Employment and Sleep Patterns

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Abstract

This paper examines how employment rates affect sleep patterns, using data from the American Time Use Survey (ATUS) and Local Area Unemployment Statistics (LAUS) from 2003 to 2022. Research suggests that while weekday sleep is countercyclical, weekend sleep is procyclical, with employed individuals sleeping more on weekends to compensate for shorter weekday sleep. The results show that a 1 percentage point increase in the employment-to-population rate reduces average sleep duration by approximately 1 minute and weekday sleep by around 2 minutes. This effect is less pronounced when using the data from 2003-2022, likely due to the increase in telework following the COVID-19 pandemic. Additionally, industries with a higher concentration of telework experience smaller decreases in sleep with increasing employment. Heterogeneous analysis shows that minorities, less educated individuals, women, and single adults face greater reductions in sleep during weekdays.

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1 Introduction

Sleep is essential for maintaining good health and productivity, and a lack of sleep could incur substantial health and economic costs. According to a report by the Centers for Disease Control and Prevention (CDC), sleeping fewer than 7 hours per night can increase the risk of developing conditions such as high blood pressure, heart disease, stroke, diabetes, obesity, and frequent mental distress (Liu, 2016).

Besides the health costs, insufficient sleep can lead to increased mortality and decreased productivity. Sleep deprivation is associated with accidents and injuries caused by fatigue (Dinges, 1995; Lockley et al., 2007; Barnes and Wagner, 2009). It affects attention, cognitive skills, coordination, motor functions, and processing speed (Dinges and Powell, 1985; Drummond et al., 2005; Banks and Dinges, 2007; Lim and Dinges, 2010). Additionally, it impacts productivity and psychological well-being (Bessone et al., 2021).

The business cycle has a significant impact on sleep patterns. According to a study by Colman and Dave (2013), sleep duration tends to be countercyclical. During the Great Recession, people spend more time sleeping and television watching (Aguiar et al., 2013). By analyzing data on sleep duration and unemployment rates, Figure 1 illustrates a positive correlation between unemployment rates and the amount of sleep. The unemployment data is seasonally adjusted, and sleep durations are smoothed using a 12-month moving average. Both sets of variables have been adjusted to remove any linear trends and normalized by subtracting the mean from the detrended data and then dividing by the standard deviation. Figure 2 indicates the countercyclical nature of sleep applies to both employed and not-employed individuals.

Individuals display different work hours and sleep patterns on weekdays versus weekends. According to Figure 3, people generally work about 5.6 hours more during the weekdays. Meanwhile, Figure 4 shows that employed individuals usually sleep an extra

1.25 hours on weekends than on weekdays. The relationship between sleep and economic conditions also varies by the day of the week. Niekamp (2019) found that while sleep duration on weekdays is countercyclical, it tends to be procyclical during weekends

This paper investigates the relationship between employment rates and sleep patterns by utilizing data from the American Time Use Survey (ATUS) and Local Area Unemployment Statistics (LAUS) covering the period from 2003 to 2022. In line with the research conducted by Niekamp (2019) on the economic impact, I replicate his analysis using data from 2003 to 2022. Moreover, I expand the analysis to encompass data up to 2022, allowing for an examination of the effects of the COVID-19 Recession, commonly referred to as the Great Lockdown. Additionally, this study incorporates an analysis of the telework component to provide a comprehensive understanding of the topic.

The analysis conducted using a standard linear regression model reveals interesting patterns in sleep behavior. Specifically, it shows that weekday sleep follows a countercyclical trend, while weekend sleep exhibits a procyclical pattern, although the latter is not statistically significant. The results indicate that a 1 percentage point increase in the employment-to-population rate leads to a reduction in average sleep duration by approximately 1 minute. Moreover, weekday sleep experiences a more substantial decrease of around 2 minutes. However, it is worth noting that the impact of employment on sleep duration appears to be smaller when considering data from 2003-2015. This could be attributed to the rise in teleworking practices following the COVID-19 pandemic. Industries with higher rates of telework also demonstrate smaller reductions in sleep as employment levels increase.

Furthermore, a heterogeneous analysis reveals that certain demographic groups experience more significant reductions in weekday sleep. Specifically, minorities, individuals with lower education levels, women, and single individuals are particularly affected.

The following sections of this paper will provide a detailed overview of the topic. Section 2 will review the existing literature on sleep and economic condition studies. In

Section 3, the data used in this paper will be described. Section 4 will outline the empirical methods employed in the study. The main results will be presented in Section 5, while Section 6 will conclude the paper and discuss potential avenues for future research.

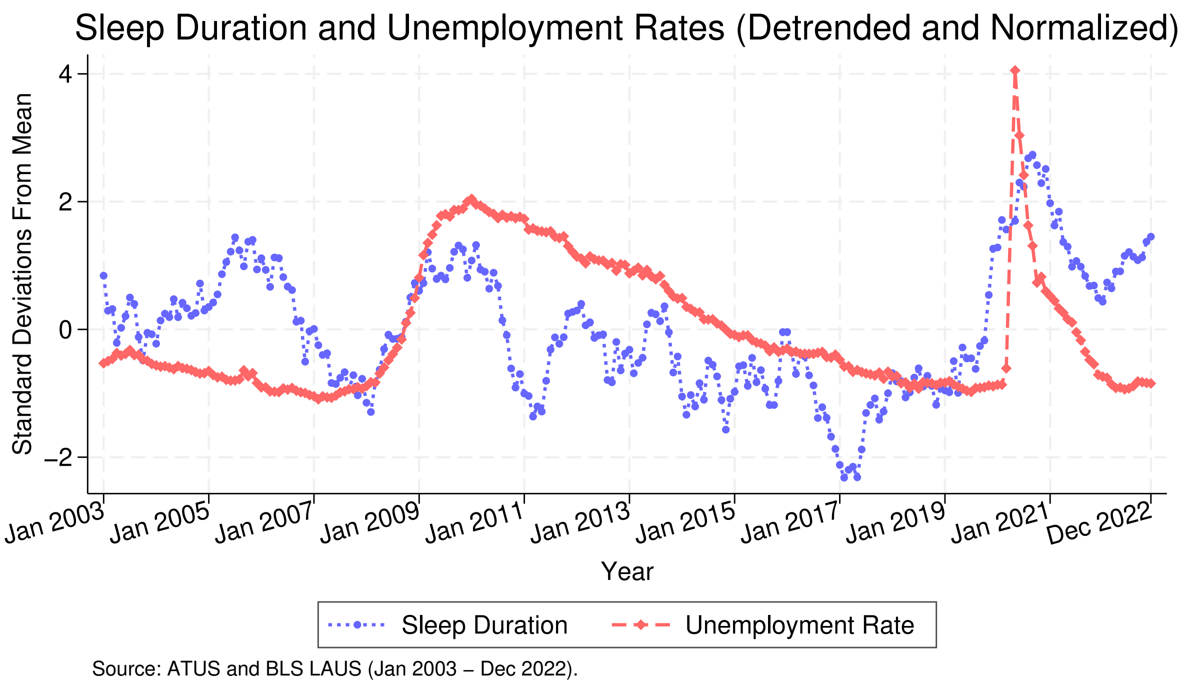

Figure 1: Sleep Duration and Unemployment Rates (Detrended and Normalized)

Unemployment rates are seasonally adjusted and sleep durations are smoothed by applying a moving average. The variables have been detrended by removing a linear trend and normalized by subtracting the mean of the detrended variables and dividing by their standard deviation. The figure shows a positive relationship between unemployment rates and sleep duration.

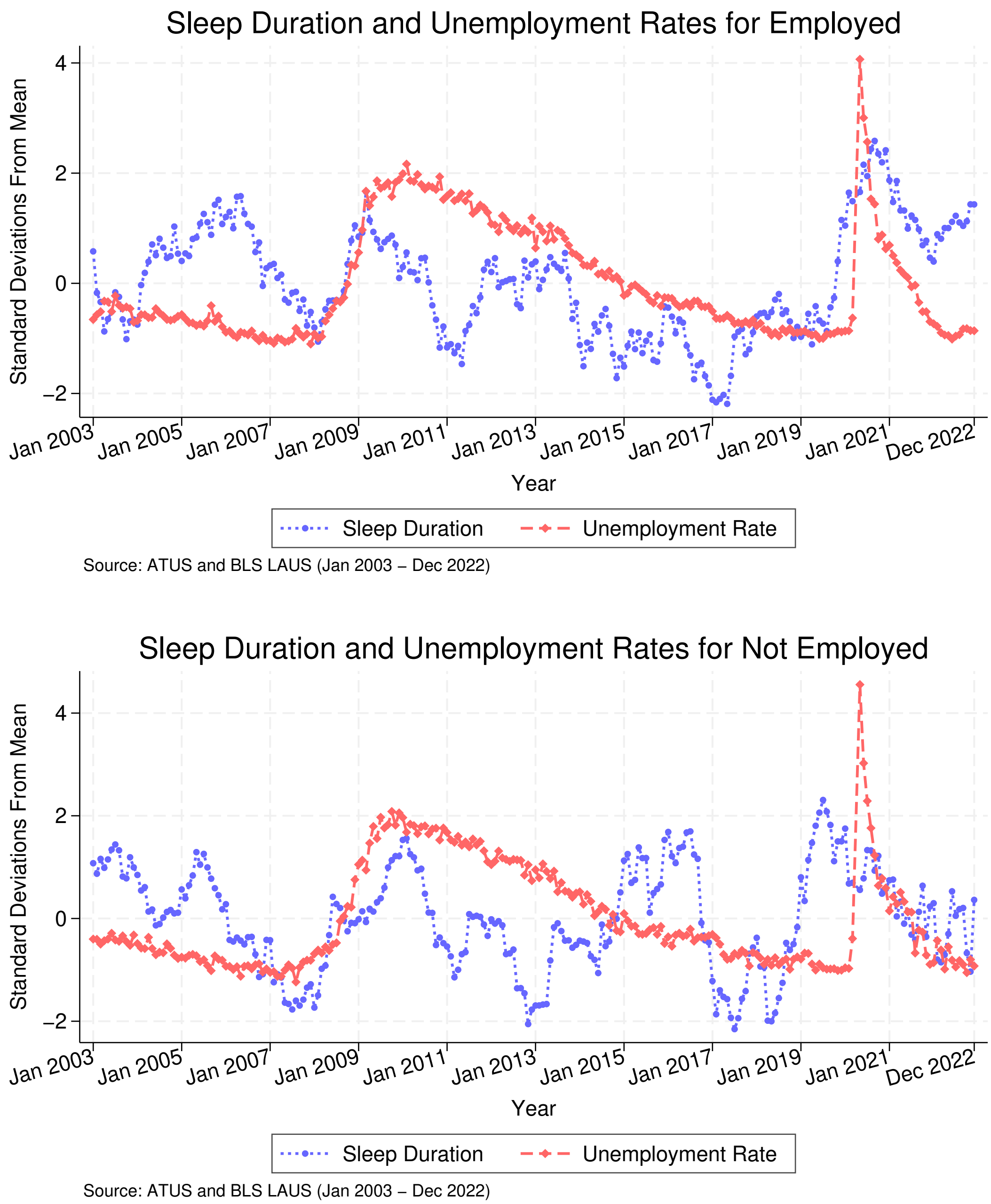

Figure 2: Sleep Duration and Unemployment Rates (Employed v.s. Not Employed)

Unemployment rates are seasonally adjusted and sleep durations are smoothed by applying a moving average. The variables have been detrended by removing a linear trend and normalized by subtracting the mean of the detrended variables and dividing by their standard deviation. The figure shows a positive relationship between unemployment rates and sleep duration. Not employed refers to those who are unemployed and not in the labor force.

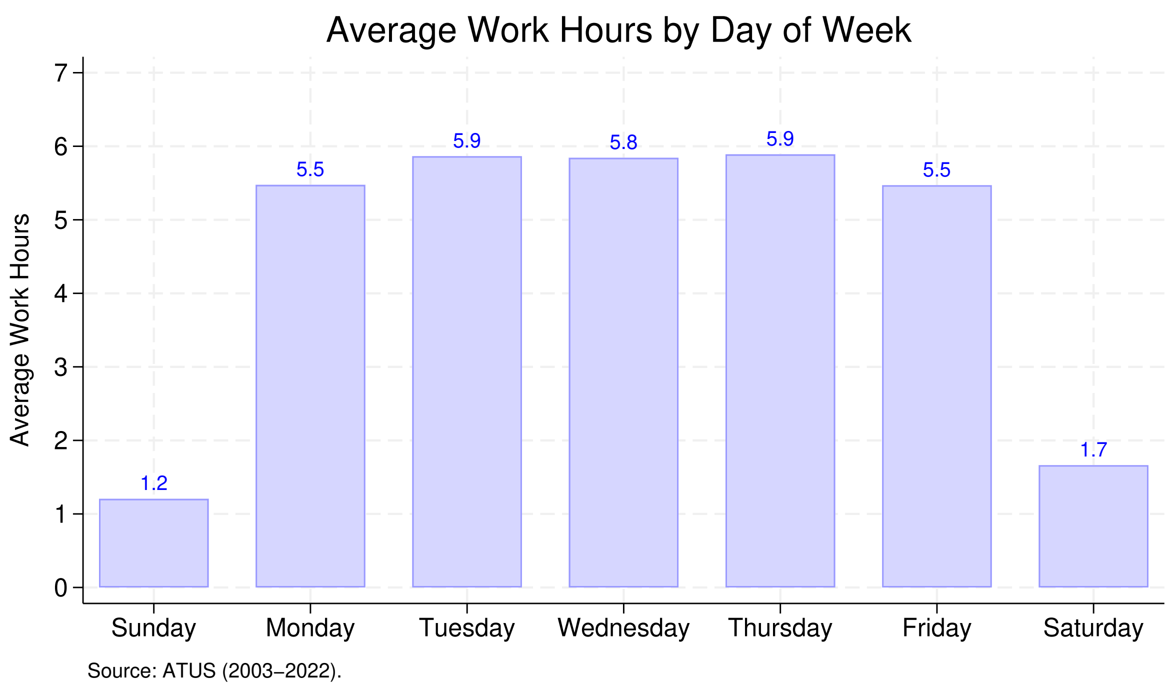

Figure 3: Average Work Hours by Day of Week

The sample averages only include data from individuals aged 25 to 55 who have reported at least 23 hours of time use.

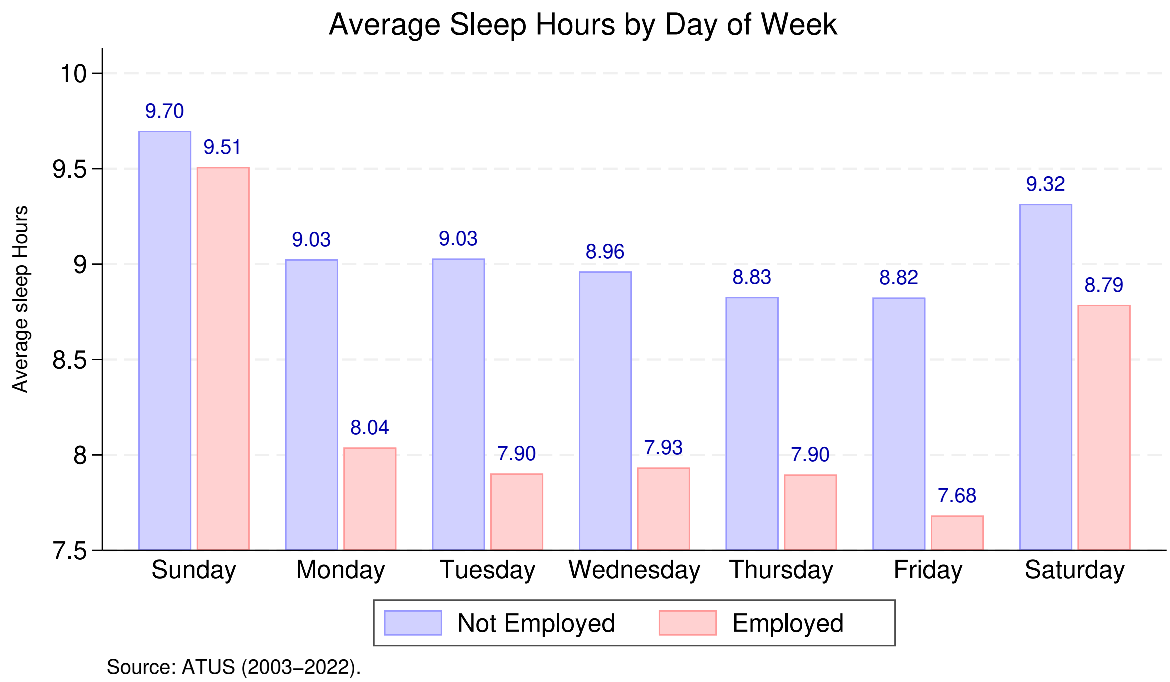

Figure 4: Average Sleep Hours by Day of Week

The sample averages only include data from individuals aged 25 to 55 who have reported at least 23 hours of time use. Not employed refers to those who are unemployed and not in the labor force.

2 Literature Review

Sleep deprivation can negatively impact both mental and physical health. Medical studies have demonstrated that lack of sleep negatively impacts attention, memory, and mood. For instance, Banks and Dinges (2007) reviewed experiments on chronic sleep restriction and found that sleep deprivation leads to attention lapses, slower working memory, reduced processing speed, symptoms of depression, and perseverative thinking. It can also result in detrimental physiological outcomes over the long term. Additionally, the Centers for Disease Control and Prevention (CDC) report that sleeping less than 7 hours per night increases the risk of developing serious health issues such as high blood pressure, heart disease, stroke, diabetes, obesity, and frequent mental distress (Liu, 2016).

Medical research has long indicated the risks of sleep deprivation, but only recently have economists begun to empirically analyze its effects. Studies have shown varying impacts of sleep on different aspects of life (Kamstra et al., 2000). For instance, Smith (2016) found a 5.6% increase in fatal crashes following the spring transition to Daylight Saving Time (DST). Similarly, Gibson and Shrader (2018) demonstrated that an extra hour of weekly sleep could increase short-term wages by 1.1% and long-term wages by 5%.

Further research includes a field experiment in Chennai, India, by Bessone et al. (2021), which increased sleep duration by 27 minutes nightly but did not significantly affect cognition, productivity, or well-being—though afternoon naps did improve these factors. Jin and Ziebarth (2020) noted a decrease in hospitalization rates following the fall transition of DST, an effect lasting four days. Additionally, studies by Giuntella et al. (2017) and Giuntella and Mazzonna (2019) found that later sunset times reduced sleep duration and were linked to several negative health outcomes, emphasizing the profound impact of sleep on health and economic variables.

This paper contributes to the literature on how economic conditions influence health outcomes, aligning with established literature that typically views recessions as beneficial for health. For instance, Ruhm (2000) noted that mortality rates fluctuate procyclically, while his later work observed health-improving behaviors such as reduced smoking and increased physical activity during economic downturns (Ruhm, 2005). Similarly, Miller et al. (2009) found that higher unemployment rates correlate with lower state-level mortality rates, and Stevens et al. (2015) found that most additional deaths that occur when the economy is strong are among the elderly, particularly elderly women and those residing in nursing homes.

Additionally, Charles and DeCicca (2008) found that deteriorating labor market conditions result in weight gain and diminished mental health among African-American men, as well as reduced mental health among less-educated males. Similarly, Colman and Dave (2013) observed that during a recession, decreased work hours lead to increased recreational exercise, TV-watching, sleeping, childcare, and housework, with the most pronounced effects seen among low-educated men.

Building on these foundations, my research draws a close parallel with the findings of Niekamp (2019), who investigated the cyclical nature of sleep patterns across different days of the week, noting that sleep duration on weekdays is countercyclical but procyclical on weekends. My study replicates Niekamp's analysis using data spanning from 2003 to 2015 and extends it to include analysis up to 2022 to examine the impacts of the COVID-19 Recession. This extension provides a comprehensive view of how recent economic disruptions, coupled with the rise in teleworking, have altered daily routines and health behaviors.

This paper also explores the impact of the COVID-19 pandemic on the labor market, building on previous studies that have documented shifts in work habits. Before the pandemic, Pabilonia and Vernon (2020) documented a rising trend in remote work in the United States, observing that teleworkers spent less time on commuting and grooming while allocating more time to leisure, sleep, household production, and family activities on work-from-home days. The pandemic significantly accelerated this shift, as Bick et al. (2023) reported a persistent rise in work from home (WFH), increasing from 14.4 percent of workdays in February 2020 to 39.6 percent in May 2020. They predict a permanent change post-pandemic, with twice as many workers expected to WFH full-time.

Similarly, Barrero et al. (2021) found that 20 percent of full workdays will likely be conducted from home after the pandemic, suggesting a lasting transformation in the labor market dynamics. My research contributes to this literature by documenting how economic conditions differently affect sleep patterns across industries, with a particular focus on those that have a high prevalence of telework.

In summary, while existing research provides substantial insights into the effects of sleep deprivation and economic conditions on health and labor market dynamics, there remains a need for a nuanced analysis of how these elements interact across different industries, especially in the context of increased telework. This paper fills this gap by leveraging recent data to assess the impacts of economic disruptions on sleep patterns, particularly during the COVID-19 recession. By focusing on industries with high rates of telework, this study contributes to a more detailed understanding of the relationship between economic conditions and health outcomes in the modern labor market.

3 Data

The individual sleep duration comes from the American Time Use Survey (ATUS) sponsored by the U.S. Bureau of Labor Statistics (BLS) and conducted by the U.S. Census Bureau since 2003. ATUS is the first continuous survey on time use in the United States. Individuals are randomly selected from the households that just finished the eight-month interview for the Current Population Survey (CPS) and the interviews for ATUS are conducted between two and five months after the last CPS interview. The goal of ATUS is to understand how people allocate their time.

The time diary of the ATUS is conducted through computer-assisted telephone interviews. The respondent is asked to recall the time spend in each activity from 4:00 am on the previous day to 4:00am on the interview day. This method allows the time diaries to be summed to 24 hours to minimize possible biases. For each activity, the ATUS gathers either the ending time or the duration of the activity and the interviewer collects the answers verbatim, which are coded later (Hamermesh et al., 2005).

Following Niekamp (2019) and Colman and Dave (2013), I limit the analysis for individuals with age between 25 to 55 and also restrict the analysis to observations with at least 23 documented hours (92% of observations). The employment data (unemployment rates and employment to population ratio) is from the Local Area Unemployment Statistics (LAUS) monitored by BLS. I exploit the variation of economic condition at the month-state level.

Table 1 shows the summary statistics.

Table 1: Summary Statistics

	(1) All mean/sd	(2) Female mean/sd	(3) Male mean/sd	(4) Employed mean/sd	(5) Not Employed mean/sd	(6) < Bachelor's mean/sd	(7) $\geq$ Bachelor's mean/sd
Sleep Time (Hours)	8.66	8.76	8.53	8.52	9.23	8.45	8.79
	(2.23)	(2.21)	(2.25)	(2.15)	(2.49)	(1.94)	(2.40)
Age	40.42	40.19	40.68	40.38	40.59	40.21	40.55
	(8.49)	(8.55)	(8.41)	(8.39)	(8.89)	(8.15)	(8.71)
Married	0.60	0.59	0.62	0.61	0.59	0.67	0.56
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.47)	(0.50)
Number of Children	1.17	1.24	1.08	1.13	1.33	1.16	1.18
	(1.19)	(1.19)	(1.19)	(1.15)	(1.32)	(1.14)	(1.23)
Children Under 3	0.16	0.16	0.15	0.15	0.20	0.18	0.14
	(0.36)	(0.37)	(0.36)	(0.35)	(0.40)	(0.38)	(0.35)
White	0.66	0.65	0.68	0.68	0.58	0.74	0.61
	(0.47)	(0.48)	(0.47)	(0.47)	(0.49)	(0.44)	(0.49)
Black	0.13	0.14	0.11	0.12	0.16	0.09	0.15
	(0.33)	(0.35)	(0.31)	(0.32)	(0.37)	(0.28)	(0.36)
Hispanic	0.15	0.15	0.15	0.14	0.19	0.08	0.20
	(0.36)	(0.36)	(0.36)	(0.35)	(0.40)	(0.27)	(0.40)
American Indian	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	(0.09)	(0.09)	(0.09)	(0.08)	(0.11)	(0.06)	(0.10)
Holiday	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Incomplete Diary	0.08	0.09	0.07	0.08	0.08	0.09	0.07
	(0.27)	(0.28)	(0.25)	(0.27)	(0.27)	(0.29)	(0.26)
N	120743	65868	54875	97713	23030	48733	72010

Data are from ATUS and BLS LAUS (2003-2022). The sample is restricted to respondents aged 25-55.

4 Methodology

To estimate the impact of employment on sleep duration, I employ a standard linear regression model:

$$Sleep_{isdmt} = \beta_0 + \beta_1 E_{smt} + X'_{ismt}\beta_2 + \gamma_s + \delta_m + \lambda_d + \theta_t + u_{isdmt} \tag{1}$$

where $Sleep_{isdmt}$ represents the daily sleep duration in minutes for individual i in state s on day d of month m in year t. The variable X_{ismt} is a vector of control variables that includes socio-demographic factors (age, gender, race, education, race interacted with education, marital status, number of children, an indicator for having a child under 3, and industry codes) and interview characteristics (indicators for holiday and incomplete diary). E_{smt} denotes the civilian employment-population ratio for state s in month m of year t.

The state fixed effects, γ_s, account for the time-invariant unobserved heterogeneity of state-specific factors. The month fixed effects are represented by δ_m, the day of the week fixed effects by λ_d, and the year fixed effects by θ_t. The error term, u_{isdmt}, has standard errors clustered at the state level. This empirical approach aligns with the extensive literature on economic conditions and health outcomes (Niekamp, 2019; Charles and DeCicca, 2008; Ruhm, 2000, 2005).

5 Results

The impact of the employment-to-population ratio on sleep duration from 2003 to 2022 are illustrated in Table 2. According to Column 2, a one percentage point increase in the employment rate reduces sleep by approximately one minute per night. The point estimate of -1.02 (using data from 2003-2022) aligns closely with the findings of -1.1 from

Niekamp (2019) and -0.97 from Colman and Dave (2013). This consistency supports the conclusion of prior research that overall sleep is counter-cyclical. The effects vary between weekdays and weekends. Columns 4 and 6 report that a one percentage point increase in the employment rate decreases weekday sleep by 2.3 minutes per night, while it increases weekend sleep by 0.26 minutes per night.

The effects of employment can vary significantly across different demographics. Table 3 presents the results segmented by education, race, and gender. Columns 2 and 3 indicate that the effects of employment on sleep are greater and statistically significant for individuals without a Bachelor's degree. Columns 4 and 5 show that the impact is more pronounced among minorities, including Blacks, Hispanics, and American Indians. Columns 6 and 7 suggest that females experience a higher impact compared to males. Column 8 reveals that white males without a Bachelor's degree are particularly sensitive to changes in the employment rate, especially during weekdays. Table 4 replicates the analysis using data from 2003 to 2015, as done by Niekamp (2019). The results are similar, with Column 1 showing slightly higher estimates (using data from 2003-2015). The weekday effects are relatively greater, while the weekend effects are smaller and not statistically significant.

Marital status can also affect the estimates in different ways. Table 5 presents the effects by marital status. Columns 1 and 2 reveal that single individuals experience a greater impact on weekday sleep. Columns 3 and 4 indicate that the employment effects are more pronounced for single parents, who tend to be less educated and belong to minority groups, making them more strongly affected. Additionally, single parents sleep less during weekends when employment rates increase. Columns 5 and 6 show that the sleep or work of low-educated females is not sensitive to economic conditions. Table 6 shows the results for the period from 2003 to 2015. The estimates are similar to those found by Niekamp (2019), except that married parents experience a stronger impact.

Table 2: Effects of Employment Rate on Sleep (2003-2022)

	All		Weekday		Weekend	
	(1)	(2)	(3)	(4)	(5)	(6)
	Sleep	Sleep	Sleep	Sleep	Sleep	Sleep
	b/se	b/se	b/se	b/se	b/se	b/se
Employment to Population Rate	-1.375***	-1.019***	-1.461***	-2.308***	-1.333***	0.259
	(0.22)	(0.35)	(0.23)	(0.44)	(0.25)	(0.53)
Mean	519	519	519	519	519	519
Controls	No	Yes	No	Yes	No	Yes
State FEs	No	Yes	No	Yes	No	Yes
Observations	120743	120743	60250	60250	60493	60493

Notes: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Controls include socio-demographics (age, gender, race, education, race interacted with education, marital status, number of children, indicator for having a child under 3, and industry codes) and interview characteristics (indicators for holiday and incomplete diary). The standard errors are robust to heteroscedasticity and clustered at state level (reported in parentheses).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effects of Employment Rate on Sleep by Subgroups (2003-2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	< Bachelor's	≥ Bachelor's	White	BHAI	Female	Male	WM < Bachelor's
All	-1.019**	-1.155*	-0.965	-0.529	-1.777*	-1.183*	-0.822	-1.113
	(0.352)	(0.541)	(0.515)	(0.507)	(0.828)	(0.564)	(0.468)	(0.809)
Observations	120743	72010	48733	80057	33617	65868	54875	20985
R^2	0.11	0.10	0.13	0.11	0.10	0.11	0.12	0.10
Weekday	-2.308***	-2.900***	-1.699*	-1.496*	-4.455***	-2.753***	-1.824**	-2.785*
	(0.441)	(0.625)	(0.675)	(0.639)	(1.136)	(0.699)	(0.595)	(1.249)
Observations	60250	35690	24560	40287	16411	32706	27544	10625
R^2	0.07	0.07	0.05	0.06	0.07	0.07	0.07	0.07
Weekend	0.259	0.512	-0.201	0.461	0.658	0.353	0.128	0.471
	(0.532)	(0.825)	(0.628)	(0.715)	(1.153)	(0.712)	(0.766)	(1.516)
Observations	60493	36320	24173	39770	17206	33162	27331	10360
R^2	0.05	0.05	0.06	0.05	0.05	0.06	0.06	0.05

Note: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Controls include socio-demographics (age, gender, race, education, race interacted with education, marital status, number of children, indicator for having a child under 3, and industry codes) and interview characteristics (indicators for holiday and incomplete diary). The standard errors are robust to heteroscedasticity and clustered at state level (reported in parentheses). Column 5 refers to (BAHI) Black, Hispanic, or American Indian. Column 8 restricts to white males with education less than a Bachelor's degree.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects of Employment Rate on Sleep by Subgroups (2003-2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	< Bachelor's	≥ Bachelor's	White	BHAI	Female	Male	WM < Bachelor's
All	-1.133*	-1.234*	-1.051	-0.710	-1.855*	-1.196	-1.058	-1.631
	(0.444)	(0.589)	(0.712)	(0.596)	(0.918)	(0.681)	(0.703)	(0.846)
Observations	91184	56659	34525	61415	24970	50314	40870	16524
R^2	0.11	0.10	0.13	0.11	0.10	0.11	0.11	0.10
Weekday	-2.875***	-3.644***	-1.709	-2.245**	-4.232***	-3.155***	-2.553**	-4.731**
	(0.512)	(0.703)	(1.063)	(0.782)	(1.203)	(0.870)	(0.932)	(1.626)
Observations	45346	28025	17321	30812	12140	24893	20453	8360
R^2	0.07	0.07	0.05	0.06	0.07	0.07	0.06	0.06
Weekend	0.549	1.042	-0.344	0.785	0.340	0.602	0.406	1.425
	(0.673)	(0.950)	(0.793)	(0.857)	(1.372)	(0.917)	(0.984)	(1.555)
Observations	45838	28634	17204	30603	12830	25421	20417	8164
R^2	0.05	0.05	0.06	0.05	0.05	0.05	0.06	0.05

Note: Data are from ATUS and BLS LAUS (2003-2015). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Controls include socio-demographics (age, gender, race, education, race interacted with education, marital status, number of children, indicator for having a child under 3, and industry codes) and interview characteristics (indicators for holiday and incomplete diary). The standard errors are robust to heteroscedasticity and clustered at state level (reported in parentheses). Column 5 refers to (BHAI) Black, Hispanic, or American Indian. Column 8 restricts to white males with education less than a Bachelor's degree.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects of Employment Rate on Sleep by Marital Status (2003-2022)

	(1)	(2)	(3)	(4)	(5)	(6)
	Single	Married	Single Parent	Married Parent	MF(sleep)	MF(work)
All	-0.791	-1.141*	-3.081**	-0.958	-1.795	2.102
	(0.643)	(0.504)	(0.974)	(0.524)	(0.972)	(1.109)
Observations	48062	72681	18122	64968	21066	21066
R^2	0.10	0.13	0.11	0.10	0.11	0.31
Weekday	-3.234***	-1.692*	-5.507***	-2.866***	-2.814*	2.080
	(0.909)	(0.681)	(1.261)	(0.759)	(1.395)	(1.854)
Observations	23969	36281	8959	32453	10325	10325
R^2	0.07	0.06	0.08	0.07	0.06	0.34
Weekend	1.447	-0.438	-0.765	0.848	-0.610	2.138
	(0.898)	(0.654)	(1.237)	(0.682)	(1.137)	(1.737)
Observations	24093	36400	9163	32515	10741	10741
R^2	0.05	0.06	0.05	0.05	0.06	0.09

Note: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 5 refers to married females without college degree for sleep in minutes. Column 6 refers married females without college degree for work in minutes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects of Employment Rate on Sleep by Marital Status (2003-2015)

	(1) Single	(2) Married	(3) Single Parent	(4) Married Parent	(5) MF(sleep)	(6) MF(work)
All	-1.080	-1.220*	-3.278*	-1.295*	-1.829	1.226
	(0.824)	(0.586)	(1.408)	(0.603)	(1.167)	(1.219)
Observations	35733	55451	13837	48373	17124	17124
R^2	0.10	0.12	0.11	0.10	0.11	0.30
Weekday	-3.849**	-2.175**	-5.476**	-3.758***	-2.532	0.282
	(1.239)	(0.759)	(1.862)	(0.988)	(1.633)	(2.096)
Observations	17766	27580	6794	24113	8381	8381
R^2	0.07	0.06	0.08	0.07	0.06	0.33
Weekend	1.532	-0.155	-1.169	1.080	-1.002	2.657
	(1.097)	(0.918)	(1.949)	(0.840)	(1.652)	(2.088)
Observations	17967	27871	7043	24260	8743	8743
R^2	0.05	0.06	0.05	0.05	0.06	0.09

Note: Data are from ATUS and BLS LAUS (2003-2015). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 5 refers to married females without college degree for sleep in minutes. Column 6 refers married females without college degree for work in minutes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

There is heterogeneity across occupation industries due to variations in work time structures. Using the CPS major industry code, I use the variable similar to Niekamp (2019),

$$\text{Percentage of Weekday Work Time} = \frac{W_{\text{weekday}}}{W_{\text{weekday}} + W_{\text{weekend}}},$$

where W_{weekday} is the mean reported work time in minutes on weekdays, and W_{weekend} is the mean reported work time in minutes on weekends. Figure 5 shows the percentage ranges from 62% in Leisure and Hospitality to 88% in Financial Activities sector.

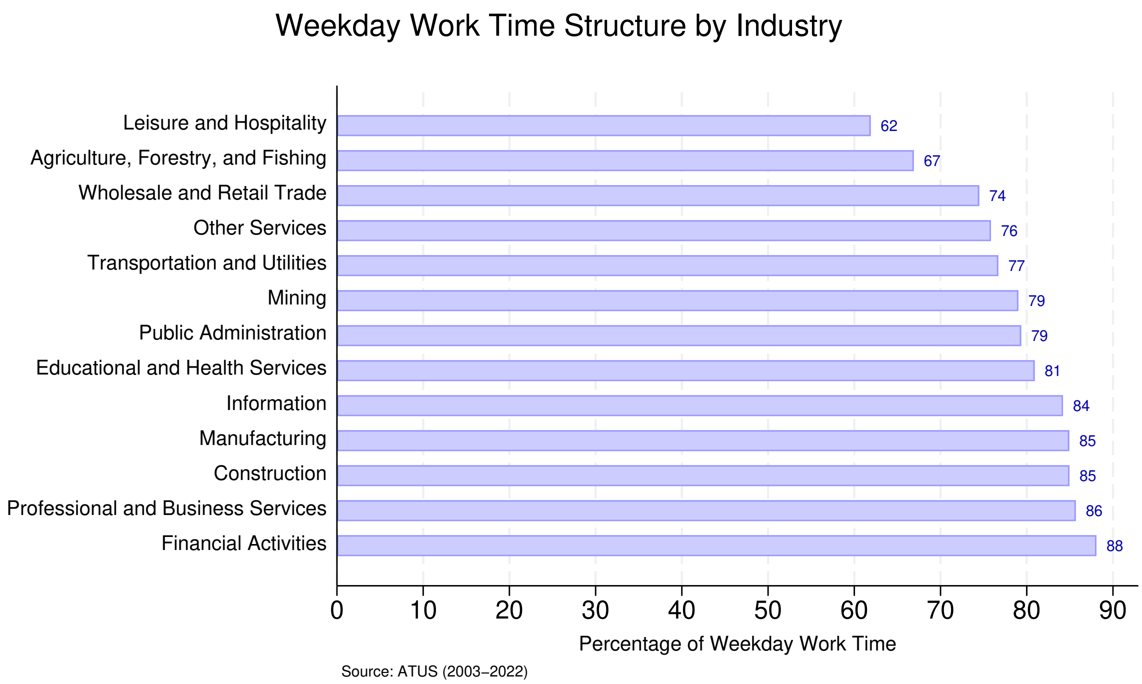

Figure 5: Weekday Work Time Structure by Industry

Data are from ATUS (2003-2022). W_{weekday} is the mean reported work time in minutes on weekdays, and W_{weekend} is the mean reported work time in minutes on weekends. The percentage of weekday work time is given by the formula:

$$\text{Percentage of Weekday Work Time} = \frac{W_{\text{weekday}}}{W_{\text{weekday}} + W_{\text{weekend}}}.$$

Table 7 presents the results by work time structure in different industries. Columns 1 and 2 indicate that the effects are primarily driven by those who are employed. Columns 3 and 4 show estimates for individuals working in industries with a percentage of weekday work time above and below the median. The impacts are comparable, albeit marginally greater for individuals below the median. Columns 5 and 6 divide the industries into blue-collar and white-collar workers, revealing a higher impact on blue-collar workers.

Table 8 shows the analysis from 2003 to 2015. The results are similar to those of Niekamp (2019), except that the not-employed individuals also experience a significant effect on weekday sleep. The results are mainly driven by those working in industries with a percentage of weekday work time below the median. The estimates for blue-collar workers are lower.

If we break the analysis into different periods as shown in Table 9, we observe that the impact of employment on sleep is smaller from 2003-2022 compared to 2003-2015 (Columns 1-2). Columns 3 to 9 show that the effects are generally larger and more significant for the periods from 2011-2015 (after the Great Recession) and 2020-2022 (after the pandemic). The effects are smaller after the pandemic, possibly due to the rise of work-from-home (WFH) or telework, which has been shown to increase sleep time according to previous literature (Pabilonia and Vernon, 2020).

To examine the impact across industries with varying levels of telework concentration, I utilize a new survey question introduced in July 2020 in ATUS. This question asks respondents, "At any time in the last 4 weeks, did you telework or work at home for pay?" Figure 6 displays the ranking of industries by their telework percentages, which range from 4% in Agriculture, Forestry, and Fishing to 43% in the Financial Activities sector.

Table 7: Effects of Employment Rate on Sleep by Work Time Structure and Industry (2003-2022)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed	Not Employed	> Med Weekday	≤ Med Weekday	Blue-collar	White-collar
All	-1.140**	0.010	-1.010*	-1.178	-1.279	-0.351
	(0.392)	(0.900)	(0.381)	(0.624)	(1.110)	(0.661)
Observations	97713	23030	73864	29712	18907	20764
R^2	0.13	0.06	0.14	0.10	0.16	0.16
Weekday	-1.992***	-2.642	-1.979***	-2.120*	-1.580	-0.313
	(0.445)	(1.391)	(0.458)	(0.804)	(1.011)	(0.844)
Observations	49045	11205	37106	14715	12859	14405
R^2	0.04	0.06	0.04	0.05	0.15	0.15
Weekend	-0.267	2.415	-0.148	-0.169	-0.111	-0.501
	(0.605)	(1.363)	(0.682)	(1.007)	(1.447)	(0.899)
Observations	48668	11825	36758	14997	12788	14291
R^2	0.06	0.05	0.06	0.05	0.14	0.15

Note: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 1 limits the sample to employed population and column 2 limites to unemployed and population that are not in the labor force. Column 3 limits to below median weekday work time percentage. Column 5 refers to blue-collar workers: construction and manufaturing. Column 6 refers to white-collar workers: financial activities and professional and business services.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effects of Employment Rate on Sleep by Work Time Structure and Industry (2003-2015)

	(1) Employed	(2) Not Employed	(3) > Med Weekday	(4) ≤ Med Weekday	(5) Blue-collar	(6) White-collar
All	-1.335*	-0.107	-0.794	-2.108**	-1.191	0.322
	(0.587)	(0.975)	(0.673)	(0.700)	(1.486)	(0.766)
Observations	73216	17968	55255	22770	14558	15132
R^2	0.13	0.06	0.13	0.09	0.16	0.16
Weekday	-2.618***	-3.176*	-2.166**	-3.042**	-3.360*	-0.676
	(0.605)	(1.400)	(0.694)	(0.984)	(1.489)	(1.019)
Observations	36579	8767	27557	11286	7234	7662
R^2	0.04	0.06	0.04	0.05	0.05	0.06
Weekend	-0.048	2.507	0.422	-0.994	0.727	1.327
	(0.775)	(1.734)	(0.922)	(1.107)	(2.138)	(1.398)
Observations	36637	9201	27698	11484	7324	7470
R^2	0.06	0.06	0.06	0.05	0.08	0.07

Note: Data are from ATUS and BLS LAUS (2003-2015). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 1 limits the sample to employed population and column 2 limites to unemployed and population that are not in the labor force. Column 3 limits to below median weekday work time percentage. Column 5 refers to blue-collar workers: construction and manufaturing. Column 6 refers to white-collar workers: financial activities and professional and business services.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effects of Employment Rate on Sleep by Periods

	(1) 2003-2022	(2) 2003-2015	(3) 2016-2022	(4) 2003-2007	(5) 2008-2010	(6) 2011-2015	(7) 2016-2019	(8) 2020-2022
All	-1.019**	-1.133*	-0.935	-1.020	-2.399	-2.889*	2.383	-1.688*
	(0.352)	(0.444)	(0.593)	(0.921)	(1.604)	(1.196)	(2.162)	(0.705)
Observations	120743	91184	29559	40772	20772	29640	18404	11155
R^2	0.11	0.11	0.12	0.11	0.12	0.11	0.12	0.12
Weekday	-2.308***	-2.875***	-1.536	-2.075	-2.694	-5.420**	4.251	-3.335**
	(0.441)	(0.512)	(0.938)	(1.118)	(1.441)	(2.021)	(2.475)	(1.052)
Observations	60250	45346	14904	20278	10230	14838	9213	5691
R^2	0.07	0.07	0.07	0.06	0.06	0.08	0.08	0.07
Weekend	0.259	0.549	-0.452	-0.063	-1.790	-1.247	0.498	-0.379
	(0.532)	(0.673)	(1.045)	(1.318)	(2.573)	(1.558)	(3.096)	(1.277)
Observations	60493	45838	14655	20494	10542	14802	9191	5464
R^2	0.05	0.05	0.06	0.06	0.06	0.06	0.05	0.06

Note: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

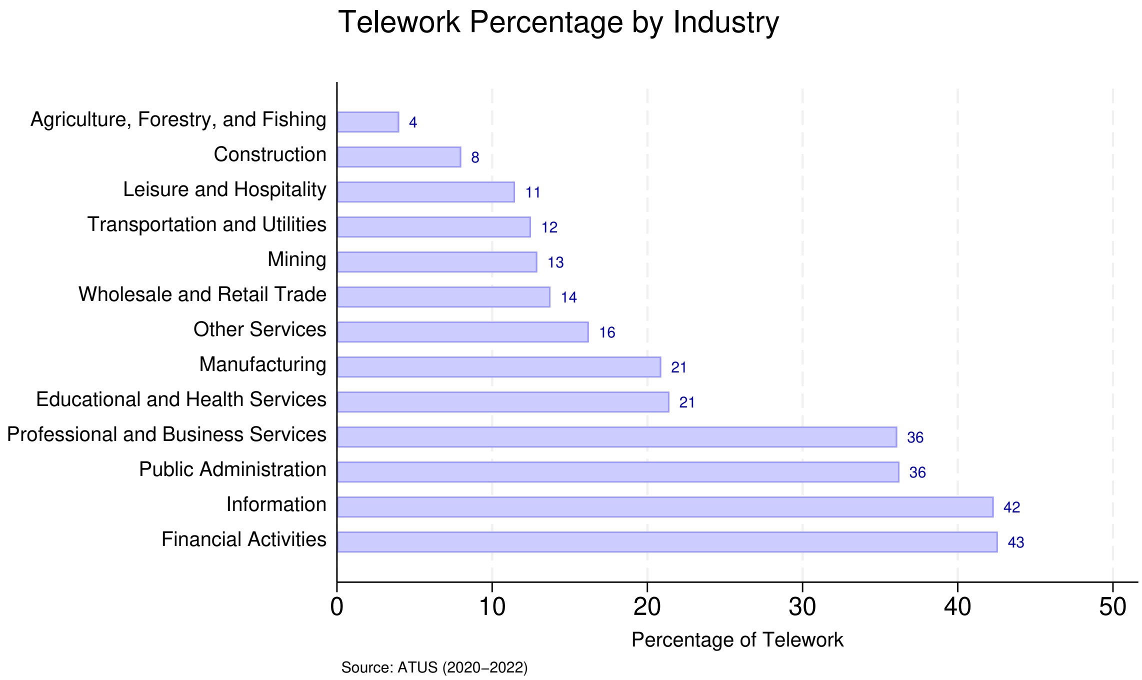

Figure 6: Telework Percentage by Industry

Data are from ATUS (2020-2022). Starting July 2020, a new survey question has been introduced asking respondents, "At any time in the last 4 weeks, did you telework or work at home for pay?" This graph depicts the percentage of telework by industry.

Table 10 shows the effects of by telework concentrated industry. Column 2 shows that those who answered yes to the telework question exhibits positive impact of employment on sleep, although the effects are not statistically significant. Table 11 show that the impact is smaller for those who work in industries where the percentage of telework exceeds the mean (Column 2 and Column 4). This indicates that the impact of employment rate on sleep could be more driven by those industries that are not telework concentrated. The rise of the telework after the pandemic may alleviate the impact of employment on sleep, especially for the industries that are telework concentrated.

6 Conclusion

This study investigates the impact of employment rates on sleep patterns using data from the American Time Use Survey (ATUS) and Local Area Unemployment Statistics (LAUS) spanning from 2003 to 2022. The analysis confirms that sleep duration is countercyclical, with higher employment rates leading to reduced sleep, particularly on weekdays.

Demographic factors significantly influence these effects, with greater impacts observed among individuals without a Bachelor's degree, minorities, females, and single parents. Industries with higher telework rates exhibit smaller sleep reductions as employment rises, suggesting that telework can mitigate some negative impacts on sleep, especially in the post-pandemic period.

These findings highlight the need for policies and employer strategies that support adequate sleep, particularly for vulnerable groups and those in less flexible work environments. Future research could explore the long-term effects of telework and economic cycles on sleep and overall well-being, as well as potential interventions to promote better sleep and work-life balance.

Table 10: Effects of Employment Rate on Sleep by Telework

	All(2003-2022)	Telework(2020-2022)	Industry(2003-2019)
	(1)	(2)	(3)
	Sleep	Sleep	Sleep
	b/se	b/se	b/se
Employment to Population Rate	-1.019***	-1.582	-0.967**
	(0.35)	(1.86)	(0.48)
Telework × Employment		0.953	
		(0.80)	
Above Mean Telework × Employment			-0.076
			(0.21)
N	120743	7445	93846
r2	0.11	0.14	0.12

Notes: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 1 uses data from 2003-2019. Column 2 includes respondents who answered yes to the telework question beginning in July 2020 (2020-2022). Column 3 represents individuals employed in industries where the percentage of telework exceeds the mean (2020-2019).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effects of Employment Rate on Sleep by Telework

	(1) All 2003-2022	(2) $>$ Mean Telework 2003-2022	(3) $\leq$ Mean Telework 2003-2022	(4) $>$ Mean Telework 2003-2019	(5) $\leq$ Mean Telework 2003-2019
All	-1.019**	-0.964*	-1.201*	-0.754	-1.317*
	(0.352)	(0.465)	(0.533)	(0.702)	(0.630)
Observations	120743	54957	48590	49436	44410
R^2	0.11	0.13	0.12	0.12	0.12
Weekday	-2.308***	-1.502*	-2.583***	-1.461	-2.802***
	(0.441)	(0.590)	(0.626)	(0.765)	(0.711)
Observations	60250	27631	24178	24774	22057
R^2	0.07	0.04	0.05	0.04	0.05
Weekend	0.259	-0.515	0.162	-0.111	0.282
	(0.532)	(0.797)	(0.833)	(1.001)	(0.946)
Observations	60493	27326	24412	24662	22353
R^2	0.05	0.06	0.06	0.05	0.06

Note: Data are from ATUS and BLS LAUS (2003-2022). The dependent variable is daily sleep in minutes for respondents aged 25-55. Each cell represents the estimates of employment to population rate on sleep. Column 1-3 uses data from 2003-2022. Column 4-5 uses data from 2003-2019. Column 2-5 represents individuals employed in industries where the percentage of telework exceeds the mean.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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