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Publication Date
2014-07-14

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July 10, 2014

Abstract

While economists have long been interested in effects of health and human capital on productivity, less attention has been paid to the influence of time use. We investigate the productivity effects of the single largest use of time—sleep. Because sleep influences performance on memory and focus intensive tasks, it plausibly affects economic outcomes. We identify the effect of sleep on wages by exploiting the relationship between sunset time and sleep duration. Using a large, nationally representative set of time use diaries from the United States, we provide the first causal estimates of the impact of sleep on wages: a one-hour increase in long-run average sleep increases wages by 16%, equivalent to more than one year of schooling. We also document the nonlinearity of the sleep-wage relationship. Our results highlight the economic importance of sleep and pose potentially fruitful questions about the effects of time use on labor market outcomes. (JEL No. J22, J24, J31)

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The authors thank Prashant Bharadwaj, Julie Cullen, Gordon Dahl, Joshua Graff Zivin, Daniel Hamermesh, Mark Jacobsen, Sendhil Mullainathan, Dale Squires, Michelle White, and seminar participants at UC San Diego for helpful comments. Shrader gratefully acknowledges support from the National Science Foundation Graduate Research Fellowship under Grant No. DGE-1144086. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. Word count: 15,333.

1 Introduction

Economists have long been interested in determinants of productivity. Understanding what makes workers more effective is a fundamental question in economics and is important for both individual decisions and public policy. While there are traditions of research in human capital (Becker, 1962, 1964) and health (Grossman, 1972), less attention as been paid to the influence of time use on worker productivity. Many types of time use, from reading to vacationing, plausibly impact productivity on the job. In this study we focus on one of the most important influences on human performance: the time workers spend sleeping.

Evidence from medical research points to the vital role sleep plays in determining productivity. Tired doctors make more mistakes (Ulmer et al., 2009). Tired students perform worse on tests (Taras and Potts-Datema, 2005). Poor sleep raises total mortality rates (Cappuccio et al., 2010). These results suggest that inadequate sleep lowers productivity, impedes the development of human capital, and imposes large direct costs on society. Moreover for the average individual, sleep takes up more time than any other activity. Despite the manifest importance of sleep, economists have largely treated it as a biological phenomenon outside of their purview. We investigate an important question that has been overlooked almost entirely in economics: what are the effects of sleep on productivity and wages?

Answering this question poses formidable challenges. First, a pioneering study by Biddle and Hamermesh (1990) shows that higher wages raise the opportunity cost of sleep time, leading individuals to decrease their sleep. This result demonstrates that causal relationships between sleep and wages could run in both directions. Additionally, sleep may be correlated with unobservable worker characteristics, like ability, that also influence wages. Finally, because sleep is a large portion of the time budget and complementary to almost all human activity, it is extremely difficult to isolate exogenous variation in sleep.

We resolve this endogeneity by using changes in sleep induced by differences in sunset time within time zones—a strategy motivated by medical research on circadian rhythm. Our identification depends on small differences in the *timing* of sunset, while controlling for other spatial characteristics of a location. These timing differences stem from US time zone boundaries drawn in 1883, which stem in turn from the historical accident that placed the Prime Meridian through Greenwich, England. Intuitively, for two locations at the same latitude and in the same time zone, the location farther east will experience sunset sooner than the location farther west. Because solar cues influence human sleep schedules, those who live farther east will go to sleep slightly earlier, on average. Because work start times are inflexible, this earlier bed time translates into more sleep for the more eastern residents.

To implement our empirical strategy, we geocode observations from the American Time Use Survey (ATUS), at the county level where possible and at the state level otherwise. ATUS provides rich labor market information about individuals, a wealth of control variables, and detailed time use data from daily diaries. Knowing the diary date and location, we assign each observation a sunset time. We then use sunset time as an instrument for sleep to estimate the causal effect of sleep on wages.

Our main result is that sleeping one extra hour per night on average increases wages by 16%, highlighting the importance of restedness to human productivity. These are, to our knowledge, the first causal estimates of how sleep affects wages.[1] This result suggests that, were the average worker in our dataset to sleep one additional hour every night without changing her number of hours worked, she would receive an additional $6,000 per year.

Our identification strategy naturally raises concerns that workers might sort on sunset time or on its correlates. As part of our large set of robustness checks, we demonstrate that our wage effects are fully offset by increased home prices, removing the incentive to sort. In addition, we conduct a variety of tests for worker sorting and find no evidence for it.

Motivated by findings from the medical literature, we also investigate non-linearities in the sleep-wage relationship. In particular, we examine whether there is a level of sleep

[1] Biddle and Hamermesh (1990) includes a regression with wages on the left-hand side and sleep on the right and finds a negative relationship. This is consistent with reverse causality and highlights the difficulty of isolating quasi-experimental variation in sleep.

above which more sleep reduces wage. Using a plausible functional form assumption in an IV setting, we demonstrate that wage-optimizing sleep is approximately 9 hours per night in the United States. This is higher than the average sleep amount reported in the data—8.3 hours—and it is much higher than the 7 to 8 hours per night that the medical literature generally considers to result in lowest total mortality (Cappuccio et al., 2010), indicating a potential tension between wage optimization, health optimization, and other time uses.

Our study demonstrates that sleep is not just an economic curiosity, but rather a vital determinant of productivity. A one-hour increase in average daily sleep raises productivity by more than a one-year increase in education (Psacharopoulos and Patrinos, 2004). These results point to the large impact that non-labor market activities can have on labor market performance. By examining the largest use of human time, our study contributes to the time-use literature following Becker (1965). We also contribute to the growing literature on how environmental forces influence worker productivity (Zivin and Neidell, 2012) and to the broader productivity literature on factors like information technology (Bloom et al., 2012) and workplace practices (Black and Lynch, 2001). Future work should extend these results to compare them to non-time intensive changes in leisure or lifestyle attributes.

The rest of the paper proceeds as follows. Section 2 presents a time use model with sleep as a choice variable, illustrating challenges associated with identifying the effect of sleep on wages, and discusses related literature. Section 3 presents the estimating equations and discusses our identification strategy. Section 4 describes the data used in the study, while Section 5 reports and discusses our primary linear model results, provides robustness checks, and discusses extensions to the main results. Section 6 reports and discusses nonlinear estimates of the sleep-wage relationship, and Section 7 concludes.

2 Identifying the effect of sleep on productivity and wages

2.1 Previous research

Existing studies of the relationship between sleep and wages in economics are few and are largely concerned with addressing the question of whether sleep should be treated as a choice variable rather than simply a biological necessity. Biddle and Hamermesh (1990) is the first paper to provide empirical evidence on this issue and remains one of the only empirical investigations of labor market impacts of sleep. The authors lay out a model with agents optimizing over sleep, work, and leisure time in an otherwise standard setting. While their theoretical model allows sleep to affect productivity, Biddle and Hamermesh do not focus on this relationship in their empirical work. Instead they emphasize the causal mechanism operating in the opposite direction, modeling sleep as a function of instrumented wage (see Biddle and Hamermesh (1990) Table 6). Brochu et al. (2012) and Szalontai (2006) also estimate the impact of changes in wage on sleep using more recent data from Canada and South Africa. Finally, Bonke (2012) has examined the impact of two chronotypes—whether the individual is a "morning" or "evening" person—on income. This study provides evidence on the related question of whether sleep quality impacts labor market outcomes.

Daylight savings time (DST) has been used in a variety of settings in economics as a proxy for sleep changes. However, the short-term nature of any sleep change induced by DST limits its use in studying slow-moving outcomes like wages. Moreover, examination of ATUS data shows that the relationship between DST and sleep is complex. Transition into DST reduces sleep by 40 minutes on the day of the change, but transition out of DST is not associated with a noticeable change in sleep time (Barnes and Wagner, 2009).

Medical studies concerned with the effect of long term differences in sleep on health or mortality[2] are closest to our study in terms of time horizon. A series of papers starting with Mckenna et al. (2007) have used laboratory tasks to examine the impact

[2] For instance Cappuccio et al. (2010) and Krueger and Friedman (2009).

of short-term sleep loss on a variety of outcomes that provide insight into how sleep could impact work performance. Van Dongen et al. (2003) conducted the longest laboratory-controlled study on the effect of sleep levels on cognitive performance. The researchers kept subjects in the lab for two weeks, placing them into groups receiving 4, 6, and 8 hours of sleep. The subjects were given daily tests of their focus in the form of psycho-motor vigilance tests (PVTs). The research found that the groups subjected to 4 and 6 hours of sleep experienced progressively worse performance on the test even though the subjects' subjective assessment stopped declining after a short habituation period. This study provides one of the most compelling pieces of evidence for the negative productivity effects of reduced sleep.

2.2 A productive sleep model

The following analytical model, adapted from Biddle and Hamermesh (1990), illustrates the trade-offs between consumption, leisure, and sleep when sleep affects wages. It also illustrates the reverse causality from wages to sleep that creates one of the main identification challenges and clarifies how we think about our instrument. Consider a consumer optimizing over sleep time T_S and a composite leisure good Z, which requires inputs of both time T_z and goods X such that $T_z = bZ$ and $X = aZ$. The good X trades at the exogenous price P. The consumer has non-labor income I and time endowment T^*. Denote work time T_w. Let an individual's market wage w_m depend on sleep as follows: $w_m = w_1 + w_2 T_S$, with $w_1 > 0$ and $w_2 > 0$.[3]

Note that this theoretical model could easily be adapted to study other non-work time uses, but the function linking wage to time use would likely be different. We assume that a function of sleep, αT_S, enters the utility function, where α is the relative utility enjoyed by the individual per hour of sleep.[4] The parameter α provides a convenient link between our analytical model and our instrumental variables estimation strategy, as discussed below. The worker optimizes over sleep and composite leisure,

[3] In section 6 we provide evidence that this relationship is non-linear, but a linear wage function suffices to illustrate the relevant trade-offs.

[4] Our predictions are qualitatively unchanged if we assume that sleep does not enter the utility function directly, but rather as an input to the production of the composite leisure good Z.

subject to time and income constraints, as follows.

$$\max_{Z,T_S,\lambda} U\left(Z,\alpha T_S\right)+\lambda\left(I+\left(w_1+w_2T_S\right)\left(T^*-T_S-bZ\right)-aPZ\right)$$

Combining first-order conditions yields a two by two system of equations that implicitly describe the worker's optimal choice.

$$U_1w_1+U_1w_2\left(T_S-T_w\right)-\alpha U_2aP-\alpha U_2bw_m=0$$

and

$$I+\left(w_1+w_2T_S\right)\left(T^*-T_S-bZ\right)-aPZ=0$$

Applying the implicit function theorem, we can evaluate several interesting derivatives. First, consider the effect of an exogenous wage increase on sleep time.

$$\frac{\partial T_S}{\partial w_1}=\left(aP+bw_m\right)\left(U_1-\alpha U_2b\right)D^{-1}+T_w\frac{\partial T_S}{\partial I}$$

In the previous expression, $D^{-1}<0$ equals the negative of the Jacobian. This is a variant of the usual Slutsky equation. The first term captures the substitution effect, which differs from the typical form in that it includes $-\alpha U_2b$. When $\alpha=1$ the value $\left(U_1-\alpha U_2b\right)>0$ and the first term is negative. Increased wages raise the opportunity cost of sleep, decreasing optimal sleep. This means that a naïve regression of wages on sleep will not recover causal effects.

To motivate our later use of an instrument for sleep, consider the effects of an exogenous increase in α. Since α controls the relative attractiveness of sleep, an increase in the parameter will induce agents to want to consume more sleep.

$$\frac{\partial T_S}{\partial \alpha}=U_2\left(a^2P^2+b^2w_m^2+2U_2abPw_m\right)\left(-D\right)^{-1}>0$$

The effect on leisure can operate in either direction.

$$\frac{\partial T_z}{\partial \alpha}=bU_2\left(aP+bw_m\right)\left(-w_m+w_2T_w\right)\left(-D\right)^{-1}\lesseqgtr 0$$

The ambiguous sign comes from the expression $(-w_m + w_2 T_w)$, which is the opportunity cost of an additional leisure hour. More specifically, this expression is the gross opportunity cost of an additional leisure hour $-w_m$, adjusted for the additional income generated by increased sleep, $w_2 T_w$ (recall that T_S increases in response to an increase in α). All else equal, individuals with low wages (low w_1) or high work hours will tend to increase leisure time in response to increased α. Intuitively, this is because in our model all workers experience the same wage gains from additional sleep. For low-wage workers this sleep-driven wage increase dominates the small wage loss incurred by switching an hour of time from work to leisure. We test these empirical predictions in Section 5.

3 Empirical strategy

3.1 Estimating equation

Our goal is to estimate an equation of the form

$$\text{wage}_{it} = f(T_{S,it}) + \varepsilon_{it}$$

where we expect $\partial f / \partial T_S > 0$, at least for low T_S. Given the reverse causality between wages and sleep, however, we might erroneously find $\partial f / \partial T_S < 0$.[5] To avoid this problem and to account for the wide variety of other omitted variables that might co-vary with sleep and wages, we instrument for sleep using the local sunset time, then

[5] The general form is given in the model above, but we can also illustrate the issue with a simple two equation system that will prove useful below. Let the sleep-wage relationship be given by

$$w = \alpha T_S + \varepsilon$$
$$T_S = \beta w + \nu$$

where ε and ν are random error terms, $E[\varepsilon\nu] = 0$, $E[T_S\varepsilon] = 0$, and $E[w\nu] = 0$. Then if $\beta < 0$ as is argued by the previous literature, the bias from OLS estimation can be signed as follows:

$$\text{plim}\,\hat{\alpha} = \alpha + \underbrace{\beta \frac{E[\varepsilon w]}{E[T_S^2]}}_{<0}$$

So plim $\hat{\alpha} < \alpha$. Naive OLS will tend to understate the effect of sleep on wages if this is the dominant source of bias.

use the instrumented values of sleep to estimate wage impacts.

$$T_{S,ijt} = \alpha \text{sunset}_{jt} + \gamma_1 \text{latitude}_j + \mathbf{x}'_{it}\gamma_2 + \nu_{ijt}$$
$$\ln(\text{wage}_{ij\tau}) = \beta T_{S,ijt} + \gamma_3 \text{latitude}_j + \mathbf{x}'_{it}\gamma_4 + \varepsilon_{ij\tau} \quad (1)$$

In the above equations $T_{S,ijt}$ is nighttime sleep for individual i in location j on date t, sunset_{jt} is the sunset time on that date in that location, $\mathbf{x}_{it}$ is a vector of controls, and $\text{wage}_{i\tau}$ is a measure of wages or earnings at time τ. We distinguish between the time subscripts on wages, τ, and sleep, t, to highlight the fact that we treat sleep on date t as a consistent estimate of average sleep at time τ.[6] Our wage measure is the answer to a question about "usual weekly earnings" rather than wages on the day of the interview, so τ may be thought of as indexing the wage-setting period, for instance a year. Controls are listed in Table I and are latitude, an indicator for female, age, age squared, race indicators, day of week of interview indicators, a holiday indicator, year indicators, and a set of occupation indicators.

It is implausible to assume that the relationship between sleep and wages is linear over the entire range of possible sleep. Purely mechanically, as sleep reaches extremely high levels, little time remains for work. A worker who sleeps 16 hours per day may have difficulty finding a job. Moreover, medical studies often find that sleep is non-linearly related to outcomes like health and memory. Motivated by these findings, we also investigate non-linear functional forms of the sleep-wage equation.

We now need additional instruments to identify the non-linear terms. Calculating sunset relies on four inputs: the date, latitude, longitude, and time zone. We can approximate three of these four components using annual average sunset time, solar declination (the angle of the sun relative to the equator) on the diary date, and the interaction of the two. Our nonlinear specifications use these variables as instruments. While this invokes additional functional form assumptions, our choice of instruments is not arbitrary. Rather it explicitly leverages the seasonal variation in sunset time over

[6] We also treat a worker's observable characteristics on date t as consistent estimates of observables at time τ. Since many such characteristics are fixed or vary extremely slowly (for example race, occupation, and education), we believe this assumption is benign.

the year as well as the purely geographic variation in annual average sunset time that occurs within a time zone. The estimating equations are

$$T_{S,it} = \alpha_1 \overline{\text{sunset}}_{it} + \alpha_2 \text{declination}_{\mathbf{it}} + \alpha_3 \overline{\text{sunset}}_{it} \times \text{dec.}_{it} + \mathbf{x}'_{it}\gamma_3 + \nu_{1it} \tag{2}$$

$$T^2_{S,it} = \alpha_1 \overline{\text{sunset}}_{it} + \alpha_2 \text{declination}_{\mathbf{it}} + \alpha_3 \overline{\text{sunset}}_{it} \times \text{dec.}_{it} + \mathbf{x}'_{it}\gamma_4 + \nu_{2it} \tag{3}$$

$$\ln(\text{wage}_{i\tau}) = \beta_1 T_{s,i} + \beta_2 T^2_{s,i} + \mathbf{x}'_{it}\gamma_5 + \varepsilon_{2i\tau} \tag{4}$$

which comprise a modified version of the linear two-stage estimate given above by Equation (1). Bolding denotes vectors and overbars indicate averages over the year. The value $-\beta_1/2\beta_2$ gives optimal sleep for wage maximization.

3.2 Local sunset time instrument

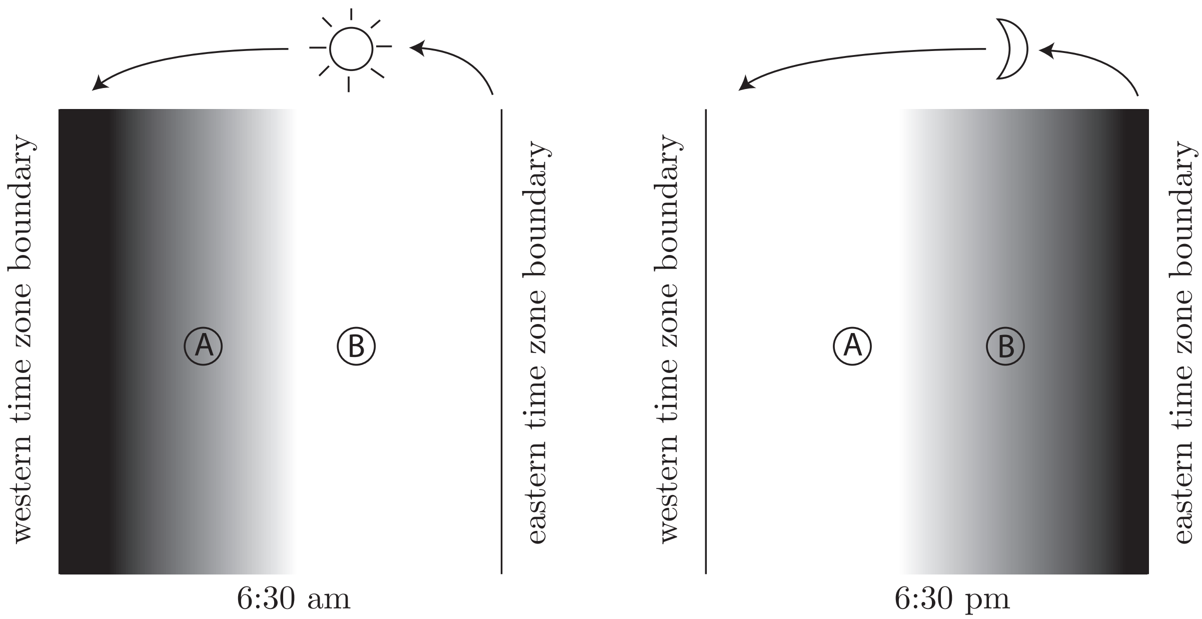
We would like to estimate the relationship between sleep and wages, but, as discussed above, sleep is plainly endogenous. To isolate exogenous variation in sleep, we predict sleep using local sunset time. In a vacuum, an earlier sunset time would cause workers to go to bed earlier and rise later, so it would not affect sleep duration. But workers coordinate work start times, often at 8am or 9am, so earlier sunset and earlier bedtime increase sleep duration. This is the exogenous variation that identifies the wage effect of sleep. We discuss the details of this argument below.

Human sleep patterns and circadian rhythm are synchronized with the rising and setting of the sun through a process known as entrainment. Roenneberg et al. (2007) show that "the human circadian clock is predominantly entrained by sun time rather than by social time," indicating that a variable based on solar cues might provide a relevant instrument for sleep duration or timing.

Figure I shows how the mismatch between standard time and solar time varies within a stylized time zone. In the morning (left panel), a city farther west (having a larger distance from the eastern time zone boundary) will be in darkness for a period of time during which a city farther east is lit. In a vacuum, we might expect residents of the eastern city to rise earlier. Hamermesh et al. (2008), however, show that work scheduling is not sensitive to solar time, and workers must wake up in time for a coordinated start—this is one reason for the widespread use of morning alarm clocks.

The right panel shows a stylized sunset, which forms the basis of our instrument. Here the eastern location grows dark earlier than the western location. As Roenneberg et al. (2007) show, this induces residents of the eastern location to begin sleep earlier than the residents of the western location, leading to longer sleep duration for the eastern residents. Unlike in the morning, there is no coordination constraint muting the effect of the solar cue. On net, workers sleep longer in the eastern than in the western city.

Figure I: Schematic effects of local sunrise and sunset time

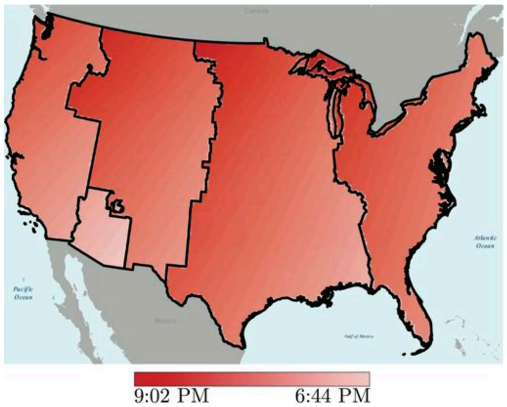


Notes: The figure gives a schematic representation of how local sunset time impacts sleep. The left panel shows the relative light levels when a worker awakes in two cities, and the right panel shows the same for when the worker returns home.

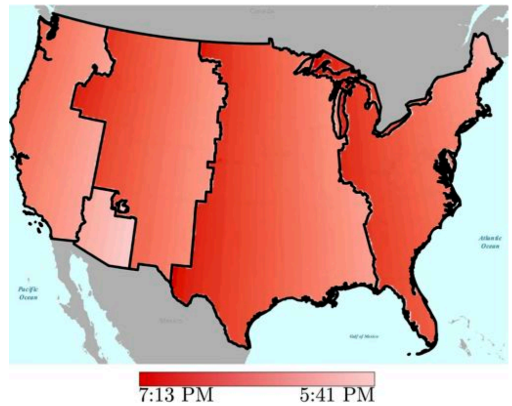
[Figure 2 about here.]

Figure II shows how Figure I looks for actual sunset times across the continental United States on the summer solstice (Panel IIa), the vernal equinox (Panel IIb), and the winter solstice (Panel IIc) in 2012. Darker reds indicate later sunset times. The sunset time difference on the equinox matches the stylized example, and one can observe that, on average during the year, locations farther west have later sunset times than

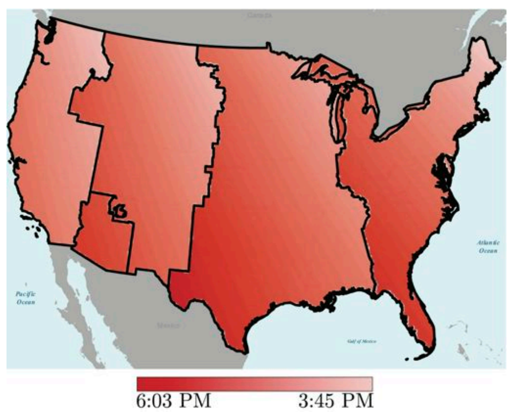
Figure II: Actual sunset time



(a) Summer solstice, Jun 20



(b) Vernal equinox, Mar 20



(c) Winter solstice, Dec 21

Notes: Each map shows sunset time for the continental United States in 2012. Panel (a) is for the summer solstice, Panel (b) is for the vernal equinox, and Panel (c) is for the winter solstice. Sunset times are indicated by color according to the scale under each figure. Darker red indicates later sunset, lighter red indicates earlier. The time zone boundaries are given by bold black lines.

locations farther east within each time zone. The exact difference, however, changes seasonally, with locations farther north experiencing later sunset during the summer and the reverse in the winter. This variation in the angle of the sunset gradient is caused by changes in solar declination, or the angle of the sun relative to the equator. For more discussion of solar mechanics, see Section B. Our estimation strategy uses both the cross-sectional (geographic) variation in sunset time and the intra-annual seasonal variation.

In summary, sunset time is a relevant instrument because human sleep timing responds strongly to solar cues. In fact, the detailed ATUS files enable us to demonstrate this phenomenon directly. Examination of ATUS activity logs shows that workers experiencing earlier sunset also go to bed earlier and that this correlation between sunset and bedtime persists even if the worker goes to bed well after dark. Coordinated work start times translate this earlier bedtime into longer sleep.

The difference in sunset time between two locations over the year is plausibly orthogonal to other factors influencing the labor market, making local sunset time a valid instrument. In particular, time zone boundaries break the link between average sunset time and longitude, and the seasonal variation in sunset time means that any given location has a large geographic comparison group that changes over the year. On average sunset time is, by construction, orthogonal to latitude, however controlling for latitude makes our estimates easier to interpret. On any given day, two locations at the same latitude will experience the same daylight duration, differing only in when sunrise and sunset occur relative to local time. The maximum difference in sunset time within a US time zone is approximately 60 minutes.

The design of US time zones derived primarily from scientific, rather than commercial, considerations. Railroads implemented the first US time zones, called Standard Railroad Time (SRT), on November 18, 1883. They replaced a patchwork of railroad time standards and were quickly adopted by the US government and Western Union (Allen, 1883; Anonymous, 1883). While railroads were the first adopters, the primary impetus for standard time and the zone plan itself came from scientists concerned with problems like simultaneous observation of the aurora borealis at different points across the US (Bartky, 1989). The width of a zone, 15 degrees of longitude, was chosen to correspond with a one-hour difference in solar time (LOC, 2010). Ultimately, US time zones derive from the speed at which the earth rotates and the historical accident that drew the Prime Meridian through Greenwich, England: King Charles II chose Greenwich as the site for the Royal Observatory in 1675.

Endogenous modifications to time zone borders could have undermined this initial randomization. Indeed, state and local governments may petition the Department of

Transportation to switch time zones, which has resulted in a long-run westward movement of boundaries (USNO, 2014). This movement means that the precise location of the boundary is endogenous and research designs based on comparing nearby communities on opposite sides of the boundary will be biased. Note, however, that the westward movement of boundaries is the opposite of what we expect if counties are choosing their time zone based on sleep-driven productivity considerations. Switching from being on the eastern side of a time zone to the western side (which is what has happened to shift the time zone boundaries) moves the county from getting the "best" sunset treatment to getting the "worst" in terms of sleep duration. Moreover, our design does not depend on the exact location of the boundary, but on the relative longitudes of cities within a time zone; the distance between the easternmost city in our data and the border is common to all observations in the time zone and does not contribute to our coefficients of interest. (In Table V we show our results are robust to the exclusion of counties on time zone borders.) Finally, while time zone borders sometimes coincide with state borders, they frequently do not, and twelve of the lower 48 US states span multiple time zones (Hamermesh et al., 2008).

Current or past worker sorting on sunset time would also threaten the validity of our sunset time instrument. We provide empirical evidence against such sorting in Section 5.3.2. Furthermore, visual inspection of Figure II makes a sorting story difficult to credit. Changes in solar declination mean that sunset time in a given location, relative to another location in the same time zone, changes throughout the year unless the other location is located at exactly the same latitude. It is hard to argue workers sort based on local sunset at the summer solstice rather than local sunset at the winter solstice. Even if we focus, for example, on sunset at the equinoxes, there is no intuitive similarity across locations with the same local sunset time. Central Kentucky is not obviously like Eastern Colorado, nor is San Francisco like Central Missouri. To test for contemporary worker sorting, we regress county demographics on our instrument in Appendix Table XII and show there is no significant relationship. We also investigate the possibility of sorting responses to the 1883 institution of time zones in Section 5.3.2.

Firms might also sort on local sunset time, but simple firm optimization theory suggests that firms do not have strong incentives to do so. If a firm pays its workers their marginal product, managers may not care whether that marginal product is slightly higher or lower. Nonetheless this sorting is a theoretical possibility, and we test for it by regressing total wage bill in a county on sunset time and find no effect. In contrast, per-capita wage bill is influenced by sunset time, as shown in Table VIII.

Other possible channels for failure of our exclusion restriction are discussed below, and for issues that are amenable to empirical investigation, results are shown in Section 5.3. First, sleep and sunset contain seasonal trends. This would bias our estimates if wages contained a correlated but causally unrelated seasonal trend. We show in Figure III that wages do not contain seasonal trends, eliminating this concern. Nonetheless, we explore the sensitivity of our estimates to different seasonal controls in Appendix Table XIV. The sign and significance of our result survive the addition of a fine set of seasonal controls, even fixed effects for each day of the year.

Second, if sunrise and sunset shift the timing of activities within a day, this could conceivably influence productivity in ways that are hard to anticipate. In part, this motivates the use of our instrument, which induces changes in sleep small enough to be unlikely to trigger schedule changes but large enough to identify effects. Hamermesh et al. (2008) show that, conditional on hours worked, sunrise and sunset do not alter within-day work schedules. In addition, we regress work hours on sunset time and find no relationship.[7] Together these results rule out within-day schedule shifts that might somehow influence productivity.

Third, introspection suggests that sunset time might have direct effects on mood and thus productivity. This is substantially more difficult to argue when comparing cities at the same latitude, which experience the same amount of daylight. Even if sunset is correlated with mood, this could be the result of changes in sleep duration (Minkel et al., 2011). We would have to believe that conditional on daylight duration and sleep time, sunrise and sunset still have direct effects on mood, perhaps through an interaction with schedule. For example, if a worker anticipates eating dinner in

[7] Estimates are presented in Table IX.

darkness, perhaps she is sad and less productive all day. If this were true, it would create downward bias in our estimates: workers closer to the eastern edge of a time zone would be sad (reducing productivity) and sleep more (boosting productivity). There are numerous such possible narratives and we cannot sign the potential net bias.

3.3 Wage timing mismatch and measurement error

Aside from the instrument validity discussed above, there is an additional issue inherent in studying wages instead of directly studying productivity—the timing mismatch between the observations of sleep, sunset, and control variables on one hand, and wages on the other. Sleep and sunset vary daily, but wages are likely set infrequently. Because there are seasonal trends in sunset time and sleep, one might worry that this timing mismatch could lead to inference failures. The question becomes whether we should use daily sunset to predict daily sleep, or instead use an alternative measure of sunset time to predict a longer-term measure of sleep.

Both options involve trade-offs. The primary benefits of using daily sunset to predict daily sleep are three-fold: first, we observe sleep at the daily level, so the natural frequency for the first stage of Equation (1) is daily. Second, if wage setting is non-annual for some workers, using daily sunset time provides us with additional identifying variation. Third, daily sunset time reduces potential endogeneity from worker location choice. The cost is the potential introduction of measurement error. Fortunately, the degree of measurement error can be calculated fairly precisely by modeling the data generating and sampling process.

Consider wages set every T days, and let the current wage setting period be indexed by τ, as in Equation (1). Let y_τ refer to the day of the year on which the τ^{th} wage setting event begins. Thus, y_τ can be defined recursively by $y_\tau = \text{mod}(y_{\tau-1}, 365)$ given an initial wage setting date. Daily date is indexed by t.[8]

Let sleep on a given day $t \in \tau$ be a function of average annual sleep, T_S, a seasonal

[8]Note that τ both indexes the wage setting periods and refers to t such that $y_\tau + 1 \leq t \leq y_\tau + T$.

trend, and a mean zero error term over the period τ, denoted by $\varepsilon_{S\tau}$. In particular

$$\begin{aligned} T_{St} &= T_S + T_S(t) + \varepsilon_{S\tau} \\ &= T_S + A\cos(\theta t) + \varepsilon_{S\tau} \end{aligned} \tag{5}$$

where $\theta = 360/365$ degrees and A is the amplitude of the seasonal trend in sleep. This choice of functional form is highly tractable, but not arbitrary: it derives from the known functional form underlying sunset seasonality given in Appendix Section B.

Suppose wage is set based on average sleep

$$w_\tau = \frac{1}{T}\sum_{d=y_\tau+1}^{y_\tau+T}(T_S + T_S(d) + \varepsilon_{S\tau})$$

so to obtain correct inference, we would like to estimate

$$w_\tau = \beta_0 T_{S\tau} + \varepsilon_\tau$$

which would yield $\hat{\beta}_0 = 1$. There is a problem, however—we do not know τ. Instead we observe one uniformly random draw of sleep for a date $t \in \tau$ with which we estimate

$$w_\tau = \alpha + \beta_1 T_{St} + \varepsilon_\tau \tag{6}$$

This is a simplified version of Equation (1) where other covariates have been dropped for ease of interpretation and analysis. Estimating $\hat{\beta}_1$ with OLS yields[9]

$$\hat{\beta}_1 = \frac{\mathrm{E}[\varepsilon_{S\tau}^2]}{\mathrm{var}(T_S(t)) + \mathrm{E}[\varepsilon_{S\tau}^2]}$$

where the variance of the seasonal component of sleep, $T_S(t)$, comes from the sampling process. This value is also equal to the attenuation associated with using daily sleep rather than period τ sleep.

Expected attenuation is greatest when wages are set once annually. In that case,

[9] See Appendix Section C for the derivation and further details.

$\text{var}(T_S(t)) = A^2/2$, and the attenuation from using daily sleep becomes[10]

$$\frac{\mathrm{E}[\varepsilon^2_{S\tau}]}{(A^2/2) + \mathrm{E}[\varepsilon^2_{S\tau}]} \tag{7}$$

The equation is almost identical to the classical measurement error formula (Carroll et al., 2012), with the true variance given by $\mathrm{E}[\varepsilon^2_{S\tau}]$ and the measurement error being controlled by the amplitude of the seasonal sleep process. Calibrating A and $\mathrm{E}[\varepsilon^2_{S\tau}]$ with ATUS data yields $A = 0.1$ and $\mathrm{E}[\varepsilon^2_{S\tau}] = 2.0$, which would make attenuation equal to 1%. Using the estimate of within individual annual sleep variance (which might be a closer empirical analogue to the variance of sleep in the model) from Lauderdale et al. (2008) of 0.15 gives an expected attenuation of 3.3%. In either case, the worst-case attenuation is extremely slight. Intuitively, this is because the cross-sectional variation in sleep dominates the measurement error created by small seasonal fluctuations. Thus we believe that the benefits from using daily sunset and sleep outweigh the costs.

4 Data

The most recent and largest data set from the United States containing both sleep time and wage information is the American Time Use Survey (ATUS), which asks a subset of Current Population Survey (CPS) participants to fill out a time use diary for one day. ATUS began in 2003 and the most recent data are for 2012. For this study, we use the sample of individuals who report receiving positive weekly wages from a primary or secondary job and who sleep between 2 and 16 hours per night. Summary statistics for variables of interest are given in Table I along with a comparison between early and late sunset time areas. The table shows values for all individuals who report earning a weekly wage. In the appendix, we discuss data processing in more detail.

Aside from giving basic information on the sample, Table I also provides initial evidence in support of our main results. One can see that early sunset locations have significantly higher wages and sleep duration than areas with later sunset times. In contrast, other individual characteristics are well balanced across the two groups. Out of 11 other tests, only one difference is significant—the fraction of the population with

[10] Again, see Appendix Section C for details.

Table I: ATUS Summary Statistics

Variable	Early Sunset Mean/(SD)	Late Sunset Mean/(SD)	Difference (SE)	Obs.
Weekly earnings	836.4	823.3	13.09***	71,947
	(632.6)	(618.8)	(4.67)	
Hourly wage	15.28	15.10	0.18*	40,352
	(9.532)	(9.225)	(0.093)	
Sleep	8.369	8.248	0.12***	71,947
	(2.016)	(1.983)	(0.015)	
Sunset time	17.64	20.10	-2.46***	71,947
	(0.745)	(0.548)	(0.0049)	
Work hours	4.090	4.075	0.015	71,947
	(4.297)	(4.298)	(0.032)	
Female	0.531	0.526	0.0043	71,947
	(0.499)	(0.499)	(0.0037)	
Age	41.67	41.56	0.12	71,947
	(12.80)	(13.02)	(0.096)	
Race, white	0.820	0.823	-0.0028	71,947
	(0.384)	(0.382)	(0.0029)	
Race, black	0.123	0.123	0.0001	71,947
	(0.329)	(0.329)	(0.0025)	
Weekend	0.509	0.506	0.0032	71,947
	(0.500)	(0.500)	(0.0037)	
HS or less	0.341	0.352	-0.0114***	71,947
	(0.474)	(0.478)	(0.0036)	
Some college	0.288	0.288	0.0005	71,947
	(0.453)	(0.453)	(0.0034)	
College	0.232	0.229	0.0033	71,947
	(0.422)	(0.420)	(0.0031)	
Number of children	0.992	0.986	0.0062	71,947
	(1.134)	(1.131)	(0.0085)	
Ever married	0.748	0.747	0.0013	71,947
	(0.434)	(0.435)	(0.0032)	

Notes: Summary statistics for two sub-samples from ATUS are shown. Early sunset is defined as having a sunset time earlier than the median, and late sunset time is later than the median. Significance is determined from a t-test on the difference between means.

a high school degree or less. This difference works in the direction of explaining the difference in wages in the two groups, but other (insignificant) differences work in the opposite direction. Results controlling for these characteristics are reported in Sections

5.1 and 5.2.

To assign locations to individuals in ATUS, we began by merging the ATUS data with the corresponding CPS data (the match rate was 100%). For a given individual, the CPS data often contain location at the county level. This variable is censored for individuals living in counties with fewer than $100,000$ residents. When county is available, we assign the county centroid as an individual's location. We have county location for approximately 44% of ATUS observations and 42% of workers. For remaining individuals, ATUS contains location at the state level. We assign the 2010 population-weighted state centroid (computed by the Census) as the location for these individuals. In all cases where we refer to Federal Information Processing Standards (FIPS) codes, we are referring to either the county level code (FIPS 6-4), if available, or the state level code (FIPS 5-2) where the county level code is unavailable.

Nighttime sleep is our primary sleep measure and is calculated net of naps. We define a nap as any sleep that starts and ends during daylight hours on the date of diary entry. ATUS gathers data on all sleep during the course of a single 24 hour period for each individual, so there are potentially other ways to calculate naps, and our results are robust to alternative definitions. By removing individuals who sleep fewer than 2 hours per night, we also likely remove night-shift workers.

Our primary wage measure is "usual weekly earnings" as reported in ATUS. This variable is defined for all respondents who have positive labor income and are not self-employed. It is top-coded above $2,884.61. We also estimate a version of our model including only workers who receive an hourly wage, "hourly earnings at main job" as reported in ATUS. This variable is likewise top-coded at the level such that hourly earnings multiplied by usual weekly hours equals $2,884.61. Some control variables (e.g. occupation codes) appear in both ATUS and CPS files, with very minor differences across the two versions. Where possible we use ATUS variables. Some variables (e.g. race) are available only in the CPS.

The main shortcoming of ATUS is that it asks a new cross section of individuals for time use diaries each year, so we cannot construct an individual-level panel. As the summary statistics make clear, however, it offers a rich set of covariates including education, gender, race, and household characteristics. For a more detailed description of ATUS, see Hamermesh et al. (2005). Importantly, ATUS also releases the exact date that the survey was conducted. Using this date and respondent location, we are able to determine sunset time for each individual in the dataset using solar mechanics algorithms from Meeus (1991).

The Quarterly Census of Employment and Wages (QCEW), collected by the US Bureau of Labor Statistics, includes information on wages and employment (workers, not hours) at the county level. We construct a panel in counties, 1990-2012, in order to investigate reduced-form effects of our instrument. Table X, in the appendix, presents summary statistics.

5 Results: Linear effect of sleep on wages

5.1 Linear results

The primary question we wish to address is whether a marginal increase in sleep will, on average, change hourly wage. Here, we present results from ATUS on this question. Estimation methodology is described in Section 3.1.

Table II shows estimates of the effect of sleep on wages using the sunset time instrument described in Section 3.2. The first column reports the first-stage estimates for sleep as a function of sunset time. Sunset time is a significant predictor of sleep duration, in the direction expected from the discussion in Section 3.2: a later local sunset time causes an individual to sleep less. The raw correlation between sleep and wage (Column 4) is slightly negative, as we would expect given strong reverse causality. Using the sunset time instrument, however, the effect of sleep on wage of 16% is large, positive, and significant. Based on Section 3.3, we interpret this as the estimated effect of increasing average sleep over the wage setting period τ.[11] This effect is larger than most estimates of the return to an additional year of education (Psacharopoulos and Patrinos, 2004). We cluster standard errors at the FIPS code level (county or state) to reflect that the exogenous variation is at the group rather than the individual level.

[11]Note that our coefficient estimate of 0.15 corresponds to a 16% change. Applying the maximum attenuation correction from Section 3.3 would move this estimate to 16.7%.

Table II: Linear ATUS Estimates

	First stage Sleep	Reduced form ln(earnings)	2SLS ln(earnings)	OLS ln(earnings)
Sunset time	-0.057***	-0.0085***		
	(0.0057)	(0.0019)		
Sleep			0.15***	-0.017***
			(0.036)	(0.0013)
Individual controls	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Observations	71947	71947	71947	71947
Adjusted R^2	0.123	0.410	0.284	0.411
F-stat on IV	101.83			

Notes: The table shows results from estimating Equation (1). The first three columns show the first stage, reduced form, and two-stage least squares estimates. The fourth column reports the OLS version of the second stage of Equation (1). The dependent variable is indicated at the top of each column. Earnings refers to "usual weekly earnings". Controls are listed in Table I and are latitude, an indicator for female, age, age^2, race indicators, day of week of interview indicators, a holiday indicator, year indicators, and a set of occupation indicators. Standard errors clustered at the FIPS (county or state) level are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Note that clustering at higher levels does not change the inference. We have clustered up to the state level without any appreciable difference in standard errors.

Note also that a one-hour increase in sleep represents a non-marginal change: approximately 12% at the mean value of 8.3 hours in the ATUS data. The implied elasticity of wage with respect to average nightly sleep is 1.1. This is similar to the result in Van Dongen et al. (2003), which shows that the elasticity of attention lapses in laboratory tasks with respect to cumulative waking time is about 1.1. Interpreting this result in units closer to a true marginal change, increasing average nightly sleep by 6 minutes raises wages 1.5%.

The first-stage F statistic of 101.8 well exceeds the relevant Stock-Yogo critical value of 16.4, so we reject the null hypothesis of weak instruments, where "weak" is defined as true size greater than 10% for a nominal 5% test (Stock and Yogo, 2002). This reassures us that the results of our t-tests are reasonable.

Using the bias calculation described in Section 3.1, we can estimate another interesting parameter: the semi-elasticity of sleep with respect to wage. This is the same object studied in Biddle and Hamermesh (1990). In that study the authors find that a one percent wage increase decreases sleep by 141 minutes on average, 181 for men and 61 for women. Together our OLS and IV estimates from Table 5.1 imply a decrease of 77 minutes, roughly in line with the established result. This provides additional evidence that our estimating equations are reasonably well specified.

Several nuances bearing on the interpretation of our estimate warrant discussion. First, our instrument affects all workers in a location identically, which changes the interpretation of our results if there are productivity spillovers across workers. While we do not know if sleep generates such spillovers, Moretti (2004) finds evidence that human capital does. In such a case our estimated β captures not the effect of increasing individual sleep, but rather the effect of increasing sleep for all workers in a location. Second, managers might set wages based on average productivity in a location rather than individual worker productivity. Under this assumption, an increase in sleep by an individual would have no effect on her wage, as it would not appreciably change average productivity. In a case like this, our estimate captures the effect of increased sleep by all workers on average productivity, rather than an individual-level effect. Finally, it is possible our instrument influences both sleep duration and sleep quality. This is true, however, of any exogenous variation in sleep, even in a laboratory setting. In such a case our estimates are still consistent for the effect of an exogenous sleep change, but the interpretation changes slightly.

Table III shows the same results as Table II but only for workers who report being paid hourly. These results are quite similar to those for the full sample of workers in Table II. In principle the coefficients are not directly comparable, since the change in weekly wage could include both wage and hour effects. As we show below, however, our instrument is not highly correlated with hours worked, so the two tables represent roughly the same change. Moreover, the elasticity of wage with respect to sleep from the hourly wage estimates is 1.2, almost identical to that for the weekly wage.

In part, we examine hourly wage earners to address concerns like those raised in

Table III: Linear ATUS Estimates: Hourly workers

	First stage Sleep	Reduced form ln(wage)	2SLS ln(wage)	OLS ln(wage)
Sunset time	-0.059***	-0.0071***		
	(0.0068)	(0.0016)		
Sleep			0.12***	-0.0071***
			(0.032)	(0.0010)
Individual controls	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Observations	42247	42247	42247	42247
Adjusted R^2	0.110	0.439	0.206	0.439
F-stat on IV	74.68			

Notes: The table shows results from estimating Equation (1). The first three columns show the first stage, reduced form, and two-stage least squares estimates. The fourth column reports the OLS version of the second stage of Equation (1). The dependent variable is indicated at the top of each column. Wage refers to hourly wage for those workers who report being paid hourly. Controls are listed in Table I and are latitude, an indicator for female, age, age^2, race indicators, day of week of interview indicators, a holiday indicator, year indicators, and a set of occupation indicators. Standard errors clustered at the FIPS code level are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Borjas (1980) about the use of constructed hourly wage measures. Note that we do not include usual hours worked as a control variable in the main specification. This has been done intentionally to allow the worker to take additional sleep time out of either work time or other (non-work, non-sleep) time. By controlling for work time, we would be forcing all changes in sleep to come out of other time, likely biasing our estimates upward. Nonetheless in one of our robustness checks we also control for a quadratic in hours worked and the results are qualitatively unchanged.

The hourly wage results also allow us to explore one interesting possible source of heterogeneity between salaried and hourly workers. One might expect that salaried workers are engaged in less routine tasks so attention lapses or other sleep-driven performance changes might be more costly. We do not find a substantial or significant difference between the two groups here, but we take a more detailed look at this comparison in Sections 5.4.1 and 5.4.2.

Taking average values for wages, hours worked per week, and assuming 50 work weeks per year, one can calculate the annual income effect of sleeping an additional amount each day. If the worker were to sleep an extra hour and take that entire hour out of non-work time, thus holding work time fixed, our estimated wage effect implies that annual income would rise by about $6,000. Increasing sleep by reducing work by the full hour each day would actually lead to a loss of income of $2,200 per year. In reality, extra sleep comes out of both work and non-work time. If a worker took roughly 74% of the extra sleep hour out of work time, then he or she would just break even on income.

5.2 Robustness checks

We test the sensitivity of our primary results to a wide variety of robustness checks. Broadly, we examine the inclusion or exclusion of controls, changes to the estimation sample, variations in how geography is treated, and placebo tests. We also conduct a deeper exploration of seasonality and geographic sorting that might invalidate our instrument in Section 5.3. All of these checks indicate that the results reported above are extremely robust to varying assumptions and changes in estimation technique.

In particular, we first show the linear results hold under alternative control variable specifications in Table IV. The first pair of rows show that including a quadratic in usual hours worked does not move the coefficient estimate appreciably. As discussed above, we exclude hours worked from the primary specification to avoid bias from forcing sleep increases to come at the expense of leisure. Moreover, without additional instruments, the inclusion of hours worked is not well identified. That its inclusion does not move the coefficient estimate, however, reassures us that bias from work hours is not driving our result.

Next, we include only latitude as a control, without any other covariates. Although the exclusion restriction for the validity of our instrumental variable estimate is based on the error term for the full model, it is reassuring to see that the coefficient on the no-controls model is very close to the baseline specification (a hypothesis test fails to reject

Table IV: Robustness of ATUS estimates: Controls

	First stage Sleep	Reduced form ln(earnings)	2SLS ln(earnings)
Usual work hours quadratic			
Sunset time	-0.056***(0.006)	-0.013***(0.002)	
Sleep			0.225***(0.040)
Only geographic controls			
Sunset time	-0.053***(0.006)	-0.011***(0.003)	
Sleep			0.215***(0.059)
No occupation indicators			
Sunset time	-0.057***(0.006)	-0.009***(0.002)	
Sleep			0.152***(0.046)
Additional individual controls			
Sunset time	-0.057***(0.005)	-0.009***(0.002)	
Sleep			0.166***(0.037)

Notes: The table shows results from estimating Equation (1). Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. For the final group, additional controls are an interaction of Hispanic with existing race indicators, indicators for 5 education levels, 6 indicators for marital status, and number of children in the household. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

the null hypothesis of zero difference in these two estimates). The controls do make the coefficient estimate more precise, however, as can be seen by comparing standard errors between the main result and robustness check. This result implies that sunset time is not highly correlated with the covariates in the main specification, which also provides initial evidence against sorting on sunset time. In the second set of results we implement a less drastic change in control variables, removing occupation indicators from our preferred specification. These variables are potentially endogenous, so it is important to show that our coefficient estimate does not change with these variables excluded.

In contrast to the first two sets of robustness checks, we next add a richer set of individual controls. These include interactions of race indicators from the main model with an indicator for whether the individual is coded as Hispanic, education category indicators, marital status, and the number of children younger than 18 in the household. Adding these additional variables does not change the results.

The second set of robustness checks, presented in Table V, deals with changes to the sample. First, we show that our results hold even with the inclusion of naps. For this specification, we still truncate sleep above 16 hours or below 2 hours per day, but we do not exclude daytime sleep, so the specification likely includes night-shift workers. We have explored many variations of this specification, including keeping naps but excluding night-shift workers, defining naps based on various fixed time windows, and not excluding any individuals. The results are robust to each of these variations and are available upon request.

Table V: Robustness of ATUS estimates: Sample

	First stage Sleep	Reduced form ln(earnings)	2SLS ln(earnings)
Sleep and naps			
Sunset time	-0.033***(0.006)	-0.008***(0.002)	
Sleep and naps			0.246***(0.070)
Observations	72394	72394	72394
Only full time workers			
Sunset time	-0.055***(0.007)	-0.012***(0.002)	
Sleep			0.215***(0.047)
Observations	58198	58198	58198
No weekend diaries			
Sunset time	-0.043***(0.007)	-0.007***(0.002)	
Sleep			0.168***(0.063)
Observations	35454	35454	35454
No time zone border counties			
Sunset time	-0.049***(0.007)	-0.007***(0.002)	
Sleep			0.136***(0.053)
Observations	45799	45799	45799

Notes: The table shows results from estimating Equation (1). Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Next, in the main specification, we do not control for full-time or part-time status of the individual, because we are interested in wage rather than income and we want to avoid introducing endogenous variables. The second specification, however, shows that our main results still hold even when we drop part-time employees entirely. In unreported results, controlling for full-time status also leaves the estimate unchanged.

ATUS oversamples weekends so that roughly half of the total observations are from weekend dates (see Table I). We account for this by including day of week indicators in our main specification to allow for different average sleep amounts on each day. We also try dropping the weekend diary entries entirely. The estimate is almost identical to baseline, and despite losing more than half of the sample, still highly significant. Lastly, we estimate our preferred model excluding counties within four degrees longitude of a time zone border. This drops all counties that might have selected into a time zone based on economic considerations. Again our results are essentially unchanged.

In a series of additional robustness checks, reported in Appendix Section D, we test alternative geographic controls, run placebo tests on the first stage and reduced form, and conduct other minor verifications. In perhaps the most important of these checks, we show that dropping any single time zone does not change our result. This is particularly important for the Eastern Time Zone, which one might believe is driving results due to high coastal wealth concentration.

All of these robustness checks support our primary result. Overall, the first-stage coefficient on sleep is remarkably stable between -3% and -6%. Delaying local sunset by one hour reduces sleep by approximately 5 minutes. The estimate is always significant at the 1% level. Likewise the reduced-form estimate on our instrument is stable near -1%. The overall pattern of results, showing stability of the coefficients under different reasonable control sets, supports our assumption of instrument validity.

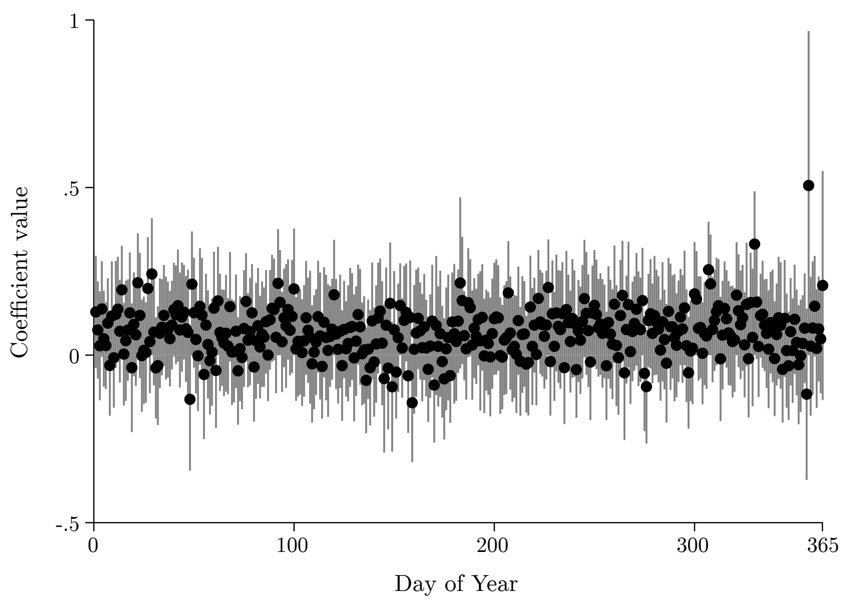
5.3 Instrument validity

The robustness checks in Tables IV and V provide evidence against some of the more plausible potential omitted variable or specification failures. In the following subsections, we conduct more direct tests for some of the potential identification failures discussed in Section 3.2.

5.3.1 Seasonality

First we empirically explore potential bias from seasonality. Sunset time and sleep exhibit seasonal trends, and although Section 3.3 shows that these trends are not inherently problematic, if wages exhibit additional seasonal trends, we might find a spurious effect driven by these seasonal patterns. Our wage data, however, do not exhibit discernible seasonality. Figure III shows estimates from a regression of log weekly wage on 365 day-of-year indicators. There is no apparent seasonal pattern, suggesting that the inclusion of such dummies in our primary models would not be appropriate. By reducing the variation in sleep and sunset time, seasonal dummies might lead to over-fitting problems. In Appendix Table XIV we show that the sign and significance of our sleep estimate survive the addition of day of year indicators, but the estimate becomes large, consistent with over-fitting.

Figure III: Wages do not exhibit seasonality



Notes: Figure shows point estimates and 95% confidence intervals from a regression of log weekly wage on 365 day of year indicators and an intercept.

Preserving the seasonal variation in sunset time has one additional attractive feature. As discussed above, seasonal variation in the angle of incidence of the sun on the Earth—the solar declination—breaks the simple link between distance from a time zone boundary and daily sunset. This helps mitigate concerns about sorting, which we next address in more detail.

5.3.2 Sorting

We might worry that workers sort across locations in ways that will create correlation between unobservable variables and our instrument. For sorting to threaten identification, workers would have to sort based on the *timing* of daylight. Sorting on daylight duration would not bias our estimates, as we hold daylight duration fixed. Note that even if workers actually sort on the sunset-induced wage differential, we can still test for the problem by examining sorting on sunset.

Before proceeding with empirical tests, it will be helpful to consider a few theoretical points. First, a worker who decides to sleep more need not move to another city; she can simply sleep more. Only if workers suffer some optimization failure, like an inability to commit to a particular bedtime, will they have an incentive to sort. Second, workers care about real, not nominal, income. If home prices in more productive (higher sleep) locations adjust to offset wage gains, workers will not have a financial incentive to move. This is exactly the prediction of a sorting model like Roback (1982). With perfect worker and firm mobility, the gains from a productive location-specific amenity accrue to owners of land, the fixed factor. Such a model predicts that locations with earlier local sunset times will have higher rents and house prices, even without worker sorting on ability. Using county-level Census data from 2010, Table VI provides evidence that this is indeed so. We regress log median county home value on average sunset time and a rich set of controls.

$$\ln(\text{median home value})_i = \beta\overline{\text{sunset}}_i + \mathbf{x}_i'\gamma + \varepsilon_i$$

A county experiencing sunset one hour earlier than a comparison county will have, on average, a median home value approximately 6% higher. This result is statistically significant at the 5% level. In levels, the estimated effect on median home value is approximately $7,000 if sunset is an hour earlier. Based on the discussion following

Table II, a worker's annual income gain from moving to a location where sunset is an hour earlier is approximately \$340. The present discounted value of this increase, assuming a five percent discount rate, is approximately \$6,800. This result implies that the wage gains from additional sleep in a location accrue to landowners, not workers, and workers do not have an incentive to sort on sunset time.

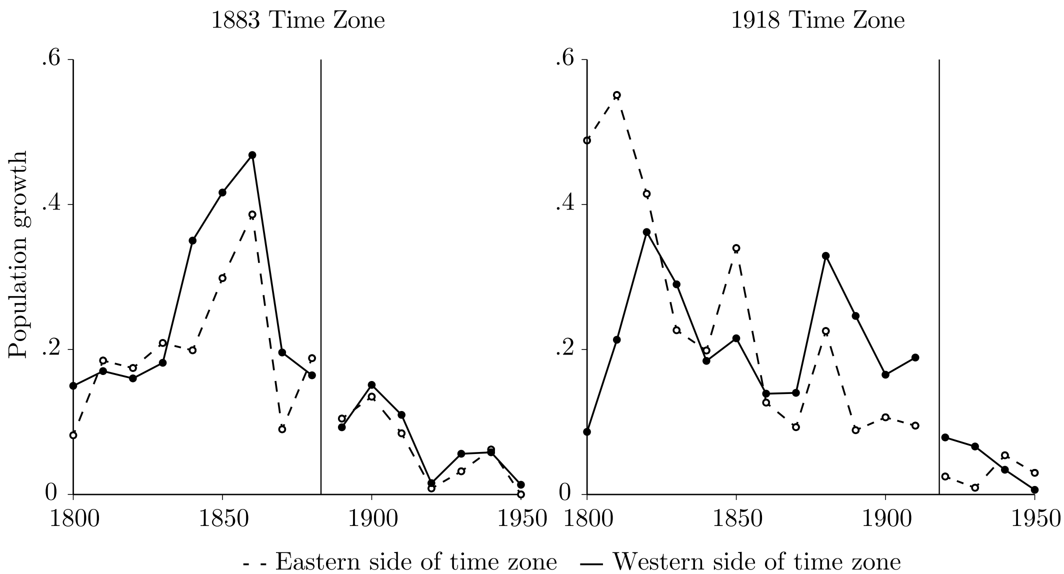
Table VI: Effects on log median home value

	Log value	Log value	Log value
Sunset time	-0.0659**	-0.0596**	-0.0447**
	(0.0261)	(0.0254)	(0.0213)
Location attributes	Yes	Yes	Yes
Population and migration	No	Yes	Yes
Education and labor	No	No	Yes
Observations	2824	2824	2824
Adjusted R^2	0.646	0.662	0.792

Notes: White standard errors are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1. Data are 2010 5-year ACS estimates. Sunset time is the average for a given county. Location attributes include latitude, land area, state dummies, and dummies for Census rural-urban categories. Population and migration controls include 2010 population, net migration, and net population change. Education and labor controls include shares with less than HS, HS, some college, and college education, plus unemployment rate and civilian labor force.

Our hedonic results support our interpretation of the findings in Section 5.1 and are consistent with a general equilibrium model in which workers do not sort on ability. They could also, however, be consistent with worker sorting. Therefore we conduct direct sorting tests: first, we examine historical population growth patterns in response to time zone creation in 1883 and 1918. Second, we examine the relationship between current county-level characteristics and sunset time. Figure IV shows the county-level growth patterns around the dates of the 1883 and 1918 time zone implementations. For both figures, the 10% of counties that are closest to the eastern or western time zone boundary are considered to be on the eastern or western side, respectively. The dashed lines show median population growth rates (inter-census) for eastern side counties, and the solid lines show the same for western side counties. The composition of these groups differs between the two panels due to changes in the location of the 1883 versus 1918 time zones.

Figure IV: Historical time zone sorting



Notes: The figure shows median growth rates between censuses in counties on the eastern and western edges of the 1883 (left panel) and 1918 (right panel) time zones. Eastern counties are represented by the dashed line and western counties are the solid line. All data are from Haines and Inter-university Consortium for Political and Social Research (2010).

If gross sorting were occurring, one would expect eastern side counties to grow faster than western side counties after time zone implementation. Indeed, one might even expect the incentive to sort with respect to the 1883 time zones to be stronger than in the present day due to the lack of electrification. Instead, one can see that there is no evidence of gross sorting in response to the 1883 time zone. After implementation, the two regions of the time zones grow at almost identical rates. Growth rates around the 1918 law are more volatile but tell a similar story. Western side counties experience a slightly larger drop in growth rates after 1918 compared to eastern side counties, but the difference in changes between the two groups is not significant.

Table XII in the Appendix compares present-day county level characteristics by regressing a number of demographic variables on sunset time. Out of nine variables, we find only one case—the unemployment rate—that is significant at the 10% level, which is not surprising given the number of tests conducted. Moreover, the results suggest that unemployment is lower for locations with later sunset time; the reverse of what we would expect if sorting or selection was driving our result. Finally, Table IV also provides present-day sorting evidence by indicating that our estimate is robust to the inclusion or exclusion of individual characteristics. This indicates that people of different ages, genders, race, and education levels are exposed to roughly equal sunset times, on average, across the United States.

Taken together, Table IV, Table XII, and Figure IV suggest that sorting does not bias our results. The lack of sorting is perhaps unsurprising given the extremely small wage differences implied by our reduced-form results: even at the extremities of the widest (Central) time zone, the wage differential between two locations at a given latitude is less than one percent. There is however, one particular form of sorting we cannot exclude. If more productive workers sort into locations with earlier sunset, if that inflow is exactly matched by outflow of less productive workers, and if these workers have similar observable characteristics, our sorting tests will not reveal this pattern. While this is a knife-edge case, we cannot rule it out, and such behavior would bias our estimated wage effects upward.

5.4 Additional linear results

5.4.1 Heterogeneity

There is some disagreement in the medical studies of sleep about whether sleep deprivation effects cognitive or manual tasks more. For instance Samkoff and Jacques (1991) argue that routine mental tasks might suffer from lack of sleep, but that performance on novel tasks does not decline. In contrast, the PVT used in Van Dongen et al. (2003) to measure sleepiness involves repeated mental tasks combined with a simple manual action (pressing a button). Performance on the PVT declines monotonically with sleepiness. To shed some light on the question of whether sleep impacts cognitive or manual tasks more, we investigate differences in the effect of sleep for high- and low-educated workers.

Table VII presents results from a variant of our model where sleep interacts with

Table VII: Linear ATUS Estimates: by Education

	First stage Sleep	Reduced form ln(earnings)	2SLS ln(earnings)
Sunset× HS or less	-0.0696***	-0.00349	
	(0.00987)	(0.00353)	
Sunset× Some college or more	-0.0526***	-0.00814***	
	(0.00616)	(0.00274)	
Sleep× HS or less			0.0436
			(0.0554)
Sleep× Some college or more			0.156***
			(0.0568)
Observations	71947	71947	71947
Adjusted R^2	0.122	0.330	0.239
F-stat on IV	53.66		

Notes: The table shows results from estimating a variant of Equation (1) modified by interacting sleep with two educational attainment indicators: one for high school completion or less, the other for some college or more. These indicators are also included as controls. Dependent variable is indicated at the top of each column. Controls and sample are the same as in Table II. Standard errors clustered at the FIPS level are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

two indicators for educational attainment: one for high school completion or less, the other for some college or more. The first-stage estimates are quite close to each other and to the estimate from our main specification. The reduced-form and 2SLS estimates, however, show much larger wage effects on more educated workers. A test for equality of the 2SLS coefficients returns a p-value of 0.15, so we cannot reject the null at a conventional threshold. Nonetheless these results provide suggestive evidence that the productivity of higher-educated workers may be more sensitive to sleep than that of lower-educated workers. In unreported results, we investigated possible heterogeneity on other dimensions, including race and gender, and generally found quite similar point estimates for different groups.

5.4.2 County average wages

To corroborate the results from ATUS data, we also estimate reduced-form models using data from the BLS Quarterly Census of Employment and Wages (QCEW). Unlike

ATUS, QCEW data allow us to observe all US counties. In the following equation, i indexes county and t quarter-year

$$\ln(w_{it}) = \alpha_i + \delta_t + \beta\overline{\text{sunset}}_{it} + \varepsilon_{it} \tag{8}$$

Table VIII: Effects on average wage

	All industries	Goods	Services
Sunset time	-0.00647**	-0.0124***	-0.00369**
	(0.00311)	(0.00328)	(0.00178)
Latitude	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Year×Quarter FE	Yes	Yes	Yes
Observations	287399	283430	284307
Within R^2	0.88	0.81	0.89

Notes: Standard errors are reported in parentheses. Clustering is at the county level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1. Data are from the BLS Quarterly Census of Employment and Wages. Sunset time is the quarterly county average.

The dependent variable is the average weekly wage per worker. We include state fixed effects and dummies for quarter-year. Results appear in Table VIII. Importantly, these results suggest that seasonal trends do not bias our primary results: we can include a rich set of seasonal controls and recover approximately the same reduced-form estimate (-.65%) as our preferred ATUS specification (-.85%). The estimate for goods (-1.2%), is substantially larger than for services (-.4%). This difference could indicate sleep is more important to productivity in goods, or it could simply be the product of a noisier wage-setting process in services, where productivity may be harder to observe. There is some superficial tension between these results and those from Table VII, which show larger effects on more educated workers. It is important to bear in mind that the sectoral division into goods and services is not equivalent to a division into high- and low-skill workers. The goods sector, for example, includes managers, technicians, and electrical engineers.

5.4.3 Other time uses

Our primary analysis demonstrates that workers experiencing an earlier sunset get more sleep. It is natural to ask where the additional sleep time comes from, and the answer to this question informs the interpretation of our estimates. Previous work has found a relationship between sleep and hours worked (Biddle and Zarkin, 1989). If workers are increasing sleep by decreasing work time, our estimates reflect the combined effects of these two changes. Table IX, however, shows that our instrument does not strongly affect hours worked. As discussed in Section 3.2, this ameliorates one type of concern about our exclusion restriction. Later sunset does, however, increase time devoted to waking non-work activities, like leisure and home production. The estimates in Table IX imply that delaying sunset by one hour increases the time devoted to waking non-work activities by approximately two minutes. If these changes in waking non-work time impact wages, our estimates remain a combination of effects from increased sleep and decreased non-work time. If, however, waking non-work time does not have wage effects, our estimates should be interpreted as the result of sleep changes alone.

Table IX: Non-work time as a function of sunset time

	Work time	Non-work time
Sunset time	0.0021	0.027***
	(0.010)	(0.0098)
Individual controls	Yes	Yes
Geographic controls	Yes	Yes
Time controls	Yes	Yes
Occupation	Yes	Yes
Observations	71947	71947
Adjusted R^2	0.353	0.246

Notes: The table shows results from estimating the first stage of Equation (1), replacing sleep time with either work time or waking non-work time as the dependent variable. Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Recall that in Section 2.2, we found the sign of the derivative $\partial T_z/\partial\alpha$, the derivative of leisure time with respect to the parameter α, was theoretically ambiguous, depending on wage and hours worked. In a regression of waking non-work time on sunset time (as in column 2 of Table IX), this prediction corresponds to smaller, possibly negative, coefficients on sunset time for workers with low wages and high work hours. To test this prediction, we estimate separate regressions for these groups. (Results are reported in Appendix Table XIII.) The results are consistent with our theoretical predictions. For individuals with high work hours, the coefficient on sunset time is modestly smaller, though still positive. For low-wage workers, the coefficient is negative, in marked contrast to the overall result from Table IX.

6 Results: Nonlinear estimates

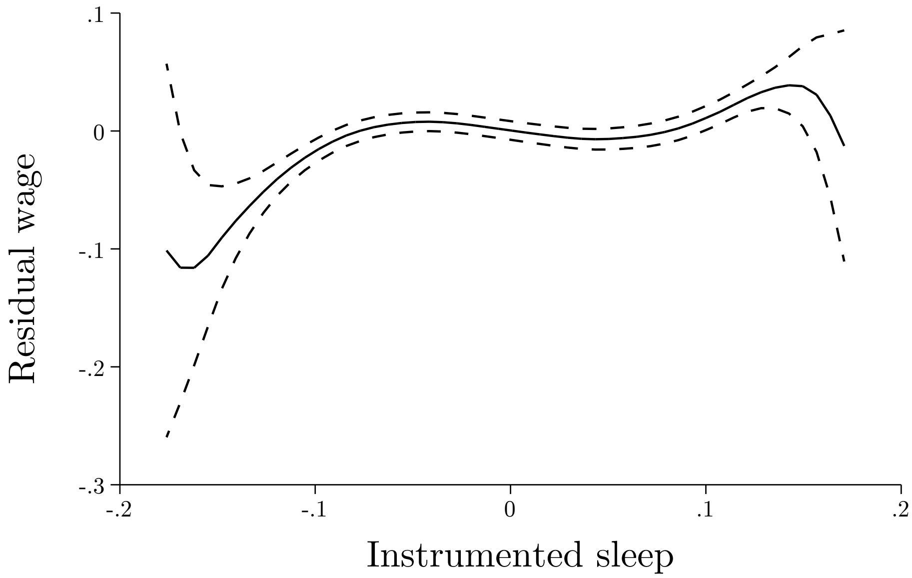
Figure V shows a local polynomial fit along with 95% confidence interval for the scatter plot of residual instrumented sleep against residual wage. This plot provides evidence that the relationship between sleep and wage is nonlinear in the way suggested by the medical literature. In particular, residual wage peaks for moderate levels of sleep and falls for both high and low levels of sleep, motivating our choice of a quadratic specification in equations (4).

The left panel of Figure VI presents our nonlinear IV estimates, based on the parametric estimation strategy from Section 3. The parameters underlying this figure are presented in Appendix Table XVI along with first stage estimates in Appendix Table XV. These results provide causal evidence that the sleep-wage relationship takes the form of an inverted U, peaking around 9 hours. This is consonant with the medical and epidemiological literature measuring the link between sleep and work performance. The minimum first-stage F statistic of 40.6 exceeds the relevant Stock-Yogo critical value of 13.43, so we reject the null hypothesis of weak instruments, where ”weak” is defined as true size greater than 10% for a nominal 5% test (Stock and Yogo, 2002).

To evaluate the robustness of our quadratic IV specification, we also estimate a cubic IV specification, an IV with a four-knot linear spline, and two control-function specifications.[12] The cubic IV provides the right panel of Figure VI. The addition of a

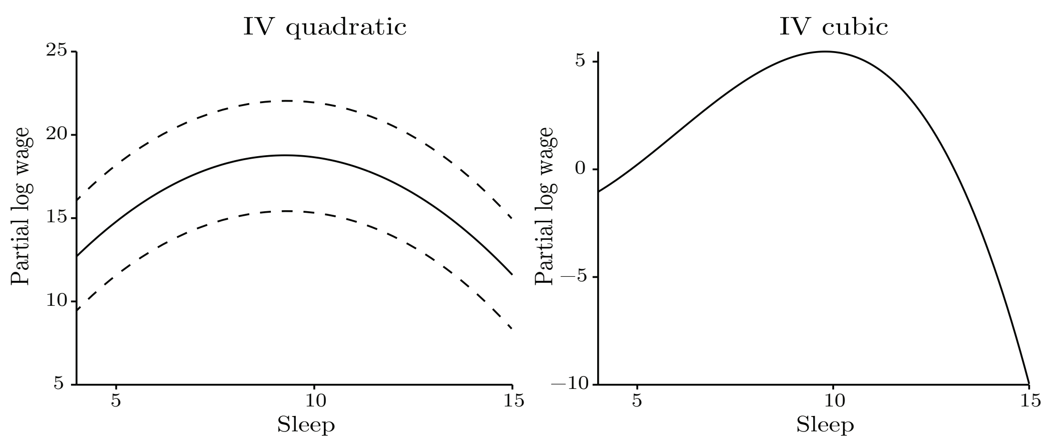
[12]The IV spline specification requires additional instruments. We square the three instruments used in our preferred (quadratic) specification, giving us a total of 6 instruments.

Figure V: Local polynomial fit of residual wage versus sleep



Notes: The figure shows a local cubic polynomial fit to the data from Table XVI. Wage residuals are from equations (4), with instrumented sleep excluded from the wage equation. Residual instrumented sleep comes from an auxiliary regression of first-stage sleep from equations (4) on our other baseline controls. An Epanechnikov kernel with bandwidth of 0.07 is used.

Figure VI: Non-linear IV specifications



Notes: The upper panels are variants of our primary non-linear IV specification (Equation (4)), allowing for second (left panel) and third (right panel) order terms in sleep. 95% confidence bands for the quadratic are given by dashed lines. Confidence bands for the cubic are large and we omit them in the interest of clarity.

cubic term makes no meaningful difference, producing an inverted U shape with a peak near 9 hours. In addition, we explore the control function approaches of Newey et al. (1999) and Kim and Petrin (2013). In these specifications we control for endogeneity by including quadratic polynomials in the first-stage residuals in the second-stage wage equation. The Kim and Petrin model also demeans the higher-order residual terms with respect to the instruments and interacts all residual terms with the instruments. In both control-function approaches, sleep enters the wage equation as a fourth-degree polynomial. In contrast to our more conventional IV specifications, these control function specifications find very little evidence of non-linearity. Plots of all estimated functions, including splines and control-function estimates, appear in Appendix Figure X.

The sensitivity of our non-linear IV results to specification recommends caution. While we find an inverted U in most specifications, the location of the peak (wage-optimizing sleep) is modestly sensitive to the choice of specification. This nonlinearity has important implications for how sleep should be viewed in a personal optimizing framework. Because the marginal effect of sleep on wages is negative at high sleep levels, the simple linear income extrapolation in Section 5 overstates the impact of sleep for individuals who already sleep a lot. For more on the interpretation of our nonlinear results, see Appendix Section E.

7 Conclusion

Although time use is entangled in a causal web with labor market outcomes, economists have largely neglected these relationships. In particular, the profession has paid scant attention to sleep. Our results demonstrate that sleep has a powerful impact on labor market outcomes and should be considered an integral part of a worker's optimization problem. Using individual time-use diaries matched with labor market variables from ATUS, we show that increasing average sleep by one hour per night produces a 16% higher wage. Our use of instrumental variables techniques addresses the reverse-causality and omitted variable problems that would bias naïve estimates. We buttress this finding with reduced-form evidence from BLS county wage data and a hedonic model of home prices.

Sleep is arguably the third most important determinant of productivity, following ability and human capital. A one-hour increase in average sleep boosts productivity by more than a one-year increase in education (Psacharopoulos and Patrinos, 2004). This finding has important implications for individuals, firms, schools, and governments. A worker who desires higher wages might be able to obtain them by increasing sleep. Firms might be able to increase profit by varying start times, providing workers with incentives to sleep more, or with information interventions (e.g. information on how to improve sleep quality or consistency). Governments conducting cost-benefit analyses of policies that change sleep time, for example daylight savings time, should consider the productivity effects to design efficient policies.

The medical literature has investigated sleep impacts on a variety of outcomes, routinely finding a nonlinear relationship. Motivated by these findings, we examine possible non-linearities in the sleep-wage relationship. In particular, we demonstrate that wage-optimizing sleep is approximately 9 hours per night in the United States. This is modestly higher than average reported sleep. Important heterogeneity in the population exists, however, as indicated by the 2-hour standard deviation in our sleep variable. Many workers sleep far below the wage-optimizing level. Further work will investigate heterogeneity by industry, with particular attention to industries characterized by chronic sleep shortages. In addition to wages, optimal sleep plausibly depends on other factors like leisure complimentarities, direct sleep utility, and health optimization. Each of these trade-offs suggests an interesting research question. More broadly, our results demonstrate that non-labor time uses can have first-order effects on labor outcomes—effects that should continue to be investigated in future work.

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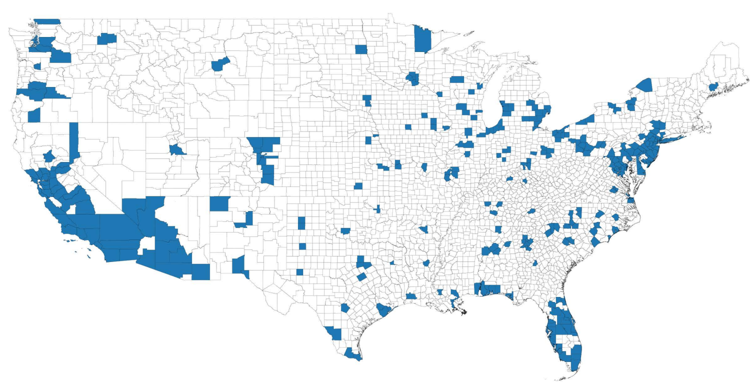
A Data and summary statistics

Figure VII: County level geocoding



Notes: The map shows, in blue, locations in the continental United States where we are able to geocode ATUS records at the county level.

Table X: QCEW summary statistics

Variable	**Mean**	**Std. Dev.**
Weekly wage	492.37	171.88
Weekly wage - goods	609.35	240.53
Weekly wage - services	431.84	161.19
Sunset time	18.38	.94
Observations	285,680	

Notes: All data are from the Quarterly Census of Employment and Wages at the county level from 1990-2012.

B Solar mechanics

Here, we provide a brief summary of how sunset time is calculated and a glossary of terms. We calculate sunset, sunrise, solar declination, and sunlight duration each day using the algorithm of Meeus (1991) as implemented by NOAA's Earth Systems Research Laboratory (ESRL). The calculator takes inputs of the date, time zone offset, latitude, and longitude. The Stata code that we used for calculation is available upon request.

Sunset and sunrise time are both calculated assuming 0.833° of atmospheric refraction, or the bending of the path of light as it passes through the Earth's atmosphere. In practice a refraction correction would need to incorporate information on air pressure and humidity. Also, we calculate sunset assuming an observer with a 0 elevation change view of the horizon. Over a full county, this assumption should introduce minimal error.

Sunlight duration is simply calculated as the difference between sunrise and sunset time for a location on a given day.

Solar declination is the angle of a line segment from the sun to the earth relative to a plane projected from the equator of the Earth. The solar declination is a function only of the day of year and time zone offset (to compute fractional days for high-resolution local time sunset), and changes in solar declination correspond to the seasonal movement of the sun. The highest solar declination, 23.44° occurs on the summer solstice, and the lowest solar declination, -23.44°, occurs on the winter solstice. On the equinox, solar declination is 0°. A rough calculation of solar declination can be made with the following equation:

$$-23.44 \cos\left(\frac{360}{365}(d+10)\right)$$

where d is the day of the year. This functional form motivates our choice of seasonal parameterization for sleep in Section 3.3.

For a much more detailed glossary, see NOAA's ESRL website.

C Seasonality model

The setup and notation are the same as in Section 3.3: Wages are set every T days, the current wage setting period is indexed by τ, y_τ refers to the day of the year on which the τ^{th} wage setting event begins, so y_τ can be defined recursively by $y_\tau = \text{mod}(y_{\tau-1}, 365)$ given an initial wage setting date. Daily date is indexed by t. Sleep on each day is given by

$$\begin{aligned} T_{St} &= T_S + T_S(t) + \varepsilon_{S\tau} \\ &= T_S + A\cos(\theta t) + \varepsilon_{S\tau} \end{aligned} \tag{9}$$

where $\theta = 360/365$ degrees and A is the amplitude of the seasonal trend in sleep. Let $n = y_\tau + 1$ and $N = y_\tau + T$ so that $T = N - n + 1$. Wages are defined as

$$\begin{aligned} w_\tau &= \frac{1}{T}\sum_{d=n}^{N}(T_S + T_S(d) + \varepsilon_{S\tau}) \\ &= \frac{1}{T}\sum_{d=n}^{N}(T_S + A\cos(\theta d) + \varepsilon_{S\tau}) \end{aligned} \tag{10}$$

Estimating Equation 6, we have

$$\hat{\beta}_1 = \frac{\text{cov}(w_\tau, T_{St})}{\text{var}(T_{St})} \tag{11}$$

Note that $T_S(t)$ is not stochastic, but we will abuse notation slightly and set $\mathrm{E}[T_s(t)] = s + \frac{1}{T}\sum_{d=n}^{N} A\cos(\theta d)$, so the expectation (and variance) of sleep is with respect to the sampling process. For a single round of wage-setting starting on day t and ending on day $t+T$, substitution and cancellation yield

$$\begin{aligned}\mathrm{cov}(w_\tau, T_{St}) &= \mathrm{E}[w_\tau T_{St}] - \mathrm{E}[w_\tau]\mathrm{E}[T_{St}] \\ &= T_S^2 + 2T_S\mathrm{E}[T_S(t)] + \mathrm{E}[T_S(t)]^2 + \mathrm{E}[\varepsilon_{S\tau}^2] - T_S^2 + 2T_S\mathrm{E}[T_S(t)] + \mathrm{E}[T_S(t)]^2 \\ &= \mathrm{E}[\varepsilon_{S\tau}^2] \end{aligned} \tag{12}$$

Let $\mathrm{E}[\varepsilon_{S\tau}^2] = \sigma_{\varepsilon S}^2$. For the denominator, we can get an abstract expression simply by noting the independence of T_S, $T_S(t)$, and $\varepsilon_{S\tau}$ give

$$\mathrm{var}(T_{St}) = \mathrm{var}(T_S(t)) + \sigma_{\varepsilon S}^2$$

To find an analytical expression, use the power reduction identity, Lagrange's identity, and simplify to find

$$\begin{aligned}\mathrm{var}(T_S(t)) &= \frac{1}{T}\sum_{d=n}^{N} A^2\cos^2(\theta d) - \left(\frac{1}{T}\sum_{d=n}^{N} A\cos(\theta d)\right)^2 \\ &= \frac{1}{T}\left(\frac{A^2}{4}(\csc(t)(\sin(2N\theta+\theta) - \sin(2n\theta-\theta)) + 2(N-n+1))\right) \\ &\quad - \left(\frac{A^2}{2T^2}(\cos(n\theta) + \cos(N\theta) + \cot\left(\frac{\theta}{2}\right)(\sin(N\theta) - \sin(n\theta)))\right)^2 \end{aligned} \tag{13}$$

For a single wage setting, this function evaluates to $A^2/2$ for $n = 1$ and $N = 365, 730, \ldots$ and oscillates above and below this value for other choices of N. We will argue informally that the bias is worst for annual wage setting: the intuition is that annual wage setting creates the largest average error between wages and a random draw from daily sleep. Algebraically, for any $N > 0$ such that $\mathrm{mod}(N, 365) \neq 0$, as the number of wage setting periods goes to infinity, Equation (13) is evaluated at all points, so the variance goes to $A^2/2$.

For $n = 1$ and $N = 365$, the function has a particularly tractable simplification by noting that $\mathrm{E}[T_S(T)] = 0$. Thus

$$\begin{aligned} \mathrm{var}(T_S(t)) &= \frac{A^2}{2T}(\csc(\theta)\sin(N\theta)\cos((N+1)\theta) + N) \\ &= \frac{A^2}{2} \end{aligned}$$

From $T = N$ and $\sin(N\theta) = 0$. Therefore, $\mathrm{var}(T_{St}) = A^2/2 + \sigma^2_{\varepsilon S}$.

Plugging this and Equation (12) back into Equation (11), we find

$$\text{attenuation} = \frac{\sigma^2_{\varepsilon S}}{(A^2/2) + \sigma^2_{\varepsilon S}} \tag{14}$$

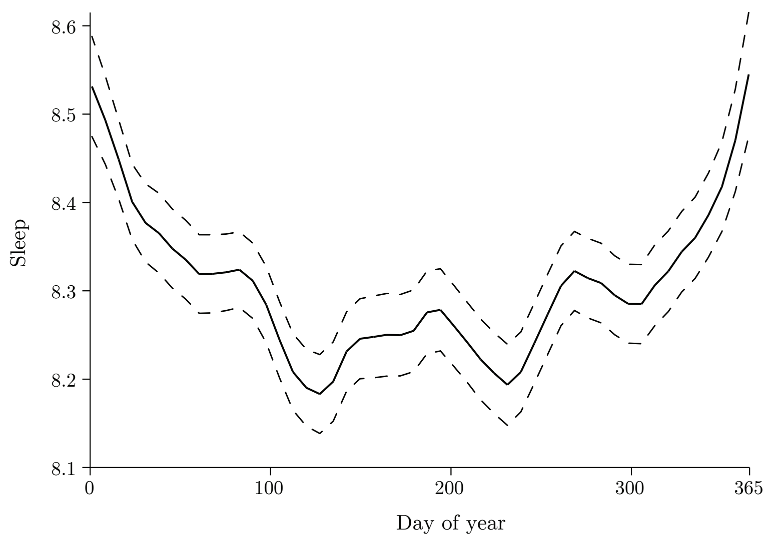
To calibrate the expected attenuation, we need an estimate for the amplitude of the seasonality of sleep, A, and an estimate for the variance of sleep over the wage-setting period. The amplitude of seasonality can be estimated by regressing sleep on a non-linear function of the day of the year. Figure VIII shows one such fit, made by fitting a local polynomial. Taking the maximum of the black curve minus the minimum and dividing by two gives 0.15 as the amplitude. One can also fit the model's parametric seasonality function to the data by regressing sleep on $\cos(D\theta)$ where D is the day of the year. The coefficient from this regression, which corresponds exactly with A in the model, is 0.1.

D Auxiliary linear robustness and results

We relax our linearity assumption on the latitude control by including indicators for each degree of latitude in the sample (between 19 and 62°). Including these indicators has almost no effect on the estimates. Indeed, in unreported results, excluding latitude also does not have an effect. This should be expected since latitude is, by construction, uncorrelated with average sunset time, however it might still be important to control for latitude to account for effects stemming from seasonal variation in sunlight timing and the very strong North-South wage differential in the United States.

Including time zone indicators reduces the precision of the estimates but does not change the magnitudes. In theory sunset timing operates the same in each time zone, so one can pool all time zones together, as we have done in the main results. Alter-

Figure VIII: Sleep seasonality



Notes: The figure shows a local polynomial fit to sleep data from ATUS. Calculations use a bandwidth of 10 days and an Epanechnikov kernel. Note that the range of sleep in the sample is 2 to 16 hours and the standard deviation is 2.03.

natively, one might believe that each time zone has unique features that interact with the biological sunset mechanism that we emphasize. The similarity of the main results to the results including time zone indicators does not support this latter story.

We also remove the eastern time zone entirely, with little impact on the results. One might worry that the high wealth concentration along the east coast is driving the results. In fact, dropping any single time zone does not change the results appreciably.

0.2% of the sample has topcoded wages. A tobit accounting for this does not change the results. Likewise, accounting for the truncation of sleep does not change inference. Results are available upon request.

We also estimated the first stage and reduced form using placebo values for sleep and wages. These estimates are reported in Figure IXa and IXb. Panel (a) shows the results for 1,000 estimates using random sleep values generated by a uniform distribution bounded between 2 and 16 (the range of sleep observed in our data). Panel (b) shows similar results with log wage generated by a normal distribution with mean of 2.6 and standard deviation of 0.5. In both panels, the red lines given the estimate from the

Table XI: Robustness of ATUS estimates: Geography

	First stage Sleep	Reduced form ln(earnings)	2SLS ln(earnings)
Latitude bins			
Sunset time	-0.058***(0.005)	-0.008***(0.002)	
Sleep			0.137***(0.036)
Time zone indicators			
Sunset time	-0.055***(0.005)	-0.007***(0.002)	
Sleep			0.132***(0.037)
Longitude			
Sunset time	-0.057***(0.005)	-0.008***(0.002)	
Sleep			0.148***(0.036)
Longitude and time trend			
Sunset time	-0.058***(0.005)	-0.008***(0.002)	
Sleep			0.144***(0.035)
No eastern time zone			
Sunset time	-0.064***(0.007)	-0.007***(0.002)	
Sleep			0.110***(0.038)

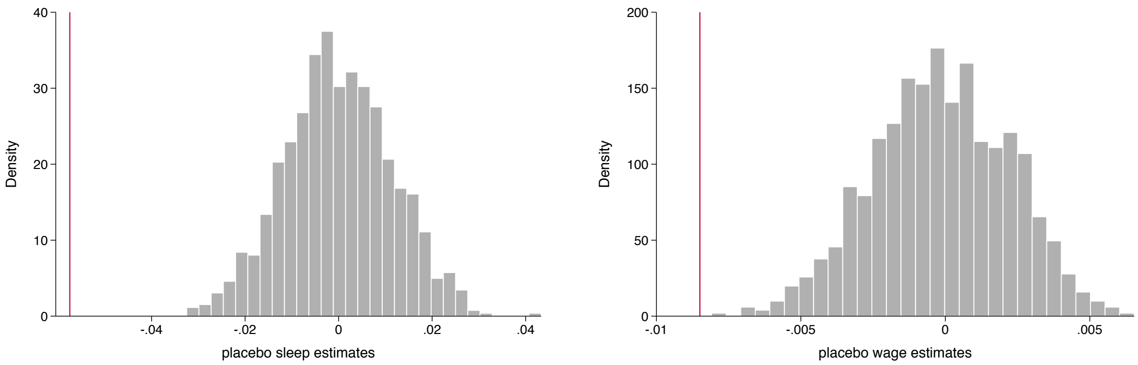
Notes: The table shows results from estimating Equation (1). Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

main results in Table II. Reassuringly, the true estimates are far in the left tails of both sets of placebo estimates, indicating that severe misspecification is not driving the observed results.

In Table XII we report estimates of county level characteristics as functions of sunset and latitude.

Table XIV presents results including seasonal dummy variables. As discussed in Section 5.3.1, there is no seasonality in wages, so the inclusion of these dummies is over-fitting; these models discard useful identifying variation in sleep. Moreover, the model in Sections 3.3 and C gives good reason to prefer daily sleep and sunset over annual sunset and daily sleep. We include these results only in the interest of comprehensiveness. Even in these problematic specifications, the sign and significance of our primary results survive. Addition of quarter of year indicators leaves the first stage

Figure IX: Placebo tests



(a) Placebo first stage

(b) Placebo reduced form

Notes: Each figure gives 1,000 estimates using placebo values for sleep (a) or wage (b). The estimate from Table II is given by the vertical red line.

Table XII: Robustness: County characteristics

	Log pop. density	Pop. change frac.	Net migration frac.
Sunset time	-0.709	-0.00101	-0.000967
	(0.510)	(0.00146)	(0.000584)
Observations	3104	3104	3104
Adjusted R^2	0.045	0.001	0.001

	Log poverty rate	Labor force change	Unemployment rate
Sunset time	-0.0169	0.000197	-1.541*
	(0.0689)	(0.0122)	(0.917)
Observations	3103	3103	3103
Adjusted R^2	0.176	0.020	0.072

Notes: Dependent variable is indicated at the top of each column. All data are from the Census and is at the county level. Population, net migration, and unemployment rate are all 2012 values. Poverty is from 2011. Labor force change is from 2000 to 2010. Standard errors clustered at the FIPS code level are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

almost unchanged, indicating that a large portion of the seasonality in sleep is indeed driven by sunset. The reduced form becomes larger in magnitude, but we cannot reject the null hypothesis that it is equal to our preferred estimate. Adding 365 day of year indicators gives still larger results.

Table XIII: Waking non-work hours as a function of sunset time, selected groups

	Non-work time High work hours	Non-work time Low wage earners
Sunset time	0.023	-0.078***
	(0.038)	(0.028)
Individual controls	Yes	Yes
Geographic controls	Yes	Yes
Time controls	Yes	Yes
Occupation	Yes	Yes
Observations	5197	8494
Adjusted R^2	0.236	0.044

Notes: The table shows results from estimating the first stage of Equation (1), replacing sleep time with waking non-work time as the dependent variable. In column 1 the sample is workers who usually work more than 60 hours per week (95th percentile). In column 2 the sample is workers with log wages below 5.44 (10th percentile). Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table XIV: Robustness of ATUS estimates: Seasonality

	First stage sleep	Reduced form ln(earnings)	2SLS ln(earnings)
Quarter fixed effects			
Sunset time	-0.059***(0.011)	-0.027***(0.004)	
Sleep			0.454***(0.104)
Day of year fixed effects			
Sunset time	-0.072***(0.022)	-0.071***(0.013)	
Sleep			0.980***(0.293)

Notes: Dependent variable is indicated at the top of each column. Unless otherwise noted, controls, number of observations, and standard error clustering are the same as in Table II. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

E Auxiliary non-linear results

Table XV shows results from the first stage regressions used in column 1 (the quadratic specification) of Table XVI. We omit the first-stage cubic results in the interest of brevity, but they are available upon request. Instrument relevance is not a problem in the cubic specification: the F statistic for the first-stage regression of the cubic sleep term on our instruments is 36.26.

Table XV: First Stage ATUS Estimates: Nonlinear Models

	Sleep	Sleep^2	Sleep	Sleep^2
Equinoctial sunset time	-0.0368	-0.523	-0.0493**	-0.784*
	(0.0281)	(0.514)	(0.0241)	(0.427)
Solar declination	-0.0568**	-1.251***	-0.0444**	-0.997***
	(0.0235)	(0.400)	(0.0221)	(0.369)
Avg. sunset× Solar dec.	0.00282**	0.0627***	0.00216*	0.0493**
	(0.00123)	(0.0209)	(0.00116)	(0.0193)
Individual controls	No	No	Yes	Yes
Geographic controls	No	No	Yes	Yes
Time controls	No	No	Yes	Yes
Industry & Occ.	No	No	Yes	Yes
F-test on IV	32.2	35.5	40.3	44.6
Observations	71947	71947	71947	71947

Notes: The table shows the results from estimating the first stage of equation (4). Dependent variable is sleep or log sleep as indicated. Standard errors clustered at the FIPS level are reported in parentheses. Significance indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

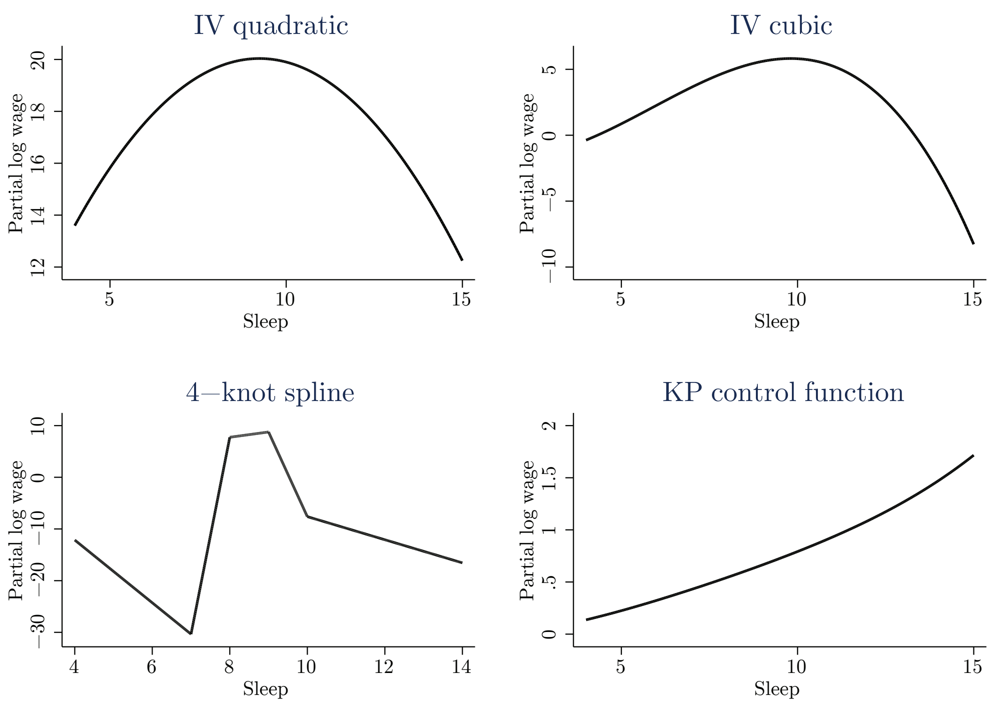
It is reasonable to ask why we observe workers on the declining portion of the wage-sleep curve. The answer, in brief, is that workers optimize over more than just wages. Figure XI formalizes this intuition. Sleep not only increases productivity, it also plausibly provides direct utility, complements leisure, and serves as an input to long-run health. This means that for at least some workers, the total marginal benefit from sleep is greater than the marginal benefit in terms of wages alone. If these workers optimize, they will locate not where the marginal wage benefit of sleep equals zero, but rather where the total marginal benefit (including leisure complementarity) is zero and the marginal effect on wages is negative. For these workers utility-optimal sleep will be greater than (to the right of) wage-optimal sleep.

Table XVI: Nonlinear ATUS Estimates

	ln(earnings)	ln(earnings)
Sleep	4.050**	-108.4
	(1.576)	(308.7)
Sleep^2	-0.218**	13.81
	(0.0875)	(38.32)
Sleep^3		-0.546
		(1.487)
Individual controls	Yes	Yes
Geographic controls	Yes	Yes
Time controls	Yes	Yes
Industry & Occ.	Yes	Yes
First stage F	(40.3, 44.6)	
Observations	71947	71947

Notes: The table shows the results from estimating equation (4). Dependent variable is log wage. The instrumental variables are sunset time, solar declination, and the interaction of the two. First stage F-statistics are for the linear and quadratic terms in sleep respectively, and first stage results can be found in Table XV. Controls, where indicated, are the same as in Table II. Standard errors clustered at the FIPS level are reported in parentheses. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Figure X: Non-linear IV specifications



Notes: The upper panels are variants of our primary non-linear IV specification (Equation (4)), allowing for higher-order terms in sleep. The lower panels reflect the control function approaches of (Newey et al., 1999) and (Kim and Petrin, 2013). In these specifications we control for endogeneity by including quadratic polynomials in the first-stage residuals in the second-stage wage equation. The Kim and Petrin model also demeans the higher-order residual terms with respect to the instruments and interacts all residual terms with the instruments. In both control-function approaches, sleep enters the wage equation as a fourth-degree polynomial.

Figure XI: Marginal benefit of sleep