Poor Sleep: Sunset Time and Human Capital Production*

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Job Market Paper

December 1, 2018

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Abstract

This paper provides evidence that arbitrary clock conventions – by generating large differences in when the sun sets across locations – help determine the geographic distribution of educational attainment levels. I show later sunset reduces children's sleep: when the sun sets later, children go to bed later; by contrast, wake-up times do not respond to solar cues. Sleep-deprived students decrease study effort, consistent with a model where sleep is productivity-enhancing and increases the marginal returns of effort. Overall, school-age children exposed to later sunsets attain fewer years of education and are less likely to complete primary and middle school. Later sunsets are also associated with fewer hours of sleep and lower wages among adults. The non-poor adjust their sleep schedules when the sun sets later; sunset-induced sleep deficits are most pronounced among the poor, especially in periods when households face severe financial constraints.

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1 Introduction

Do arbitrary clock conventions help determine the geographic distribution of educational attainment levels? Proposed in the late 19th century, a system of world-wide standard time zones was intended to accumulate smaller differences in geographical longitude, so that nearby places can share a common standard for timekeeping, but still allow local time to be approximate with mean solar time. However, many countries set their own time to assert national identity, to make political connections, or to keep one time zone within their borders, even if that may take parts of their countries far out of the designated zone. India and China cover a vast east-west range, but both countries follow a standard time zone across their territorial boundaries. Clocks in large parts of the planet – e.g., France, Spain, Algeria, Senegal, South Sudan, Russia, and Argentina – are set to be ahead of their (solar) time.[1] One consequence of these discretionary clock settings are large discrepancies in when the sun sets both within and across countries.

In this paper, I show that children in locations that experience later sunsets have worse educational outcomes due to the negative relationship between sunset time and sleep, and the consequent productivity impacts of sleep deprivation. Sunset-induced sleep deficits are most pronounced among the poor, especially in periods when households face severe financial constraints. Because education is both a driver of economic growth and a means to reduce income inequality (Barro, 2001), these results imply sunset time associated with geographic location may contribute to persistent poverty and worsening inequality.

As the sun sets and the sky grows darker, the human brain releases melatonin, a hormone that facilitates sleep (Roenneberg and Merrow, 2007). Yet social norms or uniform policy choices at the federal or state level – for example, start times for school and work – may dictate wake-up times that do not co-vary with sunset time (Hamermesh, Myers and Pocock, 2008). As a result, children may sleep less in locations exposed to later sunsets. If sleep is productivity-enhancing, later sunset may directly, adversely, affect children's learning.

However, the consequent effect of later sunsets on educational attainment is ambiguous; how children trade-off sleep with other time uses may have multiplicative or compensatory

[1] For instance, Spain switched clocks ahead one hour to be in sync with Germany in 1940, even though Spain is geographically in line with Britain, not Germany.

effects on education production. If sleep increases the marginal returns of effort, sunset time may also affect self-investment in study effort. Conversely, later sunset (more daylight after school) might make it easier for children to self-study in the evening, especially in lower income countries where electricity access is intermittent. Moreover, child labor is common in lower income countries. Therefore, any complementarities between sleep and study effort may also depend on the marginal increase in children's labor productivity with respect to sleep. As an additional channel, later sunset may similarly affect adults' sleep, and consequently household earnings and investment in children's education.

The timing of natural light is determined by time zones and is therefore predictable across locations and seasons. If sleep is important for productivity, households may adjust their sleep schedules in response to later sunset, or simply get on a consistent sleep schedule regardless of sunset time, minimizing the resulting human capital impacts. Yet, financial or behavioral considerations may impede adjusted or consistent sleep. More importantly, poverty may exacerbate these considerations.[2] Therefore, if the non-poor are better able to adjust their sleep schedules when the sun sets later, later sunsets may contribute to a sleep disparity in the population.

In the first part of the paper, I use the 1998-99 Indian Time Use Survey (ITUS) to evaluate the effect of later sunset on children's time use. ITUS provides 24-hour time use data, collected with less than a 24-hour recall lapse, allowing me to assign each observation a district-date sunset time. My baseline econometric specification exploits seasonal variation in daily sunset time at the district level after controlling for fixed district-specific characteristics as well as seasonal confounders common across all districts in the sample.

I show that an hour (approximately two standard deviations) delay in sunset time reduces children's sleep by roughly 30 minutes: when the sun sets later, children go to bed later; by contrast, wake-up times are not regulated by solar cues. Sleep-deprived children decre-

[2]While urban environments, inaccurate self-perceptions of fatigue (Van Dongen et al., 2003), or time inconsistency (Breig, Gibson and Shrader, 2018) may constrain adjustment regardless of socioeconomic status, sleep environments among low-income households in particular are associated with noise, heat, mosquitoes, overcrowding, and overall uncomfortable physical conditions (Grandner et al., 2010; Patel et al., 2010). The poor, however, may lack the financial resources to invest in sleep-inducing goods (e.g., window shades, separate rooms, indoor beds, food) and adjust their sleep schedules on later sunset days. In addition, poverty may have particular psychological consequences (e.g., stress, negative affective states, increase in cognitive load) that can affect decision-making (Haushofer and Fehr, 2014; Mani et al., 2013; Schilbach, Schofield and Mullainathan, 2016). Thus, cognitive considerations associated with poverty may make it harder to assess one's own sleep-productivity relationship and optimize sleep schedules when the sun sets later.

ase productive effort: later sunset reduces students' time spent on homework or studying, as well as child laborers' time spent on formal and informal work, while increasing time spent on indoor leisure for all children. This result is consistent with a model where sleep is productivity-enhancing and increases the marginal returns of study effort for students and work effort for child laborers.

The second part of the paper examines the consequent lifetime impacts of later sunset on stock indicators of children's academic outcomes. I use nationally-representative data from the 2015 India Demographic and Health Survey (DHS) to estimate how children's education outcomes co-vary with annual average sunset time across eastern and western locations within a district.[3] I find that an hour (approximately two standard deviations) delay in annual average sunset time reduces years of education by 0.8 years. School-age children in geographic locations that experience later sunsets are less likely to complete primary and middle school, are less likely to be enrolled in school, and have lower test scores.

To argue that these results are generalizable, I use data from China and Indonesia. Unlike ITUS, the 2004-2009 China Health and Nutrition Survey collects data on children's time use for a 'typical' day of the year, and not for a particular date. I use cross-sectional variation in annual average sunset time across districts within a state. In line with my India estimates, an hour delay in annual average sunset time reduces children's sleep by roughly 30 minutes. To corroborate the effects of later sunset on children's academic outcomes, I use the 2003 Indonesia DHS, employing a sharp regression discontinuity design that exploits time zone boundaries in Kalimantan, Indonesia. I find that an hour delay in annual average sunset time reduces years of schooling by 0.7 years, quite similar to my India estimate.

The third part of the paper shows that parental education investment may be an additional channel through which later sunset affects human capital production. Using ITUS, I find that an hour delay in sunset time reduces adults' sleep by 30 minutes. Later sunset also reduces adults' earnings in India.

In the fourth part of the paper, I investigate if poverty helps explain why families fail to adjust their sleep schedules when the sun sets later. Initially, I examine heterogeneous

[3]A one hour difference in annual average sunset time between two locations indicates that on average the sun sets an hour later *everyday* in one location compared to the other location.

impacts of later sunset on sleep by correlates of poverty (e.g., education, average monthly expenditure) in India. The negative effect of later sunset on sleep is at least 25% larger among low socioeconomic status (SES) households compared to high SES households. To evaluate whether this heterogeneity truly reflects the influence of poverty, I restrict the sample to crop cultivator households, and exploit quasi-experimental variation in income around the harvest period, comparing the effect of later sunset on sleep in the month before harvest, when crop cultivator households are poorer and typically liquidity constrained, with the month after harvest, when richer and more financially liquid. Because harvest calendars vary across seasons and locations, I also control for all fixed differences between time periods and districts. Indeed, sunset-induced sleep deficits are significantly larger before harvest compared to after harvest. I show this effect is not driven by possible changes in work effort on later sunset days. Overall, financial and psychological considerations associated with poverty help explains 25-100% of the effect of later sunset on sleep.[4]

This paper relates to several literatures. First, I contribute to a new literature that examines the effects of the timing of natural light on economic outcomes.[5] Within this literature, a small set of papers evaluate the implications of the relationship between sunset time and sleep. Gibson and Shrader (2018) observe associated impacts of later sunset on adult wages in the US, while Giuntella and Mazzonna (2018) and Giuntella, Han and Mazzonna (2017) investigate consequent effects on adult health outcomes in the US and China, respectively. I provide the first evidence that arbitrary clock conventions – by generating large discrepancies in when the sun sets across locations – help determine the geographic

[4]Like previous studies (Carvalho, Meier and Wang, 2016; Mani et al., 2013; Spears, 2011), this result speaks to the effects of sharp, anticipated but short-lived variations in financial resources around the 'payday' (harvest) period. It is this particular impoverishment that I allude to when I refer to "poverty." Although the heterogeneous effects on sleep by socioeconomic status suggest similar effects for a permanent shift in permanent income, the interpretation of these estimates may be confounded by omitted variables that are correlated with socioeconomic status.

[5]A few papers exploit variation in the timing of natural light due to daylight savings time (DST) in the US to investigate short-run effects on a number of economic outcomes: Doleac and Sanders (2015) (crime), Wolff and Makino (2017) (outdoor leisure), Jin and Ziebarth (2017) (health) and Smith (2016) (automobile accidents). Two studies also examine the relationship between DST and test scores but find contrasting results: using the variation in DST regimes among counties in Indiana, Gaski and Sagarin (2011) show that SAT scores are significantly worse in counties that advance and set back their clocks each year as compared to counties sticking to standard time permanently; Herber, Quis and Heineck (2017) use international assessment data from six European countries and fail to find evidence that the transition into daylight saving time affects elementary students' performance in low-stakes tests in the week after the time change. In any case, if one were to compare short-run effects of sleep deprivation from daylight savings time onset, to the long-run effects of sleep deprivation at issue in this paper, I foresee two differences that go in offsetting directions. First, effects of sleep deprivation on education production could accumulate; the DST transition may only affect sleep for a few days, while later sunset affects sleep every day. Second, there may be adaptation to a permanent shift in sunset time. In addition, one of the main expressed reasons for daylight savings is so children don't have to make the morning journey to school in the dark.

distribution of educational attainment levels.[6] Schooling is strongly and positively associated with both adult earnings and health outcomes (Cutler and Lleras-Muney, 2006; Duflo, 2001). Therefore, policies that promote children's sleep may also improve later-life well-being in locations exposed to later sunsets.

It also relates to several recent studies that examine the short-term consequences of later school start times on students' academic performance in the US (Carrell, Maghakian and West, 2011; Edwards, 2012; Heissel and Norris, 2017; Hinrichs, 2011; Wahlstrom, 2002). Hinrichs (2011) studies a policy change in public school start times in Minneapolis but fails to find evidence that ringing the school bell later increases student performance on a high school achievement test. Heissel and Norris (2017) show that moving school start times one hour later relative to sunrise increases test scores for adolescents in Florida. Carrell, Maghakian and West (2011) exploit random assignment of school schedules at the United States Air Force Academy and find that later school start times improve test scores among freshmen cadets. These effects (or lack thereof) are likely mediated through changes in children's time use, although the above-mentioned papers do not observe children's sleep or consequent trade-offs with other uses of time.

I estimate how later sunset affects children's sleep, and how children trade off sleep with time allocated to studying or homework (study effort) and formal or informal work (work effort), in a context where child labor is prevalent. Biddle and Hamermesh (1990) model sleep as a choice variable that affects productivity, although they did not focus on this relationship in their empirical analysis. Gibson and Shrader (2018) investigate how sleep deprivation induces trade-offs between sleep and productive effort. However, their findings relate only to adults. Unlike the American Time Use Survey, ITUS collects time use data for children. My results suggest that sleep is productivity-enhancing, increasing the marginal returns of self-investment in study effort for students, and the marginal product of work effort for child laborers. Because sleep is the largest use of non-market time, these results also relate to seminal papers of Mincer (1962) and Becker (1965), as well as recent work by Aguiar et al. (2016), that emphasize that labor supply is influenced by how time is allocated

[6]This result also speaks to the literature that shows geography or features of a geographic location (e.g., climate, elevation, terrain ruggedness, port access, latitude) have contemporaneous effects on economic outcomes (Andersen, Dalgaard and Selaya, 2016; Bloom et al., 1998; Michalopoulos, 2008; Nunn and Puga, 2012; Olsson and Hibbs, 2005; for a survey, see Nunn, 2014).

outside of market work.

Lastly, this study contributes to a large literature in the broader social sciences that explores the relationship between poverty and counterproductive behavior. The poor use less preventive health care (Katz and Hofer, 1994), fail to adhere to drug regimens (DiMatteo et al., 2002), are tardier and less likely to keep appointments (Karter et al., 2004; Neal et al., 2001), are less attentive parents (McLoyd, 1998), and worse managers of their finances (Barr, 2012; Blank and Barr, 2009; Edin and Lein, 1997). There is also some descriptive evidence from the US that suggests sleep deprivation is higher among the poor (Grandner et al., 2010; Patel et al., 2010). I provide the first evidence for a plausibly causal relationship between poverty and sleep.[7]

The rest of the paper is organized as follows. Section 2 provides a conceptual framework to understand how children trade-off sleep with other time uses. Section 3 describes the data. Section 4 investigates the effects of later sunset on children's time use, while Section 5 examines the consequent effects on children's education outcomes. Section 6 evaluates the effects of later sunset on adults' time use and wages. Section 7 examines poverty as one potential explanation for why individuals fail to adjust their sleep schedules when the sun sets later. Section 8 provides a back-of-the-envelope estimate for the human capital costs associated with existing policy regulating time zone boundaries in India, while Section 9 concludes.

2 A Conceptual Framework of Children's Time Use

Sleep deprivation impairs learning and cognition (Beebe, 2011; Killgore, 2010; Lim and Dinges, 2008, 2010; Philibert, 2005; Sadeh, 2007; Scott, McNaughton and Polman, 2006; Vriend et al., 2011), and the impacts increase with the cumulative extent of sleep deprivation (Basner et al., 2013; Van Dongen et al., 2003). Thus, if later sunset reduces the time allocated to sleep, children that observe later sunsets may have non-trivial sleep deficits with real human capital impacts.

[7]Because families get less sleep on days the sun sets later in periods when liquidity constraints bind tightly compared to later sunset days in periods when households are more financial liquid, this paper also contributes to studies that show liquidity constraints impede 'adoption' of welfare improving technologies (e.g., piped water, migration, cookstove, bednets) in developing countries (Bazzi, 2017; Bryan, Chowdhury and Mobarak, 2014; Devoto et al., 2012; Mobarak et al., 2012; Tarozzi et al., 2014).

However, the consequent impact of later sunset on schooling outcomes is ambiguous; how children trade-off sleep with other time uses may have multiplicative or compensatory effects on education production. For instance, later sunset (more daylight after school) might make it easier for children to self-study, especially in lower income countries where electricity access is intermittent. If sleep were not productive, then it would be a substitute for other time uses, including productive effort. On the other hand, if sleep is productivity-enhancing and increases the marginal returns of an extra hour of productive effort, sleep deficient children may decrease self-investment in study effort.[8,9] Moreover, in a context where child labor is pervasive, complementarities between sleep and study effort may also depend on the marginal increase in wages with respect to sleep.[10]

To formally examine how children trade-off sunset-induced reduction in sleep with other time uses, I extend the productive sleep model from Gibson and Shrader (2018) – an extension of the time use model of Gronau (1977) – to children. The child's problem is to maximize a utility function $u(x, L)$ where x are consumables, and L is leisure time. u is weakly increasing in each argument and is quasi-concave. I assume that parents induce children's investment in schooling through parental transfers (Becker, 1974).[11] Thus, the child's consumables depend on earnings through own labor, x_O, earned by working for parents, and reward, r, set by parents for educational achievement.

Work time is denoted as N, thus the child can gain output, $x_O = NW(S)$, where $W(S)$, is wage received from parents, and is a function of children's sleep, S. Price is normalized to 1. Similarly, the child can also gain goods, $x_H = rh(H, S)$, where reward, r, can be thought of as a parent's present discounted value of the returns to child's achievement in the current period, and $h(H, S)$ is the education production function, with inputs H, denoting

[8] Several studies document a positive relationship between children's self-investment in study effort and learning outcomes (Aksoy and Link, 2000; Boca, Monfardini and Nicoletti, 2017; Dolton, Marcenaro and Navarro, 2003; Eren and Henderson, 2011; Stinebrickner and Stinebrickner, 2004, 2008).

[9] Instead, children may allocate more time to indoor leisure. Multiple studies have shown that sleep deprivation increases daytime sleepiness and sedentary leisure activities (Carskadon, Harvey and Dement, 1981*a*,*b*; Fallone et al., 2001; Jae Lo, 2016; Magee, Caputi and Iverson, 2014; Owens, Belon and Moss, 2010; Sadeh, Gruber and Raviv, 2003). The effects of leisure, specifically, exposure to media, on children's cognitive outcomes has been mixed (Fiorini, 2010; Gentzkow and Shapiro, 2008; Malamud and Pop-Eleches, 2011).

[10] Even today India has roughly 9 million child laborers (Census, 2011). Also, the average Indian child allocates considerably more time to labor activities than the average child in an advanced economy like the UK (Figure A.1).

[11] Alternatively, I can assume that children's allocation of time is driven by their own preferences. Households behave like an internal market in which children select their optimal time allocation bundle, and are rewarded accordingly (Kirchberger, 2017).

time spent on schooling, including self investment in study effort. Thus, total consumables are given by $x = x_O + x_H$. I assume that the parent has full information and can fully commit to this contract. I model sleep as productivity-enhancing, more sleep will, *ceteris paribus*, increase labor productivity ($\frac{\partial W(S)}{\partial S} > 0$) and educational achievement ($\frac{\partial h(H,S)}{\partial S} > 0$). However, the total effect of sleep on earnings and achievement, and hence parental transfers, also depends on how children trade-off sleep with work ($\frac{\partial N}{\partial S}$), study time ($\frac{\partial H}{\partial S}$), and leisure time ($\frac{\partial L}{\partial S}$).

Putting all time uses together, the total time constraint is $T = L + H + N + S$. Substituting the time budget into the goods budget, the combined budget constraint is

$$x_H = rh(T - L - S - N, S) \tag{1}$$

and the optimization problem is

$$\max_{L,N,S} \tag{2}$$

$$u(NW(S) + x_H, L) + \lambda_1(rh(T - L - S - N, S) - x_H) + \lambda_2 N + \lambda_3 S$$

Consider a child who is a student, but also works at home or in the market. Also, assume sleep is positive, so $N > 0$, $S > 0$, and $\lambda_2 = \lambda_3 = 0$, by complementary slackness. Further, $h'_1 > 0$, $h'_2 > 0$, $h''_{11} < 0$, and $h''_{22} < 0$. First order conditions can be written as

$$\frac{u'_2}{u'_1} = rh'_1 \tag{3}$$

$$W(S) = rh'_1 \tag{4}$$

$$NW'(S) + rh'_2 = rh'_1 \tag{5}$$

Taking the total derivative of Equation (4), I get

$$\frac{dH}{dS} = \frac{W'(S) - rh''_{12}(H^*, S^*)}{h''_{11}(H^*, S^*)} \tag{6}$$

Thus, $\frac{dH}{dS} > 0$ if $W'(S) < rh''_{12}(H^*, S^*)$; sleep will induce study effort if marginal increase in school productivity with respect to sleep is larger than the marginal increase in wages (labor productivity) with respect to sleep. However, if the opposite condition holds, $W'(S) > rh''_{12}(H^*, S^*)$, then increase in sleep will reduce self-investment in study effort $\frac{dH}{dS} < 0$. Assume that for any student i or child whose primary activity is education, sleep will be more achievement-enhancing than work-productivity enhancing ($W'(S) < rh''_{12}(H^*, S^*)$), while for any child laborer j, sleep will be more work productivity-enhancing than achievement enhancing. That is, child i or j will have no incentive to switch his or her primary activity due to the productivity impacts of sleep.

Taking the total derivative of Equation (5),

$$\frac{dN}{dS} = \frac{[rh''_{11}(H^*, S^*) - rh''_{21}(H^*, S^*)]\frac{dH}{dS} + rh''_{12}(H^*, S^*) - rh''_{22}(H^*, S^*) - NW''(S)}{W'(S)} \tag{7}$$

Assume $W''(S) \leq 0$, and sleep is productive: $h''_{21}(H^*, S^*) > 0$ and $W'(S) > 0$, if $\frac{dH}{dS} < 0$, then $\frac{dN}{dS} > 0$.[12] So, sleep can either be work productivity enhancing or achievement-enhancing.[13]

To summarize, the model predicts that sleep increases study effort if sleep is more achievement-enhancing than work-productivity enhancing. The increase in achievement will be large enough to lead to an overall increase in the amount of study time. But if sleep is more work-productivity enhancing than achievement-enhancing, then sleep will increase work time.

If, however, sleep is not productivity-enhancing, reducing sleep will cause a pure income effect for the child, and depending on the utility function, study, work and leisure time may increase. Sleep will be a substitute for all other time uses.

[12] Medical studies often find a nonlinear relationship between sleep and health that suggests $W''(S) < 0$ (Cappuccio et al., 2010). Van Dongen et al. (2003) find that cognition declines linearly with sleep deprivation.

[13] An increase in duration of productive sleep induces an increase in 'wages', so income and substitution effects make the sign of the net effect on leisure time ambiguous.

3 Data

I use detailed time use and education data from India to analyze the negative relationship between sunset time and education production. I corroborate key results using time use data from China and education data from Indonesia. The features of the core data sets that are most relevant for my analysis are described below. Appendix A describes supplementary data; it also includes a short discussion on the two definitions of sunset time used in the analyses, daily sunset time and annual average sunset time, generated using the solar mechanics algorithms from Meeus (1991).

3.1 India Time Use Survey (ITUS)

ITUS is the first time use survey of its size and coverage amongst developing countries. Over 18,000 households were surveyed in 52 districts across 6 states between July, 1998 and June, 1999. States were selected to give geographical representation to each region of the country. Within each state, households were randomly selected based on a sampling procedure designed to ensure a representative sample at the state level. The survey was spread over one year to account for seasonal variation in activity patterns.

Time use data were collected for all household members over five years of age. Thus, ITUS collects time use data for younger, school-age children, which is rare amongst such surveys.[14] For each household, time use data were collected for three types of days: normal (usually weekdays), weekly variant (usually Sundays), and abnormal (festivals or holidays). Initially, an investigator collected information for these three types of days within the week from different members of the selected households. Then, the investigator revisited households accordingly and interviewed individuals about their time allocation decisions for those particular days. Using the interview date and district identifiers, I determine sunset time for each individual corresponding to the date for which the time use data were collected.[15,16]

[14]For instance, the American Time Use Survey only collects data for individuals over fourteen years of age.

[15]For instance, if the normal date for an individual was a Monday, the investigator visited the individual on Tuesday of the same week to collect time use data for that prior Monday. That is, interviews were conducted such that time use data could be collected with less than a 24-hour recall lapse. See Pandey (1999), for a detailed overview of the sampling strategy and data collection methods.

[16]Table A.1 presents the monthly distribution of interview dates by state. Figure A.2 maps of districts in ITUS. Figure 4(a)

To examine the effects of later sunset on children's time use, I restrict the sample to school-age children less than 17 years of age. 55% of children in the sample are male, and 70% reside in rural areas. Importantly, the primary activity is schooling for only 8 out of 10 children; 19% of the sample of school-age children primarily engages in some form of child labor. On average, 6 out of 7 days in a week are normal days, while only 1 day is a weekly variant suggesting 6-day work/study weeks. Correspondingly, time use data for only 4% of the normal day sample were collected for a Sunday, while time use data for 66% of the weekly variant sample were collected on a Sunday.[17] Thus, I will refer to the normal day sample as the 'weekday' sample, while the weekly variant sample as the 'weekend' sample.

In the survey, daily activities were classified in roughly 150 activities across 9 broad categories: 1) primary production, 2) secondary production, 3) trade, business and services, 4) household maintenance, management and shopping for own households, 5) care for children, sick and elderly, 6) community services and help to other households, 7) learning, 8) social and cultural activities, mass media etc., and 9) personal care and self-maintenance. Appendix A includes a complete list of all activities as classified in ITUS. I further grouped these categories into five brackets: sleep, study, school, leisure, and work. 'Work' includes categories 1 to 6,[18] while 'leisure' all items from categories 8 and 9 except sleep. Category 9 includes 'sleep and related activities', or all sleep during the course of a 24-hour period. I include nighttime sleep or any sleep that starts and ends between 6 pm and 12 pm in the variable 'sleep' and not 'leisure'. Naps, however, are included in 'leisure'.[19] 'Study' includes time spent on homework, tuition, and course review, while 'school' includes time spent in an educational institution like a school or university.

On weekdays, school-age children spent on average 9 hours/day on sleep, 7.5 hours/day

shows variation in daily sunset time for all 52 ITUS districts, while Figure 4(b) shows variation in daily sunset time for dates for which time use data was collected in the sampled districts. The amplitude of the wave is determined by the latitude of the location, and the vertical translations are due to longitude or east-west variation in sunset time across India. There is no reason to believe that the date of time use data would be correlated with sunset times. However, I examine this assumption explicitly, and fail to find evidence for any such relationship (Table A.2).

[17] Table A.3 presents summary statistics for both the normal day and the weekly variant sample.

[18] Both market work and home production are included in 'work' for convenience as female child laborers tend to work at home while male child laborers typically perform outdoor tasks.

[19] I follow Gibson and Shrader (2018) and Giuntella and Mazzonna (2018) and exclude naps or daytime sleep from 'sleep'. I define daytime sleep or naps as sleep that starts and ends during afternoon hours (between 12 pm and 6 pm). I include naps in 'leisure', but napping may be an adaptation to later sunset, undertaken for the productivity effects rather than because it is pleasurable. Thus, I examine the nighttime to daytime sleep trade-offs in Appendix B. Indeed, I show that later sunset increases nap time by roughly 15 minutes.

on leisure activities, and almost 4 hours/day in school. School-age children spent over 2 hours/day on average on work, but less than 1.5 hours/day on educational activities outside of school. On weekends, children don't have school, so they allocate more time to sleeping at night, studying, and on leisure activities.

School-age children tend to go to bed after 7 pm, and wake up by 7 am on weekdays. They also tend to self-study (e.g., homework) early in the morning, before school, and then after school, later in the afternoon. Time allocation to recreational activities is spread throughout the day. Work schedules are similar to school schedules but not as intensive, on average.[20]

Compared to developed countries, children in India spend less time on sleep and leisure, but more time studying outside of school, and on work-related activities. Given such prevalence of child labor, I also examine time allocations by primary activity: 'student' or 'worker', which is indicated in ITUS. Students or children attending school spent less than 1 hour/day on work, while spending 5 hours/day in school and 2 hours/day studying outside of school.[21] However, child workers allocated almost 6 hours/day on average to work. Finally, children engaged in child labor allocated more time to leisure than those who were primarily students.[22]

3.2 Demographic and Health Surveys (DHS)

The DHS are nationally-representative demographic surveys collected for USAID in collaboration with governments of the countries where the surveys are fielded. These data represent the widely-accepted gold standard for demographic and health data in the developing world.

[20] Figure A.4 presents the average time spent by children on sleep, study, school, leisure and work, respectively. Figure A.5 describes sleep patterns on a weekday among children. I also directly examine the average bed- and wake-up times for children for both weekdays and weekends in Figure A.6. I find no differences in bedtimes, and only a small increase in wake-up times during weekends. Figure A.7 examines time allocation patterns for other activities within a weekday. Figure A.8 shows seasonality in time use patterns for school-age children. In Table A.4 I show the average number of individuals who sleep above certain thresholds of sleep (7, 8, 9, 10 or 11 hours) by age group. Recently, a NSF assembled multidisciplinary expert panel recommended that children between 6 and 13 years of age sleep 9 to 11 hours while those between 14 and 17 years of age were recommended to sleep at 8 to 10 hours (Hirshkowitz et al., 2015).

[21] Figures A.9 and A.10 describe how students and child laborers spend their time on weekdays and weekends.

[22] Figures A.11 and A.12 present correlations between sunset time and children's time use using the raw data. Within each district, I disaggregate children into two groups: children interviewed when seasonal sunsets were below 25th percentile (early sunset), and those interviewed when seasonal sunsets were above 75th percentile (late sunset). Compared to days with early sunset, on late sunset days children start sleep later, but wake-up times remained unaffected. Furthermore, children spend less time studying, and more time on leisure. Importantly, while effects on sleep patterns are similar for both students and workers (Figure A.13), late sunset reduces study time for students, but work time for workers, with comparatively modest effects on work time for students and study time for workers (Figure A.14).

The DHS collects basic education data for every member in the sample household. In addition, DHS data also contain a variety of household-level survey data related to assets and household physical infrastructure. Importantly, DHS data includes geolocation information allowing me to generate annual average sunset time at the primary sampling unit (PSU) level. PSUs correspond to a village in rural areas and city blocks in urban areas. Because my core time use data are from India, I primarily draw on the 2015 India DHS. I use the 2003 Indonesia DHS to establish external validity and because it allows me to leverage a different source of variation in sunset time.

Using the 2015 Indian DHS, I exploit cross-sectional variation in annual average sunset time across eastern and western PSUs within even small administrative divisions. Next, I use the 2003 Indonesian DHS. Kalimantan is the Indonesian portion of the island of Borneo with two time zones: UTC+7 and UTC+8. I leverage a sharp discontinuity in annual average sunset time at the time zone boundary to corroborate the effects of later annual average sunset on children's academic outcomes.[23]

I restrict the sample to household members between 6 and 16 years of age across both countries.[24] In the 2015 Indian DHS, the average school-age child has roughly 4.5 years of schooling; 48% have completed primary school and 21% completed middle school. In the 2003 Indonesian DHS, the average school-age child has completed roughly 4 years of schooling. 34% have completed primary school and 10% have completed middle school.

4 Effects of Later Sunset on Children's Time Use

In this section, I use detailed time use data from India to examine how daily sunset time co-vary with children's time use, in particular, sleep and study effort, at the district level. To corroborate these effects, I use time use data from China, exploiting cross-sectional variation in annual average sunset time.

[23]Although Indonesia has multiple islands on different time zones, Kalimantan is the only contiguous Indonesian island with an internal time zone border.

[24]Table A.5 presents summary statistics for outcomes of interest. In India (Indonesia), the levels of the education system are as follows: primary school ranges from grade 1 (1) to grade 5 (6) and middle school ranges from grade 6 (7) to grade 8 (9). Figure A.15 presents the location of PSUs across India, while Figure A.16 shows the distribution of annual average sunset time across these PSUs.

4.1 Empirical Model

To formally examine the relationship between sunset time and children's time allocation, I use ITUS and estimate the following econometric model:

$$y_{idwt} = \beta Sunset_{dwt} + \mu_w + \mu_d + \epsilon_{idwt} \tag{8}$$

To estimate the average effect of an hour increase in sunset time (β), time allocated to sleep, study, leisure or work (y_{idwt}), by child i, in district d, on date t, during week-of-year w, is regressed on sunset time observed in district d on date t ($Sunset_{dwt}$). μ_w are week-of-year fixed effects, and μ_d are district fixed effects. Thus, I control for attributes that vary by week-of-year, that is seasonal trends common across districts in the sample (e.g., national festivals), as well as fixed district-specific characteristics (e.g., electricity access), that affect children's time allocation decisions. My parameter of interest that relates sunset to time allocation are identified from intra-annual or seasonal variation in daily sunset time at the district level after controlling for seasonal variation common across all districts in the sample. Put another way, the estimates are identified from the comparison of districts that observed a late sunset day with ones that observed an early sunset day within the same week-of-year, after absorbing fixed district-specific unobservables.[25] I cluster standard errors by district-week for three reasons: to allow for arbitrary spatial correlation across children within a district, to allow for autocorrelation in time allocation within a week, and to account for the fact that the same sunset time can be assigned to multiple children. I demonstrate below that results are insensitive to numerous robustness checks, supporting the validity of my baseline model.

[25] The identification of daily sunset time effects relies on variation in the timing of time use dates. The ITUS was not designed to be representative at the daily level, so I demonstrate balance by examining the relationship between sunset time and socioeconomic factors at the individual level (e.g., wealth, sex, age) as well as interview date characteristics (e.g., day-of-week). I fail to find evidence for a statistically significant relationship between sunset time and individual or household-level observables (Tables B.1 - B.3).

4.2 Results

First, I investigate the effect of late sunset on children's bedtime and wake-up time. Consistent with the above-mentioned medical literature on human circadian rhythm, later sunset delays bedtimes. A one hour (approximately two standard deviation) delay in sunset delays bedtime by an estimated 0.36 hours (Table 1). Children fail to compensate by waking up later as wake-up times do not co-vary with sunset times.

Next, I evaluate the effects of sunset time on sleep, study, leisure and work. In line with the previous result, Table 2 shows that a one hour delay in sunset reduces sleep by 0.47 hours or roughly 30 minutes. Furthermore, later sunset significantly reduces self-investment in study effort, but increases time spent on leisure. An hour delay in sunset reduces study time by 0.67 hours, increasing leisure by 1.65 hours. Indeed, sleep complements study effort and substitutes with leisure.[26,27]

These aggregate results mask substantial heterogeneity by children's primary activity. While effects on sleep are qualitatively similar for both students and child workers,[28] late sunset reduces study time for students and work time for workers, with comparatively modest effects on work time for students and on study time for workers (Table 3).[29] These effects suggest that sleep increases the marginal gains of an extra hour of study effort for students with comparatively modest marginal gains for labor productivity. Conversely, for child laborers the increase in marginal product of labor from an extra hour of sleep is larger than the increase in marginal product of an extra hour of study effort. In the analytical model, a child chooses to study if the marginal increase in parental rewards from an extra hour of study time is larger than the wage rate ($r\frac{\partial h(H,S)}{\partial H} > W(S)$). These results suggest that labor productivity gains from more sleep are not large enough to induce a student to work. Lastly, a decrease in time allocated to sleep may induce lethargy and increase time allocated to

[26] A large fraction of observations have values of zero for the time spent on study and work effort. Thus, Table B.4 also presents the Tobit estimates and find that these results are in line with the OLS estimates, although the point estimate for 'Study' is significantly larger. However, Stewart (2009) notes that zeros in time use data may arise from a mismatch between the reference period of the data (the interview date) and the period of interest, which is typically much longer. He finds that in such a context the marginal effects from Tobit are biased and that only OLS generates unbiased estimates.

[27] I find that the relationship between sunset time and sleep is roughly linear (Figure B.1).

[28] The interaction term is negative and significant, perhaps suggestive of the influence of poverty on sleep as discussed in Section 7 as 'child laborer households' tend to be poorer than 'student households'.

[29] In terms of magnitude, an hour delay in sunset time reduces study time by roughly 50 minutes. This is a large effect. I show that later sunset negatively affects study effort on the extensive margin, presumably because tired students are less likely to study at all (Table B.5).

sedentary leisure activities. Overall, these results imply that sleep is productivity-enhancing, increasing the marginal returns to study and work effort, for students and child laborers, respectively.

4.3 Robustness Checks

The identification assumption underlying this research design is that there exist no district-specific seasonal characteristics that co-vary with time use and intra-annual variation in sunset time at the district level. This may be a strong assumption, one that could plausibly be violated for several reasons, for example, local weather, provincial school calendar, or local festivals. I use three approaches to evaluate the validity of this identification assumption.

First, I control for seasonal observables (e.g., weather) at the district level. There exists considerable seasonal variation in weather patterns across India. Thus, later sunset might be correlated with higher temperatures and precipitation for specific districts. For example, it is plausible that my baseline estimates are confounded by the effects of extreme temperatures on sleep, especially in a context where air conditioning is uncommon. Or if the agricultural calendar (and relatedly the monsoon season) coincides with later sunset for particular districts my estimates could be biased. Table B.6 controls for daily precipitation and temperature at the district level and shows that my estimates remain unaffected.[30,31]

Second, I evaluate effects of later sunset on children's time use for non-school days: weekends. If my estimates were driven by district-specific school calendars, I may not find similar effects for weekends. However, the magnitudes are not significantly different for children's time use over weekends, bolstering the robustness of my findings (Table B.8). This result also suggests that there may be other factors that affect children's sleep schedules in addition to school start times.

Third, I control flexibly for district-specific seasonal unobservables by including a suite of

[30] I use the ERA-Interim daily temperature and precipitation data on a 1 x 1 degree latitude-longitude grid. These data are matched with ITUS at the district-date level.

[31] In addition, controlling for socioeconomic factors at the individual level (e.g., wealth, sex, age) and interview date characteristics (e.g., day-of-week) explains meaningful variation in the outcomes of interest, but my point estimates remain relatively unaffected (Table B.7).

interacted fixed effects: state-by-season, latitude-by-week-of-year and district-by-season.[32,33] Separately, these control for seasonal attributes specific to each state, latitudinal zone, and district, respectively. For instance, local festivals that coincide with summer months may increase children's time allocation to leisure and in turn decrease the time allocated to sleep, study effort and work effort. However, Tables B.9, B.10 and B.11 show that although the estimates are noisier, the magnitudes remain relatively unaffected by the inclusion of these fixed effects. Thus, any omitted variables must operate within a season for specific districts.[34]

Relatedly, any district-specific seasonal confounders correlated with fixed socioeconomic- or date-related attributes like age, sex, day-of-week, urban status or wealth should be picked up when I include district-by-age-by-season, district-by-sex-by-season, district-by-day-of-week-by-season, district-by-urban-by-season, or district-by-wealth-by-season fixed effects, respectively. For example, if boys are more likely to be engaged in agricultural labor during the monsoon for certain districts, district-by-sex fixed effects should control for such patterns. These interacted fixed effects fail to meaningfully affect my coefficients of interest (Tables B.16 - B.20).[35]

In sum, these three tests imply that any omitted variable that generates bias in the baseline estimates must i) operate within a season for specific districts, ii) be orthogonal to seasonal observables at the district level, iii) be uncorrelated with district-specific seasonal unobservables that co-vary with fixed observables at the individual or interview date level and iv) persist during both weekdays and weekends. Plausible omitted variables are unlikely to have all of these properties, and therefore my baseline estimates are likely unbiased.[36]

[32]To generate latitude-by-week-of-year fixed effects I divide the country into two arbitrary latitudinal zones using the median latitude and interact indicator variables for each zone with indicator variables for each week-of-year.

[33]The Indian Meteorological Department (IMD) designates four climatological seasons for the country: Winter (December-March), Summer (April-June), Monsoon (July-September), Autumn (October to November).

[34]School summer vacations in India are between April and June. In Table B.12 I drop these months to ensure that my results are not just driven by children's time use during summer vacations. I find that the coefficients are similar to my baseline estimates apart from the negative effect on 'Work', which is now large and statistically significant. In Table B.13, B.14, and B.15, I drop Winter, Monsoon, and Autumn months, respectively. The point estimates remain unaffected.

[35]In Table B.21 I adjust standard errors to reflect spatial dependence as modeled in Conley (1999), and implemented by Hsiang (2010). I allow errors to be spatially auto-correlated within a distance of 500 km. The point estimates remain precisely estimated. Similarly, in Table B.22 I cluster standard errors at the district level to allow errors to be temporally correlated across weeks within a district. The coefficients remain precisely estimated.

[36]If children are more likely to nap on late sunset days than early sunset days due to factors unrelated to the effect of later sunset on (nighttime) sleep, the effects on sleep could be driven by daytime naps and not the other way around. However, in Table B.23 I show that the effects of later sunset on children's time use are robust to dropping 'nappers' from the sample. In Table B.24 I estimate the effects of later sunset using non-linear metrics for sleep duration based on recommendations made by experts in the areas of medicine, physiology and science. I show that an hour delay in sunset significantly reduces the likelihood

4.3.1 China Time Use Results

Next, I use the 2004-2009 China Health and Nutrition Survey (CHNS) to examine the effects of later sunset on children's time use in China. Unlike ITUS, CHNS includes information on children's time allocation for a 'typical' or 'usual' day of the year, and not for a particular date. And, although CHNS only provides data on sleep, leisure and homework time, it allows me to investigate the effect of annual average sunset time on children's time allocation.[37] In this setting, I abstract away from intra-annual variation in sunset time, only exploiting cross-sectional variation in annual average sunset time.

I estimate the following econometric model:

$$y_{idst} = \beta Sunset_{ds} + \mu_t + \mu_s + \epsilon_{idst} \tag{9}$$

Time allocated to sleep, leisure or homework (y), by child i, in district (or county) d, in state (or province) s, in year t, is regressed on annual average sunset time observed in district d in state s to estimate the average effect of an hour's increase in annual average sunset time (β). μ_t are year fixed effects, and μ_s are state fixed effects. Thus, I exploit district-level variation (east to west) in annual average sunset time within a state. I control for time invariant attributes common across children within a province that are also correlated with children's time allocation and annual average sunset time.

An hour delay in annual average sunset time reduces sleep by 0.43 hours (Table B.25). This estimate is remarkably similar to the effect of late sunset on sleep in India, where I exploit intra-annual variation in daily sunset time at the district level. Furthermore, in line with the ITUS results, I find large positive effects on leisure and negative effects on time spent on homework, although these estimates are noisier.

Because I only exploit cross-sectional variation in sunset time within a state, county level attributes that are correlated with annual average sunset time as well as the outcomes of interest could potentially bias my estimates. For instance, if compared to eastern districts (early sunset), western districts (late sunset) are warmer, then the coefficients might be

that children get the recommended amount of sleep (9-11 hours). In Appendix B, I show that the effect of later sunset on leisure is driven by indoor and not outdoor leisure.

[37] There exist substantial differences in the definition of leisure between ITUS and CHNS. Furthermore, as a measure of self-investment in study effort, CHNS only provides homework time. These differences are discussed in Appendix A.

upwardly biased. In Table B.26, I control for weather and other observables like income, urban status, household size and nutritional intake, that may co-vary with children's time allocation across the east-west gradient within a province, like sunset times. My estimates remain largely unaffected. Indeed, under the strong assumption that these observables are strongly correlated with unobservable confounders, these results indicate that the estimates are unbiased (Altonji, Elder and Taber, 2005; Oster, 2017).[38]

5 Effects of Later Sunset on Academic Outcomes

Using nationally-representative DHS data from across the developing world, Figure 1 documents a strong negative correlation between annual average sunset time associated with a geographic location and years of schooling among school-age children.[39]

However, simple cross-country comparison of children's academic outcomes may be confounded by systematic differences in salient features that co-vary with annual average sunset time and children's education. To overcome this identification problem, and because my core time use data are from India, I use the geocoded 2015 India DHS to investigate the effects of later sunset on educational outcomes for school-age children, exploiting cross-sectional variation in annual average sunset time across eastern and western locations within small administrative divisions, districts. I improve external validity and assess robustness of these results using education data from Indonesia, exploiting a sharp discontinuity in annual average sunset time at the time zone boundary in Kalimantan, Indonesia. Lastly, using an individual level longitudinal panel from Andhra Pradesh, India, wherein the same child is administered comprehensive tests in math at different points in the year across survey rounds, I leverage seasonal variation in sunset time at the district level to evaluate the effects of later sunset on children's test scores.

[38] In Table B.27, I show that the effect of later sunset on leisure is driven by indoor and not outdoor leisure.

[39] In successive specifications I control for potential omitted variables – demographics, latitude, elevation, and rural-urban status (Table C.1). I find that the association is robust to controlling for these observables.

5.1 Empirical Model

Using the 2015 India DHS, I estimate the following econometric model:

$$y_{iavd} = \beta Sunset_{vd} + \mu_d + \mu_a + \epsilon_{iavd} \tag{10}$$

where y_{iavd} is the outcome of interest for child i of age a in sampling unit v in district d. Outcomes of interest include years of schooling, primary school completion, middle school completion, and enrollment status. Both primary and middle school completion are binary variables that take the value '1' if the child has completed primary and middle school, respectively, and 0 otherwise. Similarly, enrollment status is a binary variable that takes the value '1' if the child is enrolled in school, and 0 otherwise. μ_d are district fixed effects, while μ_a are age fixed effects. District fixed effects control for plausible time invariant omitted variables at the district level. I include age fixed effects to control for differences in grade progression between children of different age groups. Here, I compare the outcomes of children of the same age residing in sampling units with different annual average sunset times within a district. β is the average effect of an hour delay in annual average sunset time, i.e., β is the lifetime effect of an hour delay in sunset time.

The identification assumption underlying this research design is that there exist no omitted variables within a district that co-vary with both annual average sunset times and children's educational outcomes.[40] Lastly, I cluster standard errors at the geocoded sampling unit level as variation in annual average sunset time is at the sampling unit and not at the household level (Abadie et al., 2018).

5.2 Results

I find that an hour (approximately two standard deviation) delay in annual average sunset time reduces schooling by about 0.8 years (Table 4). A two hour difference in annual average sunset spans the entire width of the country, so another interpretation of the effect size is

[40]Residential sorting on sunset time could bias my estimates if such sorting was correlated with annual average sunset and characteristics that affect children's education outcomes. This is relatively unlikely as internal migration is very low in India, both in absolute terms as well as relative to other countries of comparable size and level or economic development (Munshi and Rosenzweig, 2016). I also investigate the possibility of sorting based on annual average sunset time in Appendix C and fail to find any evidence for it.

that a one standard deviation or 25 minute delay in annual average sunset time reduces schooling by 0.4 years. This result translates into lower educational attainment at primary and middle school level. That is, a one standard deviation delay in annual average sunset time decreases primary school completion by 5 percentage points, and middle school completion by 4 percentage points. Lastly, an hour delay in annual average sunset time decreases enrollment rates by roughly 11%.[41] These effect sizes are comparable to impacts of larger policy interventions designed to increase schooling in developing countries. For example, in Mexico, childhood exposure to conditional cash transfers through PROGRESA increases schooling by 1.5 years (Parker and Vogl, 2018). A meta-analysis of 94 studies from 47 conditional cash transfer programs in low- and middle-income countries worldwide finds that the average conditional cash transfer program increases school enrollment by roughly 7% (Garcia and Saavedra, 2017).

These estimates are identified by exploiting small variation (up to 10 minutes) in annual average sunset time across the east-west gradient within a district.[42] The underlying assumption when extrapolating the identifying variation to calculate the effect of an hour delay in sunset time is that the relationship between annual average sunset time and academic outcomes is linear. I find support for such an assumption. First, as mentioned above, I find that the effect of sunset time on sleep is roughly linear. Second, results from the longest laboratory-controlled study on the relationship between sleep and cognitive performance indicate that cognition declines linearly with sleep deprivation (Van Dongen et al., 2003). Third, in Section 5.3.1, I exploit a sharp, one-hour discontinuity in average annual sunset time across locations on either side of the time zone boundary on Kalimantan, Indonesia.

[41] These point estimates are robust to the inclusion of other observables like elevation, latitude and socioeconomic indicators (Table C.2). The attainment results are also robust to restricting estimation for each tier of education – primary and middle – to the corresponding age-appropriate sample (Table C.3). In Table C.4 I show my results are robust to the use of an alternative indicator for educational attainment: if a child is in primary (secondary) school or has completed primary (secondary) school. I find that an hour delay in annual average sunset reduces the likelihood that school-age children are in primary (secondary) school or have completed primary (secondary) school by roughly 11% (25%). In Table C.5 I show my results are robust to dropping the widest districts in the sample. In Table C.6 I show my results are robust to restricting the sample to include only the widest Indian districts. In Table C.7, I cluster standard errors at the district level to allow errors to be spatially correlated across PSUs within a district. Although the standard errors increase, the point estimates, for the most part, remain precisely estimated. In Tables C.8 and C.9, I show the negative association is present under a less demanding, state fixed effects specification, where I exploit cross-sectional variation in annual average sunset time within a state. Lastly, if younger children (with less completed schooling) are sampled in locations with later annual average sunset, my estimates for years of schooling and educational attainment may be biased. However, I fail to find evidence for such a hypothesis (Table C.10).

[42] Figure C.1 plots the relationship between residualized annual average sunset time and residualized academic outcomes. Figure C.2 shows the distribution of the difference in annual average sunset time between the easternmost and westernmost locations within a district. The difference in annual average sunset time between two locations encompasses larger differences in daily sunset times between the easternmost and westernmost locations within a district.

I find that the regression discontinuity estimate of the effect of an hour delay in annual average sunset on years of schooling is similar to the India estimate obtained by scaling smaller variation in annual average sunset time.

These are large effects. Therefore, it is important to add context to help interpret these magnitudes. First, it is important to note that these estimates capture the 'lifetime' impacts of later annual average sunset on educational outcomes or the long-term effects of chronic sunset-induced sleep deficits on learning and cognition.

Second, a series of laboratory experiments that assess the causal effects of short-term sleep loss on cognition find very large effects. The typical elasticity of task performance with respect to sleep duration is approximately four (see Gibson and Shrader, 2018, for a brief review of short-term causal studies). In Section 4, I find that an hour delay in sunset time reduces children's sleep by roughly 30 minutes. If one were to extrapolate, these results suggest that 30 minutes decrease in sleep (one hour delay in annual average sunset time) everyday decreases years of schooling by approximately 0.8 years. Expressed as an elasticity, this estimate is 3.5.

Third, these estimates capture all location-level general equilibrium effects; every child and parent in a location experiences the same, permanent annual average sunset time.[43] Thus, the estimated β includes any spillovers and peer effects from decreasing the mean sleep in a location. In Section 6, I show that later annual average sunset reduces adults sleep and earnings, and presumably household expenditures on education. Carrell, Fullerton and West (2009) estimate an elasticity of academic achievement with respect to peer quality of roughly 0.9. Parental education is positively associated with children's academic outcomes (Oreopoulos, Page and Stevens, 2006). Azam and Bhatt (2015) estimate an intergenerational education elasticity of 0.6 in India. Therefore, β may also include intergenerational educational effects of early-life sleep deprivation among parents exposed to later sunsets in childhood.

Fourth, similarly large effects are observed in two studies that evaluate the consequences of the relationship between sunset time and sleep on adult wages and health outcomes in the US. Gibson and Shrader (2018) find a one-hour delay in daily sunset reduces sleep by roughly

[43] India has not revised her time zone since the early 1950s.

20 minutes per week and decreases weekly (short-run) earnings by a statistically significant 0.44%. They also show a one-hour delay in annual average sunset reduces weekly sleep by roughly one hour and decreases long-run earnings by 4%. Expressed as an elasticity with respect to sleep duration, their long-run earnings estimate is 2.6. Giuntella and Mazzonna (2018) find an hour delay in annual average sunset decreases sleep by roughly 20 minutes per day and increases the likelihood that individuals are obese by 21%.

In Appendix C, I use the 2006 Rural Economic and Demographic Survey (REDS), a nationally representative rural sample of Indian households, to control for a rich set of observables (e.g., migration, electricity access, access to roads). Moreover, as a complement to the effects on educational outcomes and a robustness check on the underlying conceptual framework, I document a statistically significant negative relationship between annual average sunset time and children's daily wage rate.[44]

5.3 Robustness Checks

5.3.1 Indonesia: Regression Discontinuity Estimates

Next, I use the 2003 Indonesian DHS I exploit time zone boundaries in Kalimantan to generate plausibly exogenous variation in annual average sunset time and examine the effects on schooling outcomes for children between 6 and 16 years of age. Kalimantan is the Indonesian portion of the island of Borneo with two time zones: UTC+7 and UTC+8 (Figure C.3). In PSUs lying on the eastern (right) side of the time zone boundary, sunset time occurs an hour later than in nearby PSUs on the western (left) side of the time zone boundary. Thus, school-age children on the later sunset side of the border are more likely to be sleep deprived and have worse educational outcomes.

The first stage is presented in Figure C.4. By construction, I observe a clear discontinuity in annual average sunset time at the border. To estimate the effects on schooling I include age fixed effects to control for differences in grade progression between children of different age groups. My identification strategy rests on the assumption that there are no discontinuities in observable or unobservable variables potentially correlated with outcomes of children of

[44] Appendix A describes the REDS data.

the same age. Indeed, I find that school-age children living in PSUs on the later sunset side are less likely to be enrolled in school, have fewer years of schooling, and relatedly, are less likely to complete primary and middle school. Figure C.5 presents these discontinuities graphically, while Table C.11 presents the formal results. Specifically, school-age children living close to the time zone boundary but on the later sunset side have years of education by 0.72 years fewer years of schooling. This point estimate is remarkably similar to the effects of annual average sunset time on years of schooling for school-age children in India.[45]

I test for the optimal polynomial order by comparing the local linear regression approach with higher polynomial orders, up to the fourth order. Figures C.7 - C.9 show that the point estimates are relatively stable. Next, I evaluate my identification assumption by controlling for a rich set of PSU level geographic and household level socioeconomic indicators. If wealthier households were sorting across the time zone border one would expect these controls to correct the bias emanating from such omitted variables. I control for latitude and elevation as well as wealth, access to electricity and indicator variables for ownership of various assets like television or car. I do not find evidence for any residential sorting as my point estimates remain unaffected (Table C.12). Finally, focusing on outcomes that should not be affected by later sunset I provide a set of placebo tests. Specifically, I find no evidence of discontinuity in children's age, children's gender or household head's age (Table C.13).

The time zone boundary perfectly overlaps with provincial administrative boundaries on Kalimantan, Indonesia. That is, the regression discontinuity design examines differences in children's education outcomes for PSUs closest to the administrative border between West and Central Kalimantan (UTC+7) and South and East Kalimantan (UTC+8). If administrative boundaries are drawn to ensure that economically developed locations fall on a certain side of the time zone boundary then my point estimates may be biased. However, all four provinces followed the Central Indonesian Time or UTC+8 until 1987. West and Central Kalimantan only switched to UTC+7 in 1988.[46] Importantly, to my knowledge, administrative boundaries were not altered during or after this switch. In addition, this means that I can use older cohorts or individuals who completed their education before 1988

[45]In Figure C.6 I show my estimates are relatively unaffected by the choice of bandwidth.

[46]West Kalimantan followed UTC+7.5 between 1945 and 1963, with the exception of a brief period between 1948 and 1950 when the province followed UTC+8. West Kalimantan switched to UTC+8 in 1964.

(>40 year-olds), under UTC+8, as a placebo sample. As one might expect, I fail to find evidence for a statistically significant discontinuity in years of schooling at the time zone border for individuals over 40 years of age (Figure C.10 and Table C.14).

5.3.2 Test Scores

Here, I use an individual level longitudinal panel from Andhra Pradesh, India, the 2002-2013 Young Lives Survey (YLS), and show that later sunset is negatively associated with children's test scores.[47]

The impacts of later sunset on academic progression are mediated through the effect of sunset-induced sleep deficits on learning and cognition. Thus, children exposed to later sunsets may also have lower test scores. To provide evidence for this hypothesis, I use comprehensive tests administered in YLS, and examine the effect of later sunset on math scores for school-age children. The study followed two cohorts of children, born in 1994/95 and 2001/02, respectively, over a period of more than 10 years. Children between the ages 5 and 19 were administered comprehensive tests in math at regular intervals between 2002-2014. Unlike DHS, YLS is conducted in a single state in India, Andhra Pradesh, and only provides district-level identifiers. Given these features of the YLS data, I exploit both cross-sectional variation in annual average sunset time at the district level as well as seasonal variation in daily sunset time at the district-test-date level to estimate the long- and short-run impacts of sleep deprivation on math test scores, respectively.

First, I estimate the long-run impact of sunset-induced sleep deficits on test scores. I compare test scores of children of the same age residing in districts with different annual average sunset times within the state of Andhra Pradesh. I show that children residing in districts with later annual average sunset times have lower test scores. A one hour delay in annual average sunset time (approximately two standard deviation) is associated with a 0.8 standard deviation decrease in math scores (Table C.15). Controlling for latitude and weather does not affect the point estimate. If district-specific unobservables, that are correlated with children's test scores, co-vary with annual average sunset time across eastern and western districts within Andhra Pradesh, then these estimates may be biased. Because

[47] I briefly describe the YLS data in Appendix A.

YLS does not provide village/city block identifiers, I am unable to exploit within-district cross-sectional variation in annual average sunset time.[48]

Next, I examine the short-run impacts of sunset-induced sleep deficits on math scores. Because the same child is tested at different points in the year across survey rounds, I exploit seasonal variation in sunset time at the district-test-date level after absorbing fixed child-specific confounders via lagged test scores or child fixed effects. I control for seasonal confounders common across all children in the sample via week-of-year fixed effects. I find an hour delay in sunset time on the day of the test reduces children's test scores by 0.5 standard deviation (Table C.16).[49] I control for potential omitted variables using lagged test scores as a proxy for child-specific unobservables (e.g., ability) that plausibly co-vary with daily sunset time and educational output. It is reassuring that controlling for lagged test scores explains meaningful variation in subsequent test scores, but does not affect the sunset-test score relationship. Moreover, although the point estimate is noisily estimated, I show that the short-run impact of sunset time on test scores is robust to the inclusion of child fixed effects.[50] The short-run impacts of later sunset are comparable to the short-run effects of later school start times on test scores. For example, Carrell, Maghakian and West (2011) find that a start time of 7 am reduces test scores for a course taught in the first period class by 0.15 standard deviation while a 7.50 am start time has no effect on test scores. Furthermore, with a 7 am start time students performed significantly worse (-0.10 standard deviation) even in subsequent classes, suggesting poor performance throughout the day.

6 Effects of Later Sunset on Adults' Time Use and Wages

Many studies have shown that both parental money and time investments are important for children's human capital production (Cunha and Heckman, 2007; Cunha et al., 2006; Fiorini

[48]The comparison of DHS estimates under state vs. district fixed effects specification suggest that these estimates may be biased downwards. Moreover, districts in western Andra Pradesh are close to two leading economic centres of India: Bangalore and Hyderabad.

[49]This estimate should not be interpreted as the single day effect of later sunset on test scores; sunset time on the day of the test is strongly correlated with sunset time observed days or weeks prior to the test date.

[50]In Table C.17 I show sunset time on the previous survey round test date and sunset time on the next survey round test date do not affect children's math scores in the current survey round.

and Keane, 2014). Later sunset may affect children's education production by decreasing adults' wages, and consequently parental investment in children's human capital (Jacoby and Skoufias, 1997; Jensen, 2000; Maccini and Yang, 2009; Thomas et al., 2004).

Later sunset may reduce adults' sleep duration, and depending on how adults trade-off sleep with work, home production and leisure, later sunset may affect monetary and time investments in children's education. If labor markets are competitive, workers are paid their marginal revenue product, and sleep is more work-productivity enhancing than home-productivity enhancing, later sunset may reduce sleep and wages, disincentivizing work effort but increasing time allocated to home production. In such a scenario, later sunset may reduce household expenditure on children's education but increase parental time investment in children. On the other hand, if sleep is more home-productivity enhancing than work-productivity enhancing, later sunset will reduce time allocated to home production but increase time allocated to labor activities.

To test these hypotheses, I estimate the baseline ITUS specification (Equation 8) and examine the effects of later sunset on adults' time allocation. I find that an hour delay in sunset time reduces adults' sleep and work effort by 30 minutes, but increases time allocated to home production and leisure (Table 5). However, I fail to find evidence for an effect on parental time investments in children. The magnitude is smaller than 5 minutes and statistically insignificant.[51,52]

Next, I estimate the baseline DHS specification (Equation 10) using data from the Rural Economic and Demographic Survey (REDS), and evaluate the effect of later annual average sunset on adults' daily wage rate. That is, I compare the prevailing wage rate among adult daily wage laborers who reside in villages with different annual average sunset time within a district. In line with the effects on time use, an hour delay in annual average sunset reduces adult wage rate by INR 8. Although the point estimate both males and females is

[51] I do not find evidence for a significant relationship between later sunset and time spent with children even when restricting the sample to households with school-age children, households with younger children, or households with multiple children (Table D.1).

[52] In Tables D.2-D.4, I control flexibly for district-specific seasonal unobservables that may be correlated with both adults' time use and sunset time by including a suite of interacted fixed effects: state-by-season, latitude-by-week-of-year and district-by-season. I find the point estimates for the effect of later sunset on sleep and leisure are relatively unaffected by the inclusion of these fixed effects. However, the coefficient on time allocated to work is now roughly zero. This may reflect the presence of downward nominal wage rigidities in village labor markets in the face of transitory negative shocks (Kaur, 2018).

negative, the effect on male wage rate noisier (Table 6).[53] Overall, an hour delay in sunset is associated with a decrease of roughly INR 2,500 (INR 8 x 312 working days) or USD 40 in annual earnings of a rural daily wage worker.[54,55]

7 Can Poverty Help Explain Why Households Fail to Adjust?

If sleep is productivity-enhancing, why don't families adjust their sleep schedules when the sun sets later? Investigating the determinants of such an adjustment failure, and not just the reduced form impacts, is necessary for effective policy design. In this section, I investigate if poverty helps explain why households fail to adjust to later sunset.

Poverty may impede adjustment in two ways. First, the sleep environment in developing countries is associated with noise, heat, mosquitoes, overcrowding, and overall uncomfortable physical conditions (Grandner et al., 2010; Patel et al., 2010), and the poor may simply lack the financial resources to invest in sleep-inducing goods (e.g., window shades, separate rooms, indoor beds, food) and adjust their sleep schedules when the sun sets later. Second, poverty may cause stress and negative affective states, such as depression, impede cognitive function by consuming mental resources or through reduced food intake, all of which affect decision-making (Boswell Dean, Schilbach and Schofield, 2018; de Quidt and Haushofer, 2018; Haushofer and Fehr, 2014; Mani et al., 2013; Schilbach, Schofield and Mullainathan, 2016; Schofield, 2014; Shah, Mullainathan and Shafir, 2012; Spears, 2011).[56] Therefore, psychological considerations associated with poverty may make it harder to assess one's own

[53]Rural markets for hired labor in India are active with most households buying and/or selling labor (Bardhan, 1973; Rosenzweig, 1980). Labor is typically traded in decentralized markets for casual daily workers. In fact, 98% of agricultural wage employment is through casual wage contracts (Kaur, 2018). Within a village, there is typically a sex-age-specific wage for casual daily labor for any given task (Bliss and Stern, 1982; Dreze and Mukherjee, 1989; Rosenzweig, 1978). Minimum wage policies are in practice ignored and there is little government intervention in the private wage labor market (Rosenzweig, 1980, 1988). Therefore, these point estimates capture the effect of a fixed (time-invariant) feature – annual average sunset time – associated with a village on the prevailing gender-specific wage rate.

[54]Because I fail to find evidence for a significant relationship between sunset time and adults' work hours under more demanding econometric specifications, any decrease in wages likely results from wage changes due to the productivity impacts of sleep, rather than changes in hours worked.

[55]By increasing dropouts, later sunset may increase the supply of child labor at the village level, in turn reducing adults' wage rate. Because the estimates are at the village level I cannot rule out such a general equilibrium effect. In addition, these wage effects might also be mediated by the childhood impacts of later sunset on education production.

[56]Several medical studies have linked poverty with elevated levels of the stress hormone cortisol and poor cognitive function in children (Chen, Cohen and Miller, 2010; Dickerson and Popli, 2016; Evans and English, 2002; Lupien et al., 2001, 2000; McLoyd, 1998; Noble et al., 2015; Saridjan et al., 2010).

sleep-productivity relationship and optimize sleep schedules when the sun sets later. On the other hand, the non-poor, by the virtue of owning these physical and psychological goods, may be better able to adjust their sleep schedules.

To explore this hypothesis, I use ITUS and examine the heterogeneous impacts on sleep by correlates of poverty: type of house structure (temporary vs. permanent), rural vs. urban status, education, and average monthly household expenditure.[57] I find that households that reside in a temporary structure are more affected by later sunset and sleep less (Table 7). The interaction term is statistically significant and exacerbates the level effect by 25%. Less-educated individuals are significantly more affected by later sunset, while the impact of an hour delay in later sunset is almost 10 minutes larger for rural households compared to urban households. Lastly, the negative effect of later sunset on sleep is significantly larger for households with average monthly expenditure less than that of the 75th percentile household in the sample compared to households above the 75th percentile household. Furthermore, this interaction effect is largest for households with average monthly expenditure below the 25th percentile.[58] Overall, these results suggest that socioeconomic status (SES) plays an important role in explaining unadjusted sleep.

However, it is plausible that these interaction effects are confounded by omitted variables that are correlated with socioeconomic status, particularly for adults. For instance, if low-SES individuals are disproportionately employed in occupations with formal work start times, it is possible that the interaction effect reflects morning work constraints rather than poverty;[59] unlike self-employed high-SES individuals (e.g., agricultural cultivators), low-SES individuals or daily wage workers (e.g., agricultural laborers) may fail to compensate for later bedtimes – due to later sunset – by waking up later. Therefore, I exploit quasi-experimental variation in income around the harvest period to present a plausibly causal relationship

[57]Average monthly expenditure for households that reside in permanent structure is INR 3,500 compared to roughly INR 2,000 for households that reside in a temporary structure. Similarly, average monthly expenditure among rural households is INR 2,200 compared to INR 3,600 among urban households. While average monthly household expenditure for individuals who have at least primary education is INR 3,100 compared to INR 2,100 for individuals who are illiterate or have not completed primary school.

[58]These heterogeneous impacts are of similar magnitudes among both children and adults (Table E.1).

[59]In Table E.2 I examine the heterogeneous impacts on children's time use by electrification status, as proxied by district-level annual average nighttime lights. I find the negative effect of later sunset on sleep and study time are significantly larger for children in districts with poor electricity access. This may be consistent with an explanation that better electricity access facilitates adjusted sleep when the sun sets later, and because sleep is productivity-enhancing, it also increases study effort. Although recent papers have used nighttime lights to capture intensity of electrification in India (Burlig and Preonas, 2016; Jagnani and Khanna, 2018), nighttime lights may be associated with other socioeconomic characteristics of the district. Therefore, these results should be interpreted with caution.

between poverty and unadjusted sleep.

7.1 Empirical Model

My research design compares the effects of later sunset on sleep allocation before harvest, when crop cultivator households are poorer, with after harvest, when richer. Crop cultivator households in India receive much of their annual income at harvest time or shortly after and are unable to smooth consumption over states of nature and across time (Deaton, 1997; Dercon and Krishnan, 2000; Paxson, 1993; Rosenzweig, 1989; Rosenzweig and Wolpin, 1993; Townsend, 1994). Mani et al. (2013) find that farmers in India show diminished cognitive performance and higher stress levels before harvest as compared with after harvest. They also show that poverty reduces cognitive capacity as poverty-related concerns consume mental resources. Thus, financial and psychological considerations associated with pre-harvest poverty may induce unadjusted, sub-optimal sleep.

For the main analysis, I restrict the ITUS sample to individuals from households whose primary source of income is agricultural cultivation, comparing the effect of later sunset on sleep between the pre- and post-harvest period. India has two agricultural seasons, and the agricultural calendar for each state varies by crop. Therefore, for both agricultural seasons in each of the six states in ITUS, I define pre- and post-harvest month according to the agricultural calendar for the main crop grown in each state during a particular agricultural season.[60] Because harvest calendars vary across locations and seasons, I also include calendar and location fixed effects, controlling for all fixed differences between time periods and districts.[61]

[60] India's first agricultural season is the kharif season, and broadly the growing season lasts from June through October and harvest from October through November. While the second agricultural season in India is called rabi, and broadly the growing season lasts from October through March and harvest from April through May. In Appendix E, I describe the pre- and post-harvest periods across the two agricultural seasons for all 6 states in ITUS.

[61] Figure E.1 presents the relationship between the pre-post harvest periods and sleep among crop cultivator households in the raw data. As expected, crop cultivator households allocate less time to sleep in the pre-harvest period compared to post-harvest period. It also presents the relationship between the pre-post harvest periods and time allocated to crop sale (and purchase) related activities in the raw data. Unfortunately, ITUS does not provide time use separately by crop sale and purchase related activities. I find no crop sale (and purchase) related activity in the first two weeks of the pre-harvest period. And as one might expect, crop sale (and purchase) related activity increases towards the end of the pre-harvest period. Importantly, most of sale (and purchase) related activity takes place in the post-harvest period.

I estimate the following econometric model:

$$
\begin{aligned}
y_{idwt} = & \beta_1 Sunset_{dwt} + \beta_2 PreHarvest_{dw} \\
& + \beta_3 Sunset_{dwt} * PreHarvest_{dw} + \mu_w + \mu_d + \epsilon_{idwt}
\end{aligned} \tag{11}
$$

where y_{idwt} is time allocated to sleep by individual i, in district d, on date t, during week-of-year w. $Sunset_{dwt}$ is sunset time observed by that individual i, in district d on date t. $PreHarvest_{dw}$ is the state-specific indicator equal to 1 if week w is the pre-harvest period for district d, 0 otherwise. I also control for district (μ_d) and week-of-year (μ_w) fixed effects. My coefficient of interest is the interaction between the indicator variable for pre-harvest month and daily sunset time (β_3). It captures the effect of pre-harvest poverty on sleep by comparing the difference in sleep duration between late sunset days and early sunset days during the pre-harvest period with the difference in sleep duration between late sunset days and early sunset days during the post-harvest period.

The identification assumption underlying this econometric strategy is that there is no time-varying district-specific confounder that differentially affects sleep on only later sunset days during the pre-harvest month. I evaluate the validity of this assumption through various falsification and robustness checks.

Lastly, because pre- and post-harvest months only include four months of data corresponding to two agricultural seasons, the week-of-year specification may absorb significant identifying variation in daily sunset times. Therefore, I also estimate econometric models that instead include season or month fixed effects. As before, standard errors are clustered at the district-week level.

7.2 Results

Table 8 shows that the negative effect of later sunset on sleep is significantly larger before harvest (interaction effect). In fact, almost the entire effect of later sunset on adults' sleep seems to be associated with pre-harvest poverty. That is, an hour delay in sunset time during the pre-harvest period decreases adults sleep by roughly 25 minutes, but the effect of later sunset during the post-harvest period (the level effect) is closer to zero. As adult crop cultivators are self-employed, and not constrained by start times for work, sub-optimal sleep for adult crop cultivators almost surely arises due to considerations related to poverty. However, as one might expect, both the level and interaction effects are economically meaningful for school-age children, who unlike adult cultivators face other constraints – e.g., school start times – in addition to poverty.[62,63] Importantly, although the point estimates are not always precisely estimated, the magnitude of the interaction term (and the level effects for children) is statistically indistinguishable across specifications. Overall, for individuals with formal morning start time constraints – school-age children from crop cultivator households – pre-harvest poverty explains about a quarter of the effect of later sunset on sleep. But for individuals that don't have formal work start time constraints – adults from crop cultivator households – the entire effect of later sunset on sleep is driven by the period when the household is poor (pre-harvest).

7.3 Robustness Checks

There is more agricultural work to be done in the pre-harvest period. If crop cultivator households work longer hours when the sun sets later during the pre-harvest month, because they have more daylight, and this increase in work effort is correlated with sleep, then the interaction effect (β_3) may be explained by an increase in work hours instead of 'pre-harvest poverty'. I control for possible changes in hours worked by crop-cultivator cultivators on later sunset days (Table E.5). The interaction effect remains unaffected, suggesting that changes in work hours do not explain the decrease in sleep during the pre-harvest period compared to the post-harvest period.[64]

Next, because non-cultivator households do not depend on lumpy harvest income and have other, stable sources of income, I use non-cultivator households as a falsification test. I fail to find evidence for pre-harvest period effects for individuals from non-cultivator hou-

[62] In Table E.3 I provide evidence that although adult cultivators delay bedtimes on later sunset days during the post-harvest period, they are able to compensate by waking up later. On the other hand, during the pre-harvest period, adult cultivators go to bed even later on late sunset days; moreover, they are less able to compensate by waking up later. While children from crop cultivator households fail to adjust to later bedtimes by waking up later on later sunset days, both before and after harvest. But during the pre-harvest period children are less able to compensate by waking-up later on late sunset days, exacerbating effects of later sunset before harvest.

[63] As one might expect, the lack of level effects for adult crop cultivators are driven by farmers with no children. I find that the level effect is negative for farmers with school-age children (Table E.4).

[64] In Table E.11 I show controlling for daylight duration does not have a significant effect on the magnitude of the interaction term.

seholds (Table E.6). The interaction effects are not statistically significant or economically meaningful. However, as expected, the level effects of later sunset on sleep for adults from non-cultivator households, either employed in urban locations or working as daily wage laborers in rural locations, are economically and statistically significant.[65] In addition, as before, the level effects of later sunset on sleep for school-age children are economically significant and statistically indistinguishable across specifications.

I implement another falsification test using non-cultivator households whose primary source of income is agricultural labor. Daily wage agricultural laborers perform the same tasks as crop cultivators during the pre-harvest month – e.g., land clearing, weeding, threshing and harvesting etc. – but unlike crop cultivators, who depend on lumpy harvest income, agricultural laborers are paid daily wages for these services throughout the agricultural season.[66] Thus, agricultural laborers are not poorer before harvest compared to after harvest. In fact, agricultural laborers might be poorer after harvest; in the post-harvest period they increase work hours in non-agricultural sectors (Table E.8), however, total work hours for an individual from the average agricultural laborer household declines slightly. Agricultural laborers are significantly poorer in terms of absolute wealth than cultivator households.[67] Even so, Table E.9 fails to find evidence that effect of later sunset is larger before harvest compared with after harvest for agricultural laborers. The interaction term is positive but not statistically significant. The existence of a significant pre-harvest effect among richer cultivator households and an insignificant pre-harvest effect among poorer agricultural laborer households is consistent with the explanation that the interaction term arises from financial and psychological considerations related to liquidity constraints, precisely as one would expect.

Interestingly, the level effects for agricultural laborers are economically and statistically large. This may either be because of other constraints on sleep in the form of work start times or material and mental constraints related to poverty. To explore this further, I compare

[65] In Table E.7 I show that adults from non-cultivator households are unable to compensate for later bedtimes due to later sunset by waking up later both before and after harvest.

[66] Agricultural wage contracts in Indian rural labor markets are typically bilaterally arranged between employers and workers and are of short duration, usually one day (Dreze and Mukherjee, 1989; Kaur, 2018).

[67] The average monthly household expenditure among agricultural laborers is roughly INR 1,605, compared to INR 2,240 among other non-cultivators. Similarly, while agricultural laborers have negligible landholdings, the average landholdings among cultivator households is 3.5 acres.

level effects between agricultural laborers and other non-cultivator households. Both sets of individuals likely face some manner of structured work schedule, but agricultural laborers are much poorer than other non-cultivators on average.[68] I find that the level effects among agricultural laborers are economically larger compared to other non-cultivators, perhaps again suggesting that considerations associated with poverty are at least partially responsible for sub-optimal sleep among poorer households like agricultural laborers.

Lastly, using the sample of crop cultivator households, I estimate a triple-difference research design by adding interactions between an indicator variable for wealth, $Richer_{idwt}$, and $Sunset_{dwt}$, $PreHarvest_{dw}$ and $Sunset_{dwt} * PreHarvest_{dw}$ to Equation 11. $Richer_{idwt}$ is equal to 1 if individual i belongs to a household with average monthly household expenditure greater than that of the median household in the sample, 0 otherwise. The identification assumption for the triple-interaction term is that there is no time-varying district-specific confounder that differentially affects sleep of only richer crop cultivator households on late sunset days during the pre-harvest month. As before, individuals lose significantly more sleep before harvest, when poorer, that after harvest, when richer (Table E.10). However, as one would expect, these interaction effects are economically smaller for individuals from richer households. Together these results suggest a causal effect of poverty on sleep.

8 India-Wide Human Capital Costs

Emerging out of the British Empire in the mid-20th century, India reckoned a single time zone would serve as a unifying force, and adopted the Indian Standard Time or IST (UTC+5.5) across her territorial boundaries. However, India measures 3,000 km from east to west, spanning roughly 30° longitude, corresponding with a two-hour difference in mean solar time.[69] That corresponds roughly to New York and Utah sharing one time zone, but with a billion more people, of whom 200 million live below the USD 1.90-a-day poverty line (The World Bank, 2016). In such a context, individuals in western India may begin sleep later than those in eastern India due to the relationship between the timing of sunset and bedtime,

[68] The average monthly household expenditure among other non-cultivators is roughly INR 3,170, almost 100% greater than agricultural laborers.

[69] Figure F.1 shows the spatial variation in annual average sunset times across India.

but fail to compensate by waking up later as India uniformly follows a standard time zone, resulting in potentially large implications for human capital production across the east-west gradient, ceteris paribus.

To generate India-wide, back-of-the-envelope human capital costs, I use the point estimate of the effect of a one-hour difference in annual average sunset time on adults' wages as it plausibly includes both the life-cycle impacts on human capital production as well as the contemporaneous effects on worker productivity. Importantly, for each district I compute estimates relative to the central meridian. The meridian passing through at 82.5° E is the central meridian for India. Thus, clocks across the country are set to the solar noon of the central meridian, but clock noon corresponds to solar noon only at 82.5° E. But, residents west of 82.5° E are ahead of the solar clock (late sleepers), while residents east of the central meridian are behind the solar clock (early sleepers) (Figure 3(a)).[70] Therefore, I compute the following equation for each district i:

$$HumanCapitalCosts_i = -8 * 312 * Population_i * (MeanSolarTime_i - IST) \tag{12}$$

where INR -8 is the point estimate for adults' wages and 312 are the number of working days in a year as per the ITUS data. While $Population_i$ is the population of adults at the district level and $MeanSolarTime_i - IST$ is difference between the district-specific annual average sunset time and the annual average sunset time at 82.5° E.

The countrywide estimate is calculated as follows:

$$HumanCapitalCosts_{India} = \sum_{i=1}^{N} HumanCapitalCosts_i \tag{13}$$

where N is the total number of districts in the country.

I find that India incurs annual human capital costs of roughly 4.1 billion USD or 0.2% of India's nominal GDP due to the existing policy regulating time zone boundaries in the country.[71] This is a significant number as India's education expenditure is less than 3% of

[70] Thus, the point estimate of a one-hour difference in annual average sunset time can also be interpreted as the effect of a one-hour difference between mean solar time and clock time.

[71] Using the 95% confidence interval for the point estimate on adults' wages, the lower and upper bounds for these human capital costs are roughly 2 million USD and 6 billion USD, respectively.

the GDP (Economic Survey, 2018). Moreover, note that this net estimate masks substantial spatial heterogeneity. I find that while highly-populated western districts incur large human capital costs, while their counterparts in the east accrue substantial gains (Figure 3(b)).

These estimates are calculated against an unrealistic counterfactual of continuous time zones across India. Therefore, I also calculate human capital costs associated with the existing time zone policy against the counterfactual of a two time zone policy: UTC+5 for western India and UTC+6 for eastern India, where western (eastern) India includes districts to the left (right) of 82.5° E, and the meridian passing through 75° E (90° E) defined as its central meridian. In fact, this counterfactual is precisely what was intended by the worldwide standard time zone scheme at conception (Benediktsson and Brunn, 2015). Figure F.3 calculates human capital costs associated with this hypothetical time zone policy against the counterfactual of continuous time zones. While Figure F.4 presents estimates for human capital costs associated with the existing time zone policy – UTC+5.5 – compared to this hypothetical counterfactual – UTC+5/UTC+6. Interestingly, the net human capital costs of this hypothetical policy compared to the counterfactual of continuous time zones are positive, albeit small (+100 million USD). Therefore, the net human capital gains associated with a switch to the realistic two time zones policy – UTC+5/UTC+6 – are comparable to the gains from a switch to the unrealistic continuous time zones policy. That is, India would incur annual human capital gains of over 4.2 billion USD if she switches from the existing time zone policy to the proposed two time zone policy.

The assumption underlying these calculations is that daily schedules fail to adjust to differences between solar time and clock time. This is a strong assumption. I evaluate it in four ways. First, a review of the existing literature suggests that work schedules are unaffected by solar cues instead responding to social norms (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2018; Hamermesh, Myers and Pocock, 2008). Second, as shown above, in India, individuals fail to compensate for sunset-induced delays in bed time by waking up later. Third, I find that school schedules fail to adjust to sunset times across the east-west gradient (Table F.1). Fourth, reports in the popular press indicate that work hours for government offices across the country do not respond to solar cues.[72]

[72]The Chief Minister of Arunachal Pradesh, a state in the northeast, is quoted as saying, *"Several daylight hours are wasted*

There may be benefits associated with the synchronization of daily schedules across the country (Stein and Daude, 2007), and one must be cautious about proposing changes to the existing time zone policy without a thorough cost-benefit analysis. In Appendix G, I also explore two other policy interventions that may mitigate the effects of later sunset on children's education outcomes: (i) later school start times and (ii) social protection programs. I find suggestive evidence that later school start times allow children to compensate for later bedtimes by waking up later, and attenuate the effect of later sunset on schooling outcomes. Meanwhile, each additional year of exposure to a conditional cash transfer program mitigates the effect of later sunset on children's test scores.

9 Conclusion

In this paper, I provide evidence that arbitrary clock conventions – by generating large discrepancies in when the sun sets across locations – help determine the geographic distribution of educational attainment levels. I establish four results. First, later sunset reduces children's sleep: when the sun sets later, children go to bed later; by contrast, wake-up times are not regulated by solar cues. Sleep-deprived students decrease study effort, consistent with a model where sleep is productivity-enhancing and increases the marginal returns of effort. Second, sunset-induced sleep deficits have significant negative effects on academic outcomes; school-age children exposed to later sunsets attain fewer years of education, are less likely to complete primary and middle school, are less likely to be enrolled in school, and have lower test scores. Third, later sunsets are also associated with fewer hours of sleep and lower wages among adults. Fourth, the non-poor adjust their sleep schedules when the sun sets later; the negative effects of later sunset on sleep are most pronounced among the poor, especially in periods when households face severe financial constraints.

as government offices open only at 10 am." Meanwhile, the Chief Minister of another northeastern state, Assam, proposed advancing working hours in the state, *"The sun rises here earlier than rest of the country and we can start our work half an hour earlier, from 9.30am."* (e.g., NDTV, 2017; The Hindu, 2017; The Indian Express, 2017; The Telegraph India, 2017)

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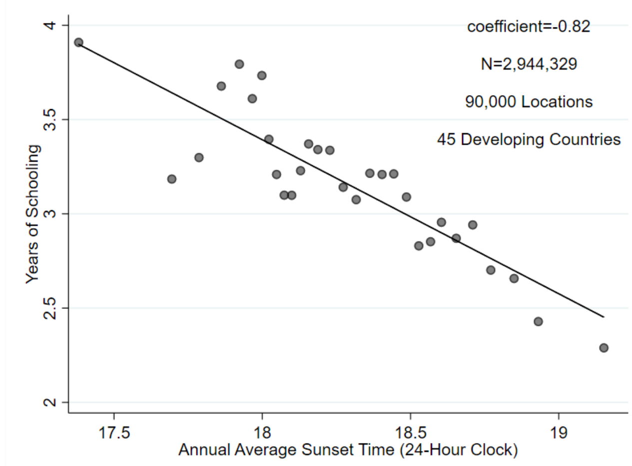
Tables and Figures

Figures

Figure 1: Annual Average Sunset Time and Children's Education in the Developing World



Notes: This figure presents a binned scatterplot and linear fitted values for the raw relationship between years of schooling and annual average sunset time for children between 6 and 16 years of age across the developing world. Data on years of schooling is obtained from nationally representative surveys conducted by the Demographic and Health Survey (DHS). I assembled and harmonized all DHS datasets collected through 2016 for which latitude and longitude of the primary sampling unit (PSU) or cluster was recorded allowing me to generate annual average sunset time at the PSU level. That is, I use the universe of DHS data with geolocation information from Latin America, Africa, South Asia, and Southeast Asia: 90,000 locations in 45 countries. The 45 countries include Angola, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Cameroon, Chad, Colombia, Comoros, Democratic Republic of the Congo, Dominican Republic, East Timor, Egypt, Ethiopia, Ghana, Guatemala, Guinea, Haiti, Honduras, India, Indonesia, Ivory Coast, Kenya, Lesotho, Liberia, Malawi, Mali, Morocco, Mozambique, Myanmar, Namibia, Nepal, Niger, Nigeria, Pakistan, Peru, Philippines, Rwanda, Senegal, Sierra Leone, Uganda, United Republic of Tanzania, Zambia and Zimbabwe.

Tables

Table 1: Effect of Late Sunset on Bedtime and Wakeup Time (Hours)

	(1) Bedtime β / SE	(2) Wake-up Time β / SE
Sunset Time (Hours)	0.36***	-0.13
	(0.10)	(0.08)
District FE	Yes	Yes
Week-of-Year FE	Yes	Yes
Mean	21.33	6.43
Observations	13863	13911
R^2	0.178	0.250

Notes: This table presents the effect of daily sunset time on bedtime and wakeup time for children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. I generate bedtimes using ITUS for all children who started sleep between 6 pm and 12 am such that they slept continuously for at least two hours. While wake-up times are generated for all children who ended sleep between 4 am and 10 am such that they were continuously awake for at least two hours. Unfortunately, this means that I am unable to generate bedtimes (wakeup times) for 101 (53) school-age children out of the 13,964 in the entire sample. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 2: Effect of Late Sunset on Children's Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.47***	-0.67***	1.65***	0.10
	(0.14)	(0.24)	(0.41)	(0.33)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.169	0.294	0.070

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work (in hours) by children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 3: Effect of Late Sunset on Children's Time Use by Primary Activity (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE
Sunset Time (Hours)	-0.44***	-0.88***	2.03***	0.21
	(0.14)	(0.24)	(0.41)	(0.26)
Sunset Time*Worker	-0.11**	0.82***	-1.36***	-0.69***
	(0.06)	(0.08)	(0.20)	(0.17)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	9.07	1.50	7.60	2.05
Observations	13964	13964	13964	13964
R^2	0.091	0.342	0.321	0.477

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure and work (in hours) by children between 6 and 16 years of age on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable with an interaction term between daily sunset time and child's primary activity; the interaction term captures the effect of an hour delay in daily sunset time for child laborer compared to a student. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 4: Effect of Late Sunset on Years of Schooling, Educational Attainment, and Enrollment Status

	(1) Years of Schooling β / SE	(2) Primary (0/1) β / SE	(3) Middle (0/1) β / SE	(4) Enrolled (0/1) β / SE
Annual Average Sunset Time (24-Hour Clock)	-0.86***	-0.13***	-0.08**	-0.11**
	(0.31)	(0.04)	(0.03)	(0.05)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean	4.44	0.48	0.21	0.90
Observations	638682	638682	638682	638682
R^2	0.732	0.643	0.561	0.093

Notes: This table presents the effect of annual average sunset time on years of schooling, likelihood of completing primary (0/1) and middle school (0/1), and enrollment status (0/1) for children between 6 and 16 years of age in India. Each column represents a separate regression estimating Equation (10) on the outcome variable. All regressions include age and district fixed effects. Standard errors are in parentheses, clustered at the PSU level. Source: 2015 India DHS.

Table 5: Effect of Late Sunset on Adults' Time Use (Hours)

	(1) Sleep β / SE	(2) Study β / SE	(3) Leisure β / SE	(4) Work β / SE	(5) HH Chores β / SE	(6) Time With Kids β / SE
Sunset Time (Hours)	-0.50***	-0.03	0.90***	-0.56***	0.21*	0.08
	(0.10)	(0.03)	(0.21)	(0.21)	(0.12)	(0.05)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.11	0.11	7.06	5.40	2.72	0.43
Observations	48804	48804	48804	48804	48804	48804
R^2	0.078	0.012	0.044	0.026	0.018	0.022

Notes: This table presents the effect of daily sunset time on time allocated to sleep, study, leisure, work, home production and time spent with children by individuals (in hours) over the age 16 on weekdays in India. Each column represents a separate regression estimating Equation (8) on the outcome variable. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 6: Effect of Late Sunset on Adults' Daily Wage Rate

	(1) Adult Wage (INR) β / SE	(2) Male Wage (INR) β / SE	(3) Female Wage (INR) β / SE
Annual Average Sunset Time (Hours)	-8.03**	-3.92	-13.98**
	(3.69)	(3.91)	(5.81)
District FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Place FE	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes
Mean	63.97	67.49	49.66
Observations	6055	5952	2491
R^2	0.592	0.612	0.550

Notes: This table presents the effect of annual average sunset time on adult's daily wage rate by industry at the village level in India. Each column represents a separate regression; all regressions include district, industry and place (inside or outside the village) fixed effects, and geographic controls: latitude, rainfall, temperature and elevation. Daily wage rates are winsorized at the 1% level. Standard errors are in parentheses, clustered at the village level. Source: REDS.

Table 7: Heterogeneity by Correlates of Poverty: Effect of Late Sunset on Sleep (Hours)

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE	(4) Sleep β / SE
Sunset Time (Hours)	-0.44*** (0.10)	-0.39*** (0.10)	-0.42*** (0.10)	-0.43*** (0.10)
Sunset Time*Temporary House Structure (0/1)	-0.11*** (0.04)			
Sunset Time*Rural (0/1)		-0.19*** (0.05)		
Sunset Time*No Primary Education (0/1)			-0.13*** (0.03)	
Sunset Time*HH Expenditure∈(50p,75p)				-0.09* (0.04)
Sunset Time*HH Expenditure∈(25p,50p)				-0.08** (0.04)
Sunset Time*HH Expenditure∈(0p,25p)				-0.17*** (0.05)
District FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
Mean	8.33	8.33	8.33	8.33
Observations	62768	62768	62768	62768
R^2	0.073	0.075	0.075	0.072

Notes: This table presents the heterogeneous effect of daily sunset time on time allocated to sleep by correlates of socioeconomic status on weekdays for all individuals over the age of 6 in India. Each column represents a separate regression. Column 1 shows the effect of daily sunset time on sleep for households that live in a temporary house structure compared to households that live in a permanent house structure. Column 2 shows the effect of daily sunset time on sleep for households living in rural areas compared to households living in urban areas. Column 3 shows the effect of daily sunset time on sleep for individuals that have completed primary education compared to individuals that have not completed primary education. Column 4 shows the effect of daily sunset time on sleep for households with average monthly expenditure below the 25th percentile, between 25th and 50th percentile, and between 50th and 75th percentile, compared to households with average monthly expenditure above the 75th percentile. All regressions include district and week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.

Table 8: Crop Cultivator Households: Effect of Late Sunset on Individuals' Sleep (Hours) in Pre- vs. Post-Harvest Month

	(1) Sleep β / SE	(2) Sleep β / SE	(3) Sleep β / SE
All			
Sunset Time (Hours)	-0.69***	-0.06	0.04
	(0.15)	(0.23)	(0.26)
Sunset Time*Pre-Harvest	-0.28***	-0.47**	-0.35*
	(0.09)	(0.20)	(0.18)
Mean	8.42	8.42	8.42
Observations	10827	10827	10827
R^2	0.102	0.107	0.117
Adults			
Sunset Time (Hours)	-0.65***	-0.01	0.18
	(0.15)	(0.25)	(0.29)
Sunset Time*Pre-Harvest	-0.25***	-0.44**	-0.39**
	(0.10)	(0.21)	(0.19)
Mean	8.20	8.20	8.20
Observations	8460	8460	8460
R^2	0.139	0.144	0.157
Children			
Sunset Time (Hours)	-0.73***	-0.52	-0.57
	(0.19)	(0.37)	(0.43)
Sunset Time*Pre-Harvest	-0.23*	-0.31	-0.13
	(0.12)	(0.29)	(0.27)
Mean	9.19	9.19	9.19
Observations	2367	2367	2367
R^2	0.131	0.141	0.157
District FE	Yes	Yes	Yes
Season FE	Yes	No	No
Month FE	No	Yes	No
Week-of-Year FE	No	No	Yes

Notes: This table presents the effect of daily sunset time on time allocated to sleep before harvest compared to after harvest on weekdays for crop cultivator households in India. Panel 'All' includes all individuals over the age of 6. Panel 'Adults' includes all individuals over the age of 16. Panel 'Children' includes all individuals between 6 and 16 years of age. Each panel-column combination represents a separate regression estimating Equation (11) on the outcome variable. The interaction term captures the effect of an hour delay in daily sunset time for crop cultivator households in the pre-harvest month compared to the post-harvest month. All regressions include district fixed effects. Column 1 includes season fixed effects, while Column 2 includes month fixed effects and Columns 3 includes week-of-year fixed effects. Standard errors are in parentheses, clustered at the district-week level. Source: ITUS.