Later Sunset, Better Health?*

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Abstract

Previous research, focusing primarily on high income countries, has linked later sunsets to sleep deficits and worse health outcomes. These results might not generalize to low- and middle-income countries, which have different socioeconomic, cultural, and environmental conditions. Using data from the 2015-16 and 2019-21 waves of India's Demographic and Health Surveys (DHS) and exploiting within-district variation in annual average sunset times, we estimate the causal impact of later sunsets on the long-term health outcomes of individuals. We find that later sunsets lead to a lower prevalence of anemia, diabetes, and thyroid disorders and an improvement in the overall health index. To explore mechanisms, we analyze variation in time allocation due to a later sunset time using the 2019 Time Use Survey. We find that individuals experiencing later sunsets sleep better and exercise more, but do not change their sedentary leisure activities. Additionally, they consume healthier food and increase labor supply. These lifestyle changes may explain the health improvements associated with delayed sunsets in India.

JEL-codes: J22, I12, I14
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1 Introduction

There is growing evidence that environmental conditions play an important role in shaping health behaviors and health outcomes. One such factor is the timing of sunsets, which can disrupt sleep cycles and adversely impact health. Later sunset times have been linked to worse cognitive function and higher rates of obesity, diabetes, heart disease, breast cancer, depressive symptoms, and hospitalizations related to cardiovascular diseases (Giuntella & Mazzonna, 2019; Giuntella et al., 2017; Jin & Ziebarth, 2020; Tanaka & Koizumi, 2024). Most of this evidence comes from high-income countries such as the United States or Germany, where chronic sleep deprivation is a growing public health concern (Kocevska et al., 2021). The extent to which these findings generalize to low- and middle-income countries is unclear, given the substantial variation in culture, lifestyle, resources, and environment across countries (Simonelli et al., 2018). We contribute to this literature by examining the effects of later sunset times on health outcomes in India.

While sleep has been identified as the primary channel through which later sunset times affect health outcomes in high-income countries, this mechanism may not fully explain the relationship in a low- and middle-income country context such as India. Sleep patterns in India differ markedly from those observed in high income nations. On average, Indians sleep approximately eight hours per night, with only 3% reporting fewer than six hours of sleep, a figure substantially lower than the 6.5% observed in countries like the United States, the United Kingdom, and the Netherlands (Kocevska et al., 2021).[1] The proportion of individuals sleeping less than the recommended 7 to 9 hours is also lower in India compared to other low- and middle-income countries (Hirshkowitz et al., 2015; Simonelli et al., 2018). A recent study by Bessone et al. (2021) shows that improving nighttime sleep among low-income adults in Chennai led to a reduction in labor supply, an effect that contrasts with findings from high-income countries. Given these differences, it is important to examine the

[1] Authors' calculations based on data from the 2019 India Time Use Survey.

relationship between sunset time and health in diverse settings and to explore mechanisms beyond sleep.

Later sunset times may influence health through multiple channels. By delaying bedtimes while wake times remain fixed due to work or school schedules, later sunsets reduce sleep duration, which can negatively impact health (Gibson & Shrader, 2018; Giuntella & Mazzonna, 2019). Sleep deprivation has also been linked to cravings for high-calorie foods (Knutson et al., 2007), automobile accidents (Gillmore, 2025; Smith, 2016), worse educational outcomes (Heissel & Norris, 2018; Jagnani, 2024), and reduced labor productivity and earnings (Gibson & Shrader, 2018), which may indirectly affect health outcomes. At the same time, individuals may reallocate their time in the evening toward physical activity or leisure (Wolff & Makino, 2013). Increased exposure to sunlight may also improve health by promoting better sleep quality, regulating mood, and facilitating vitamin D synthesis (Anderson et al., 2025; Osborne-Christenson, 2022; Tanaka & Matsubayashi, 2025). Overall, the net impact of later sunset times on health is theoretically ambiguous.

Using geocoded data from the 2015-16 and 2019 waves of the India Demographic and Health Survey (DHS), we examine the long-term health impacts of delayed sunsets. To identify causal effects, we rely on plausibly exogenous within-district variation in average annual sunset time, drawing on the approach used by Gibson and Shrader (2018), Giuntella et al. (2017), and Jagnani (2024). Our baseline specification includes demographic characteristics and district, survey wave, and week-of-the-year fixed effects. As support for our identifying assumption, we show that our main estimates are robust to including a wide range of agricultural, economic, and environmental controls and are not driven by latitude or the size of the district. Placebo tests using health outcomes that have not been linked to sunset times, such as sexually transmitted illnesses, also provide support for the identifying assumption. We find significant reductions in the prevalence of diabetes, anemia, and thyroid disease. Among women, a 10-minute delay in sunset time reduces the prevalence of diabetes by 0.7 percentage points, of anemia by 4.3 percentage points, and of thyroid disease by 0.4 percentage points. We also find a significant improvement in the Overall Health Index (OHI), a composite measure combining all available health indicators, among women. Other than a 3.6 percentage point increase in hypertension, most estimates for men are not statistically significant.

To investigate the mechanisms underlying these health improvements, we supplement the DHS with data from the India Time Use Survey (TUS) and Periodic Labour Force Surveys (PLFS), which capture the short- and medium-term impacts of delayed sunsets. The TUS includes the date of the survey, which allows us to investigate how daily time allocation across various activities responds to variation in the daily sunset time, conditional on demographics, and district and week-of-the-year fixed effects. This analysis relies on district-specific seasonal variation in sunset time for identification. We find that although later sunsets decrease sleep duration, there is an increase in the likelihood of sleeping the recommended 7-9 hours and a reduction in sleeplessness, suggesting that sleep quality may have improved. In addition, later sunset times increase time spent on sports and exercise, and on paid work, conditional on working. We use the PLFS to explore effects on labor supply and earnings, finding an increase in labor supply and earnings among daily-wage workers. We also find a reduction in the consumption of fried foods and sweetened beverages in the DHS sample. With the exception of reduced sleep duration, all of these pathways are consistent with an improvement in health.

This study contributes to the growing literature examining the impact of sunset times on health and other economic outcomes (Gibson & Shrader, 2018; Giuntella & Mazzonna, 2019; Heissel & Norris, 2018; Jagnani, 2024; Jin & Ziebarth, 2020). Our finding that delayed sunsets improve health contrasts with the results of Giuntella and Mazzonna (2019), Giuntella et al. (2017), and Jin and Ziebarth (2020). While these studies identify sleep deprivation as the sole mechanism by which sunset time influences health, we find evidence that multiple pathways play a role in the Indian context. Moreover, in India, a later sunset time leads to healthier behaviors (sleep quality, diet, and exercise) and better labor market outcomes, which may explain the observed health improvements. Our results are consistent with evidence linking greater sunlight exposure to improved mental health (Osborne-Christenson, 2022; Tanaka & Matsubayashi, 2025), and with evidence that the economic impacts of sleep observed in high-income countries such as the US do not generalize to low-income, urban populations in India (Bessone et al., 2021). Our study advances the literature on sunset time and health by providing new evidence of health improvements and by identifying alternative pathways beyond sleep deprivation.

2 Data and Descriptive Statistics

2.1 India Demographic and Health Surveys

To estimate the effect of sunset time on health, we use data from the India Demographic and Health Surveys (DHS), which are nationally representative surveys that collect detailed information on a wide range of topics, including health, fertility, employment, and demographic characteristics. These surveys are administered by the United States Agency for International Development (USAID) in partnership with the Indian Ministry of Health and Family Welfare. We use the two most recent waves of DHS, 2015-16 and 2019-21, since geocode information is not available in earlier waves.

Our dependent variables include body mass index (BMI) and binary indicators for diabetes, hypertension, heart disease, anemia, and thyroid disease. We focus on these measures since sunset times and mechanisms such as sleep and sunlight exposure have been linked to metabolic health, anemia, and thyroid disease (Kim et al., 2018; Nedeltcheva & Scheer, 2014). The survey includes multiple measurements of hypertension and diabetes, which we combine into a single indicator. Respondents are asked whether a health professional had diagnosed them with high blood pressure, and their blood pressure was recorded three times during the visit. We define the indicator for hypertension as one if the individual either reported a prior diagnosis by a health professional or exhibited elevated blood pressure in at least two out of three readings on the day of the survey, and zero otherwise.[2] For diabetes, respondents are asked to self-report whether they have the condition and blood glucose levels were recorded during the visit. We define the indicator for diabetes as one if the respondent self-reported having diabetes or had a measured blood sugar level above 140 mg/dL on the day of the survey.[3] In addition, we construct two health indices to account for multiple hypothesis testing and improve statistical power. Following Hoynes et al. (2016), we define the "Metabolic Syndrome Index" (MSI) as the simple average of the z-scores of four binary indicators: obesity, diabetes, hypertension, and heart disease. The "Overall Health Index" (OHI), is defined as the simple average of the z-scores of all available health indicators - BMI, diabetes, hypertension, heart disease, anemia, and thyroid disease.

To investigate the mechanisms by which sunset time may influence health, we examine dietary patterns, labor supply, and financial resources. The DHS asks respondents whether they consume any of the following nine food items on a daily basis: dairy products, lentils, vegetables, fruits, meat, fish, eggs, fried food, and sweetened beverages. Based on their responses, we construct four dietary variables. The first measures the consumption of unhealthy foods, coded as one if an individual consumes fried food or sweetened beverages on a daily basis and zero otherwise. The second, protein consumption, is an indicator of daily consumption of lentils, meat, fish, or eggs. The third measures greens and dairy consumption based on a daily intake of fruits, vegetables, or dairy products. The fourth measures diet diversity, a commonly used proxy for micronutrient adequacy (FAO, 2016; Gupta et al., 2024). It is calculated as the sum of all food groups consumed (excluding fried food and sweetened beverages), and ranges from 0 to 7, with a higher value indicating a more diverse diet. Labor supply is measured using two indicators: whether an individual is currently employed and

[2]Elevated levels of blood pressure are defined as systolic blood pressure above 135 mmHg and diastolic blood pressure above 85 mmHg. Individuals with these blood pressure levels were encouraged to see a doctor for a full evaluation during the survey.

[3]The 2015-16 wave also included self-reported high blood pressure and a professional diagnosis of diabetes. However, since these variables are not available across both waves, we do not use them in our analysis.

whether they have worked in the past year. Although the DHS does not include information on wage earnings or income, it includes a wealth index ranging from 1 (poorest quintile) to 5 (richest quintile).[4] We construct a binary indicator for whether an individual belongs to the top two quintiles of the wealth distribution.

We merge the DHS data with average annual sunset time at the Primary Sampling Unit (PSU) level obtained from the National Oceanic and Atmospheric Administration (NOAA). In rural areas, PSUs correspond to villages, while in urban areas, they represent city blocks. Using the latitude and longitude coordinates provided by the DHS, we match the 2015 average sunset time to PSUs in the 2015-16 wave and 2019 average sunset time to PSUs in the 2019-21 wave of the DHS.[5] In some specifications, we also include agricultural, weather, and economic characteristics of the PSU. Agricultural controls include a vegetation index, growing season length, irrigation, and livestock. Weather controls include precipitation, aridity, drought episodes, maximum, minimum, and average temperature, rainfall, and the number of wet days. Economic variables include population, global human footprint, composite nightlights, elevation, and travel time to the nearest high-density urban center. Table A1 in the Appendix presents detailed information on the variables.

Our sample includes all women aged 15-49 years and men aged 15-54 years, for whom these variables are available. To ensure that our results are not driven by health shocks related to the COVID-19 pandemic, we restrict our sample to individuals surveyed before March 2020 for the main analysis. In Appendix Figure A1, we examine the robustness of our results to including individuals surveyed after March 2020. To ensure that our estimates are not confounded with the health effects of pregnancy and childbirth, we exclude women who

[4]The wealth index is a composite measure based on a household's ownership of various assets such as bicycles and televisions, materials used for housing construction, and types of water access and sanitation facilities.

[5]GPS coordinates in the DHS are displaced up to 2 km in urban areas and up to 10 km in rural areas, within the same district. Although this introduces measurement error in our key independent variable, the error is likely to be minimal as sunset time varies very little within a 10 km radius.

gave birth within the past two months or who report being pregnant during the survey. To capture the long-term effects of sunset time on health, we restrict our sample to individuals who have resided in their current location for at least three years. Figure A2 shows robustness to alternative cutoffs based on years of residence, while Appendix Table A2 shows that sample characteristics do not change substantially when we make these restrictions. After these exclusions, our final sample consists of 1,173,814 individuals: 1,002,462 women and 171,352 men.[6]

Table 1 presents summary statistics for the dependent variables in the DHS sample. Over half of the women in the sample have anemia compared with 17% of men. Approximately one-third of the population has hypertension, and around 8% have diabetes. The incidence of thyroid and heart disease is relatively low, with only about 1-2% of respondents self-reporting these conditions—possibly reflecting the younger, working-age population studied. Regarding dietary outcomes, 14% of individuals report consuming unhealthy food items (such as fried foods or sweetened beverages) on a daily basis. Nearly half of the population consumes at least one source of protein daily, and about 71% report daily consumption of vegetables, fruits, or dairy products. Nevertheless, the average diet diversity score of 1.59 indicates that most individuals in the sample have limited dietary variety. In terms of employment, about 50% of the individuals report being employed. However, the employment rate among women (26%) is significantly lower than that of men (75%), highlighting the persistent problem of low participation of women in the labor force in India.

[6]The DHS is primarily conducted to assess maternal and child health, and therefore includes a substantially larger sample of women than men to enable a more representative analysis of women's outcomes.

Table 1: Summary Statistics of outcomes: DHS Sample

	Mean (Std. Dev.)		
	Female	Male	All
Health Outcomes			
BMI	21.98 (4.26)	22.04 (3.87)	21.99 (4.20)
Hypertension	0.27 (0.44)	0.35 (0.48)	0.27 (0.45)
Diabetes	0.07 (0.26)	0.10 (0.30)	0.08 (0.27)
Heart	0.01 (0.12)	0.01 (0.11)	0.01 (0.11)
Anemia	0.54 (0.50)	0.17 (0.38)	0.49 (0.50)
Thyroid	0.02 (0.15)	0.01 (0.07)	0.02 (0.14)
Metabolic Syndrome Index	0.02 (0.57)	-0.001 (0.55)	0.01 (0.57)
Overall Health Index	0.01 (0.46)	-0.01 (0.50)	0.01 (0.46)
Dietary Outcomes			
Unhealthy Food	0.14 (0.35)	0.16 (0.36)	0.14 (0.35)
Protein	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)
Greens and Dairy	0.71 (0.45)	0.71 (0.46)	0.71 (0.45)
Diet Diversity	1.58 (1.21)	1.59 (1.26)	1.59 (1.22)
Wealth and Employment			
Rich	0.37 (0.48)	0.39 (0.49)	0.37 (0.48)
Wealth	2.92 (1.37)	3.01 (1.35)	2.94 (1.37)
Currently Working	0.26 (0.44)	0.75 (0.43)	0.51 (0.50)
Worked in last 1 year	0.33 (0.47)	0.81 (0.39)	0.58 (0.49)
Observations	1,002,462	171,352	1,173,814

Note: BMI is expressed in kilogram per meter square and health indices are averages of z-scores. Diet diversity is a categorical variable taking values 0 to 7, depending on number of food items consumed daily. Wealth is a categorical variable taking value 1 to 5, depending on the wealth quintile of the individual. All remaining variables are binary indicators taking value 1 or 0. Sample is restricted to the pre-Covid period (before March 2020) and those who have stayed in the current location for at least three years. For the sample of women, pregnant women and those who have given birth in last 2 months are excluded. There is variation in the observations for different health outcomes. Employment related information is available for 164,335 women and 171,351 men. Source: India DHS waves 2015-16 and 2019-21.

Table 2 presents the summary statistics for the explanatory variables in the DHS sample. The population is predominantly young, with two-thirds of individuals under the age of 35. The majority are Hindus, followed by Muslims as the largest minority group. Figures 1 and 2 present the 2019 mean and the standard deviation of sunset time, respectively, for each of the 594 districts in our sample. The sun sets later as one moves from east to west across

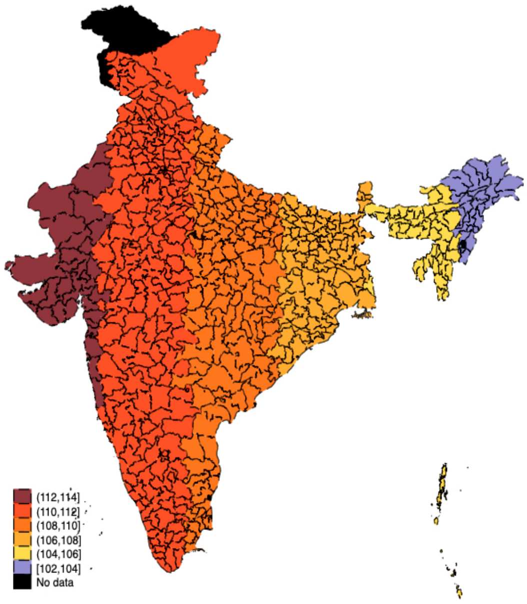
India. While the within district variation in sunset time shows no clear geographic pattern, it is generally higher in larger districts than in smaller ones. The maximum difference in sunset time within a single district is 9.5 minutes, while the minimum difference is 5.4 seconds. The average variation in sunset time across districts is 1.75 minutes.

Table 2: Summary Statistics of control variables: DHS Sample

	Mean (Std. Dev.)		
	Female	Male	All
Age Group			
15 to 25	0.34 (0.48)	0.34 (0.47)	0.34 (0.48)
26 to 35	0.30 (0.46)	0.28 (0.47)	0.30 (0.46)
36 to 45	0.27 (0.44)	0.23 (0.42)	0.26 (0.44)
46 and above	0.09 (0.28)	0.15 (0.36)	0.10 (0.29)
Religion			
Hindu	0.73 (0.44)	0.74 (0.44)	0.74 (0.44)
Muslim	0.14 (0.35)	0.14 (0.35)	0.14 (0.34)
Christian	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)
Others	0.05 (0.21)	0.05 (0.21)	0.05 (0.21)
Caste			
SC	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)
ST	0.20 (0.39)	0.19 (0.39)	0.19 (0.40)
OBC	0.40 (0.49)	0.41 (0.49)	0.40 (0.49)
General	0.21 (0.41)	0.21 (0.41)	0.21 (0.41)
Observations	1,002,462	171,352	1,173,814

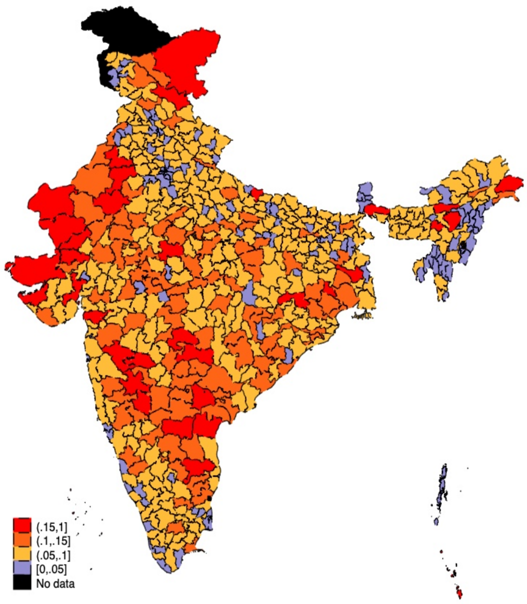
Note: All variables are binary indicators taking value 1 or 0. Sample is restricted to the pre-Covid period (before March 2020) and those who have stayed in the current location for at least three years. For the sample of women, pregnant women and those who have given birth in last 2 months are excluded. There is variation in the observations for different control variables. Source: India DHS waves 2015-16 and 2019-21.

Figure 1: Average Sunset Time (in 10 minutes) across districts in India (2019)



Notes: The shade represents the within-district annual average sunset time by considering all the PSUs within each district. The value represents the 10-minute interval in which the annual average sunset time lies in the district. Source: Global Monitoring Laboratory of the National Oceanic and Atmospheric Administration (NOAA) 2019.

Figure 2: Variation (Standard Deviation) in Sunset Time across districts in India (2019)



Notes: The shade represents the within-district variation in the annual average sunset time. It is measured by standard deviation across the PSUs within each district. Source: Global Monitoring Laboratory of the National Oceanic and Atmospheric Administration (NOAA) 2019.

2.2 India Time Use Survey 2019

We use data from the 2019 wave of the India Time Use Survey (TUS) to assess how sunset time influences an individual's daily activities, which may have direct health implications. India TUS 2019 is the first nationally representative time use survey of India and is one of the largest time use surveys globally (Hirway, 2023).[7] The survey collects detailed time allocation information from 447,250 individuals across 138,799 households. Data on time use is collected using the personal interview method, covering 24 hours starting from 4 A.M. on the day before the interview to 4 A.M. on the day of the interview.[8] The TUS records the day of the week on which interviews are conducted, and respondents also declare whether a day is a "normal" or "other" day. A normal day is one where individuals pursue most of their routine activities, whereas days when routine activities are altered for any reason, for example, weekly off-days, holidays, days of leave, ceremonies, or disruption due to illness, are referred to as other days.

Time use information is collected in 30-minute blocks for 165 activities. The respondent may report up to three activities in each time slot, provided that they spent at least 10 minutes on that activity. Activities are recorded in chronological order using the major criteria format, where the respondent identifies the most important activity during each time slot. For each activity, respondents also report whether the activity was performed within the premise of the dwelling unit or outside of it and whether it was paid or unpaid. Our analysis includes all activities in each time slot with time equally distributed among them to estimate time allocations (Folbre & Yoon, 2007; Zick & Bryant, 1996).[9] We classify the 165 activities into eight broad categories: (1) sleep, which includes any sleep that starts

[7]An earlier time use survey conducted in 1998-99 only covered six states.

[8]Sharma et al. (2025) show that proxy- vs self- reporting influences the reported time across activities. Therefore, as a robustness check, we estimate a specification that includes a dummy for self-report (with proxy report as the reference group). Our key findings are robust to this alternative specification.

[9]If an individual reports three activities during a 30-minute block, each activity is allocated 10 minutes. If two activities are reported, each one is allocated 15 minutes, and if only one activity is reported, it is allocated the full 30 minutes.

and ends between 6 pm and 12 noon, (2) nap, which includes any sleep that starts between 12 pm and 6 pm, (3) non-sedentary leisure, which includes sports and exercise (4) sedentary leisure, which includes activities related to socializing and communication, culture and mass media, that is, all forms of leisure excluding sports and exercise, (5) housework, which includes time spent on housework and care work for family members, (6) work, which includes paid employment-related activities, (7) eating and drinking, and (8) other activities, which include learning, personal maintenance, unpaid employment-related activities, volunteering and tasks not covered in the (1) to (7) categories.

We restrict the analysis to individuals aged between 15-49 years, to make it comparable to the DHS sample, and to normal weekdays — Monday through Friday — when individuals report engaging in their routine activities.[10] Summary Statistics for the TUS sample are presented in Table 3. On average, individuals sleep around 8 hours and nap for a little over half an hour. While women sleep less than men at night, they compensate by spending more time on daytime naps. The combined duration of sleep and nap time is higher for women. The average time spent on non-sedentary activities is 4 minutes, primarily driven by the low participation rate of 6 percent in the population. Conditional on participation, individuals spend approximately an hour on sports and exercises. Individuals in our sample work for 3.25 hours per day. Conditional on being employed, they spend 6.3 hours. Those who are employed as regular wage or salaried workers work close to 8 hours per day (see Appendix Table A4).

[10] Appendix Table A3 shows that the demographic characteristics of the DHS and TUS samples are comparable.

Table 3: Summary Statistics for adults aged 15-49 years

	Men	Women	Total
Time Allocations (in Minutes)			
Sleep	490.27 (98.95)	469.56 (89.59)	479.86 (94.93)
Nap	21.51 (46.96)	50.08 (63.26)	35.87 (57.55)
Non-sedentary	5.58 (22.83)	1.58 (11.29)	3.57 (18.09)
Sedentary	234.07 (141.29)	236.72 (132.31)	235.40 (136.86)
Housework	37.24 (69.55)	342.63 (190.98)	190.67 (209.87)
Work	321.11 (238.48)	70.66 (153.26)	195.28 (236.18)
Eating	102.38 (46.61)	94.29 (40.96)	98.31 (44.05)
Other activities	202.16 (227.84)	174.47 (186.04)	201.03 (196.06)
Other variables			
Age (in Years)	30.60 (9.55)	30.85 (9.37)	30.73 (9.46)
Observations	95,281	96,198	191,479

Source: Author's calculation from TUS 2019

2.3 Periodic Labour Force Survey

Since neither the DHS nor TUS has information on wages or income, we supplement our analysis with data from the Periodic Labour Force Survey (PLFS). The PLFS is a nationally representative survey conducted by the Government of India to collect data on labor force activity at quarterly intervals. We use data from the 2017-18, 2018-19, and 2019-20 waves of the PLFS and restrict the sample to individuals aged 15-49. The survey includes information on hours worked and earnings for all persons who report being employed. Hours worked are reported at the daily level for all workers, while earnings are reported at the monthly level for salaried and self-employed workers, and at the daily level for daily wage workers. We aggregate both variables up to the monthly level.

3 Empirical Methodology

We follow the approaches used by Gibson and Shrader (2018), Giuntella et al. (2017), and Jagnani (2024) to estimate the impact of later sunset times on health and explore the potential mechanisms underlying any effects.[11] We identify long-run impacts on health using data from the DHS and district-specific variation in annual average sunset times. We also use this approach to explore mechanisms such as diet and employment. For time allocation mechanisms, we exploit daily variation in sunset time within districts using the TUS data. For the analysis using PLFS data, we rely on district-specific monthly variation in sunset time to identify effects on labor market outcomes. In other words, we separately identify short-, medium-, and long-run effects on proximate mechanisms, which may accumulate over time to explain long-run health impacts.

To estimate the long-run impact of sunset time on health outcomes, we use:

$$y_{ivwr} = \beta Sunset_{vr} + \delta X_{ir} + \gamma_d + \lambda_w + \mu_r + \epsilon_{ivwr} \tag{1}$$

Where, y_{ivwr} represents the health of individual i, living in PSU v, surveyed in the week-of-the-year w in survey wave $r \in \{2015, 2019\}$. $Sunset_{vr}$ is the average annual sunset time in PSU v in wave r, measured in 10 minute increments. Individual-level covariates, denoted by X_{ir}, include age groups, gender, age-gender interactions, caste, and religious affiliation. The interaction between age and gender allows for differential effects of age on health outcomes across genders. Caste and religion are included as they can influence lifestyle factors, such as dietary habits, which may affect long-term health. District fixed effects (γ_d) capture unobserved time invariant characteristics of the district of residence. We also include week-of-the-year fixed effects (λ_w) to account for seasonality and survey wave fixed effects (μ_r) to capture macro trends. ϵ_{ivwr} represents the random error term. Standard errors are clustered at the PSU level.

The parameter of interest, β, captures the causal effect of a later sunset time on health under the assumption that there are no omitted variables that are correlated with both

[11]Unlike previous studies, we do not use an instrumental variables approach since sunset time potentially affects health through multiple mechanisms in our setting as discussed above.

annual average sunset time and health outcomes. The inclusion of district fixed effects implies that identification relies on within-district variation in sunset time and health outcomes, which mainly reflects east-to-west differences across PSUs in the same district. Given that average annual sunset times exhibit minimal year-to-year variation, our estimates capture the long-term health impacts of residing in an area with a delayed sunset. To ensure that we are capturing long-term effects rather than transient effects from recent migration, we restrict our main analysis sample to individuals who have resided in the same region for at least 3 years.[12] Note that our approach does not isolate the effect of sunset time from sunrise time, as the two are strongly correlated (correlation coefficient = 0.99 in our sample). Following prior literature, we focus on sunset time rather than sunrise time as sleep schedules are more responsive to sunset time (Gibson & Shrader, 2018; Jagnani, 2024). However, we can distinguish these effects from average annual daylight duration, which is roughly constant across locations. Actual sunlight exposure may still vary across PSUs within a district due to behavioral responses to sunset time, such as time spent outdoors, a mechanism we explore below. To rule out potential bias due to sample selection or omitted variables correlated with both sunset time and health, we conduct a series of robustness checks. These include controlling for a broad set of individual and PSU-level characteristics, assessing sensitivity to alternative specifications and sample definitions, and testing for bias due to selective internal migration and district size. As an additional test of our identification assumption, we estimate a placebo regression using sexually transmitted illness as the dependent variable, as there is no physiological mechanism linking sunset time to such illnesses.

To evaluate the mechanisms by which sunset time may influence health, we adapt Equation 1 to TUS data, which are recorded daily but do not include geographic identifiers

[12] Less than 10% of the sample has lived in the current location for less than 3 years (see Appendix Table A5).

more granular than the district.

$$y_{idswt} = \theta Sunset_{dswt} + \delta X_{idswt} + \mu_w + \gamma_d + \epsilon_{idswt} \tag{2}$$

Where, y_{idswt} measures time allocation for individual i residing in district d on date of interview t during season s and week-of-the-year w. $Sunset_{dswt}$ measures the average sunset time in 10-minute intervals in district d on date of interview t during season s and week-of-the-year w. District fixed effects are denoted by γ_d and week-of-the-year fixed effects by μ_w. Covariates (X_{idswt}) are the same as in Equation 1 and include age groups, gender, interaction of age groups and gender, religion and caste of individuals. Standard errors are clustered at the district-week level. In alternative specifications, we include district-level weather controls, specifically temperature and precipitation. We also estimate specifications that include district-by-season fixed effects instead of district-fixed effects to capture district-specific seasonal trends.

For the outcomes in the PLFS data, we modify Equation 2 to capture variation at the monthly level:

$$y_{idmk} = \phi Sunset_{dmk} + \mu_{mk} + \gamma_d + \delta X_{idmk} + \epsilon_{idmk} \tag{3}$$

Where, y_{idmk} denotes work hours or earnings at the monthly level for individual i residing in district d in the interview month m and year k. Sunset time is measured at the month-year level for each district. The regression includes month-year fixed effects (μ_{mk}) and district-fixed effects (γ_d). Individual covariates, denoted by X_{idmk}, are the same as in the earlier models and include age groups, gender, interaction of age and gender, religion and caste. In contrast to the DHS analysis, which exploits within-district variation, Equations 2 and 3 rely on district-specific seasonal variation in sunset time and outcomes to identify causal effects.

4 Results

Table 4 presents the estimated long-term effects of later sunset times on health outcomes for the full sample, as well as separately for men and women. Among women (Panel a), a 10-minute delay in sunset time reduces the prevalence of diabetes by 0.7 percentage points, of anemia by 4.3 percentage points, and of thyroid disease by 0.4 percentage points. These represent relative declines of approximately 10% in diabetes, 8% in anemia, and 20% in thyroid disease prevalence. We do not find statistically significant effects on BMI, hypertension, or heart disease. Both the metabolic syndrome index and overall health index exhibit declines, although the estimate for the MSI is significant only at the 10% level. Among men (Panel b), a 10-minute delay in sunset time increases the prevalence of hypertension by 3.6 percentage points, and decreases the prevalence of anemia by 2.6 percentage points, with the latter effect significant at the 10% level. None of the other health outcomes, including the two composite indices, show statistically significant changes among men. For the full sample (Panel c), we find statistically significant improvements in diabetes, anemia, thyroid disease, and the overall health index. Other indicators, such as BMI and heart disease, are statistically insignificant. These findings differ from those documented in high-income settings. For example, Giuntella and Mazzonna (2019) find that employed individuals in the US living on the later sunset side of a time-zone border had a 21% higher likelihood of being obese, a 5% higher prevalence of diabetes, and a 19% higher incidence of heart attacks.

Appendix Figure A1 presents evidence on the robustness of our findings to several alternative specifications. First, we add an indicator for urban-rural residence to account for differences in factors such as lifestyle or access to outdoor spaces that may influence the relationship between sunset time and health. Second, we include latitude and a comprehensive set of PSU level variables capturing agricultural activity, weather conditions, and local economic activity. The full list of variables is detailed in Appendix Table A1. Including these controls helps rule out the possibility that unobserved differences in agricultural patterns or economic conditions are driving our results. Third, we estimate the regression using survey sampling weights. Fourth, we include individuals who were surveyed in March 2020 or later (post-COVID sample). Fifth, we add district-year fixed effects to account for unobserved district specific trends which may be correlated with sunset time and health. Sixth, we control for pollution and cloud cover, which reduce the amount of sunlight reaching the earth's surface and may be correlated with health. Controlling for these variables allows us to isolate the impact of sunlight exposure related to sunset time. We consistently find improvements in diabetes, anemia, thyroid disease, and the overall health index across these alternative specifications, although effects on diabetes are marginally significant in some cases.

In Figure A2, we examine the potential for bias due to selective migration. Our main analysis is based on a sample of individuals who have resided in the same region for at least 3 years. As a robustness check, we progressively restrict the sample to those residing in the same region for at least four, six, eight, or ten years. We continue to find significant improvements in diabetes, anemia, thyroid disease, and the overall health index, suggesting that our results are not driven by selective migration. Next, we examine whether our estimates are influenced by district size, given that variation in sunset time increases with the geographic size of the district, as shown in Figure 2. To address this concern, we apply k-means clustering to group smaller districts into clusters of comparable size (Balietti et al., 2022). This approach allows us to form clusters of approximately uniform size while preserving district boundaries. This ensures that the clusters remain representative of the underlying population, consistent with the design of the DHS, which is representative at the district level. Figure A3 presents the constructed clusters of 200 and 300 using Indian districts as examples, overlaid with state boundaries. Figure A4 presents estimates based on different numbers of clusters ranging from 200 to 450. Our main conclusion that a later sunset time improves health remains unchanged across varying cluster sizes, confirming that the results are driven by sunset time rather than district size. In addition to diabetes, anemia, and thyroid disease, we observe statistically significant improvements in BMI, heart disease, and MSI for some cluster sizes.

In Appendix Table A6, we present results from placebo regressions using outcomes related to sexually transmitted infections (STIs), as there is no known relationship between sunset time and the prevalence of STIs. We find no statistically significant effect of sunset time on indicators for having any STI in the last 12 months (Column 1), having a sore or genital ulcer in the last 12 months (Column 2), and having any bad smelling abnormal genital discharge in the last 12 months (Column 3). These variables are only available for selected households in the DHS. The lack of significant effects supports our identifying assumption, suggesting that the observed health impacts are driven by variation in sunset time rather than by unobserved confounders.

Finally, we use an alternative approach to statistical inference. While the health indices address concerns related to multiple hypothesis testing by aggregating outcomes, we also use the Benjamini-Hochberg procedure which applies a correction based on the false discovery rate (Benjamini & Hochberg, 1995). Table A7 reports the corresponding q-values, alongside the p-values from our baseline specification for reference. After the correction, the effect on anemia remains significant at the 5% level, the effect on thyroid disease is significant at the 10% level, and the effect on diabetes is no longer statistically significant.

Table 4: Effect of average sunset time on health outcomes

	BMI	Hypertension	Diabetes	Heart	Anemia	Thyroid	MSI	OHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a: Women								
Avg Sunset Time (in 10 Mins)	0.049	-0.001	-0.007**	-0.001	-0.043***	-0.004**	-0.013*	-0.028***
	(0.0730)	(0.0070)	(0.0034)	(0.0015)	(0.0086)	(0.0018)	(0.0080)	(0.0067)
Avg of Outcome Variable	21.98	0.27	0.07	0.01	0.54	0.02	0.02	0.01
Observations	924,371	924,461	944,889	939,487	918,817	938,258	916,714	906,871
R-squared	0.178	0.098	0.036	0.012	0.060	0.020	0.097	0.087
Panel b: Men								
Avg Sunset Time (in 10 Mins)	-0.072	0.036**	-0.008	-0.005	-0.026*	-0.003	0.003	-0.008
	(0.1460)	(0.0167)	(0.0092)	(0.0037)	(0.0151)	(0.0037)	(0.0186)	(0.0224)
Avg of Outcome Variable	22.04	0.35	0.10	0.01	0.17	0.01	-0.001	-0.01
Observations	154,930	155,110	161,128	160,282	153,968	98,306	153,780	94,631
R-squared	0.161	0.117	0.051	0.019	0.080	0.031	0.102	0.096
Panel c: All								
Avg Sunset Time (in 10 Mins)	0.033	0.005	-0.007**	-0.001	-0.039***	-0.004**	-0.011	-0.026***
	(0.0705)	(0.0069)	(0.0033)	(0.0014)	(0.0080)	(0.0017)	(0.0077)	(0.0065)
Avg of Outcome Variable	21.99	0.27	0.08	0.01	0.49	0.02	0.01	0.01
Observations	1,079,301	1,079,571	1,106,017	1,099,769	1,072,785	1,036,564	1,070,494	1,001,905
R-squared	0.174	0.103	0.039	0.011	0.121	0.020	0.098	0.085

Note: Except BMI and the two indices, all outcomes are binary indicators taking value 1 if they have the disease or 0 otherwise. To construct MHI for the combined sample, Z-score for anemia for the men sample is taken as 0. Robust standard errors in parentheses, clustered at PSU level. Sample is restricted to the pre-Covid period (before March 2020). For women sample, pregnant women and those who have given birth in last 2 months are excluded. Control Variables include: age groups, district fixed effects, week of the year fixed effects, caste, religion of the household, and DHS wave fixed effects. For panel c, age and gender interactions are also included as control variables. *** p<0.01, ** p<0.05, * p<0.1

4.1 Potential Mechanisms

In this section, we explore various potential mechanisms through which a delayed sunset may influence health. While previous studies on the impact of sunset time on adult health identify sleep as the primary mechanism, these findings may not apply to India, where the average sleep duration is approximately eight hours, and only 3 percent of the population reports sleeping less than six hours. Given this context, it is important to explore alternative mechanisms that may explain our findings. In addition to sleep, we examine time allocation to other activities, as well as dietary patterns, labor supply, income, and wealth. Note that these various mechanisms may interact with each other in complex ways. For example, sleep deprivation may increase the consumption of unhealthy food, thereby amplifying its impact on health. Similarly, income may affect health both directly and indirectly through changes in diet and other activities.

4.1.1 Sleep

Human sleep patterns or circadian rhythms respond to sunrise and sunset times and to the amount of sunlight exposure. When the sun sets later in the day, individuals tend to go to bed later but continue to wake up at the same time due to work or school schedules, leading to reduced sleep (Gibson & Shrader, 2018; Giuntella & Mazzonna, 2019). Insufficient sleep disrupts critical physiological processes involved in glucose metabolism and insulin sensitivity, impairing the body's ability to maintain metabolic health and leading to weight gain, obesity, and a heightened risk of type-2 diabetes (Knutson et al., 2007; Nedeltcheva & Scheer, 2014). In addition, disrupted sleep has been linked to an increased risk of thyroid dysfunction and chronic sleep deprivation is associated with a higher prevalence of anemia, through its impact on iron metabolism and the production of red blood cells (Kim et al., 2018).

Consistent with previous literature, we find that a later sunset time reduces sleep duration. Specifically, a 10-minute delay in sunset time reduces nighttime sleep by 4.64 minutes, which is only partially offset by an increase of 2.5 minutes in daytime naps (Table

5, Panel c, Columns 1 and 2). Individuals facing a 10-minute delay in sunset go to bed 3 minutes later and wake up 4 minutes earlier, leading to a reduction in overall sleep time (Columns 3 and 4). Although the delayed onset of sleep due to later sunset is consistent across different models, the earlier wake time is inconsistent, as seen in Appendix Table A8 and Appendix Figure A5. Thus, it is not the effect of earlier sunrise, but the effect of delayed sunset that we capture in our results.

Since the recommended amount of sleep for adults is 7-9 hours (Hirshkowitz et al., 2015), we also estimate a regression in which the dependent variable is a binary indicator for sleeping within this range. In our sample, both the average and median sleep durations are 8 hours, and approximately 24 percent of individuals report sleeping outside the recommended range — substantially lower than estimates for developed countries (Kocevska et al., 2021). We find that a 10-minute delay in sunset time increases the likelihood of sleeping 7-9 hours by 2 percentage points. Further analysis using the unconditional quantile regression method of Firpo et al. (2009) shows that the effect of sunset time on sleep duration is largest at the 75th percentile, followed by the 50th and 25th percentiles (Figure A6 in the Appendix). These results point to a leftward shift in the sleep distribution, with individuals exposed to delayed sunsets more likely to sleep the recommended amount, while those exposed to earlier sunsets more likely to oversleep.

The reduction in oversleeping may indicate an improvement in the quality of sleep, a critical component of health outcomes (Czeisler, 2015), which evidence suggests is often inadequate in India. Using actigraphy, Bessone et al. (2021) show that low-income adults in Chennai, despite reporting 8 hours spent in bed, experience up to 31 sleep disruptions and only achieve 5.5 hours of actual sleep.[13] To assess the impact on sleep quality, we examine the relationship between sunset time and self-reported minutes of sleeplessness in Column 6. In our sample, 4 percent of the people reported sleeplessness, averaging 3 minutes in

[13] Actigraphy is a non-invasive method of monitoring human rest or activity cycles using wearable devices.

duration. However, among those who reported sleeplessness, the average duration was 74 minutes. We find a weakly significant reduction of 0.17 minutes in sleeplessness due to a 10-minute delay in sunset time, with stronger effects among men (Column 6 in Table 5). These findings are robust to alternative specifications that control for weather, district-by-season fixed effects, proxy responses, sampling weights, and urban vs rural residence, as shown in Appendix Figure A7.

Table 5: Effect of Sunset time on sleep

	Sleep	Nap	Bedtime	Wake time	Sleep 7-9 hours	Sleepless
	(1)	(2)	(3)	(4)	(5)	(6)
Panel a: Women						
Sunset time (10 mins)	-5.16***	3.37***	0.04***	-0.05***	0.01***	-0.12
	(0.64)	(0.41)	(0.01)	(0.01)	(0.00)	(0.12)
R^2	0.11	0.15	0.18	0.07	0.04	0.08
Observations	96,198	96,198	96,198	96,198	96,198	96,198
Sample Mean	469.56	50.08	22.14	6.04	0.74	3.43
Panel b: Men						
Sunset time (10 mins)	-4.08***	1.56***	0.03***	-0.03**	0.02***	-0.22**
	(0.68)	(0.26)	(0.01)	(0.01)	(0.00)	(0.10)
R^2	0.08	0.10	0.16	0.06	0.04	0.05
Observations	95,281	95,281	95,281	95,281	95,281	95,281
Sample Mean	490.27	21.51	22.17	6.27	0.78	2.08
Panel c: All						
Sunset time (10 mins)	-4.64***	2.49***	0.03***	-0.04***	0.02***	-0.17*
	(0.76)	(0.44)	(0.01)	(0.01)	(0.00)	(0.10)
R^2	0.10	0.16	0.16	0.07	0.04	0.06
Observations	191,479	191,479	191,479	191,479	191,479	191,479
Sample Mean	479.87	35.87	22.16	6.16	0.76	2.76

Note: Controls include the individual's age group and gender, interaction of age group and gender, religion, caste, district fixed effects and week-of-year fixed effects. Sleep includes all activities related to sleep between 6 pm and 12 noon. Nap includes sleep-related activities between 12 noon and 6 pm. Column 5 represents the odds ratio of sleeping between 7-9 hours, and Column 6 represents the minutes of reported sleeplessness. Weights are not used in the estimation of time on normal weekdays. Standard errors clustered at the district-week level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.1.2 Sedentary and Non-sedentary Activities

Sunset times may change how individuals allocate time to activities such as exercise, outdoor leisure, or work. This can happen directly, for instance, if outdoor activities require daylight, or indirectly, if sleep loss leads to lower productivity or less motivation to exercise. Wolff and Makino (2013) find that individuals respond to increased daylight in the evening by increasing the time spent on outdoor activities while Jin and Ziebarth (2020) and Giuntella and Mazzonna (2019) find no effects of sunset time on exercise. Doleac and Sanders (2015) find that an increase in ambient light reduces crime, which may indirectly improve health by reducing stress and increasing outdoor activity.

Table 6 presents evidence on the impact of later sunset times on non-sedentary leisure activities. In contrast to Giuntella and Mazzonna (2019) and Jin and Ziebarth (2020), who show that physical activity does not respond to sunset time in the US, we find that a later sunset time significantly increases the time spent on non-sedentary leisure activities (sports and exercise). A 10-minute delay in sunset time increases time spent on sports and exercise by 0.32 minutes. The small effect size is likely driven by the low overall participation rate of six percent (Column 2). A 10-minute delay in sunset time increases the probability of participating in sports and exercise by 0.3 percentage points and, conditional on participation, it increases time spent on the activity by 2.1 minutes. Note that our measure of non-sedentary leisure activities is likely to be an underestimate of total physical activity since it does not capture activities such as walking or cycling to work. In India, over 51 percent of commuters walk or bike to work, which is much lower than the US rate of 3.5 percent.[14] To the extent that a later sunset shifts transportation modes from motorized vehicles (e.g., auto-rickshaws or buses) to walking or cycling, our analysis may underestimate the true effect on physical

[14] The estimate for India is based on the authors' calculation using data from the 2011 Census of India, available at https://censusindia.gov.in/nada/index.php/catalog/13954. The estimate for the US is obtained from the US Bureau of Transportation Services, available at https://www.bts.gov/archive/publications/transportation_statistics_annual_report/2013/table3_2.

activity. Although we lack data on individuals' mode of transportation, we explore this possibility by examining the impact of delayed sunsets on commuting time. We do not find significant changes using our baseline specification (Table A9 in the Appendix), but conditional on weather, we find that a 10-minute delay in sunset time increases commuting time by 0.6 minutes. This could indicate a longer commute to work, which would not apply to those with fixed work locations, or a change in the mode of transport. Our analysis also does not capture time spent on work-related physical activity, which may respond to sunset times. For example, individuals in physically demanding outdoor occupations, such as construction, may work longer hours on days with later sunsets. We explore the effects on hours worked in Section 4.1.4, but we cannot accurately distinguish between physically demanding and sedentary occupations[15].

We find that a later sunset significantly reduces time spent on housework among men, with no corresponding changes in sedentary leisure or other activities (Table 7). For women, there are no statistically significant effects on any of these activities. We also examine watching TV separately, as it has been linked to bedtime and sleep duration (Hamermesh et al., 2008) and long-term health (Hancox et al., 2004), but find no meaningful changes.

[15] Although we do not have precise measures of job physical intensity, we examine industries that are typically associated with physical labor. Specifically, we find that individuals employed in Agriculture, Forestry, Fishing and Construction spend significantly more time on their jobs when faced with delayed sunset times (Table A10 in the Appendix)

Table 6: Time spent on sports and exercise and odds of participation

	Participation (Coefficients)	Minutes Unconditional	Minutes Conditional
	(1)	(2)	(3)
Panel a: Women			
Sunset time (10 mins)	0.003***	0.26***	1.04
	(0.001)	(0.06)	(1.12)
R^2	0.05	0.04	0.37
Observations	96,198	96,198	2,717
Sample Mean	1.59	0.03	56.13
Panel b: Men			
Sunset time (10 mins)	0.002	0.36**	2.03***
	(0.002)	(0.14)	(0.74)
R^2	0.07	0.05	0.23
Observations	95,281	95,281	8,459
Sample Mean	5.58	0.09	62.88
Panel c: All			
Sunset time (10 mins)	0.003**	0.32***	2.10**
	(0.001)	(0.09)	(0.83)
R^2	0.06	0.05	0.21
Observations	191,479	191,479	11,176
Sample Mean	3.57	0.06	61.24

Note: Controls include the individual's age group and gender, interaction of age group and gender, religion, caste, district fixed effects and week-of-year fixed effects. Column 1 represents the coefficients from LPM, denoting minutes spent on sports and exercise. Column 3 denotes minutes spent, conditional on spending positive time on sports and exercise. Weights are not used in the estimation of time on normal weekdays. Standard errors clustered at the district-week level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Effect of sunset on time spent on sedentary leisure, housework and other activities

	Sedentary leisure	Housework	Others
	(1)	(2)	(3)
Panel a: Women			
Sunset time (10 mins)	-0.62	0.07	0.72
	(0.88)	(0.99)	(1.04)
R^2	0.12	0.19	0.20
Observations	96,198	96,198	2,717
Sample Mean	236.72	342.63	174.47
Panel b: Men			
Sunset time (10 mins)	0.15	-0.69**	0.88
	(0.93)	(0.33)	(1.06)
R^2	0.11	0.08	0.22
Observations	95,281	95,281	8,459
Sample Mean	234.07	37.24	227.84
Panel c: All			
Sunset time (10 mins)	-0.23	-0.29	0.82
	(0.77)	(0.56)	(0.87)
R^2	0.09	0.60	0.22
Observations	191,479	191,479	11,176
Sample Mean	235.40	190.67	201.03

Note: Controls include the individual's age group and gender, interaction of age group and gender, religion, caste, district fixed effects and week-of-year fixed effects. Standard errors clustered at the district-week level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.1.3 Dietary Patterns

Sleep deprivation also alters the balance of appetite-regulating hormones, elevating ghrelin levels (which stimulates hunger) and reducing leptin levels (which signals fullness), which can lead to increased food intake, cravings for high-calorie foods, and subsequent weight gain (Knutson et al., 2007). In the Indian context, where dietary patterns are already imbalanced, with excessive consumption of whole grains and insufficient intake of fruits, vegetables, legumes, and proteins (Sharma et al., 2020), health effects may be magnified.

Table 8: Time spent on meals and dinner

	All Meals	Dinner			Gap dinner
	Duration	Start	End	Duration	Sleep
	(1)	(2)	(3)	(4)	(5)
Panel a: Women					
Sunset time (10 mins)	0.21	0.11***	0.11***	0.09	-0.96***
	(0.29)	(0.01)	(0.01)	(0.16)	(0.29)
Observations	96,198	93,119	93,119	93,119	91,532
R^2	0.15	0.42	0.43	0.12	0.32
Sample Mean	94.29	20.16	21.03	38.95	46.81
Panel b: Men					
Sunset time (10 mins)	0.21	0.09***	0.09***	-0.12	-0.65**
	(0.34)	(0.01)	(0.01)	(0.18)	(0.30)
Observations	95,281	93,436	93,436	93,436	91,550
R^2	0.16	0.40	0.40	0.19	0.29
Sample Mean	102.38	20.13	21.02	39.96	45.63
Panel c: All					
Sunset time (10 mins)	0.22	0.10***	0.10***	-0.01	-0.82***
	(0.28)	(0.01)	(0.01)	(0.26)	(0.16)
Observations	191,479	186,555	186,555	186,555	183,082
R^2	0.15	0.40	0.41	0.11	0.31
Sample Mean	98.32	20.16	21.02	39.45	46.21

Note: Controls include the individual's age group and gender, interaction of age group and gender, religion, caste, district fixed effects and week-of-year fixed effects. Column 1 represents the minutes spent on eating and drinking throughout the day. Column 2 represents the frequency of slots in which the individual reported consuming meals or snacks. Weights are not used in the estimation of time on normal weekdays. Dinner is defined as the last meal of the day that starts and ends between 4 pm and midnight. The fall in observation is caused by individuals who do not adhere to this definition or the definition of sleep, and hence are not considered in the estimation. Standard errors clustered at the district-week level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

To assess whether changes in dietary patterns could explain the estimated health effects, we use TUS data to analyze time spent on eating and drinking, and DHS data to examine daily consumption of various food groups. Table 8 shows that while dinner time is delayed in response to a later sunset, there is no significant change in the overall time spent eating and drinking. We also find that the interval between dinner and bedtime decreases by 0.82 minutes for every 10-minute delay in sunset time. Although this change is likely too small to meaningfully disrupt circadian rhythms (Boege et al., 2021), we cannot rule out the possibility that a shorter gap between dinner and sleep negatively affects health.

Table 9 presents the results on daily consumption of various food groups using DHS data. Note that while the TUS estimates capture daily changes in dietary patterns, the analysis using DHS data captures long-term effects on diet. Among women, we find that a 10-minute delay in sunset time reduces the likelihood of daily consumption of unhealthy food by 2 percentage points, which translates to a 14% reduction in the daily consumption of unhealthy food items. This effect is statistically significant at the 5 percent level. Reduced consumption of fried foods and sweetened beverages is associated with a lower risk of type-2 diabetes (Gadiraju et al., 2015; Hirahatake et al., 2019; Qin et al., 2021), anemia (Paramastri et al., 2021), and thyroid disorders (Neto et al., 2024), particularly among women. There is a corresponding increase in the consumption of proteins, greens & dairy, and in diet diversity among women, but none of these estimates are statistically significant. We do not find any significant changes in food consumption among men. For the full sample, a 10-minute delay in sunset time reduces daily consumption of unhealthy food items by 1.3 percentage points, which is significant at the 10% level.

4.1.4 Labor Supply, Earnings, and Wealth

Given prior evidence linking sunset times to educational outcomes, labor productivity, and earnings (Gibson & Shrader, 2018; Heissel & Norris, 2018; Jagnani, 2024), we next examine whether income effects could be a potential mechanism through which sunset time influences long-term health. We use data from all three surveys for this analysis. The DHS includes information on employment status and captures long-term effects on labor supply. The TUS includes information on time spent on work and captures short-term (daily) effects on labor supply. The PLFS includes information on work hours across different employment categories and captures medium term (monthly) effects on labor supply. Neither the DHS nor the TUS include information on income or earnings. However, the DHS has information on wealth, and the PLFS has information on earnings.

Table 9: Effect of average sunset time on daily dietary patterns

	Unhealthy Food	Protein	Greens and Dairy	Diet Diversity
	(1)	(2)	(3)	(4)
Panel a: Women				
Average Sunset Time (in 10 Mins)	-0.020**	0.012	0.004	0.035
	(0.0079)	(0.0121)	(0.0109)	(0.0299)
Average of Outcome Variable	0.14	0.49	0.71	1.58
Observations	945,072	945,072	945,072	945,072
R-squared	0.276	0.183	0.108	0.164
Panel b: Men				
Average Sunset Time (in 10 Mins)	0.025	0.015	-0.039	-0.018
	(0.0205)	(0.0291)	(0.0256)	(0.0723)
Average of Outcome Variable	0.16	0.49	0.71	1.59
Observations	161,160	161,160	161,160	161,160
R-squared	0.209	0.177	0.116	0.176
Panel c: All				
Average Sunset Time (in 10 Mins)	-0.013*	0.012	-0.002	0.033
	(0.0076)	(0.0116)	(0.0104)	(0.0288)
Average of Outcome Variable	0.14	0.49	0.71	1.59
Observations	1,106,232	1,106,232	1,106,232	1,106,232
R-squared	0.258	0.175	0.104	0.159

Note: All variables, except diet diversity, are binary indicators taking value 1 if the individual consumes that food category daily, and 0 otherwise. Diet diversity is a categorical variable ranging from 0 to 7, with 7 being highly diverse diet. Robust standard errors in parentheses, clustered at PSU level. Sample is restricted to the pre-Covid period (before March 2020). For the sample of women, pregnant women and those who have given birth in last 2 months are excluded. Control variables include: age groups, gender, age and gender interactions, district fixed effects, week of the year fixed effects, caste, religion of the household, and DHS wave fixed effects. For panel c, age and gender interactions are also included as control variables. *** p<0.01, ** p<0.05, * p<0.1

First, using DHS data, we show that residing in a region with a later sunset time increases the likelihood of having worked in the past year or being currently employed (Table 10). A 10-minute delay in average annual sunset time is associated with a 3 percentage point increase in the probability of currently working and a 3.1 percentage point of having worked in the past 12 months (Panel c). These effects are stronger among women, who have lower baseline levels of employment than men. We do not find significant increases in the likelihood of being in the top two wealth quintiles (labeled "Rich"), but there is a significant increase of 0.08 units in the wealth index. Next, we use TUS data to assess how a delayed sunset influences daily time spent on work (Table 11). We do not observe a significant change in total work time (Column 1), however, conditional on engaging in paid work, a 10-minute delay in sunset time increases the time spent on paid work by roughly 4 minutes (Column 2). Finally, using PLFS data, we find significant increases in monthly hours worked among self-employed men and daily wage earners, but not among salaried men (Panel b, Table 12). We also find that the monthly earnings of male daily wage workers increase by 51 rupees or 0.5 percent in response to a 10-minute delay in sunset time. Other than a significant decrease in monthly earnings among self-employed women, most estimates for women are not statistically significant, likely reflecting the smaller sample size.

Overall, the evidence suggests that delayed sunsets increase labor supply along both the intensive and extensive margins, and these changes translate to higher earnings and higher wealth in the long term, which may facilitate better access to healthcare, improved nutrition, and healthier living conditions (Prinja et al., 2017; Sharma et al., 2020). There is suggestive evidence of larger long term impacts on women's employment and larger medium term impacts on the work hours of daily wage earners, though these patterns may reflect limited statistical power rather than true heterogeneity. Our findings on employment and earnings contrast with evidence from the US, where a later sunset time reduces sleep duration and lowers earnings (Gibson & Shrader, 2018), but are consistent with evidence from India showing that increased sleep reduces labor supply among the urban poor (Bessone et al., 2021).

Table 10: Effect of annual average sunset time on wealth and employment: DHS

	Rich	Wealth	Working	Employed
	(1)	(2)	(3)	(4)
Panel a: Women				
Average Sunset Time (in 10 Mins)	0.018	0.079**	0.031*	0.046**
	(0.0130)	(0.0378)	(0.0188)	(0.0209)
Average of Outcome Variable	0.37	2.92	0.26	0.33
Observations	945,072	945,072	154,497	154,497
R-squared	0.263	0.364	0.092	0.115
Panel b: Men				
Average Sunset Time (in 10 Mins)	0.039	0.071	0.026*	0.012
	(0.0258)	(0.0724)	(0.0152)	(0.0120)
Average of Outcome Variable	0.39	3.01	0.75	0.81
Observations	161,160	161,160	161,159	161,158
R-squared	0.256	0.356	0.250	0.291
Panel c: All				
Average Sunset Time (in 10 Mins)	0.022	0.079**	0.030**	0.031**
	(0.0134)	(0.0387)	(0.0125)	(0.0124)
Average of Outcome Variable	0.37	2.94	0.51	0.58
Observations	1,106,232	1,106,232	315,656	315,655
R-squared	0.261	0.362	0.353	0.362

Note: Except wealth, all outcomes are binary indicators taking value 1 or 0. Robust standard errors in parentheses, clustered at PSU level. Sample is restricted to the pre-Covid period (before March 2020). Working is a binary indicator taking value 1 if the individual has worked in the past 7 days and 0 otherwise. Employed is a binary indicator taking value 1 if the individual has worked in the past 12 months and 0 otherwise. For women sample, pregnant women and those who have given birth in last 2 months are excluded. Control variables include: age groups, gender, age and gender interactions, district fixed effects, week of the year fixed effects, caste, religion of the household, and DHS wave fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Effect of sunset time on minutes spent on paid work on the day: TUS

	Unconditional Minutes	Conditional Minutes
	(1)	(2)
Panel a: Women		
Daily Sunset time (10 mins)	1.16	3.75**
	(0.86)	(1.69)
Sample mean	70.65	335.90
Observation	96,198	20,235
R-squared	0.12	0.16
Panel b: Men		
Daily Sunset time (10 mins)	1.60	2.62**
	(1.24)	(1.08)
Average	321.10	449.78
Observation	95,281	68,024
R-squared	0.26	0.16
Panel c: All		
Daily Sunset time (10 mins)	1.30	2.86***
	(0.81)	(1.01)
Average	195.28	423.66
Observation	191,479	88,259
R-squared	0.42	0.21

Note: Controls not shown in the table include the individual's age group and gender, the interaction of age group and gender, religion and caste. Standard errors clustered at the district-week level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Effect of monthly average sunset time on total monthly hours worked and earnings: PLFS

	Monthly Hours				Monthly Earnings (in Rupees)			
	All	Salaried	Self-emp	Daily	All	Salaried	Self-emp	Daily
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a: Women								
Average Sunset time (in 10 mins)	0.23	0.13	-0.15	0.84	12.82	107.01	-65.30**	2.96
	(0.32)	(0.41)	(0.45)	(0.80)	(47.78)	(117.07)	(30.56)	(31.62)
Average of outcome variable	163.96	188.83	149.62	160.94	6276.47	13082.60	2644.095	4144.48
Observations	76,724	24,899	39,307	12,158	76,724	24,899	39,307	12,158
R-squared	0.25	0.21	0.29	0.28	0.26	0.12	0.19	0.34
Panel b: Men								
Average Sunset time (in 10 mins)	0.54**	0.48	0.78**	0.79**	61.26	46.69	92.73	50.87**
	(0.23)	(0.30)	(0.34)	(0.36)	(38.96)	(67.87)	(64.10)	(21.76)
Average of outcome variable	205.12	219.13	204.58	183.02	11343.12	16251.86	9721.10	7087.40
Observations	244,092	79,896	116,408	47,788	244,092	79,896	116,408	47,788
R-squared	0.18	0.20	0.18	0.23	0.21	0.17	0.17	0.36
Panel c: All								
Average Sunset time (in 10 mins)	0.40*	0.32	0.46	0.76**	42.29	52.55	38.58	34.34*
	(0.22)	(0.27)	(0.31)	(0.35)	(36.25)	(67.18)	(47.12)	(19.16)
Average of outcome variable	195.27	211.92	190.58	178.43	10,131.42	15,498.86	7934.66	6476.52
Observations	320,816	104,795	155,715	60,306	320,816	104,795	155,715	60,306
R-squared	0.24	0.22	0.28	0.25	0.24	0.15	0.23	0.42

Note: Control variables not shown in the table include age group, gender, interaction of age group and gender, caste and religion, district, month-year fixed effects. The standard errors are clustered at the district-month level. The table is based on individuals aged 15-49 years who reported working as salaried employees, or being self-employed or daily wage workers in the week of the survey. It also includes those who identified themselves in either of the three categories but could not work due to sickness or other reasons. The category "All" includes dummies to represent salaried employees, self-employed individuals and daily wage earners. Sample weights are not used. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Additional Mechanisms and Heterogeneous Effects

In addition to the mechanisms described above, delayed sunsets may increase sunlight exposure, which can improve health through its effect on sleep quality, mood, and vitamin D synthesis (Anderson et al., 2025; Aparna et al., 2018; Tanaka & Matsubayashi, 2025). This pathway may be particularly important in the Indian context, given the low quality of sleep and high rates of vitamin D deficiency.[16] Although we do not directly observe sunlight exposure, we explore this pathway using time spent outdoors in the TUS data (Appendix Figure A8). While our baseline specification shows no significant change, we find that, conditional on weather controls for temperature and precipitation, a delayed sunset significantly increases time spent on outdoor activities between 7 am and 7 pm by 1% relative to the average time spent outside. Moreover, the increase is seen between 10 am and 4 pm, when vitamin D synthesis from sunlight is highest (Harinarayan et al., 2013), and between 4 pm and 7 pm, when sunlight can still contribute to vitamin D synthesis (Marwaha et al., 2016). Further, the increase in outdoor time is stronger among women, as seen in Table A11, consistent with the patterns observed for health outcomes.

Next, we examine heterogeneity by urban-rural residence, education, age, and dietary practices (vegetarian vs. non-vegetarian). These results should be interpreted as descriptive, as some subgroup classifications are based on potentially endogenous variables. Appendix Figure A9 presents the heterogeneity results for health outcomes. Appendix Figures A10, A11, present heterogeneity results for diet, employment and wealth, respectively. For most health outcomes, we do not observe consistent differences between subgroups (Appendix Figure A9). In general, the confidence intervals are wide and overlap, suggesting that the estimated effects are not statistically distinguishable from one another.

One notable pattern is that a later sunset time significantly increases BMI and heart

[16] Estimates of the prevalence of vitamin D deficiency in India range from 50% to 94%, which may be due to factors such as sociocultural norms regarding clothing and limited availability of fortified foods (Aparna et al., 2018).

disease among vegetarians, defined as individuals who have never consumed chicken, fish, or eggs. In contrast, among non-vegetarians, a later sunset significantly decreases diabetes. For hypertension, we find a positive effect among non-vegetarians and a negative effect among vegetarians, but neither estimate is statistically significant. Overall, a later sunset seems to worsen metabolic health among vegetarians while improving it for non-vegetarians, with the exception of hypertension. In addition, we find that later sunset times are associated with a shift away from unhealthy food towards protein-rich foods among non-vegetarians. Among vegetarians, the diet shifts away from unhealthy foods and protein towards greens and dairy. A later sunset time also increases household wealth and the probability of working in the past year among non-vegetarians, but not among vegetarians. This evidence is consistent with vegetarians having more limited options for protein-rich foods, which may compromise nutritional adequacy and increase the risk of metabolic diseases, potentially also reducing labor productivity or compounding the impact of reduced wealth.[17]

Appendix Figure A12 illustrates how sunset time differentially affects time allocated to various activities. The increase in the likelihood of sleeping 7–9 hours is larger among rural and low-income individuals compared to their urban and wealthier counterparts (Panel b).[18] We also find that later sunsets significantly increase both conditional and unconditional time spent on paid work among rural residents. In contrast, the estimates for urban residents are not statistically significant, and the unconditional estimates are negative in sign (Panels e and f).

[17]We do not explore heterogeneity between vegetarians and non-vegetarians in time allocation as information on diet type is not available in the TUS.

[18]Individuals with monthly household consumption expenditure in the bottom three quintiles are classified as poor, while those in the top two quintiles are classified as rich in the TUS.

5 Conclusion

Our study provides novel evidence on the long-term impacts of sunset time on health in India. In contrast to evidence from high-income countries, where later sunsets have been shown to adversely affect health outcomes by reducing sleep duration, we find that delayed sunsets lead to improvements in health. Specifically, a 10-minute delay in sunset time reduces the prevalence of diabetes by 0.7 percentage points, of anemia by 3.9 percentage points, and of thyroid disease by 0.4 percentage points. We also find suggestive evidence that these health improvements may be driven by multiple channels, including but not limited to sleep. Although delayed sunsets reduce total sleep duration, the average individual in our sample sleeps 8 hours, and we observe an increase in the likelihood of sleeping the recommended 7–9 hours. This suggests a reduction in oversleeping. Combined with evidence of reduced self-reported sleeplessness, this points to potential improvements in sleep quality. In addition, individuals spend more time outdoors and on physical activity, and consume fewer fried foods and sweetened beverages when the sun sets later in the day. We also find evidence of an income channel, reflected in increased employment, hours worked, and earnings. With the exception of shorter sleep duration, which may negatively affect health, all of these changes represent plausible mechanisms through which later sunset times may improve health. On balance, the positive pathways appear to outweigh any potential negative effects of reduced sleep duration.

We find that the health effects are generally stronger among women, suggesting potential gender differences in responses to sunset time. However, these differences should be interpreted with caution given the smaller sample size for men. There is some indication that mechanisms differ by gender: the reduction in unhealthy food consumption is concentrated among women while the decline in sleeplessness is more pronounced among men. Although both men and women experience gains in physical activity, the benefits may be greater for women, given their lower baseline rates of participation — potentially contributing to the stronger health improvements observed among women. The DHS and TUS samples show larger increases in labor supply among women, likely reflecting their lower rates of labor force participation compared to men. We also find that the employment impacts of later sunsets are larger among rural residents and among daily wage earners and self-employed individuals, consistent with greater responsiveness among those with more flexible or informal work schedules.

In conclusion, our results suggest that later sunsets lead to healthier behaviors and higher income among Indian populations, potentially contributing to better health outcomes in the long run. Our study highlights the importance of studying diverse contexts to understand how environmental factors influence health outcomes.

Declaration of generative AI and AI-assisted technologies in scientific writing

During the preparation of this work, the authors used ChatGPT in order to improve the manuscript's readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix: Additional Tables and Figures

Table A1: Explanation of variables used in computing PSU Indices

Variable Name	Variable Description
Agriculture Index	
Vegetation index	The average vegetation index value at the PSU at the time of measurement (year). This data is computed from atmospherically corrected bidirectional surface reflectance data that have been masked for water, clouds, heavy aerosols, and cloud shadows.
Growing season length	Number of days (categorized) within the period of temperatures above 5°C when moisture conditions are considered adequate for crop growth
Irrigation	Proportion of area equipped for irrigation
Livestock	The average density of livestock at the PSU location.
Weather Index	
Precipitation	The average monthly precipitation measured at the PSU in a given year. This dataset was produced by taking the average of the twelve monthly datasets.
Aridity	It is defined as the average monthly precipitation divided by average monthly potential evapotranspiration to measure drought.
Drought episodes	Number of drought episodes, where drought events are identified when the magnitude of a monthly precipitation deficit is less than or equal to 50 percent of its long-term median value for three or more consecutive months.
Maximum temperature	The average maximum temperature at the PSU in a year. The maximum temperature is calculated from the model mean temperature and the model diurnal temperature range.
Minimum temperature	The average minimum temperature at the PSU in a year. The minimum temperature is calculated from the model mean temperature and the model diurnal temperature range
Average temperature	The average temperature at the PSU in a year. The mean temperature is a model surface based on weather station data.
Rainfall	The average annual rainfall at the PSU.
Number of wet days	Number of days (per month) receiving more than or equal to 0.1 mm precipitation

Note: The information is taken from The DHS Program Geospatial Covariate Datasets Manual (Third Edition), 2015.

Table A1: Explanation of variables used in computing PSU Indices (Contd.)

Variable Name	Variable Description
Economic Index	
Population	The count of individuals living in the 5 x 5 kilometer pixel in which the PSU is located at the time of measurement (year)
Global human footprint	Global human footprint index is created from nine global data layers covering human population pressure (population density), human land use and infrastructure (built-up areas, nighttime lights, land use/land cover), and human access (coastlines, roads, railroads, navigable rivers).
Composite nightlights	The average nighttime luminosity of the area at the PSU.
Elevation	Average land elevation through near-global Digital Elevation Models, in meters
Travel time to nearest urban centre	The average time (minutes) required to reach a high-density urban centre.

Note: The information is taken from The DHS Program Geospatial Covariate Datasets Manual (Third Edition), 2015.

Table A2: Comparing Samples

Variables	Analysis Sample	+ Stayed less than 3 years	+ Pregnant women
Health Outcomes			
BMI	21.99 (4.20)	21.96 (4.19)	21.96 (4.17)
Hypertension	0.27 (0.45)	0.27 (0.45)	0.27 (0.44)
Diabetes	0.08 (0.27)	0.07 (0.26)	0.07 (0.26)
Heart	0.01 (0.11)	0.01 (0.11)	0.01 (0.11)
Anemia	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)
Thyroid	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)
Metabolic Syndrome Index	0.01 (0.57)	0.01 (0.57)	0.00 (0.56)
Overall Health Index	0.01 (0.46)	0.01 (0.45)	0.00 (0.45)
Dietary Outcomes			
Unhealthy Food	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)
Protein	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)
Greens and Dairy	0.71 (0.45)	0.71 (0.45)	0.71 (0.45)
Diet Diversity	1.59 (1.22)	1.59 (1.22)	1.59 (1.22)
Wealth and Employment			
Rich	0.37 (0.48)	0.38 (0.49)	0.38 (0.49)
Wealth	2.94 (1.37)	2.96 (1.37)	2.95 (1.37)
Currently Working	0.51 (0.50)	0.50 (0.50)	0.49 (0.50)
Worked in last 1 year	0.58 (0.49)	0.56 (0.49)	0.55 (0.49)
Age Group			
15 to 25	0.34 (0.48)	0.36 (0.48)	0.38 (0.49)
26 to 35	0.30 (0.46)	0.30 (0.46)	0.30 (0.46)
36 to 45	0.26 (0.44)	0.25 (0.43)	0.24 (0.43)
46 and above	0.10 (0.29)	0.09 (0.29)	0.08 (0.28)
Religion			
Hindu	0.74 (0.44)	0.74 (0.44)	0.74 (0.44)
Muslim	0.14 (0.34)	0.14 (0.34)	0.14 (0.35)
Christian	0.08 (0.27)	0.08 (0.27)	0.08 (0.27)
Others	0.05 (0.21)	0.05 (0.21)	0.05 (0.21)
Caste			
SC	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)
ST	0.19 (0.40)	0.19 (0.40)	0.19 (0.40)
OBC	0.40 (0.49)	0.40 (0.49)	0.40 (0.49)
General	0.21 (0.41)	0.21 (0.41)	0.21 (0.41)
Share of Whole Sample	0.86	0.95	1.00
Observations	1,173,814	1,303,052	1,372,953

Note: Variable explanation is same as before. Sample is restricted to the pre-Covid period (before March 2020). There is variation in the observations for different health outcomes. Source: India DHS waves 2015-16 and 2019-21.

Table A3: Comparing DHS and TUS Sample

Variables	DHS Sample			TUS Sample		
	Female	Male	All	Female	Male	All
Age Group						
15 to 25	0.34 (0.48)	0.34 (0.47)	0.34 (0.48)	0.35 (0.48)	0.34 (0.47)	0.34 (0.47)
26 to 35	0.30 (0.46)	0.28 (0.47)	0.30 (0.46)	0.34 (0.47)	0.34 (0.47)	0.34 (0.47)
36 to 45	0.27 (0.44)	0.23 (0.42)	0.26 (0.44)	0.26 (0.48)	0.26 (0.44)	0.26 (0.44)
46 and above	0.09 (0.28)	0.15 (0.36)	0.10 (0.29)	0.07 (0.25)	0.06 (0.24)	0.06 (0.24)
Religion						
Hindu	0.73 (0.44)	0.74 (0.44)	0.74 (0.44)	0.77 (0.42)	0.78 (0.42)	0.78 (0.42)
Muslim	0.14 (0.35)	0.14 (0.35)	0.14 (0.34)	0.13 (0.34)	0.13 (0.33)	0.13 (0.33)
Christian	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)	0.06 (0.23)	0.06 (0.23)	0.06 (0.23)
Others	0.05 (0.21)	0.05 (0.21)	0.05 (0.21)	0.04 (0.20)	0.04 (0.20)	0.04 (0.20)
Caste						
SC	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)	0.18 (0.38)	0.18 (0.38)	0.18 (0.38)
ST	0.20 (0.39)	0.19 (0.39)	0.19 (0.40)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)
OBC	0.40 (0.49)	0.41 (0.49)	0.40 (0.49)	0.40 (0.49)	0.40 (0.49)	0.40 (0.49)
General	0.21 (0.41)	0.21 (0.41)	0.21 (0.41)	0.28 (0.45)	0.29 (0.45)	0.28 (0.45)
Observations	1,002,462	171,352	1,173,814	96,198	95,281	191,479

Note: All variables are binary indicators taking values 1 or 0. Sample is restricted to the pre-Covid period (before March 2020) and those who have stayed in the current location for at least three years. For the sample of women, pregnant women and those who have given birth in the last 2 months are excluded. There is variation in the observations for different control variables. Source: India DHS waves 2015-16 and 2019-21.

Table A4: Minutes spent on work and paid work by employment status

	Work	Paid Work
Employed: all	450	380
Employed: regular salaried/wage	505	456
Employed: others	428	350
Unemployed	34	11
Total	242	195

Note: Calculated using TUS data for adults aged 15-49 years. Unemployed includes individuals who are currently not working but seeking or available for work and those who are not in the labor force.

Table A5: Share of individuals based on their stay in current residence

	Less than 3 years	More than 3 years	Lifetime	Visitors	Observations
	(1)	(2)	(3)	(4)	(5)
Women	9.22	67.90	21.43	1.45	1,122,199
Men	4.52	26.78	67.97	0.73	180,853
Total	8.57	62.19	27.89	1.35	1,303,052

Note: For the analysis, we have used individuals in Columns (2) and (3). Sample is restricted to the pre-Covid period (before March 2020). For the sample of women, pregnant women and those who have given birth in last 2 months are excluded. Source: India DHS waves 2015-16 and 2019-21.

Table A6: Effect of average sunset time on sexually transmitted infections

	STI	Genital Sore	Genital Discharge
	(1)	(2)	(3)
Panel a: Women			
Avg Sunset Time (in 10 Mins)	-0.005	-0.002	-0.001
	(0.006)	(0.006)	(0.010)
Avg of Outcome Variable	0.03	0.03	0.08
Observations	154,378	153,252	153,213
R-squared	0.032	0.020	0.045
Panel b: Men			
Avg Sunset Time (in 10 Mins)	-0.004	0.0001	0.002
	(0.004)	(0.007)	(0.008)
Avg of Outcome Variable	0.01	0.03	0.04
Observations	161,115	160,802	160,647
R-squared	0.025	0.026	0.039
Panel c: All			
Avg Sunset Time (in 10 Mins)	-0.005	-0.001	-0.001
	(0.004)	(0.005)	(0.007)
Avg of Outcome Variable	0.02	0.03	0.06
Observations	315,493	314,054	313,860
R-squared	0.024	0.016	0.037

Note: All outcomes are binary indicators taking value 1 if they have the infection or 0 otherwise. Robust standard errors in parentheses, clustered at PSU level. Sample is restricted to the pre-Covid period (before March 2020). For women sample, pregnant women and those who have given birth in last 2 months are excluded. Control Variables include: age groups, district fixed effects, week of the year fixed effects, caste, religion of the household, and DHS wave fixed effects. For panel c, age and gender interactions are also included as control variables. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7: Multiple Hypothesis Correction, Using Benjamini-Hochberg Criterion

Outcomes	p-value (1)	q-value (2)
Health Outcomes		
BMI	0.64	0.64
Hypertension Combined	0.46	0.64
Diabetes Combined	0.03	0.12
Heart	0.54	0.64
Anemia	0.00	0.00
Thyroid	0.02	0.10
Wealth and Employment Outcomes		
Rich	0.10	0.10
Wealth	0.04	0.08
Currently Working	0.01	0.03
Worked in Last Year	0.01	0.03
Dietary Outcomes		
Unhealthy Food	0.08	0.32
Veggies and Dairy	0.86	0.86
Protein	0.30	0.60
Diet Diversity	0.25	0.60

Note: In Column (1), we present the p-values using baseline regression. Column (2) presents the q-values using Benjamini-Hochberg criterion. For every panel, the p-values of only the variables in the panel are used to calculate the q-values.

Table A8: The effect of delay in sunset time on wake time

	Panel A	Panel B	Panel C	Panel D
Sunset time (in 10 mins)	-0.05***	-0.04***	-0.02	-0.02
	(0.01)	(0.02)	(0.02)	(0.02)
District FE	Yes	Yes	No	No
Week of the year FE	Yes	Yes	Yes	Yes
Weather controls	No	Yes	No	Yes
District by season FE	No	No	Yes	Yes
Mean	2.76	2.76	2.76	2.76
Observations	191,479	191,479	191,479	191,479
R-squared	0.07	0.07	0.10	0.10

Note: Robust standard errors clustered at the district-week level are in parentheses following the baseline specification. The columns represent Panels, where Panel A is based on the baseline specification in Eq 2 and Panels B-D test for robustness using alternate specifications and weather controls. All the models control for age group, gender, their interaction, religion and caste. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Effect of delay in sunset time on commuting time to work

	Controlling for temperature and precipitation									
	All	Rural	Urban	Rich	Poor	Less Edu	More Edu	Man	Woman	Baseline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sunset (10 mins)	0.60***	0.53*	0.97***	0.62**	0.57**	0.97***	0.38	0.85**	0.32**	0.15
	(0.23)	(0.28)	(0.36)	(0.30)	(0.29)	(0.27)	(0.28)	(0.38)	(0.15)	(0.20)
Constant	-66.87***	-56.16*	-99.69**	-67.93**	-60.59*	-102.86***	-43.36	-109.06**	-31.13*	-15.02
	(25.26)	(30.62)	(40.18)	(33.82)	(31.85)	(30.45)	(31.60)	(42.79)	(17.12)	(21.89)
Observations	191,479	115,316	76,163	83,581	107,898	99,136	92,343	95,281	96,198	191,479
R-squared	0.19	0.20	0.22	0.21	0.19	0.20	0.20	0.17	0.09	0.19

Note: Robust standard errors clustered at the district-week level are in parentheses following the baseline specification. The columns (1) - (9) control for weather controls and Column (10) is based on the baseline specification without accounting for weather controls. All the models control for age group, gender, their interaction, religion and caste and district controls. *** p<0.01, ** p<0.05, * p<0.1

Table A10: The effect of delay in sunset time on work time for those employed in Agriculture, Forestry, Fishing and Construction

	Panel A	Panel B	Panel C	Panel D
Sunset time (in 10 mins)	3.99**	8.12***	6.15	9.62**
	(1.81)	(2.12)	(3.90)	(3.98)
District FE	Yes	Yes	No	No
Week of the year FE	Yes	Yes	Yes	Yes
Weather controls	No	Yes	No	Yes
District by season FE	No	No	Yes	Yes
Mean	319.05	319.05	319.05	319.05
Observations	46,658	46,658	46,658	46,658
R-squared	0.26	0.26	0.35	0.35

Note: Robust standard errors clustered at the district-week level are in parentheses following the baseline specification. The columns represent Panels, where Panel A is based on the baseline specification in Eq 2 and Panels B-D test for robustness using alternate specifications and weather controls. All the models control for age group, gender, their interaction, religion and caste. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A11: Effect of sunset time on time spent outside at different day times

	7-10 am	10-4 pm	4-7 pm	7 am -7 pm
	(1)	(2)	(3)	(4)
Panel a: Women				
Sunset Time (in 10 Mins)	0.04	2.45**	0.66*	3.14**
	(0.33)	(0.96)	(0.39)	(1.46)
Avg of Outcome Variable	21.55	80.19	33.22	134.98
Observations	68,738	68,738	68,738	68,738
R-squared	0.10	0.14	0.10	0.14
Panel b: Men				
Avg Sunset Time (in 10 Mins)	0.09	0.63	1.05**	1.77
	(0.45)	(0.85)	(0.47)	(1.33)
Avg of Outcome Variable	90.94	274.60	120.46	486.00
Observations	66,253	66,253	66,253	66,253
R-squared	0.11	0.09	0.13	0.08
Panel c: All				
Sunset Time (in 10 Mins)	0.32	1.38**	1.19***	2.89***
	(0.28)	(0.64)	(0.31)	(0.98)
Avg of Outcome Variable	55.61	175.61	76.04	307.26
Observations	191,479	191,479	191,479	191,479
R-squared	0.30	0.38	0.38	0.45

Note: All outcomes are time allocated to outdoor activities in minutes per day. Control Variables include: age groups, gender, age and gender interactions, district fixed effects, week of the year fixed effects, caste, and religion of the household. We control for weather controls, that is, temperature and precipitaion on the day in all models. *** p<0.01, ** p<0.05, * p<0.1

Figure A1: Effect of later sunset time on health, robustness checks

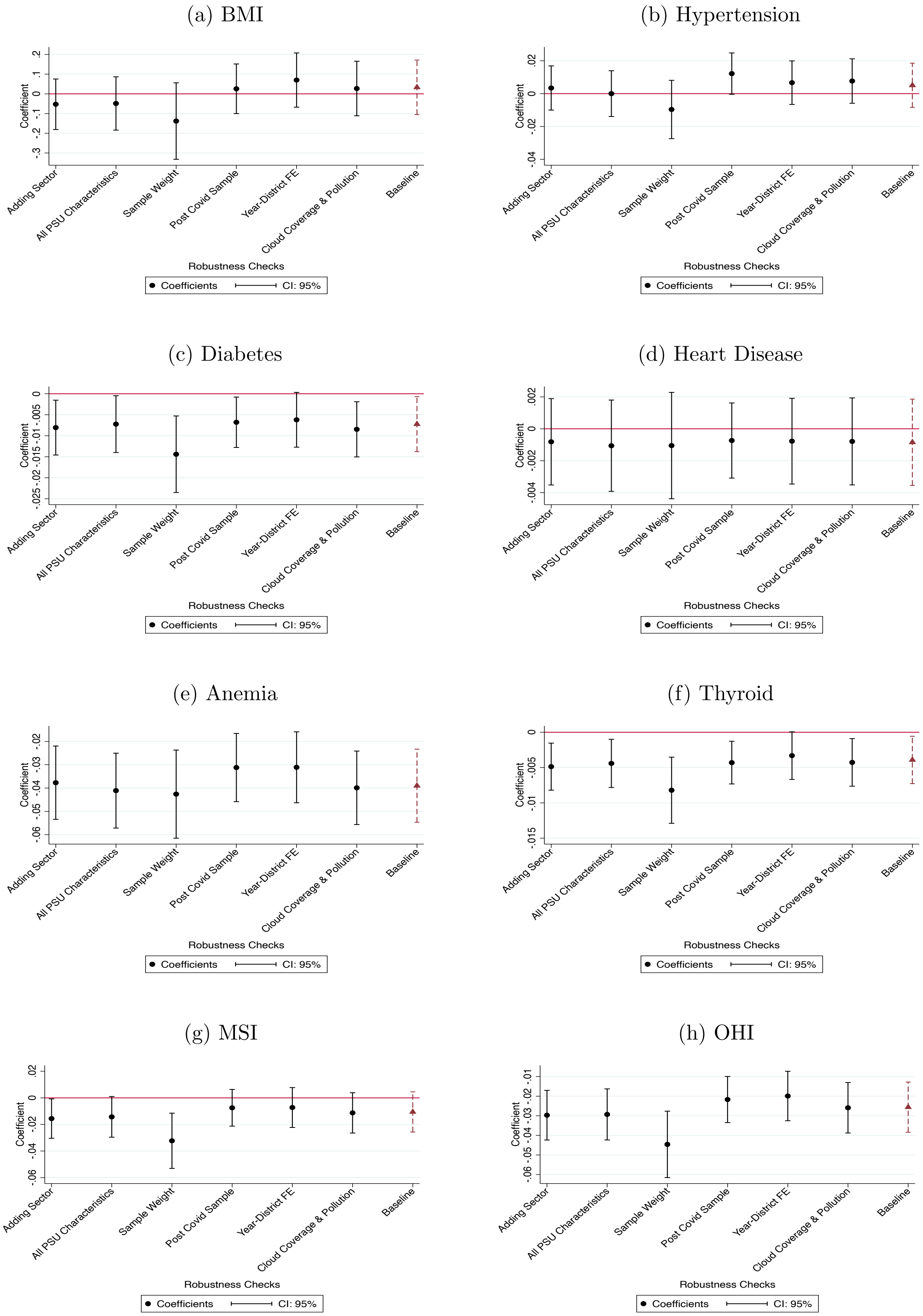
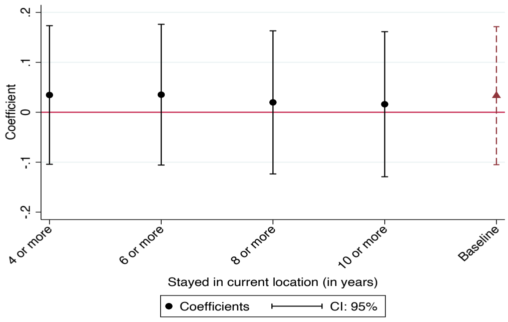
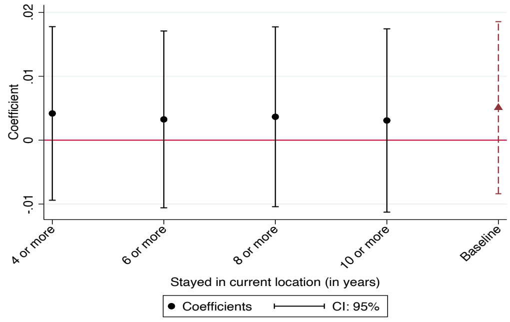


Figure A2: Effect of later sunset time on health, sensitivity

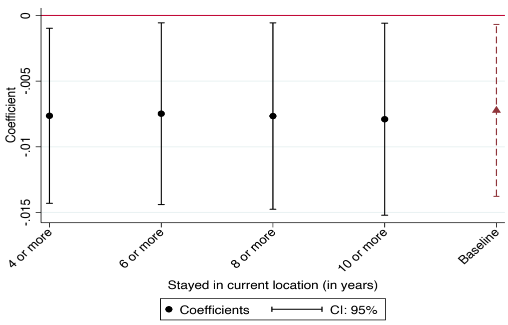
(a) BMI



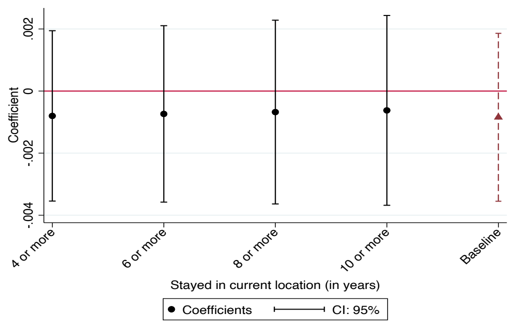
(b) Hypertension



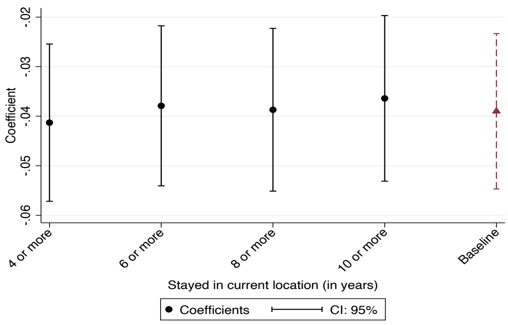
(c) Diabetes



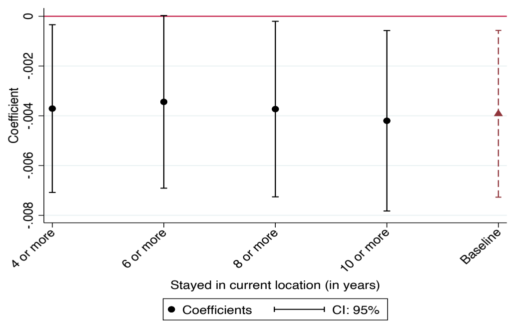
(d) Heart Disease



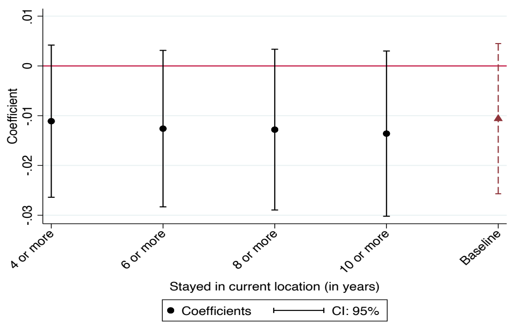
(e) Anemia



(f) Thyroid



(g) MSI



(h) OHI

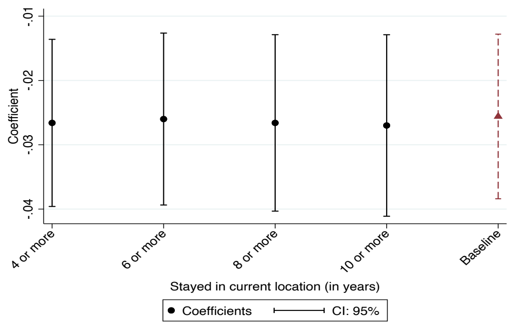
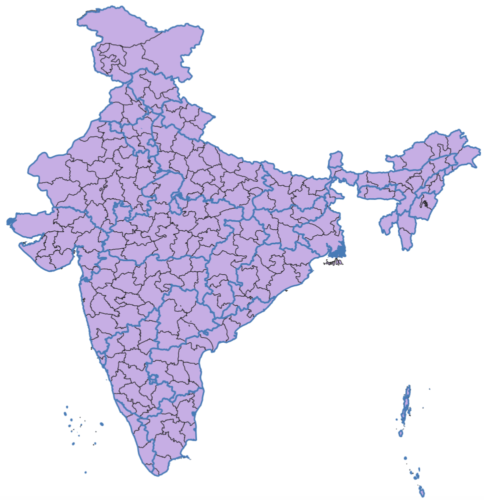


Figure A3: Clusters of District with State Boundaries

(a) 200 Clusters



(b) 300 Clusters

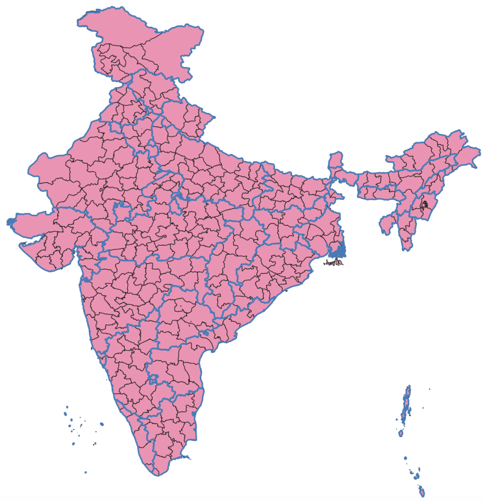
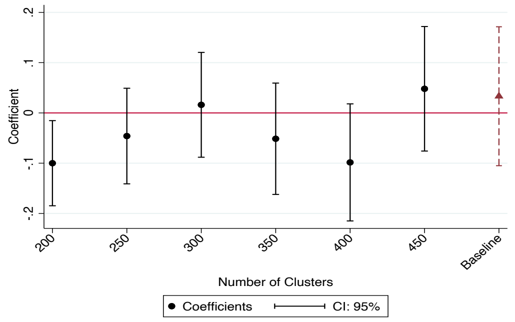
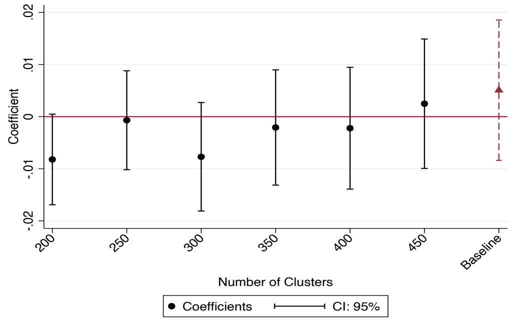


Figure A4: Effect of later sunset time on health, by varying number of clusters

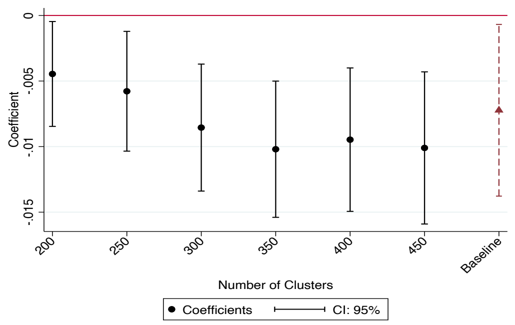
(a) BMI



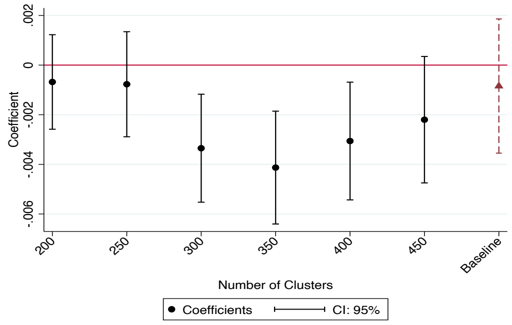
(b) Hypertension



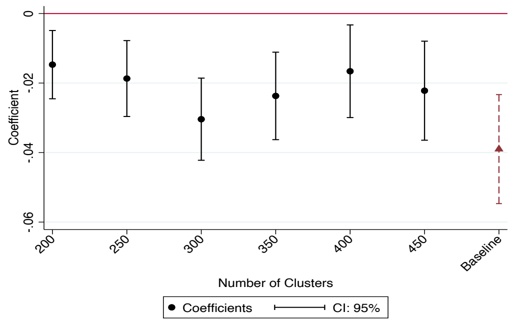
(c) Diabetes



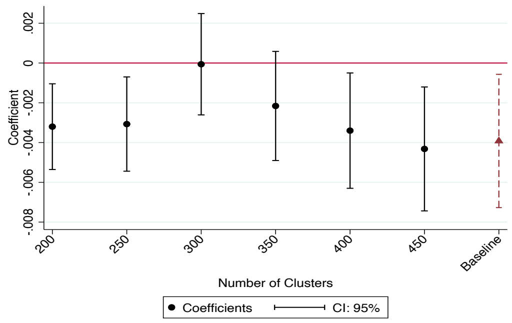
(d) Heart Disease



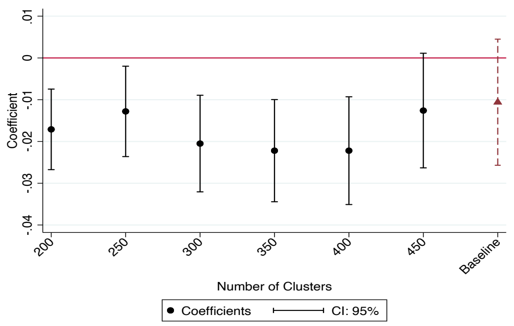
(e) Anemia



(f) Thyroid



(g) MSI



(h) OHI

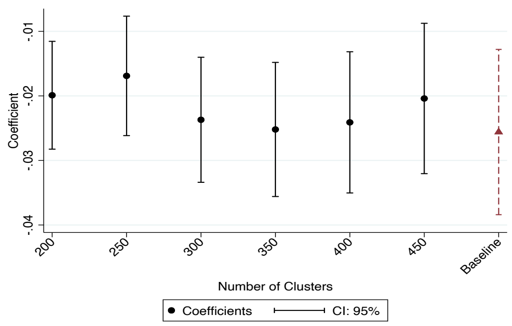
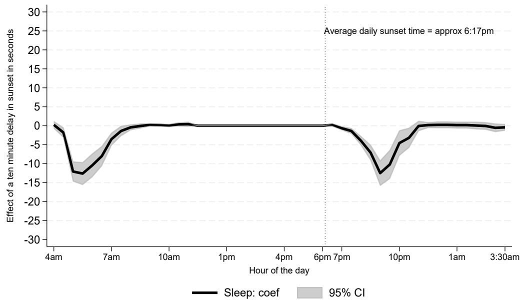
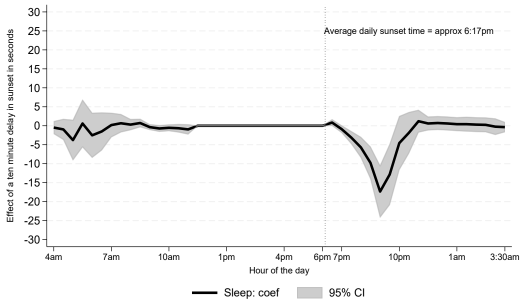


Figure A5: Effect of later sunset on time allocations every half-hour

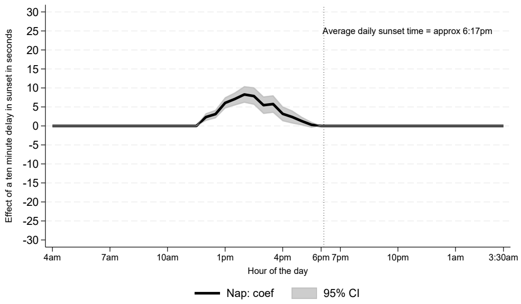
(a) Sleep



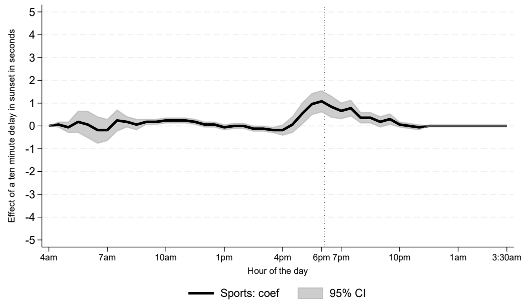
(b) Sleep: District season controls



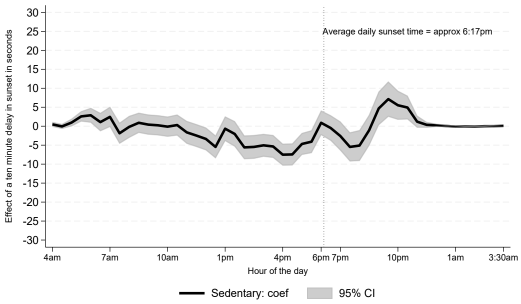
(c) Nap



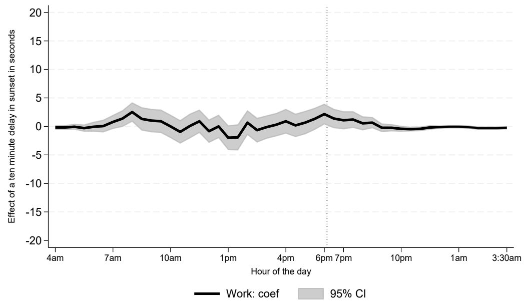
(d) Non-Sedentary



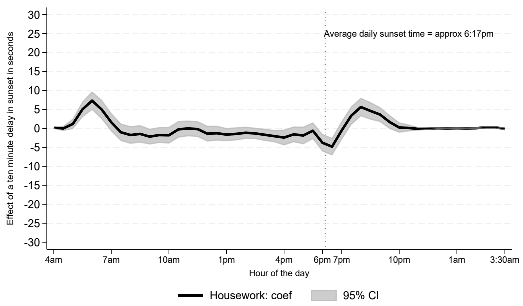
(e) Sedentary



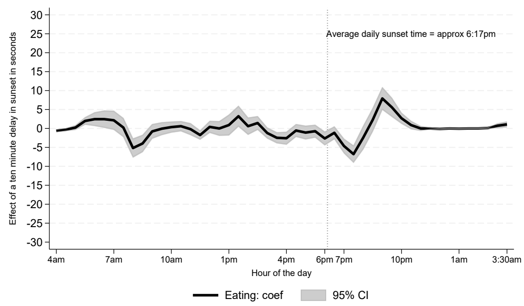
(f) Work, unconditional



(e) Housework

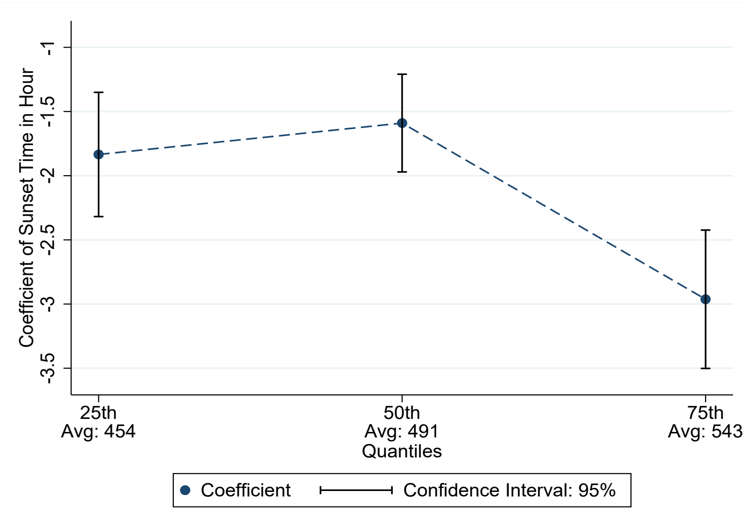


(f) Eating



Source: TUS 2019. Unless specified otherwise, all figures follow the baseline specification.

Figure A6: Quantile Regression Results at 25th, 50th and 75th Quartile; Change in sleep time due to a 10-minute delay in sunset

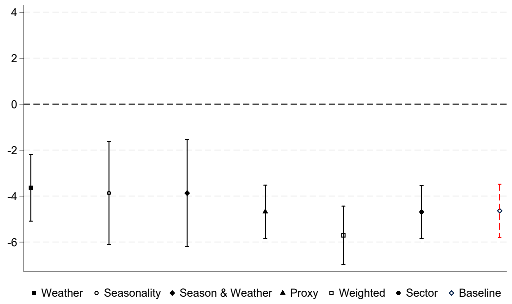


Author's calculation using TUS 2019

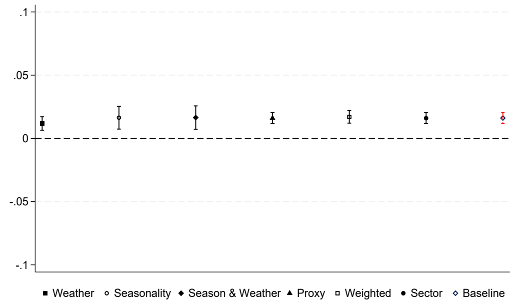
Note: Unconditional quantile regression using '*rifreg*' command in Stata at 1st, 2nd and 3rd quarter of the distribution for time spent on sleep. The average time spent at all three quarters is also presented in the figure.

Figure A7: Effect of later sunset on time allocations, robustness

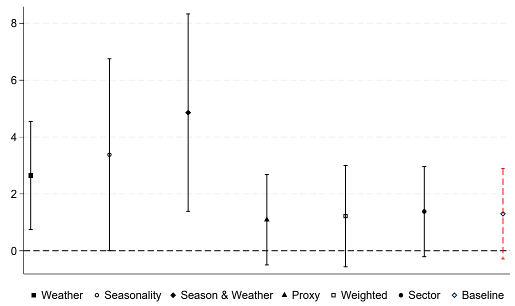
(a) Sleep



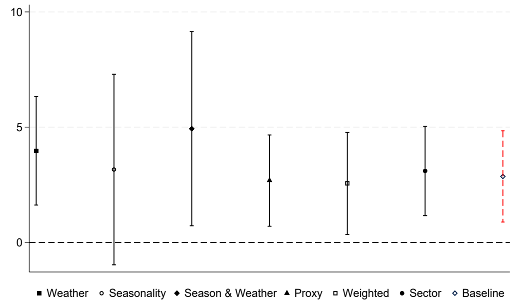
(b) Sleeping 7-9 hours



(c) Work, unconditional



(d) Work, conditional on working



(f) Sports and Exercise

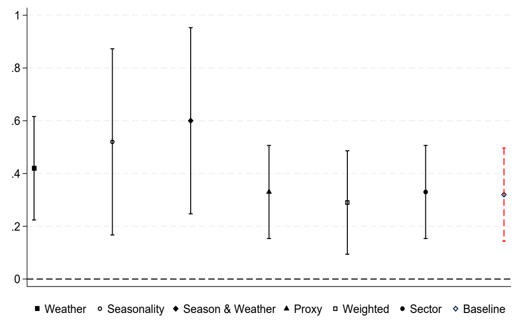
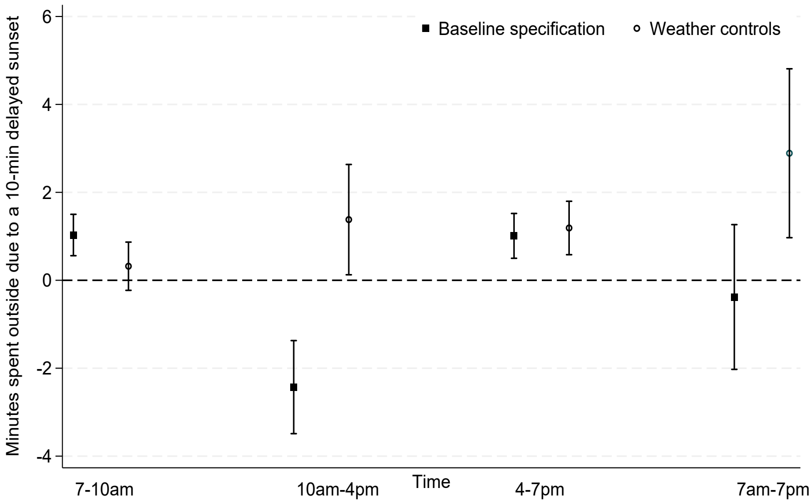


Figure A8: Effect of later sunset time on time spent outside

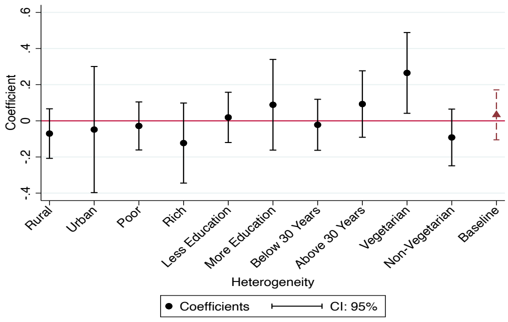
(a) Time outside



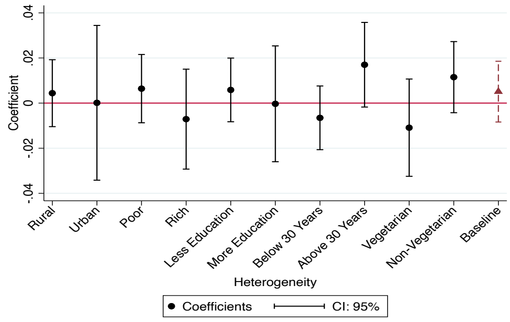
Source: TUS 2019. Weather controls include temperature and precipitation on the day of the survey.

Figure A9: Effect of later sunset time on health, heterogeneity

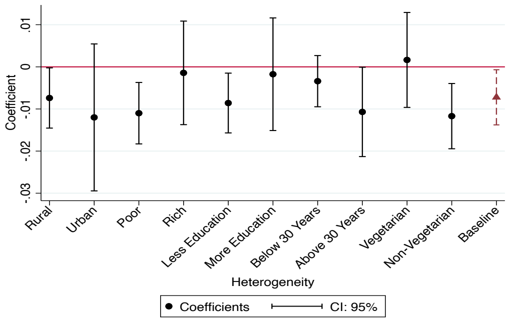
(a) BMI



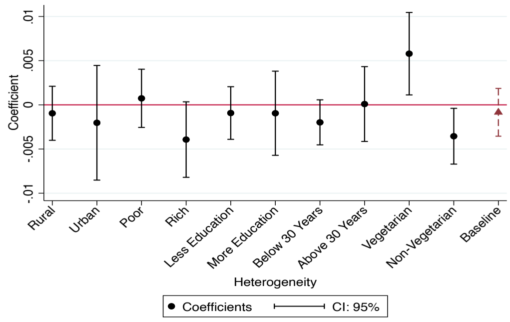
(b) Hypertension



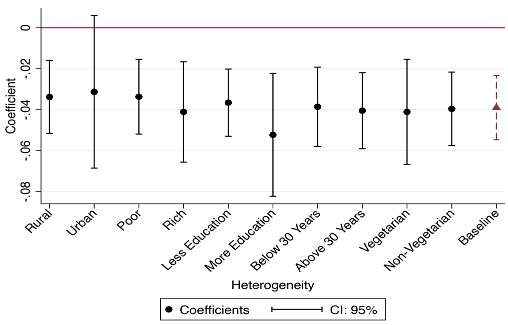
(c) Diabetes



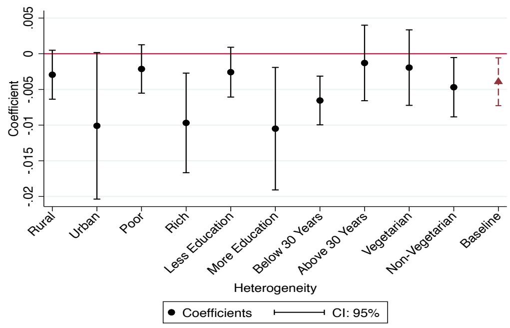
(d) Heart Disease



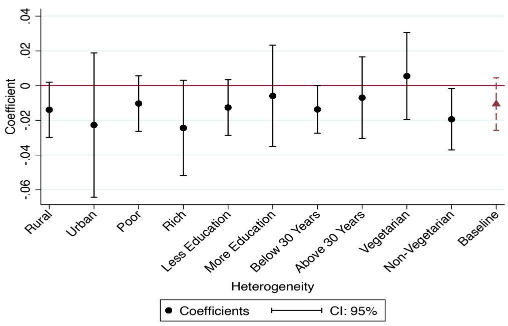
(e) Anemia



(f) Thyroid



(g) MSI



(h) OHI

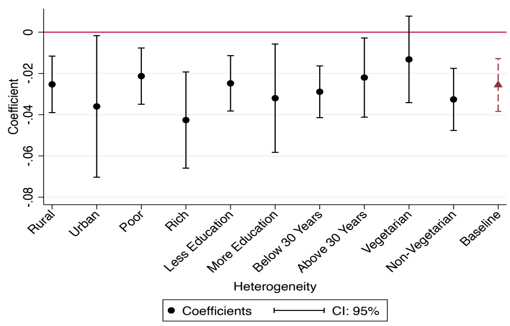
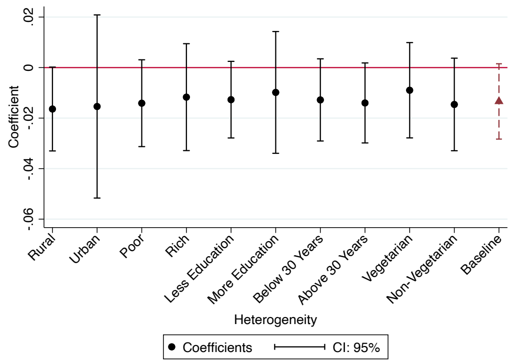
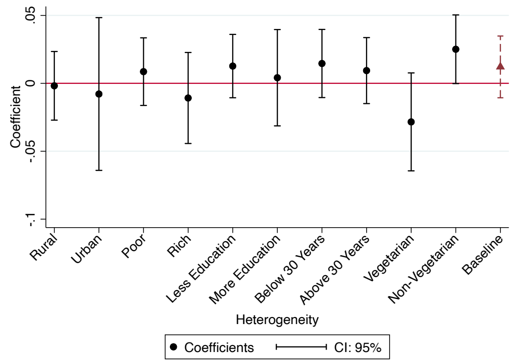


Figure A10: Effect of later sunset time on dietary outcomes, heterogeneity

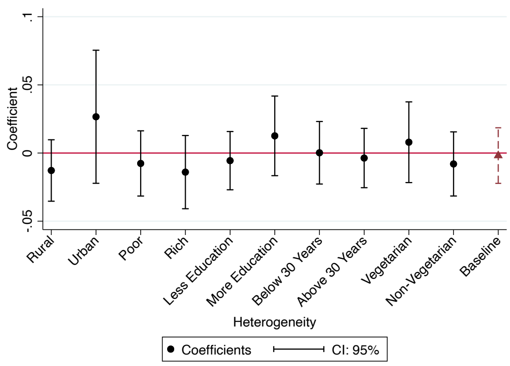
(a) Unhealthy Food



(b) Protein



(c) Greens and Dairy



(d) Diet Diversity

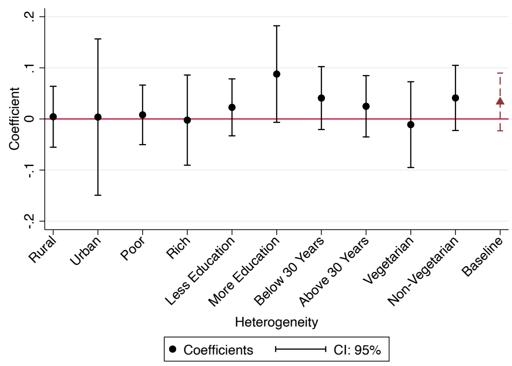
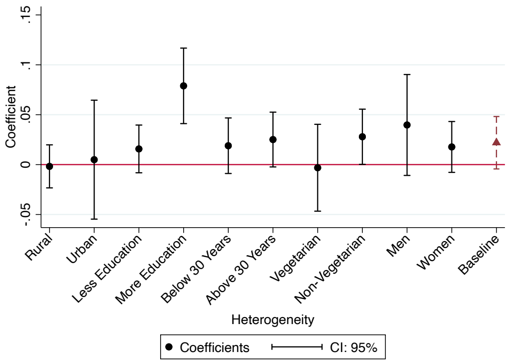
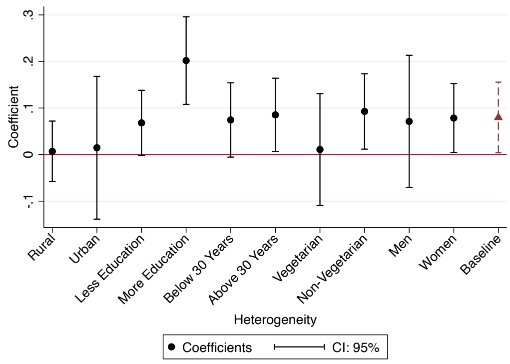


Figure A11: Effect of later sunset time on wealth and employment, heterogeneity

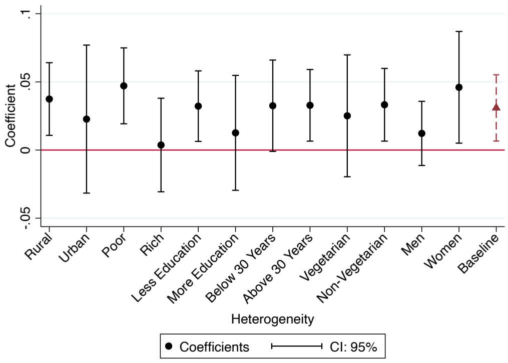
(a) Binary Indicator for Rich



(b) Wealth Quintiles



(c) Currently Working



(d) Worked in last 1 year

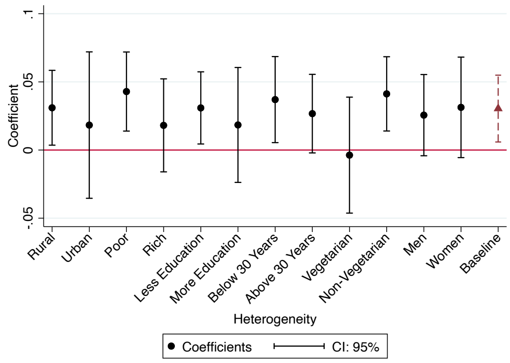


Figure A12: Effect of later sunset on time allocations, heterogeneity