 to 2012. All regressions include individual-level controls for month of the survey, marital status, education, sex, race, the presence of one, two, or three or more children in the household, and intervals for income and age, as well as county-level controls for population, population density, labor force participation, and unemployment. "Employees" were employed for wages and "Non-Workers" were not employed at the time of the survey. Standard errors are clustered by county. Coefficients are exponentiated for ease of interpretation.
*: Significant at 10%.
**: Significant at 5%.
***: Significant at 1%.

Table 6: Effects on Not Getting Enough Sleep

Logit Regression
Dependent Variable: > 0 Days of Not Enough Sleep in Past 30

	Employees		Non-Workers
Daily Commute Time	1.002***	1.004***	1.002***
	(0.001)	(0.001)	(0.001)
% Early Commuters	1.002	0.997	0.995
	(0.004)	(0.003)	(0.003)
% Late Commuters	1.010***	1.003	1.007***
	(0.002)	(0.002)	(0.002)
Weekly Work Hours	0.984**	0.978***	0.984***
	(0.006)	(0.005)	(0.005)
State FE		✓	
N	481174	481174	482131

Sample is pooled over all observations from the BRFSS core survey from 2008 to 2010. All regressions include individual-level controls for month of the survey, marital status, education, sex, race, the presence of one, two, or three or more children in the household, and intervals for income and age, as well as county-level controls for population, population density, labor force participation, and unemployment. "Employees" were employed for wages and "Non-Workers" were not employed at the time of the survey. Standard errors are clustered by county. Coefficients are exponentiated for ease of interpretation.
*: Significant at 10%.
**: Significant at 5%.
***: Significant at 1%.

Table 7: Sex-Specific Effects

	Male Employees				Female Employees			
Dependent Variable:	Minutes of Sleep Per Day	≤6 Hours of Sleep Per Day	Fell Asleep During Day	Fell Asleep While Driving	Minutes of Sleep Per Day	≤6 Hours of Sleep Per Day	Fell Asleep During Day	Fell Asleep While Driving
Daily Commute Time	-0.170**	1.005*	1.003	1.004	-0.447***	1.009**	1.009***	1.025***
	(0.084)	(0.002)	(0.003)	(0.005)	(0.157)	(0.004)	(0.003)	(0.009)
% Early Commutes	-1.073***	1.040***	1.018*	1.036**	-0.888	1.034*	1.046***	1.097***
	(0.409)	(0.013)	(0.011)	(0.016)	(0.747)	(0.020)	(0.014)	(0.039)
% Late Commutes	-0.042	1.000	0.997	0.981	-0.624***	1.019***	1.012*	1.008
	(0.216)	(0.007)	(0.006)	(0.012)	(0.240)	(0.007)	(0.007)	(0.014)
Weekly Work Hours	0.229	0.991	1.006	0.967	-2.127***	1.088***	1.071***	1.107**
	(0.527)	(0.015)	(0.015)	(0.029)	(0.563)	(0.017)	(0.020)	(0.045)
N	19643	19643	19643	19591	28225	28225	28225	28200

Male and female samples are pooled over all observations from the BRFSS sleep module from 2009 to 2012 of males and females, respectively. For each regression, all four reported variables are specific to the sex to which the sample is restricted. All regressions include individual-level controls for month of the survey, marital status, education, race, the presence of one, two, or three or more children in the household, and intervals for income and age, as well as county-level controls for population, population density, labor force participation, and unemployment. All samples are restricted to respondents who were employed for wages at the time of the survey. Standard errors are clustered by county. Logit coefficients (columns 2-4 and 6-8) are exponentiated for ease of interpretation.
*: Significant at 10%.
**: Significant at 5%.
***: Significant at 1%.