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The labour market returns to sleep[☆]

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ABSTRACT

Despite the growing prevalence of insufficient sleep among individuals, we still know little about the labour market return to sleep. To address this gap, we use longitudinal data from Germany and leverage exogenous fluctuations in sleep duration caused by variations in time and local sunset times. Our findings reveal that a one-hour increase in weekly sleep is associated with a 1.6 percentage point rise in employment and a 3.4% increase in weekly earnings. Such effect on earnings stems from productivity improvements given that the number of working hours decreases with longer sleep duration. We also identify a key mechanism driving these effects, namely the enhanced mental well-being experienced by individuals who sleep longer hours.

1. Introduction

There is a widespread concern that average sleep duration has decreased over the past 50 years, and that insufficient sleep has become a major public health issue (Roenneberg, 2013).[1] The adverse effects of sleep deprivation have potentially important consequences for economic activity. Insufficient sleep can impair cognitive abilities (Nuckols et al., 2009) and brain plasticity (Saper et al., 2005). It can give rise to errors in judgment, influencing organizational capacities (Barnes and Hollenbeck, 2009) as well as risk-taking (Harrison and Horne, 1998). Sleep deprivation can also predict a higher rate of workplace accidents (Barnes and Wagner, 2009) and a higher prevalence of heart attacks and chronic diseases (Moore et al., 2002; Giuntella and Mazzonna, 2019; Jin and Ziebarth, 2020). Yet despite such detrimental consequences, little attention has been paid to the economic consequences of sleep deprivation, and especially its impact on labour market performance.

To estimate the causal effects of sleep on work performance, it is important to control for individual heterogeneity in sleep routines (Jansson-Fröjmark et al., 2019), genetic pre-dispositions in sleep time (Shi et al., 2019) or ability to deal with sleep

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[1] Although a recent Gallup survey in the US shows that the hours of sleep have not changed from the 1990s, there is an hour difference in sleep compared to 1942.

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deprivation, which is likely to be correlated with both sleep duration and labour market outcomes.[2] While some of these underlying factors may vary over time, they are likely to be fixed across individuals. In order to deal with such omitted variables, it is therefore essential to rely on longitudinal data and include individual fixed effects to estimate the causal effect of sleep on work performance. Previous studies have relied on evidence from repeated cross-sections (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019). In contrast, this paper, is the first to use longitudinal data and rely specifically on the German Socio-Economic Panel (SOEP) which collects data on both individual sleep and labour market performance between 2008 and 2019. To exploit exogenous individual variation in sleep duration and avoid reverse causality, we combine our longitudinal data with an instrumental strategy that draws on both time and local variation in sunset time to instrument for sleep duration. The intuition behind this first-stage relationship is straightforward: earlier sunset times induce workers to go to bed earlier, and because work schedules do not respond as strongly to variation in sunset times (Hamermesh et al., 2008), earlier bedtimes encompass more sleep (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019).

We make several contributions to the literature. First, we identify the effect of sleep duration on a range of outcomes including labour force participation, hours worked, and earnings — using a large-scale longitudinal dataset. Second, we dig into the specific mechanisms through which sleep affects labour market performance through the detailed analysis of workers' self-reported efficiency, stress, psychological well-being and health. This allows us to provide novel insights into how sleep can boost workers' productivity. Finally, we investigate the extent to which labour market returns to sleep are heterogeneous across different subgroups. This allows us to identify who are the individuals most likely to suffer from sleep deprivation and to opt out from the labour market or decrease their working hours due to sleep problems.

Providing empirical evidence on the causal impact of sleep on labour market performance requires large and exogenous variations in sleep duration. Our methodology relies on two sources of variation. First, within a location, earlier sunset times during the year can be associated with longer sleep. Using the interview date and respondent's state (länder) of residence, we assign daily local sunset time to each observation in the dataset and exploit the differences in interview days between survey waves for each respondent to capture the effect of daily local sunset time on respondent's sleep. Second, respondents living further east experience on average earlier sunset times than respondents living further west. We observe a bit less than 10% of individuals relocating to different states between two survey waves in our dataset. We thus also rely on these geographical variations to capture the effect of sunset time on sleep duration. To the best of our knowledge, we are the first to capture exogenous variations in sleep duration relying on within-individual variations in interview days and state of residence. This research design allows us to get as close as possible to a quasi-natural experiment dealing with important confounders (such as sleeping routines, ability to deal with sleep deprivation or reporting bias) that are likely to affect results from cross-sectional estimates. By restricting our sample to non-movers, we can also disentangle how much of the sleep effects come from seasonal versus geographical variations.

Some clear results emerge from our analysis. We find that later sunset times significantly reduce sleep duration conditional on individual fixed effects. In fact, a 1-hour increase in sunset time reduces weekly sleep duration by 0.08–0.11 h (roughly 5–7 min). 50% of our sample experienced more than 30 min variations in sunset times over two consecutive interviews (among whom 20% experience more than 2 h). And there are about 40 min differences in sunset times between east and west residents in Germany. For comparison, using cross-sectional variations in weekly sleep, Gibson and Shrader (2018) find that a 1-hour increase in sunset time reduces weekly sleep by 20 min. We then assess the impact of sleep variations induced by sunset times on respondents' labour market outcomes. We find that sleep exerts a positive effect on employment. An increase of 30 min in sleep duration increases labour force participation by 0.8 percentage points. The effects are large in economic terms. We also find that sleep increases workers' earnings. Among full-time workers, a 30-minutes increase in sleep would increase weekly earnings by 1.7%.

Changes in earnings may reflect changes in productivity or changes in the number of hours spent at work. Our dataset uniquely allows us to provide evidence on both channels. We find that a 30-minutes increase in sleep is associated with significant increases in hourly wages. In contrast, a 30-minutes increase in sleep reduces working hours by 0.4% among full-time workers. These results suggest that respondents who sleep more tend to be more productive at work. They also tend to spend less time in the labour market.

Investigating potential mechanisms, we find that an increase in sleep duration substantially increases workers' self-reported efficiency in completing tasks. We also document evidence that an increase in sleep duration increases (i) workers' ability to deal with stress, (ii) decreases the probability to experience negative emotions during the day and, (iii) is associated with better self-reported health. These results suggest that workers sleeping longer are more efficient and experience better mental health. In quantitative terms, a 30-minutes increase in sleep duration increases workers' mental health by 0.09 points on a 1–5 scale. This is equivalent to the mental health effects of having an increase in autonomy or security at work of about 25% (Clark et al., 2018). Under competitive markets, our results suggest that this increase in productivity through better mental health ultimately results in higher wages.

Importantly, we find that women and in particular mothers are those who are more likely to benefit from longer sleep time. Women who sleep 30-minutes more per week are 1.1 percentage points more likely to work, and when they work, their weekly earnings increase by 2.5%. This increase in labour market participation and weekly earnings is twice as much as that observed for men. This suggests that women would be those who would benefit the most from policies promoting sleep and encouraging individuals to allocate more time to sleep. Such policies would ultimately help reduce gender inequalities. Moreover, there is evidence that a 30-minutes increase in sleep would not decrease women's working hours (compared to a 0.6% decrease for men). In addition, we find that parents are those who benefit the most from longer sleep times. A 30-minutes increase in sleep would increase parents' earnings by 6.9% on average (compared to 2.2% for non-parents). These are large differences consistent with the

[2] One could also imagine that individuals who have a bias in reporting sleep duration may also have a consistent bias in reporting labour market outcomes.

idea that parents and in particular mothers are more likely to suffer from sleep deprivation and to opt out of the labour market or experience lower earnings due to sleep deprivation (Costa-Font and Fleche, 2020).

Our findings are robust to a number of robustness checks, e.g. including individuals' socio-demographic controls, job characteristics, as well as housing characteristics, the day temperature and other environmental factors. The identification assumption underlying our sunset time instrument is that there are enough variations in time and local sunset times within individuals and that these variations are exogenous to labour market performance (that is, they only affect respondents' labour market performance through sleep, conditional on our control variables). We provide support for this assumption by restricting our baseline specification to non-movers — using only seasonal variations to identify our sleep effects. We use this specification to test if endogenous sorting of respondents across locations could not bias our results. We also test that our results are not driven by seasonal confounders which would co-vary with both daily sunset time and labour market performance.

Our paper contributes to several strands of literature. First, it relates to the scarce literature on the relationship between sleep and labour in economics. Standard economic models of time allocation (Becker, 1965; Gronau, 1977) focus on "productive time" and "leisure time" and do not tend to model "sleep time" (Dunn, 1979). In a seminal work, Biddle and Hamermesh (1990) extend the analysis and consider a model where individuals optimize sleep and other time uses (e.g. work, leisure and home production). While their model allows sleep to affect productivity at work, they do not test this relationship in their empirical analysis. Instead, Biddle and Hamermesh provide evidence for the opposite relationship, that is the impact of wages on sleep duration. They find that individuals, whose time is more valuable, tend to substitute away time for sleep. Consistently, Szalontai (2006), Grandner et al. (2010), Bonke (2012) et Brochu et al. (2012) estimate a negative relationship between wages and sleep duration.

Our study most closely relates to Kamstra et al. (2000), Gibson and Shrader (2018) and Giuntella and Mazzonna (2019). Using Daylight Saving Time as an exogenous variation in sleep duration, Kamstra et al. (2000) provide evidence that insufficient sleep impairs how individuals process information and negatively affects the performance of stock market participation. Using cross-sectional time use data from the United States, Gibson and Shrader (2018) investigates sleep changes induced by variations in sunset times. They provide evidence that a 1-hour reduction in weekly sleep decreases earnings by 1.1% in the short run and 5% in the long run. Similarly, Giuntella and Mazzonna (2019) use US time zone variations and provide evidence that later sunset times induce a reduction in income per capita by roughly 3% across commuting zones spanning across a time-zone boundary. Other studies focus on the relationship between insomnia, work accidents and absenteeism (see Metlaine et al., 2005 for a review), or cyberloafing (Wagner et al., 2012). Our approach differs from theirs in that we use longitudinal data and consider only differences in sleep patterns within individuals through time, rather than between individuals. This is important as it allows us to take into account genetic effects on sleep which are time-invariant unobserved characteristics alongside sleep routines formed in early life which are likely to be correlated with both sleep and future labour market outcomes. Indeed, sleep routines can influence individuals' educational attainment as well as the ability to deal with sleep reduction, alongside the amount of sleep needed to stay alert. Following the same individuals over time is rare in observational studies investigating the relationship between sleep and labour market performance, one exception being Costa-Font and Fleche (2020) which rely on birth cohort data and focus on children-related sleep deprivation. They provide evidence that sleep disruptions induced by children negatively affect mothers' labour market performance. However, the effect is restricted to mothers, and therefore is not extensive to the entire active population.

This paper also complements recent work by Bessone et al. (2021). In their paper, the authors conduct a randomized three-week sleep intervention in India. They find that increased night-time sleep exerts no effects on participants' cognition, productivity, decision making or well-being but leads to small decreases in labour supply. These results stand at odds with previous findings showing that sleep reduces mistakes (Ulmer et al., 2009), increases students' tests (Taras and Potts-Daterma, 2005; Carrell et al., 2011; Heissel and Norris, 2018), or improve cognitive performance (Van Dongen et al., 2003) and depend on the experimental setting.[3] Our study allows us to investigate how sleep affects workers' self-reported efficiency, decreases stress and improves psychological well-being using large-scale observational data. To capture the mechanisms through which sleep can affect labour market performance, it is important to study all these effects within the same sample of individuals. To the best of our knowledge, we are the first to provide evidence on these mechanisms using large-scale observational data and to show that these productivity effects are significantly related to mental health improvements.

Finally, our study relates to another important piece of literature, which investigates the determinants of workers' productivity. The finding that sleep boosts workers' productivity relates to a recent stream of research, which has begun to incorporate insights from health and psychology literature to consider influences on work performance such as the individual cognitive functioning, mood and affective states to understand workers' productivity (e.g., Krueger et al., 2009; Oswald et al., 2015; Bellet et al., 2021). It also relates to the growing literature that estimates the effect of environmental factors on workers' productivity. Relative to these studies, our paper focuses on sleep duration and how a longer sleep time can improve workers' productivity.

2. Data and empirical strategy

This section describes the data, explains how we identify exogenous variations in sleep duration and presents the empirical specification.

[3] Other studies have also found a relationship between sleep and workplace accidents (Barnes and Wagner, 2009), car accidents (Smith, 2016), health (Jin and Ziebarth, 2020), depression or emotional states (Hansen et al., 2017).

Table 1
Descriptive statistics.

	Mean (1)	SD (2)	Min (3)	Max (4)
Sleep variables				
Sleep during workdays	6.73	1.00	2	10
Sleep during weekends	7.89	1.20	2	10
Total weekly sleep	49.46	6.53	14	70
Employment variables				
Employed	0.98	0.13	0	1
Working full-time	0.75	0.43	0	1
Weekly hours worked	43.71	6.65	25	80
Weekly earnings	498.08	298.17	5.08	11 538.46
Hourly wages	11.35	6.03	0.13	174.82

Notes: This table provides the list, arithmetic mean and standard deviations alongside extreme values of all sleep and labour variables of interest. Figures in rows (1) to (5) are estimated on the full sample of respondents aged between 15 and 64, who are not self-employed and for whom we have sleep duration observations. Figures in rows (6) to (8) are estimated on the sample of respondents aged between 15 and 64, who are not self-employed, who report positive weekly earnings and are working full-time.

2.1. Data

To evaluate the labour market returns to sleep, we rely on the German Socio-Economic Panel (SOEP), which is a longitudinal survey of households and individuals produced by the German Institute for Economic Research (DIW Berlin) and which includes information on household composition, demography, employment, health, income, education, satisfaction indicators, among others. One of the main advantages of the German SOEP is its longitudinal dimension, which allows us to follow the same individuals over time and control for unobserved heterogeneity. Respondents are interviewed annually and most interviews occur between February and June (about 82%).

Although the SOEP began in 1984, we only use data from 2008 to 2019, which includes information on respondents' sleep duration and labour market outcomes. As we are interested in the labour market effects of sleep, our final sample is restricted to those individuals aged between 15 and 64 and who are not self-employed. This gives us a sample size of roughly 20,200 individuals, for a total of approximately 86,000 observations. Additionally, for the analysis of employed individuals, we restrict our sample to individuals aged between 15 and 64 who report not being self-employed, who report receiving positive weekly earnings and who work full-time, as in Gibson and Shrader (2018). This sample contains about 15,300 respondents for a total of approximately 63,800 observations.

Sleep Data. The SOEP data include rich information on sleep. In particular, the dataset provides precise information on the number of hours slept. We use the individuals' answers to the following question: "How many hours of sleep do you have on average on a normal day during the working week? How many hours on a normal weekend day?" All these answers are given in complete hours. From these variables, we have also created another sleep variable, "weekly sleep", which measures the hours of sleep on a normal week, and allows us to match the frequency of our earnings variable:

Weekly sleep = (5*Sleep hours on workdays + 2*Sleep hours on weekends)

Table 1 reports the descriptive statistics. In our sample, respondents sleep on average 6.73 h on a normal workday and 7.89 h on weekends. This amounts to 49.46 h on a normal week. The sleep information in SOEP relies on the cognitive ability of respondents to be able to estimate the average time they devote to different activities. One concern lies in that the sleep information refers to an average sleep duration, which may not vary with daily sunset times if respondents average it over the year. This issue means that our estimates relying on seasonal variations in sleep duration would be attenuated. Similarly, it would be an issue if respondents who recently moved provide an average duration of sleep across a window that includes time in both locations. If our first-stage estimates are attenuated, this could inflate our resulting IV estimates. An alternative to measuring sleep is time diaries which focus on a restricted number of days where respondents are asked to fill their diaries. Unfortunately, this is not how sleep data are collected in SOEP. Reassuringly, Sonnenberg et al. (2011) find large associations between experience sampling time use questions and the standard survey questions of the SOEP for long-lasting and externally structured activities such as sleep. We also provide evidence that within a year, earlier sunset times are associated with longer sleep duration. Similarly, respondents living further East report on average longer sleep. We also find that average sleep responses vary with interview days and locations in a meaningful way. This suggests that the average reference period used by SOEP respondents to report their sleep duration allows for capturing meaningful seasonal (daily) and geographical variations (see Sections 3 and 2.2).[4]

Labour Market Outcomes. We use several variables to capture the labour market effects of sleep. Table 1 provides the descriptive statistics for these outcomes. The first employment variable is a measure of employment status (whether the respondent is currently

[4] The SOEP data also include questions on sleep satisfaction and sleep disorder. Sleep satisfaction is assessed using the following question: "How satisfied are you today with your sleep?". Possible answers range from 0 (completely satisfied) to 10 (completely satisfied). Appendix Table A1 in the Online Appendix examines the correlation between the different measures of sleep used in this paper. Overall, we find significant correlations that suggest that sleeping more hours increases sleep satisfaction and having a sleep disorder reduces sleep duration and sleep satisfaction.

working). In our sample, 98% of respondents work and 75% declare working full-time. We also have information on weekly hours of work. The question included in SOEP refers to the actual hours currently worked per week by respondents. The second-to-last row gives information on weekly earnings (i.e., the net monthly income reported by respondents multiplied by 12 and divided by 52). The last employment-related outcome gives information on hourly wages (that is the weekly earnings reported by the respondent divided by the number of actual hours currently worked per week). In our sample, full-time workers work on average 43.71 h per week. They earn 498.08 euros on average per week and 11.34 euros per hour of work. Comparisons with other data sources suggest that these figures capture employment and earnings accurately in Germany.[5]

Work Efficiency, Stress, Psychological Well-being, and Health. Insufficient sleep may impair workers' performance at work by decreasing their alertness and their ability to process information (Kamstra et al., 2000; Killgore, 2010; Kahn et al., 2014; Wagner et al., 2012). It can also increase the risk of mental impairment and depression as well as workplace injuries (Barnes and Wagner, 2009). To test for these mechanisms, the SOEP data collect detailed information on worker's self-reported efficiency (e.g., whether a worker is thorough; efficient and effective in completing tasks), stress (e.g., the feeling of being rushed by time; whether the respondent is nervous), emotional states (e.g., frequency of being angry; worried; sad or happy), mental and physical health (using the SF-12 questionnaire or whether the state of health affects daily activities). Detailed definitions of all these variables from the SOEP questionnaire can be found in the online Appendix.

2.2. Empirical strategy

The main empirical issue in estimating the causal effect of sleep on labour market outcomes is that sleep and labour market performance may be endogenous. First, individuals who spend more time on the labour market and earn higher wages may sleep less on average. Second, both sleep and labour market performance may result from unobserved characteristics, which are not included in the model. Third, sleep duration on a normal week may be an imperfect proxy of sleep quantity. Due to these issues, OLS estimates may be biased.

To overcome these issues, it is essential to rely on longitudinal data which allows us to identify the effect of sleep on labour market performance by exploiting within-individual variations in sleep quantity and to deal with unobserved heterogeneity likely to affect both sleep duration and labour market outcomes. Furthermore, to account for omitted variables and deal with reverse causality, we implement an instrumental strategy based on time and local variations in sunset times within individuals to instrument for sleep variations using information from sunset map logs.[6]

First-stage. Using the interview date and respondent's state of residence, we assign sunset time to each observation in the dataset and begin by estimating the following first-stage equation:

$$Sleep_{ist} = \lambda_1 S_{st} + X_{ist}\beta_1 + \delta_{1,t} + \mu_{1,s} + \eta_{1,i} + \epsilon_{1,ist} \tag{1}$$

where $Sleep_{ist}$ is our measure of sleep duration of individual i at time t, in state (länder) s. S_{st} is the sunset time (in hour) at time t in state s that individual i experiences. X_{ist} is a vector of covariates that includes respondents' age group dummies and occupation dummies. $\delta_{1,t}$ are time-fixed effects (i.e., day-of-week fixed effects and a dummy for being interviewed during summer).[7] $\mu_{1,s}$ are state fixed effects and $\eta_{1,i}$ are individual fixed effects. Standard errors are clustered at the state level.

Our source of identification corresponds to deviations in respondents' sleep duration through time. Sleep, and especially sleep time, evolves across the individual's life cycle. Indeed, middle-aged individuals appear to sleep less than both their older and younger counterparts (Bonke, 2012). Therefore, it is important to control for age. Similarly, occupation and job characteristics are likely to be related to both respondents' sleep and labour market performance (Mezick et al., 2008; Antillon et al., 2014). We, therefore, control for occupation dummies. Finally, individual fixed effects allow us to control for any unobserved heterogeneity across respondents, including a genetic propensity for interrupted sleep, ability to deal with sleep deprivation, time-invariant environmental triggers (such as the presence of curtains, bed quality, or insulation at home, etc.) and respondent specific persistent reporting bias in sleep duration.

The relevance of sunset time as an instrument for sleep comes from a large medical literature, which has demonstrated that the human body reacts to environmental light. As such, the human circadian rhythm is synchronized with sunrise and sunset times. Based on this idea, Roenneberg et al. (2007) provide evidence using German data that later sunset times induce individuals to go to bed later and reduce sleep duration. Similarly, Gibson and Shrader (2018) and Giuntella and Mazzonna (2019) demonstrate using time use data in the United States that a 1-hour increase in sunset time is associated with a reduction in sleep duration of roughly 20 min per week. Note that if people were able to compensate for later sunset time by waking up later, we would not observe any effect on sleep duration. But because work schedules often tend to be rigid, many individuals are not able to compensate in the morning by waking up one hour late (Hamermesh et al., 2008).

Using sunset time as a source of exogenous variations actually provides two types of variation: (1) within a location, earlier sunset time during the year induces longer sleep duration. (2) comparing two locations, respondents living further east will experience earlier average sunset time than respondents living further west. As a consequence, respondents from the eastern location will sleep

[5] See https://www.destatis.de/.

[6] https://sunrise.maplogs.com/ This website uses google maps to search and choose a location on Earth. Then the location (with its latitude and longitude) is sent to a back-end server to perform sunrise and sunset time calculations. It provides sunrise and sunset times for a number of countries and regions worldwide.

[7] Sleep may vary across time due to temperature or holidays. We, therefore, control for a summer dummy to capture some of these effects.

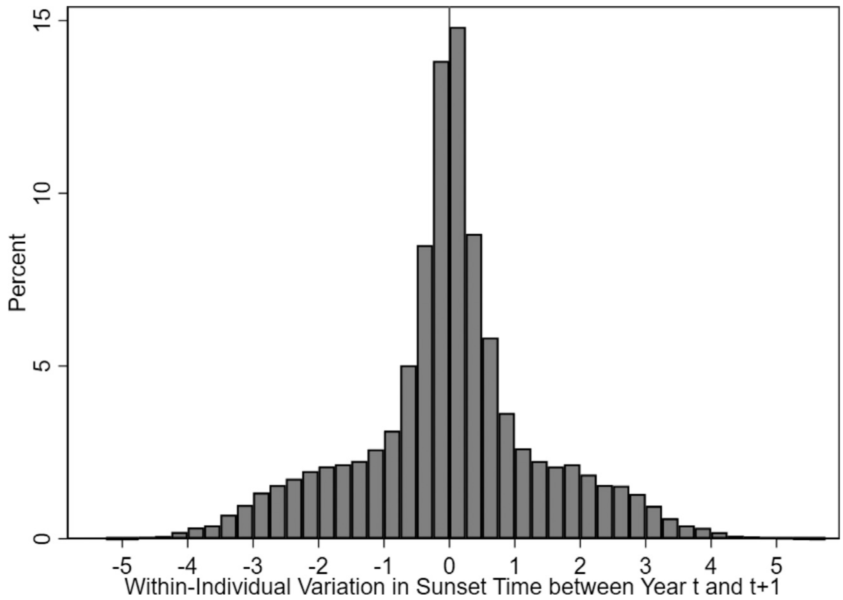


Fig. 1. Within-individual variation in sunset time
Notes: The figure is a histogram of within-individual variation in daily local sunset time across two consecutive interview dates.

longer. We rely on these two types of sunset variations to estimate our sleep effects. More specifically, conditional on individual fixed effects, we first rely on differences in interview days between survey waves for each respondent to capture the seasonal effect of sunset time on respondent's sleep. By focusing on within-individual variations in interview days, our estimation strategy allows us to reduce the possibility that individual confounders correlated with seasonal effects (e.g. individuals with consistent reporting bias being systematically interviewed in Summer) would affect our estimates. Second, relying on individuals who relocate to different states across survey waves, we also capture sunset time effects through spatial differences in sunset times for movers and their impacts on sleep duration. In contrast with cross-sectional estimates, this allows us to deal with geographical factors that would be systematically correlated with individual unobserved heterogeneity.

However, one important assumption underlying this strategy is that there are enough variations in time and local sunset times within individuals in our dataset. To provide evidence for this, we first compute within-individual variations in sunset times across two interview dates in our sample. We then plot the distribution in Fig. 1. We see that 50% of our sample experience more than 30 min variations in sunset times over two consecutive interviews (among whom 20% experience more than 2 h). 20% of our sample experience between 15- and 30-minute variations in sunset times and 30% less than 15-minute variations.[8] This suggests that there are significant variations in interview dates (or states of residence) between interviews in our dataset.[9],[10] Note however that the distribution is not uniformly distributed over days of the year, which suggests that the timing of interviews is not unconditionally random.

We also graphically examine the relationship between within-individual variations in sunset times and within-individual variations in sleep duration to provide evidence that these variations are meaningful. To construct Fig. 2, we first average within-individual variations in weekly sleep between two interviews by within-individual variations in sunset times (in a quarter of an hour). We then plot the means of the y-variable within each sunset time change. The solid line shows the linear fit estimated. As expected, there is a strong relationship between variations in sunset times and variations in weekly sleep. Consistent with our hypothesis and previous findings from Gibson and Shrader (2018) and Giuntella and Mazzonna (2019), this indicates that later sunset times reduce sleep duration on average. To interpret the magnitude, a 1-hour increase in sunset time decreases the average duration of sleep by 6 min within-individuals.[11],[12]

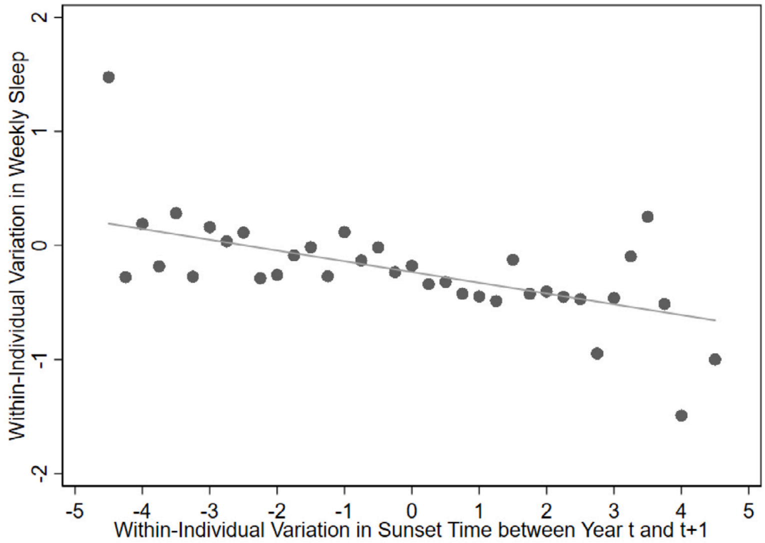
[8] Note that 10.5% of respondents are observed only once in our sample.

[9] Only 10% of our sample were interviewed in the exact same week between two interviews (see Appendix Figure A1).

[10] There are a bit less than 10% movers in our sample. This means that most of our identification comes from seasonal variations.

[11] For comparison purposes, we can also replicate Fig. 2 using cross-sectional variations in weekly sleep and sunset times. Consistent with Gibson and Shrader (2018), we find that a 1-hour increase in sunset time would increase weekly sleep duration by 15 min. See Appendix Figure A2.

[12] Similarly, we can plot a histogram of the predicted values for sleep using within-individual variations in sunset times to check that there are enough variations in sleep time generated by our sunset time instrument. According to Appendix Figure A3, our first stage generates enough variation in sleep duration, ranging from 46 to slightly less than 54 h per week.



Coef = -0.094*** (0.000) R2=0.426

Fig. 2. Changes in sleep hours on a normal week by changes in sunset time
Notes: The figure is a scatter plot of within-individual variation in weekly sleep duration against within-individual variation in sunset time across two interview dates. To construct this scatter plot, we first average within-individual weekly sleep duration by within-individual variation in sunset time (in quarter of an hour). We then plot the means of the y-variable within each sunset time quarter change. The solid line shows the linear fit estimated.

2SLS estimates. We build on this first-stage relationship and examine the effect of sleep on respondents' labour market outcomes using sunset time as an instrument for sleep. More specifically, the 2SLS empirical specification we estimate is the following:

$$Sleep_{ist} = \lambda_1 S_{st} + X_{ist}\beta_1 + \delta_{1,t} + \mu_{1,s} + \eta_{1,i} + \epsilon_{1,ist}$$

$$Y_{ist} = \alpha_2 Sleep_{ist} + X_{ist}\beta_2 + \delta_{2,t} + \mu_{2,s} + \eta_{2,i} + \epsilon_{2,ist} \tag{2}$$

where Y_{ist} is the employment status, the number of hours worked, weekly earnings or hourly wages of individual i at time t in the state s. $Sleep_{ist}$ is our measure of sleep duration instrumented by S_{st} the daily sunset time at time t in state s. X_{ist} is the same set of covariates in both Eqs. (1) and (2), and $\delta_{2,t}$, $\mu_{2,s}$ and $\eta_{2,i}$ are time, state, and individual fixed effects. Standard errors are clustered at the state level. Our coefficient of interest, α_2, is the labour market effect of 1-hour increase in sleep duration.

The validity of our instrumental strategy relies on the idea that variations in sunset times affect respondents' labour market performance only through sleep — conditional on our control variables. While we control for individual, time, and state-fixed effects, one could still be concerned about potential correlations between sunset times and labour market performance.

The primary threat to this identification strategy is seasonal confounders which would covary with labour market outcomes and sunset times within a location. We provide evidence that our results are robust to a wide range of seasonal confounders. We also provide evidence that our results are insensitive to the inclusion of individuals' socio-demographic characteristics, job characteristics, and housing characteristics. We can also make use of the amount of selection on observables as a guide to the amount of selection on unobservables (see Oster, 2017). Overall, the insensitivity of the results to our controls and the "modest" association between observables that determine the respondents' labour market outcomes allows us to conclude that the exclusion restriction is reasonable.

A residual source of variation relies on movers and geographical variations in sunset times. Endogenous sorting of respondents across locations could be correlated with unobserved characteristics related to both sunset times and labour market performance. In particular, if more productive individuals are more likely to move and to move to states with earlier sunset times, that could violate the exclusion restriction. To test for this issue, we split the sample of movers by median sunset time of new location and test whether more educated individuals are more likely to move to states with earlier sunset times. Appendix Table A2 provides the results and shows that this does not seem to be the case. Among movers, we also find that 20% of them move from East to West, while 11% move from West to East. The resulting 69% are respondents moving within East or West regions. However, to avoid potential endogeneity, we provide evidence that our results remain similar when including state*individual fixed effects or restricting our sample to non-movers (that is, focusing on seasonal variations in sunset times to estimate our effects).

3. Results

3.1. Baseline results

Table 2 presents the central results of this paper and reports two-stage least square (2SLS) estimates of the labour market returns to sleep. Appendix Table A3 reports control coefficients. We focus on respondents' weekly sleep duration — although robustness checks for the workday and weekend sleep duration are reported in Appendix Tables A9 and A10.

First-stage regressions for the IV estimates are reported at the bottom of Table 2. The coefficients on sunset times are negative and significant, which confirms that an increase in sunset time decreases respondents' sleep duration. Quantitatively, a 1-hour increase in sunset times reduces respondents' weekly sleep duration by 0.08–0.11 h (roughly 5–7 min). The weak identification tests produce large Kleibergen–Paap statistics (F> 10) that compare favourably to the statistics reported in Stock and Yogo (2005). This allows us to reject the hypothesis of weak instruments for all regressions.

The coefficients on the instrumented sleep variable suggest a large labour market returns to sleep. Column (1) is estimated on the full sample of respondents aged between 15 and 64, and who are not self-employed. The result shows a positive and significant relationship between respondents' sleep duration and employment probability. In terms of magnitude, the estimate in column (1), 0.016, indicates that a 1-hour increase in weekly sleep duration would increase the employment probability by 1.6 percentage points. In columns (2), (3) and (4), we then restrict the sample to full-time workers. We first test the effect of respondents' sleep duration on the number of hours worked (column (2)). The coefficient on respondent's sleep is negative and significant, indicating that a 1-hour increase in weekly sleep would reduce working hours by 0.8% on average. In column (3), we then use the log of weekly earnings as the dependent variable. The coefficient on the respondent's sleep duration is statistically significant. The estimate in column (3) indicates that a 1-hour increase in weekly sleep would increase weekly earnings by 3.4%. Note that weekly earnings are a function of the number of hours worked per week times the hourly wage earned by the respondent. Hence, if the number of hours worked per week decreases with sleep but weekly earnings increase, this may suggest that most of the increase in weekly earnings is due to an increase in hourly wages. To test for this, column (4) presents the effect of respondents' sleep duration on the log of hourly wages (which we expect to pick up productivity effects). The effect is statistically significant and indicates that a 1-hour increase in weekly sleep would increase hourly wages by 4.2%, consistent with a productivity-enhancing role of sleep.

Overall, the results in Table 2 are consistent with the existence of large labour market returns to sleep. They suggest that respondents who sleep more hours on average tend to be more productive at work. They also tend to spend less time in the labour market. Does the magnitude of the 2SLS make sense? Overall, our results are consistent with available evidence from the sleep-labour literature. For example, Gibson and Shrader (2018) find that a 1-hour increase in weekly sleep increases earnings by 1.1% in the short run (using seasonal variations) and 5% in the long run (using geographical variations). Similarly, Costa-Font and Fleche (2020) find that a 1-hour increase in a mother's night-time sleep is associated with a 6.2% increase in household income. In practice, the estimates might be biased by measurement errors. But overall, they imply not implausibly large effects of sleep on respondents' labour market performance conditional on individual fixed effects.

One issue would be that first-stage estimates are likely to be attenuated, which would inflate the resulting IV estimates. To bound the potential magnitude of the IV results, one could consider first stage estimates from Gibson and Shrader (2018) and rescale our IV estimates based on those. Specifically, Gibson and Shrader (2018) find that a 1-hour increase in sunset time is associated with about a 20-minute reduction in sleep duration (this is about 3–4 times what we find in our study). This could mean that we only capture 25%–30% of the variations in sleep duration and as a result, our IV estimates are 3–4 times their true size. If we rescale our IV estimates based on this, we would find that a 1-hour increase in sleep duration increases labour force participation by 0.45 percentage points, weekly earnings by 1%, and reduces working hours by 0.2%. Note that this is consistent with weekly earnings' estimates from Gibson and Shrader (2018).

These results have large policy implications. They suggest that employers and firms aiming to increase their workers' productivity should consider adopting work schedules that allow them to allocate enough time to sleep.[13] Long working hours have been associated with sleep disturbances (e.g., short sleep, difficulty falling asleep, frequent waking) and sacrificing sleep for work can become an exhausting cycle. Our results suggest that allocating enough time to sleep could be an important step toward productivity. The effects are equivalent to the earnings effect of 6 additional months of schooling (Angrist and Krueger, 1991). This is substantial. Sleeping more hours is not only beneficial for workers' productivity, but it also increases the probability of working. Individuals who are sleep deprived are more likely to remain out of the labour force. As a result, policies aiming to reduce unemployment should consider taking sleep deprivation into account. As an illustration, fatigue has been estimated to cost employers around $1,967 annually per employee (Rosekind et al., 2010) and up to 3% of GDP (Hafner et al., 2017).

3.2. Robustness checks

The previous results show that respondents' sleep increases labour force participation, decreases the number of hours worked and boost weekly earnings. However, several biases could affect our estimates. Therefore, this section is devoted to testing whether our results are robust to several robustness checks and specification tests.

13 See also the importance of school schedules for sleep and academic achievement (Carrell et al., 2011; Heissel and Norris, 2018).

Table 2
IV estimates of the effect of sleep on labour market outcomes.

	Working (1)	Log (hours worked) (2)	Log (weekly earnings) (3)	Log (hourly wages) (4)
Panel A: 2SLS				
Sleep	0.016***	−0.008**	0.034***	0.042***
	(0.005)	(0.003)	(0.010)	(0.012)
Individual controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	86,044	63,179	63,811	63,122
	Sleep (1)	Sleep (2)	Sleep (3)	Sleep (4)
Panel B: First-Stage				
Sunset	−0.083***	−0.109***	−0.112***	−0.110***
	(0.014)	(0.016)	(0.014)	(0.015)
Observations	86,044	63,179	63,811	63,122
F-statistics	34.09	51.77	56.74	53.11

Notes: This table reports the IV estimates of the effect of 1-hour increase in weekly sleep on the four labour market outcomes. Weekly sleep duration is instrumented using local variations in daily sunset times. The first estimate (working) is estimated on the full sample of respondents aged between 15 and 64, who are not self-employed. The three estimates to the right are estimated on respondents aged between 15 and 64, who are not self-employed, who report positive weekly earnings and who declare working full-time. We control for age group dummies, indicators for summer season, day of week, and occupation codes. We also include individual and state fixed effects. Standard errors are clustered at the state level.

We begin by including various additional controls which are likely to be correlated with sunset times, respondent's sleep, and labour market performance, such as socio-demographic characteristics, job characteristics, house characteristics and environmental factors. Overall, we find that our results remain remarkably stable when including those controls. In Panel A of Table 3, we first examine the effects of additional socio-demographic controls such as education, marital status, the presence of children in the household, citizenship, and health status. Indeed, the existing literature on sleep has shown that groups of individuals with specific socioeconomic characteristics tend to suffer more from sleeping problems (Arber et al., 2009; Asgeirsdottir and Olafsson, 2015; Grandner et al., 2010). For instance, adults with more education report fewer sleeping problems. Other salient individual's characteristics include the fact that partnered individuals exhibit better sleep quality (Grandner et al., 2010). One of the most common disruptions to sleep comes from newborn arrival (Costa-Font and Fleche, 2020). A recent study using British data finds that children reduce sleep by 4.2 min a day, single people sleep 4.8 min less and separated people 6.5 min less on average (Hafner et al., 2017). When including those controls in our baseline specifications, we find little effect on our 2SLS estimates. For example, the estimate of the effect of sleep duration on employment is 0.015 (s.e. = 0.005) with these additional socio-demographic controls. The effects on hours worked and earnings are now −0.008 (s.e. = 0.003) and 0.029 (s.e. = 0.009), respectively.

Similarly, job characteristics can influence respondents' sleep and labour market performance. Work stress and the social situation at work are strongly linked to disturbed sleep and impaired awakening (Metlaine et al., 2005). To control for this, in Panel B, we include controls for the type of contract (temporary versus permanent), the number of years spent at the current firm, and whether the respondent is a civil servant or not. Again, including these controls has small quantitative effects on our 2SLS estimates. The coefficient on employment is now 0.012 (s.e. = 0.005). The coefficient on hours worked is −0.006 (s.e. = 0.003) and the one on weekly earnings is now 0.027 (s.e. = 0.009).

Finally, house characteristics such as home insulation, the presence of curtains, as well as bed quality are likely to influence sleep quantity. The individual fixed effects capture most of these effects. However, in Panel C, we control for whether there is air conditioning in the respondent's house. This may help respondents to deal with excessive temperatures at night. Our estimates of the effect of sleep on labour market performance do change but remain statistically significant. Overall, some deviations from our baseline estimates emerge after controlling for socio-demographic characteristics, job characteristics and house characteristics (Panel D). But overall, they remain remarkably similar and we can reject the null hypothesis that the coefficient on sleep is zero, with little effects from socio-demographic, job and house characteristics.[14]

Despite the inclusion of a wide range of controls, our estimates could still be biased by unobservable factors correlated with both sunset times and respondents' labour market performance. We try to assess this issue by implementing a strategy proposed by Oster (2017). In Panel D, we run two sets of regressions. We first run unconditional 2SLS regressions of respondents' labour market

[14] Still, it could be argued that if there are measurement errors in the controls, this could bias the control coefficients towards zero, and mechanically implies that including the controls does not affect our coefficients of interest. To deal with this issue, we run additional regressions where the additional individual variables, job and house characteristics variables are included as dependent variables in the baseline regressions. The regressions are presented in Appendix Table A4 and indicate positive and significant effects of respondents' sleep duration on these variables.

Table 3
IV estimates of the effect of sleep on labour market outcomes — robustness checks.

	Working (1)	Log (hours worked) (2)	Log (weekly earnings) (3)	Log (hourly wages) (4)
Panel A: Socio-demo. controls				
Sleep	0.015***	−0.008**	0.029***	0.037***
	(0.005)	(0.003)	(0.009)	(0.011)
Observations	86,014	63,156	63,787	63,099
F-statistics	37.08	57.05	61.85	58.27
Panel B: Job characteristics				
Sleep	0.012***	−0.006**	0.027***	0.033***
	(0.005)	(0.003)	(0.009)	(0.010)
Observations	82,181	60,678	61,252	60,630
F-statistics	38.34	49.69	55.53	50.84
Panel C: House characteristics				
Sleep	0.019***	−0.010**	0.055***	0.066***
	(0.006)	(0.004)	(0.018)	(0.021)
Observations	75,585	54,253	54,826	54,195
F-statistics	22.14	23.21	26.30	23.70
Panel D: All controls				
Sleep	0.012***	−0.008**	0.034***	0.041***
	(0.004)	(0.003)	(0.013)	(0.014)
Observations	69,817	51,796	52,310	51,746
F-statistics	27.56	26.93	30.23	27.33
Oster(2017)	14.88	23.40	59.26	43.75
Panel E: Reduced-form estimates				
Sleep	−0.001***	0.001***	−0.004***	−0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	96,202	71,334	71,976	71,269
Panel F: Including min. temperature				
Sleep	0.016***	−0.008**	0.031***	0.039***
	(0.005)	(0.003)	(0.010)	(0.012)
Observations	85,778	62,990	63,620	62,933
F-statistics	34.98	58.76	62.69	60.45
Panel G: Including max. temperature				
Sleep	0.029**	−0.008	0.095***	0.107***
	(0.012)	(0.010)	(0.028)	(0.038)
Observations	85,778	62,990	63,620	62,933
F-statistics	7.896	6.129	7.844	6.332
Panel H: Including hours of sunshine				
Sleep	0.019**	−0.007***	0.036***	0.044***
	(0.005)	(0.003)	(0.010)	(0.010)
Observations	85,448	62,753	63,378	62,696
F-statistics	30.28	42.68	46.87	43.93

(*continued on next page*)

performance on weekly sleep duration (Appendix Table A5). We use the same instrumental strategy as before but only control for individual fixed effects. Our full regressions are those presented in Panel D of Table 3. Comparing the R-squared from these two sets of regressions and computing the ratios suggested by Oster (2017), we find that none of the ratios associated with employment, the number of hours worked, weekly earnings and hourly wages (reported in Table 3), are less than 1. Their values which range from 14.88 to 59.25 suggest that evidence of selection on unobservables would have to be at least 15 times that on observables and on average over roughly 35 times as strong to account for the full effect of sleep on labour market performance. As additional evidence, Panel E reports the reduced-form effects of respondents' labour market performance on sunset times. All the relationships are statistically significant and have the expected signs. This suggests economically important effects of sunset times on labour market performance without requiring any exclusion restriction.

One might still argue that seasonal effects and selective migration may affect our results. One can try to further deal with seasonal effects by including daily minimum temperatures (Panel F), daily maximum temperatures (Panel G) and hours of sunshine (Panel H). Temperature data are derived from the European Climate Assessment & Dataset (ECA & D). They are merged using the information on the date of the interview and the location of the respondent. Including deviations in daily minimum temperature barely changes our estimates. The coefficient on employment is 0.016 (s.e. = 0.005). The coefficient on the number of working hours is now −0.008 (s.e. = 0.003). Further, the effect on earnings is 0.031 (s.e. = 0.010). When controlling for maximum temperature instead of minimum temperature, the coefficients largely increase but remain significant. Finally, including hours of sunshine does not change our results.

Table 3 (*continued*).

	Working	Log (hours worked)	Log (weekly earnings)	Log (hourly wages)
	(1)	(2)	(3)	(4)
Panel I: Including quarter FEs				
Sleep	0.010	−0.007	0.030*	0.037*
	(0.006)	(0.006)	(0.017)	(0.019)
Observations	86,044	63,179	63,811	63,122
F-statistics	17.71	28.12	25.82	29.10
Panel J: Including month FEs				
Sleep	0.049	−0.029	0.071	0.104
	(0.052)	(0.055)	(0.129)	(0.204)
Observations	86,044	63,179	63,811	63,122
F-statistics	1.060	0.406	0.626	0.400
Panel K: Restricting to non-movers				
Sleep	0.015***	−0.009**	0.034***	0.043***
	(0.005)	(0.003)	(0.013)	(0.014)
Observations	81,277	59,703	60,290	59,647
F-statistics	32.44	43.02	47.31	44.12
Panel L: Including ind.*state FEs				
Sleep	0.015**	−0.009**	0.035***	0.044***
	(0.005)	(0.004)	(0.012)	(0.013)
Observations	85,527	62,796	63,426	62,739
F-statistics	33.13	45.82	50.40	47.04
Panel M: Restricting to movers				
Sleep	0.026	−0.005	0.049	0.047
	(0.035)	(0.012)	(0.036)	(0.037)
Observations	4,224	3,094	3,137	3,093
F-statistics	1.246	3.992	4.052	3.901

Notes: This table reports the IV estimates of the effect of 1-hour increase in weekly sleep on the four labour market outcomes. Weekly sleep duration is instrumented using local variations in daily sunset times. The first estimate (working) is estimated on the full sample of respondents aged between 15 and 64, who are not self-employed. The three estimates to the right are estimated on respondents aged between 15 and 64, who are not self-employed, who report positive weekly earnings and who declare working full-time. All regressions control for age group dummies, indicators for summer season, day of week, and occupation codes. We also include individual and state fixed effects. Standard errors are clustered at the state level.

We could alternatively include quarter fixed effects (Panel I) or month fixed effects (Panel J) to deal with seasonal effects. The estimates including quarter fixed effects do change. The coefficient on employment is 0.010 (s.e. = 0.006) and is not significant anymore. The coefficient on the number of working hours is now −0.007 (s.e. = 0.006). However, the effect on earnings remains very similar, at 0.030 (s.e. = 0.017) and significant at the 10% level. When including months fixed effects, the results all become non-significant. Although they remain quantitatively the same, this could suggest that within-month variations in sunset times are not enough to identify sleep effects on labour market outcomes.

To deal with potential selective migration, Panel K replicates our baseline estimates restricting our sample to non-movers. Alternatively, Panel L includes individual*state fixed effects. This restricts our source of identification to within individual within state variation in sunset times. Our estimates slightly increase and remain statistically significant. In Appendix Tables A6–A7–A8, we also replicate our baseline estimates (i) including quarter fixed effects and individual*state fixed effects, (ii) months fixed effects and individual*state fixed effects, and (iii) individual*quarter fixed effects to restrict our source of identification to spatial differences in sunset time within individuals. Our results remain qualitatively the same, which suggests that neither selective migration nor seasonal confounders fully explained our estimates. However, Panel M suggests some interesting findings. When restricting our source of identification to spatial differences in sunset time within individuals (that is, focusing on movers), our coefficients on earnings increase by almost 50% at 0.049 (s.e. = 0.036) (although they are barely significant). These results are consistent with Gibson and Shrader (2018) who find that a 1-hour increase in sleep duration would increase earnings by 5% in the long run (relying on geographical variations to identify their effects) compared to only 1.1% in the short run (using seasonal variations). When restricting our sample to movers, our results however become imprecisely estimated and we have a weak instrument problem. Therefore, these results should be taken with caution. This also suggests that most of our identification comes from seasonal variations and is presumably driven by the non-movers.

As additional robustness checks, in Appendix Tables A19 and A10, we also estimate our baseline results using sleep duration during a normal weekday and a normal weekend day as endogenous variables. Arguably, sleep-deprived people may catch up with their sleep during weekends; hence sleep on workdays may have a larger impact on labour market performance than sleep during weekends. Our estimates confirm that insufficient sleep during workdays has larger negative effects on respondents' labour market performance than insufficient sleep experienced during weekends. We also replicate our findings controlling for sleep satisfaction (Appendix Table A11) and sleep disorder (Appendix Table A12). This allows us to control for sleep quality in addition to sleep quantity. Finally, in Appendix Table A13, we instrument respondents' sleep by deviations in minimum night temperature in addition to sunset time and in Appendix Table A14, we instrument respondents' sleep by sunrise time instead of sunset time. Similar results are obtained.

One could argue that for these results to be valid, there should be some wage flexibility, such that when sleep increases hourly wages could increase. In other words, we would expect those results to depend on how much workers are able to influence their hourly wages — within a week (or a month).[15] If we expect some wage rigidity, by contrast, it is possible that most of the effects come from the fact that people sleep more in the winter and are more likely to get pay rises then (in the new year). To test for this, Appendix Table A15 controls for a new year dummy (January month effect) in our baseline specifications. Our results remain very similar. Finally, we replicate our results on all workers (not only full-time workers) and include part-time workers (Appendix Table A16) and self-employed (Appendix Table A17). We find that when increasing our sample size, our coefficients increase. The coefficient on weekly earnings is now 0.064 (s.e. = 0.017) and the one on hourly wages is now 0.072 (s.e. = 0.020) in Appendix Table A16 and the coefficients on labour force participation is now 0.017 (s.e. = 0.005) and the one on working hours is −0.011 (s.e. = 0.003) in Appendix Table A17. This could suggest that productivity (and wage) gains from longer sleep are higher among part-time workers, who might have more opportunities to adjust their hourly wages. Similarly, self-employed workers have more opportunities to adjust their labour supply and work schedules.[16]

4. Potential mechanisms and heterogeneity

The previous section has shown that respondents are more likely to work, work fewer hours and earn higher salaries when they sleep more hours on average per week. These results are robust to various tests. If sleep affects labour market performance, one might expect that one mechanism through which these relationships occur is via the positive effect sleep exerts on cognitive functioning and attention to work (Lim and Dinges, 2010; Killgore, 2010). Another mechanism would be the effect of sleep on workers' ability to deal with stress and mental well-being. Arguably, if workers are more focused and less stressed, they are more likely to report better health, which in turn increases their productivity at work. In this section, we document the impact of sleep on alternative outcomes and test for these underlying mechanisms. We then focus on the existence of heterogeneous effects across respondents.

Work Efficiency, Stress, Psychological Well-being and Health. One advantage of the SOEP data is the inclusion of several variables, which allow us to contribute to the literature by providing unique insights on the potential mechanisms through which sleep affects labour market performance. The first potential explanation advanced for the increase in productivity is that workers are more efficient at work. To test for this, we examine the effect of sleep duration on the worker's probability to report (i) being a thorough worker, and (ii) being effective and efficient in completing tasks. Self-reported measures of workers' efficiency at work are not necessarily high-quality measures of productivity. Yet, we believe that this provides the first piece of evidence of whether workers sleeping more hours on average tend to be more efficient at work. Table 4, Panel A, reports the results. The estimated coefficients reveal that a 1-hour increase in weekly sleep duration is associated with a 2.5 percentage point increase in the probability of being a thorough worker and a 4.3 percentage point increase in the probability of being effective and efficient in completing tasks. The coefficient is only significant on the latter.

The second explanation invoked was that sleep duration reduces workers' stress and increases psychological well-being. In other words, workers are more productive because they feel more relaxed and less under pressure. In SOEP, respondents are asked whether they feel (i) nervous, and (ii) rushed by time. Columns (3) and (4) of Panel A indicate that a 1-hour increase in weekly sleep duration decreases the probability of being nervous by 2 percentage points and significantly reduces the probability of feeling rushed by time by 17.3 percentage points. This latter estimate reveals meaningful effects of sleep duration on worker's stress — equivalent to a decrease of roughly 50% in worker's stress, relative to a sample mean of 41%. Arguably, if workers feel more relaxed, they are more likely to enjoy working and be more productive at work.

We provide further evidence for this mental health channel, by investigating the effects of sleep on workers' affective states and self-reported mental health. In the SOEP data, respondents are asked "during the last four weeks, how often did they feel: (i) angry, (ii) worried, (iii) sad, and (iv) happy". Possible answers range from (1) very rarely to (5) always. Sleep deprivation is likely to affect workers' moods. In our sample, 25% declare being very often or always angry, 5% worried, 10% sad and 60% happy. If respondents who sleep less on average, are also respondents who report more negative emotions, they may experience more problems at work or be less productive. Panel B of Table 4 reports the results. The estimates reveal that workers who sleep more hours tend to be less angry and less sad on average. We do not find any significant effect on the frequency of being worried or happy. We also investigate the effects of sleep duration on respondents' mental health using a summary measure of the SF-12 questionnaire. We

[15] The German system of wage formation is still dominated by sectoral collective bargaining. However, over time, workers' pay have become increasingly linked to their own performance. In particular performance pay was increasingly used from the 80 s up to 2009 in Germany (Sommerfeld, 2013). In a recent study by Baktash et al. (2022) using the SOEP data, in 2004, 2008 and 2016, 26% of the sample were subject to performance pay.

[16] As placebo tests, we also examine specific occupation groups that are expected to have the least flexibility in their labour supply and income. In particular, Appendix Table A18 presents the replication of our baseline results using only seasonal variations (non-movers), but with a restricted sample of trainees (Panel A) and civil servants (Panel B). As anticipated, we do not find any wage effects for trainees, as their wages are predetermined based on predetermined schedules. Similarly, we do not observe any labour supply effects for civil servants, which aligns with the fact that most civil servants have lifelong appointments and are less likely to respond to variations in sleep. It is important to note, however, that the results remain significant and within the same range of magnitude as the rest of the sample in terms of weekly earnings and hourly wages. This might be attributed to performance bonuses that civil servants receive, which could vary on a monthly basis.

Table 4
IV estimates of the effect of sleep on work efficiency, stress, affective states and health.

	A thorough worker	Effective and efficient in completing tasks	Nervous	Feel rushed by time
	(1)	(2)	(3)	(4)
Panel A: Work efficiency & Stress				
Sleep	0.025	0.043***	−0.020	−0.173*
	(0.032)	(0.016)	(0.022)	(0.093)
Observations	21,593	21,563	21,560	13,193
Outcome mean	0.45	0.72	0.26	0.41
Outcome SD	0.50	0.45	0.44	0.49
F-Statistics	22.17	22.39	21.64	2.534
	Angry	Worried	Sad	Happy
	(5)	(6)	(7)	(8)
Panel B: Affective states				
Sleep	−0.102***	−0.035	−0.116**	−0.012
	(0.021)	(0.033)	(0.051)	(0.019)
Observations	56,913	56,847	56,878	56,878
Outcome mean	2.88	1.79	2.20	3.63
Outcome SD	0.96	0.88	0.96	0.79
F-Statistics	35.97	35.17	34.68	35.89
	Mental health score	State of health affect tiring tasks	General health	
	(9)	(10)	(11)	
Panel C: Health				
Sleep	0.184*	−0.132	0.161*	
	(0.095)	(0.085)	(0.091)	
Observations	13,211	13,191	13,198	
Outcome mean	3.21	1.44	3.41	
Outcome SD	0.70	0.59	0.67	
F-Statistics	2.663	2.638	2.539	

Notes: This table reports the IV estimates of the effect of 1-hour increase in weekly sleep on work efficiency, stress, affective states, and health. Weekly sleep duration is instrumented using local variations in daily sunset times. All coefficients are estimated on respondents aged between 15 and 64, who are not self-employed, who declare positive weekly earnings and who are working full-time. We control for age group dummies, indicators for summer season, day of week, and occupation codes. We also include individual and state fixed effects. Standard errors are clustered at the state level.

replicate the baseline regression with this variable as an alternative outcome. Interestingly, a 1-hour increase in sleep duration increases respondents' mental health by 0.18 points on a 1–5 scale.

Finally, if workers are less under pressure and experience higher well-being, this might give rise into better health. To examine such health effects, we study the effect of sleep duration on workers' probability of reporting that (i) their state of health affects their ability to perform tiring tasks and (ii) a composite measure of respondents' general health from the SF-12 questionnaire. In our sample, 13% of workers declare being limited in their activities due to health problems. Panel C reports the results. The estimates reveal a (non-significant) negative effect of weekly sleep duration on the probability that workers report being affected in their ability to perform tiring tasks. We do however find significant and positive effects on workers' general health. In terms of magnitude, a 1-hour increase in weekly sleep duration would increase respondents' general health by 0.16 points on a 1–5 scale. These results are consistent with the idea that better sleep reduces absenteeism and workplace accidents. If workers are in better health, they tend to be more productive.

Overall, these results are important — they provide a first attempt to explore potential mechanisms through which sleep can affect workers' productivity using large-scale longitudinal data. They highlight the influence of sleep on workers' efficiency, stress, psychological well-being, and health and shed new light on previous findings from the literature (Bessone et al., 2021). However, our results are also somewhat hindered by the quality of the data and the small sample size.

Other activities. While more hours of sleep improve productivity at work, it can also increase productivity in other day-to-day activities. In other words, it is likely that longer sleep affects market work but also non-market activities such as leisure and home production. In the SOEP data, we have information on respondents' satisfaction with several times allocations, including leisure, home production and family life. We replicate our baseline regressions with these variables as alternative outcomes in Appendix Table A19. Interestingly, a 1-hour increase in sleep duration substantially increases housework satisfaction. The effects are large and meaningful, which suggests that the productivity effects of sleep duration are pervasive and go beyond work effects. We do not find any significant effects on leisure, family or life satisfaction though.

Heterogeneity. In Table 5, we also investigate heterogeneous effects with respect to (i) gender, (ii) education, (iii) age, and (iv) parenthood. We find evidence of significant differences across these different subgroups. We see that the employment effects – on the extensive margins – are concentrated among women and respondents aged below 42 (the median age in our sample). This

Table 5
Heterogeneity of the effect of sleep on labour market outcomes.

	Working (1)	Log (hours worked) (2)	Log (weekly earnings) (3)	Log (hourly wages) (4)
Panel A: Sex				
Male	0.012**	−0.013***	0.026**	0.040***
	(0.006)	(0.005)	(0.011)	(0.014)
Observations	46,069	42,578	42,994	42,547
F-statistics	28.22	29.57	36.10	30.87
Female	0.022**	−0.001	0.050***	0.047***
	(0.009)	(0.004)	(0.019)	(0.016)
Observations	39,975	20,601	20,817	20,575
F-statistics	13.59	25.23	23.95	26.39
Panel B: Education				
Low educated	0.017**	−0.009*	0.031***	0.040***
	(0.008)	(0.005)	(0.009)	(0.011)
Observations	41,260	30,155	30,494	30,124
F-statistics	17.91	20.53	22.31	21.19
Highly educated	0.016***	−0.007	0.038**	0.044**
	(0.005)	(0.007)	(0.017)	(0.019)
Observations	44,500	32,820	33,105	32,794
F-statistics	20.53	19.65	20.37	20.14
Panel C: Age				
Below median	0.031***	−0.014**	0.021	0.034
	(0.011)	(0.006)	(0.023)	(0.025)
Observations	38,151	26,890	27,157	26,854
F-statistics	13.48	25.39	27.65	25.63
Above median	0.007	−0.004	0.042***	0.046***
	(0.005)	(0.004)	(0.011)	(0.012)
Observations	45,970	34,797	35,163	34,775
F-statistics	23.74	31.84	31.45	33.58
Panel D: Children				
No child	0.013***	−0.005	0.022	0.028*
	(0.004)	(0.004)	(0.016)	(0.014)
Observations	44,699	34,481	34,875	34,464
F-statistics	13.40	39.66	37.12	40.95
With children	0.019*	−0.012	0.069***	0.081***
	(0.011)	(0.008)	(0.018)	(0.022)
Observations	38,812	26,767	27,003	26,726
F-statistics	14.43	22.23	24.67	22.44

Notes: See Table 2.

suggests that young women experiencing sleep deprivation are the ones who are more likely to opt out of the labour market. We also find that the productivity effects (looking at hourly wages for instance) are more pronounced for respondents with children and respondents aged above 42. Again, these results are important and suggest that women and in particular mothers would be those who would benefit the most from policies promoting sleep and encouraging firms to pay attention to sleep issues allowing to reduce gender inequalities.

5. Conclusions

To estimate the causal effects of sleep duration on labour market performance, it is essential to rely on longitudinal data that draws on within-individual variations in sleep duration and control for specific sleep routines, genetic predisposition to cope with sleep deprivation or reporting bias that would be correlated with both sleep duration and labour market outcomes. In this paper, we use the data from the German Socio-Economic Panel and exploit daily variations in local sunset times as an instrument for sleep duration. Importantly, our dataset allows us to investigate the causal effects of sleep on a range of labour market outcomes, including labour force participation, hours worked and earnings, and to provide unique evidence on how sleep affects labour market performance.

We find that an increase in sleep duration significantly increases labour force participation and weekly earnings. We document that a 1-hour increase in sleep duration increases labour force participation by 1.6 percentage points and weekly earnings by 3.4%. Moreover, we find that the number of working hours slightly decreases with sleep duration; that is, most of the earnings effects come from productivity changes. Interestingly, women and in particular mothers are more likely to experience an increase in labour force participation and earnings when allocating more time to sleep. These results are consistent with sleep playing an important barrier for women with young children to go back to work and could be an additional explanation for the child wage penalty experienced by women.

Investigating potential mechanisms, we find that an increase in weekly sleep duration increases workers' efficiency in completing tasks and substantially decreases the feeling of being rushed by time. Although other mechanisms are likely to be at work, we find that the mental health effects associated with sleep seem to play a key role in shaping the labour market returns to sleep. Finally, we find beneficial effects of sleep on workers' physical health.

The results of our study are important because they highlight how sleep can exert economically significant productivity gains. They can also help us shed light on the returns to interventions attempting to address sleep deprivation. For instance, we find that workers who sleep 1 h longer are more efficient at work by 4.3 percentage points; they are more productive within shorter hours of work (0.8% reduction in weekly working hours). Therefore, if a policy is introduced that allows workers to sleep 1 h more per week then our results suggest that they are more likely to work by 1.6 percentage points and to earn higher salaries by 3.4% in response to this change.

One promising avenue for policy could be to engage workers in training, nudging and information campaigns that convey the notion that sleep is a productivity-enhancing investment, and enough time should be allocated to sleep per night. Another avenue for policy could be to encourage firms to recognize the importance of sleep and to adopt flexible working hours allowing workers to have enough time to sleep. However, whether such interventions successfully imrpove sleep and labour market performance is beyond the scope of this article and is an open question that future research should address.

Declaration of competing interest

None of the author of this paper has received any funding nor have any conflict of interest to disclose.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2023.102840.

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