Uncertainty After Dark: Evidence from 19 Million Nights of Sleep *

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Abstract

Using minute-level wearable-device data on 51,191 adults from the National Institutes of Health (NIH), covering over 19 million person-nights, we show that sleep quality is a high-frequency biomarker of macroeconomic and financial uncertainty. Positive shocks to uncertainty reduce deep sleep and sleep efficiency for several nights—a "wake-and-see" effect that complements the classic "wait-and-see" channel. Heterogeneity is economically meaningful: effects are larger in higher-income areas, yet comparable across race, gender, and education. Finally, nights of unusually poor sleep—net of environmental or time-zone effects—predict lower next-day market liquidity and weaker opening-hour equity returns. Conversely, when worse-than-expected macro news is released before the market opens, better sleep is associated with more negative early-session returns—consistent with improved market efficiency. These results connect uncertainty to a measurable human capital cost and reveal a two-way link between nightly physiology and market conditions.

Preliminary & Incomplete

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Uncertainty plays a major role in macro-finance by slowing investment and hiring through "*wait-and-see*" behavior, which also leaves a negative imprint on asset prices. This study shows that uncertainty also leaves a measurable imprint on people's health—nightly, and at scale. Using minute-level sleep-stage data from 51,191 adults and 19.5 million person-nights in the National Institutes of Health (NIH)'s *All of Us* Research Program,[1] we document that macroeconomic and financial uncertainty systematically reduces sleep quality for several nights. We term this a "*wake-and-see*" effect: when uncertainty rises, people lie awake longer and achieve less deep sleep, revealing an immediate health and human-capital cost of these shocks. This physiological response is robust, economically meaningful, and more strongly associated with uncertainty (EPU, equity volatility) than with market returns. Sleep quality does, however, predict next-day market quality, closing a two-way link between nightly physiology and the financial system.

Sleep is a useful welfare indicator. Unlike surveys, sleep is passively and objectively measured at high frequency, and its core biological functions (memory consolidation, emotion regulation, metabolic restoration) directly affect cognitive performance and productivity. We build daily time series of two standard measures of sleep quality: (i) the proportion of deep (slow-wave) sleep and (ii) sleep efficiency (minutes asleep divided by minutes in bed). When constructing these series, we control for seasonality (day-of-the-week effects), weather (sunlight, temperature, rainfall), infectious disease exposure (COVID-19 cases), physical activity, heart-rate variability, and population mood inferred from social media to isolate *abnormal* movements in sleep quality. We then aggregate the resulting measures daily to the cross-sectional median across individuals. The scope and granularity of the data—minute-level sleep staging for a national cohort—make it possible to trace high-frequency physiological responses to shifts in macroeconomic and financial conditions.

Our first set of facts comes from an event study around 40 salient domestic and geopolitical news dates between 2017 and 2023 that capture large and arguably exogenous events that raise economic and geopolitical uncertainty in the short run (e.g., the COVID-19 pandemic declaration, the U.S. Capitol attack, Russia's invasion of Ukraine, the Silicon Valley Bank collapse). Abnormal sleep falls sharply on the event day, by roughly half a standard deviation for both deep-sleep share and sleep efficiency, before reverting over the following

[1]We gratefully acknowledge All of Us participants for their contributions, without whom this research would not have been possible. We also thank the National Institutes of Health's All of Us Research Program for making available the participant data examined in this study.

days. These patterns confirm that our abnormal-sleep measure captures credible exogenous shocks and that macroeconomic news is immediately reflected in nightly physiology.

We then turn to a comprehensive regression analysis to quantify the role of uncertainty. In daily data, a one–standard-deviation rise in economic policy uncertainty (EPU) is associated with a 0.15 standard-deviation decline in deep-sleep share and a 0.18 standard-deviation decline in sleep efficiency, controlling for the full set of environmental and behavioral controls. Uncertainty's effects on sleep quality are stable in sign and magnitude across specifications. Sunlight, temperature, rainfall, activity, mood, COVID-19 incidence, and heart-rate variability enter with expected signs, and their inclusion does not materially attenuate coefficients on uncertainty. In fact, the marginal effect of uncertainty on sleep is on par with the effects of COVID-19 on these measures. The effects are robust to alternative uncertainty proxies, such as equity volatility, but do not hold when we substitute first-moment proxies, daily market returns, the investment–minus-consumption spread, or the intermediary-capital factor.

To characterize the dynamics of the effect, we estimate VAR-based impulse response functions (IRFs) with recursive identification. A one–standard-deviation uncertainty shock immediately reduces the deep-sleep share and sleep efficiency, with each decline in sleep quality persisting for several nights. Generalized IRFs and smooth local projections deliver nearly identical IRFs, and the patterns repeat when we replace EPU with equity return volatility. In contrast, we once again show that first-moment shocks to equity returns do not produce comparable changes in sleep quality. Together, these results show that elevated uncertainty, rather than contemporaneous adverse market return realizations, drives the physiological channel. This implies a persistent body-level cost of uncertainty.

Heterogeneity is economically informative. The IRFs associated with uncertainty shocks are larger in higher-income areas, consistent with greater exposure to or stakes in financial shocks, while they are comparable across racial, gender, and educational groups and are only modestly different by age. This cross-sectional evidence is inconsistent with a narrow sample-composition story (e.g., only select individuals are affected) and indicates a broad population-wide physiological response that scales with economic exposure.

Finally, we show a reverse channel from physiology to markets. Nights of unusually poor sleep at the population level deteriorate metrics of market efficiency during the following trading day. Lower sleep quality, and particularly reduced deep sleep, predicts weaker early-session equity returns and lower market liquidity (higher Amihud illiquidity) the next day. The effects are concentrated in the first 60 to 150 minutes of trading and taper off by about 180 minutes, consistent with sleep-impaired attention, slower information processing, and transient shifts in risk appetite. Evidence also suggests that these findings are not driven by reverse causality (i.e., the former negative association between uncertainty and sleep quality). While *higher* uncertainty reduces sleep quality, the negative impact of poor sleep quality on subsequent returns is more pronounced when uncertainty is *low*. We also find that when bad macroeconomic news is released before the market opens, better sleep predicts more negative early returns and improved liquidity, consistent with well-rested investors better processing adverse information. Taken together, the results indicate that sleep degradation measurably impairs short-run market quality, extending limits to arbitrage to include nightly physiological restoration as a binding constraint.

Economic magnitude. How large are these effects in economic terms? Two back-of-the-envelope calculations help shed light on this question. First, we follow Bloom (2009) and focus on the effects of a two–standard-deviation shock to uncertainty. Our impulse responses show that *sleep efficiency* and the *deep-sleep share* cumulatively decline by 0.92 and 0.42 standard deviations, respectively, in the week following such a shock. As the unconditional standard deviation of sleep efficiency (deep sleep share) is 1.8% (3.6%) per night, the impact of this uncertainty shock reduces total sleep by about 55.62 minutes and deep sleep by about 52.06 minutes in the week following the shock, assuming eight hours in bed each night.[2] Aggregating this average effect across the 51,191 individuals in the cohort suggests that the shock reduces sleep time by over 47,000 hours and deep sleep by 44,000 hours.

Second, we translate minutes of sleep into labor productivity using the causal estimates in Gibson and Shrader (2018): a 1-hour increase in weekly sleep raises worker earnings by about 1.1% in the short run. Applying this elasticity to the computations above indicates that a two-standard-deviation uncertainty shock that trims 55.62 minutes of sleep per-week implies roughly $(55.62/60) \times 1.1\% \approx 1.02\%$ lower short-run earnings for just that week. This conversion is conservative, as it gives no extra weight to reduced time in deep sleep.[3]

[2] These estimates are based on a two-standard-deviation shock to uncertainty, reducing sleep efficiency by $0.92 \times 0.018 = 0.01656$. Given eight hours of sleep per night, this reduced sleep efficiency translates into $0.01656 \times (8 \times 60) \times 7 = 55.62$ fewer minutes of sleep. Similarly, as the average sleep efficiency ratio is 0.875 and the average deep sleep ratio is 0.152, post-shock deep sleep lasts $[(0.875 - 0.01656) \times (8 \times 60 \times 7) \times (0.152 - (0.42 \times 0.036))] = 394.81$ minutes. This is in contrast to a baseline of $0.875 \times (8 \times 60 \times 7) \times 0.152 = 446.88$ minutes of deep sleep per week.

[3] RAND Europe estimates that insufficient sleep costs the U.S. economy up to $411 billion (about 2% of GDP) and 1.23 million working days per year, underscoring the plausibility that repeated uncertainty-driven

In sum, sleep metrics provide high-frequency, objective welfare statistics linking uncertainty to real-time human-capital depreciation. For macroeconomics, the results reveal a new welfare margin: uncertainty shocks not only depress investment but also tax nightly restoration, impairing cognition and productivity. Moreover, since uncertainty itself is hard to measure and quantify, tracking abnormal sleep can help in this regard by providing a real-time, model-free bioindicator that responds to changes in second moments. For finance, our results document a feedback effect between markets and physiology. Uncertainty worsens sleep, and poor sleep, in turn, measurably degrades next-day market quality. The availability of population-scale wearable device data means that health-based indicators can be integrated with economic uncertainty dashboards and used to evaluate policies in ways that not only consider growth and volatility but also biological costs.

Related Literature. Existing research shows that uncertainty is welfare decreasing, with theoretical and empirical evidence that it depresses real economic growth (see, e.g., Gilchrist, Sim and Zakrajšek, 2014; Jurado, Ludvigson and Ng, 2015; Fernández-Villaverde, Guerrón-Quintana, Kuester and Rubio-Ramírez, 2015; Arellano, Bai and Kehoe, 2019; Basu and Bundick, 2017), while also lowering valuations and raising risk premia (see, e.g., Bansal and Yaron, 2004; Boguth and Kuehn, 2013; Buraschi, Trojani and Vedolin, 2014; Kung and Schmid, 2015; Johannes, Lochstoer and Mou, 2016; Ai and Kiku, 2016; Bretscher, Hsu and Tamoni, 2023; Bekaert, Engstrom and Xu, 2022). Real-options models such as McDonald and Siegel (1986) and, more recently, Bloom, Bond and Van Reenen (2007), Bloom (2009), and Alfaro, Bloom and Lin (2024) link these negative effects of uncertainty to "*wait-and-see*" behavior. Firms pause investment and hiring, thereby generating short-run contractions. We complement this literature by uncovering a "*wake-and-see*" channel: uncertainty shocks register on people's bodies by reducing deep sleep and sleep efficiency for several nights. These effects load on risk (policy uncertainty and return volatility) rather than first-moment market fluctuations, revealing a new welfare margin through which uncertainty imposes immediate human-capital costs.

Our focus on deep sleep and sleep efficiency as economically relevant, high-frequency

sleep losses lead to large output costs (see https://www.rand.org/pubs/research_reports/RR1791.html). The CDC also recommends at least seven hours of sleep for adults, so even modest repeated disruptions push a large share of the population further below healthy thresholds (see https://www.cdc.gov/sleep/data-research/facts-stats/adults-sleep-facts-and-stats.html).

health metrics is grounded in sleep medicine research. Irish, Kline, Gunn, Buysse and Hall (2015) review evidence that stress exposure is associated with lower sleep quality. Banks and Dinges (2007) review experimental evidence that sleep restrictions carry behavioral and physiological costs, including attention lapses and reduced cognitive performance. Regarding deep sleep, slow-wave sleep supports learning and memory consolidation (Rasch and Born, 2013), and suppressing slow-wave sleep for just a few nights measurably worsens insulin sensitivity, despite unchanged total sleep time (Tasali, Leproult, Ehrmann and Van Cauter, 2008).

Our paper is also related to a broader body of evidence linking adverse macroeconomic conditions to worsened mental health. Following the 2008 crash, older U.S. adults experienced significant increases in depressive symptoms and antidepressant use (McInerney, Mellor and Nicholas, 2013). Parmar, Stavropoulou and Ioannidis (2016) and Chang, Stuckler, Yip and Gunnell (2013) document higher rates of anxiety, depression, and suicide during the Great Recession. Engelberg and Parsons (2016) show more broadly that adverse stock returns can trigger an uptick in hospital admissions, particularly for the treatment of psychological conditions. The aforementioned studies either focus on a specific episode (e.g., GFC or Dot-Com) or on health outcomes after bad first-moment shocks have already materialized. By contrast, we show an anticipatory physiological response: uncertainty itself (before negative outcomes are realized) degrades nightly sleep, even after controlling for market return realizations. Moreover, our results suggest that the health costs of poor economic conditions are more widespread than previously thought: whereas hospitalizations are triggered by extreme left-tail events and only affect a small fraction of the population, sleep quality responds even to diffusive shocks and is continuously borne by all individuals, thereby creating a channel for a feedback effect onto the real and financial economy.

Economic uncertainty, in particular, can impact health measures. Higher U.S. suicide rates have been associated with economic policy uncertainty (Antonakakis and Gupta, 2017); and uncertainty correlates with unhealthy choices consistent with self-control costs, such as greater consumption of alcohol and cigarettes (Kalcheva, McLemore and Sias, 2021). Importantly, these studies rely on *aggregate and low-frequency* outcomes (suicides, health-care utilization, or annually reported lifestyle behaviors) that are informative but cannot capture immediate physiological responses or day-to-day heterogeneity.[4] In contrast, we use

[4]We note that sleep data are also available from the American Time Use Survey (ATUS). However, relative

wearable device data to show that uncertainty registers within nights, and we quantify the persistence and economic magnitude of these effects.

Socioeconomic disparities in sleep are well documented. Poor sleep quality is prevalent among lower-income and minority groups (Patel, Grandner, Xie, Branas and Gooneratne, 2010; Grandner, Patel, Gehrman, Xie, Sha, Weaver and Gooneratne, 2010). Recent evidence also shows that sleep duration declines with income across countries and within households (Jara, Perez and Wagner, 2025). While most of this work characterizes static or long-run differences, we study *dynamic* sleep responses to economic shocks, revealing an opposite effect. Notably, the sleep of affluent households' is more adversely affected by rising uncertainty.

Finally, our analysis linking nightly physiology to next-day market quality connects to research on sentiment and attention in financial markets. Non-economic shocks that affect mood move prices and liquidity: national soccer defeats predict next-day market declines (Edmans, García and Norli, 2007); daylight-saving transitions (with potential sleep loss) may be followed by abnormally low returns (Kamstra, Kramer and Levi, 2000; Pinegar, 2002); sunshine correlates with higher returns (Hirshleifer and Shumway, 2003); later sunsets, which delay circadian rhythms, reduce investors' alertness and gains from trade (Han, Hirshleifer, Sheng and Sun, 2025); and distracting events lead investors to underreact to earnings news (Hirshleifer, Lim and Teoh, 2009).[5] Broader sentiment measures also forecast returns and trading activity (see, e.g., Baker and Wurgler (2007) and Da, Engelberg and Gao (2015)). Our analysis complements these studies by demonstrating a *continuous* impact of lowered attention and risk processing after restless nights, which can measurably impair market functioning. We differ from earlier studies linking sleep to trading behavior by using direct, wearable-based sleep measures that capture *time-series* variation in unexpected sleep quality, rather than predictable *cross-sectional* differences driven by geography or daylight cycles.

to the *All of Us* data, the ATUS relies on a single-day, telephone time-diary recall of minutes "sleeping," which is subjectively measured, whereas the *All of Us* data provides objective measures from wearable devices (i.e., Fitbits). Moreover, ATUS is primarily cross-sectional, with respondents interviewed once about the prior 24 hours, with annual samples on the order of approximately seven to 13 thousand individuals per year. This means that the ATUS data cannot track day-to-day dynamics within an individual. By contrast, *All of Us* now includes longitudinal Fitbit data for about 50 thousand participants, many of whom provide months or years of daily records. Finally, ATUS records sleep duration only and thus cannot capture stage-specific physiology (e.g., changes in deep sleep) that is central to our analysis.

[5] Other sentiment-based effects on valuations include Cao and Wei (2005); Da, Engelberg and Gao (2011); Goetzmann, Kim, Kumar and Wang (2015); Stambaugh, Yu and Yuan (2012); Antoniou, Doukas and Subrahmanyam (2013); Hillert, Jacobs and Müller (2014); Peress (2014); Hirshleifer, Jiang and DiGiovanni (2020).

Our focus on deep-sleep dynamics, rather than sleep duration or timing, reveals a distinct physiological pathway through which attention and risk processing affect market quality.

The rest of the paper is organized as follows. Section 1 describes and summarizes the data. Section 2 shows empirical results related to the impact of uncertainty on sleep. Section 3 explores the converse relation between sleep and market quality, while Section 4 concludes.

1 Data

1.1 Primary Database

We source all health-related data from the *All of Us* Research Program that is administered by the US National Institutes of Health (NIH). This research program, which was launched in 2015 and is described by All of Us Research Program Investigators (2019), aims to accelerate health and medical breakthroughs by gathering comprehensive and granular health care data from a diverse population in the United States. As of October 2025, the program has enrolled more than 597,000 individuals who have completed the initial steps required to join (e.g., agreeing to share their electronic health records and providing at least one biospecimen to be stored at the program's biobank). The dataset is continuously expanding and includes anonymized health records, genomic data, survey responses that capture social, environmental, and lifestyle characteristics, as well as real-time health measurements from wearable devices for a subset of individuals.[6]

Our analysis specifically leverages the wearable device data available for 51,191 adults included in the *All of Us* cohort. This data is made available through a partnership between the NIH and Fitbit, a leading manufacturer of wearable devices that was acquired by Google in January 2021. This partnership allows Fitbit owners who are registered with the *All of Us* Research Program to consent to contributing their data from the wearable device to the research program. Users can provide their wearable device data via either the Bring Your Own Device (BYOD) program or the Wearables Enhancing *All of Us* Research (WEAR) study, which provides Fitbit devices to individuals who identify with communities that are underrepresented in medical research.[7]

[6] More detailed summary statistics related to the *All of Us* database are available online at https://www.researchallofus.org/data-tools/data-snapshots/.

[7] See additional details on this WEAR initiative online at https://allofus.nih.gov/article/announcement-

For the purpose of our study, the data from these wearable devices include granular (minute-level) data on sleep. Beyond recording the total amount of time each individual sleeps each night, these devices also record (i) the amount of time spent in bed, which captures the combination of how long it takes to fall asleep and the time spent awake during the night, and (ii) the number of minutes spent in the light, rapid-eye movement (REM), and deep (slow wave) stages of sleep. This granular data allows us to capture the length and quality of each individual's sleep on a daily basis. Moreover, the wearables' device data also include details on the user's physical activity (e.g., minutes engaged in physical activity) and heart rate (e.g., beats per minute).

We employ data from Version 8 of the Controlled Tier of the *All of Us* Curated Data Repository. This version runs from March 26, 2017, through October 1, 2023. In pre-processing the data for our study, we only include observations for which the data's "is_main_sleep" flag is set to one: we focus on each individual's main sleep event each day, dropping entries in the dataset that are related to naps. Overall, these filters provide us with sleep data on 19,542,781 person-nights across 51,191 unique individuals included in the sample.

1.2 Individual Measures

Motivated by the importance of an individual's deep sleep and sleep duration for both short-term outcomes, such as cognitive performance and productivity, and long-term effects, such as cardiovascular risks and mortality, we use the individual-level sleep data to construct two main variables of interest — deep sleep and sleep efficiency — that are defined as

$$\text{DeepSleep}_{i,t} = \frac{\text{Minutes of Deep Sleep}_{i,t}}{\text{Minutes of Sleep}_{i,t}}, \tag{1}$$

and

$$\text{SleepEfficiency}_{i,t} = \frac{\text{Minutes of Sleep}_{i,t}}{\text{Minutes in Bed}_{i,t}}. \tag{2}$$

Here, $(\text{Minutes of Sleep})_{i,t}$ captures the total number of minutes (i.e., the sum of light, REM, and deep minutes) that individual i spent sleeping on day t, $(\text{Minutes of Deep Sleep})_{i,t}$ captures the number of minutes the individual spends in slow-wave sleep, and $(\text{Minutes in Bed})_{i,t}$ reflects the number of minutes an individual spends in bed. We set the sleep day t to cor-

all-of-us-adds-data-from-50-more-participants-in-largest-data-expansion-to-date.

respond to the date on which the individual falls into their main sleep, rather than the date on which the individual wakes up from their main sleep. For example, if an individual goes to sleep at 10:00pm on Wednesday, Feberary 8, 2023, and wakes up at 7:00am on Thursday, Feberary 9, 2023, then sleep date t corresponds to Wednesday, Feberary 8.

1.3 Summary Statistics

Panel A in Table 1 provides summary statistics related to these two proxies of sleep quality. The data show that, on average, an individual spends 15.2% of their sleep time in deep sleep. These figures are in line with the notion that deep sleep should comprise approximately 10% to 20% of a healthy adult's total sleep time. The data also show that the average adult has a sleep efficiency of 87.5%, in line with the view that a healthy adult should spend 85% or more of their time in bed asleep.

Panel B of Table 1 reports personal characteristics for the participants in our sample. The majority of individuals identify as White (81.2%), while 3.3%, 4.7%, and 10.7% identify as Asian, Black, or another race, respectively. Most participants (91.7%) are non-Hispanic, with 6.7% identifying as Hispanic and 1.6% identifying as another ethnicity. The sample is also skewed toward females, who comprise 69.7% of participants. The average age of participants is 54 years, with a median of 55 years. Five percent of individuals are 27 years of age or younger, while another five percent are 77 years of age or older.

The *All of Us* Research Program also provides demographic characteristics related to each participant's geographic location in the US, measured at the three-digit ZIP code level. These measures are drawn from the annual American Community Survey (ACS) administered by the Census Bureau. On average, participants reside in areas where 88.5% of individuals have obtained at least a high school degree, and the average annual income is $66,000. Educational attainment shows relatively little variation across geographies, with 90% of participants living in areas where between 80.2% and 94.5% of residents have completed high school. By contrast, income varies more substantially: the standard deviation is $17,000 per annum, and 90% of participants live in areas where average income ranges from $45,700 to $99,500 per year.

The average person lives in an area where 13.3% of individuals received income assistance benefits in the past 12 months, and 14.5% of households lived below the federal poverty line in the previous year. Finally, the typical individual lives in a location where the Nationwide

Table 1: Summary statistics: Sleep, individual, and demographic characteristics
The table reports summary statistics for the two measures of sleep quality (Panel A) and the sample's individual and demographic characteristics (Panel B). Panel A summarizes the distribution of deep sleep, defined in equation (1), and sleep efficiency, defined in equation (2), across all individual-day observations. We report the mean, standard deviation, median, and the 5th, 10th, 25th, 75th, 90th, and 95th percentiles of these variables. In Panel B, each individual's race, ethnicity, and sex are self-reported upon their enrollment in the *All of Us* Research Program. We express these variables as the share of individuals reporting each category. Birth date, also collected upon onboarding, is used to compute each individual's age (in years). We report the mean, median, standard deviation, and the 5th, 10th, 25th, 75th, 90th, and 95th percentiles of age. The remaining demographic variables come from the American Community Survey (ACS) and are mapped to each participant on the basis of their location, defined at the three-digit ZIP-code level. "Education," "Income," and "Assistance" denote, respectively, the share of adults with at least a high-school diploma, the median household income (in thousands of dollars), and the share of households receiving income assistance in the corresponding area. "Uninsured," "Poverty," and "Vacant" denote the percentage of households without health insurance, living below the poverty line, and percent of vacant households. "Deprivation" reflects the value of an area-level deprivation index at the three-digit ZIP-code level. A complete definition of each variable is provided in Section IA.A of the Internet Appendix.

Panel A: Sleep-Related Characteristics									
	Mean	Std	p5	p10	p25	Median	p75	p90	p95
Deep sleep	0.152	0.036	0.094	0.106	0.126	0.152	0.177	0.199	0.211
Sleep efficiency	0.875	0.018	0.844	0.852	0.864	0.876	0.887	0.897	0.902

Panel B: Individual and Demographic Characteristics				
	Asian	Black	White	Other
Race	0.033	0.047	0.812	0.107
	Hispanic	Non-Hispanic	Other	
Ethnicity	0.067	0.917	0.016	
	Female	Male	Other	
Sex	0.697	0.300	0.004	

	Mean	Std	p5	p10	p25	Median	p75	p90	p95
Age (Years)	53.856	16.385	27.132	31.168	40.214	55.233	68.256	74.292	77.292
Education	88.493	4.834	80.150	82.824	86.003	89.307	91.913	93.789	94.487
Income ($k)	66.015	17.232	45.696	47.874	54.647	61.390	74.163	88.430	99.513
Assistance	13.284	5.394	5.998	7.276	9.643	12.637	16.193	20.172	22.939
Poverty	14.451	5.107	6.669	8.160	10.958	13.982	17.715	20.588	22.654
Deprivation	31.066	5.869	21.919	24.027	27.592	30.322	34.779	38.846	40.578

Community Deprivation Index of Brokamp, Beck, Goyal, Ryan, Greenberg and Hall (2019), a multifaceted index of community wellbeing constructed from ACS data, is 31.1%. This is broadly in line with the national mean value of this index and suggests that individuals represented by the data live in similar locations to those of the typical U.S. household.

1.4 Aggregate Measures

1.4.1 Sleep Quality at the Aggregate

Although our data includes detailed biometric information on over 50 thousand *unique* individuals, we are primarily interested in how adverse economic conditions affect the *typical* individuals' sleep quality. As such, we aggregate the raw data on approximately 19 million person-day sleep records into two time series, DeepSleep_t and SleepEfficiency_t, that represent the typical individual's sleep quality on each day of the sample period. We obtain these time series through the steps outlined below.

First, an analysis of variance (ANOVA) test shows that about 30% of the variation in sleep quality arises between individuals. Thus, we remove individual fixed effects from all health metrics of interest to eliminate across-individual differences and cleanly isolate within-individual variation in sleep quality. We then aggregate the *individually-demeaned* data for $\text{DeepSleep}_{i,t}$ and $\text{SleepEfficiency}_{i,t}$ across all individuals i in the sample by computing their daily median value. The median is used to minimize sensitivity to any outlier observations, although similar results are obtained by computing daily across-individual averages.

Second, we only retain aggregate observations if the underlying cross-section is sufficiently large. Although the wearables data begin on March 26, 2017, days prior to April 27, 2017 feature fewer than 1,000 unique individuals per day. As such, we set the start date of the aggregate time series to April 27, 2017. Figure IA.C.1 in the Internet Appendix shows how coverage, measured in thousands of participants per day, evolves over the remainder of the sample period. The figure shows that the number of participants in the *All of Us* program is steadily increasing over time, leading to potential time trends. For instance, the left panel of Figure IA.C.2 in the Internet Appendix shows that the raw median values of DeepSleep and SleepEfficiency trend down over time. To ensure stationarity, we linearly detrend each of the time series (see the right panel of the same figure). We ensure that our baseline results are robust to this detrending.

Third, as both measures of sleep quality exhibit intra-week seasonality, we remove day-of-the-week fixed effects. Figure IA.C.3 in the Internet Appendix shows that the proportion of deep sleep tends to peak in the middle of the week but sharply declines between Friday and Sunday. Similarly, sleep efficiency tends to peak on Friday night but drops on both Saturday and Sunday. By eliminating these predictable patterns in sleep quality, we ensure that our findings do not merely capture weekly seasonality in the news cycle. Empirical evidence shows that bad news is often released on a Friday (Gersen and O'Connell, 2009).

Lastly, we winsorize the aggregate sleep series at the 1% level to ensure that we systematically mitigate the effects of extreme but predictable changes in sleep quality. Figure IA.C.4 in the Internet Appendix plots the winsorized and the non-winsorized aggregate sleep quality measures, DeepSleep_t and SleepEfficiency_t. Prior to winsorizing, sleep efficiency exhibits an almost 20-standard-deviation decline upon the start of Daylight Saving Time.[8] Winsorizing the series results in sleep efficiency declining by a more modest five standard deviations.[9]

1.4.2 Abnormal Sleep Quality

For the purpose of our analysis, we define abnormal sleep as sleep quality that cannot be explained by observed physiological conditions, environmental conditions, or mood (driven by non-economic factors). Specifically, abnormal sleep quality on day t is the residual of the projection:

$$\text{SleepQuality}_t = \beta_0 + \boldsymbol{x}_t'\boldsymbol{\beta} + \varepsilon_t, \tag{3}$$

where $\text{SleepQuality}_t \in \{\text{DeepSleep}_t,\ \text{SleepEfficiency}_t\}$, and $\boldsymbol{x}_t$ is a vector of control variables that includes typical determinants of sleep. These controls include the amount of sunlight (measured in hours per day), average daily temperature (measured in degrees Celsius), daily rainfall (measured in millimeters per day), newly diagnosed COVID-19 cases (per one million people), average daily activity (measured by the number of "very active" minutes from the physical activity Fitbit data provided by *All of Us*), heart-rate variability (measured via the standard deviation of an individual's heartbeats per minute), and general happiness (proxied

[8]This figure is based on the fact that sleep efficiency declines from about 0.88 to 0.79 upon the onset of Daylight Saving Time (9% decline), and the daily standard deviation of the aggregate sleep efficiency measure is about 0.5% per day.

[9]This figure is based on the fact that, in the winsorized data, sleep efficiency drops by about 0.5% upon the onset of Daylight Saving Time, and the standard deviation of sleep efficiency in the winsorized data is about 0.09% per day.

by the language-based Hedonometer index of Dodds, Harris, Kloumann, Bliss and Danforth (2011) and Dodds, Clark, Desu, Frank, Reagan, Williams, Mitchell, Harris, Kloumann, Bagrow *et al.* (2015)).

The definitions of all control variables are provided in Section IA.A of the Internet Appendix, and their summary statistics are reported in Table IA.B.1 of the Internet Appendix. We scale each variable by its unconditional standard deviation to account for the different units of measurement of the controls included in $\boldsymbol{x}_t$ and estimate this projection using daily data from April 26, 2017, to May 26, 2023 (the last day all control variables are available).

The key variable of interest in equation (3) is the residual ε_t. For each measure of sleep quality, it reflects an abnormal variation in sleep that is orthogonal to the comprehensive set of controls.

1.5 Validation vis-à-vis Google Search

If the residuals from projection (3) capture meaningful unexpected variation in sleep quality—that is orthogonal to the known determinants of sleep included in $\boldsymbol{x}_t$, such as temperature and the amount of daylight—then they should covary with the intensity with which individuals search sleep-related terms on Google. This validation test is inspired by Da *et al.* (2015), who use Google search volumes to measure market-wide sentiment.

To implement this test, we download data on the intensity with which households in the US are searching the internet for terms that include "bad sleep" and "can't sleep," catch-all phrases for low-quality sleep, and "insomnia," a common sleep disorder that can reduce the time and quality of sleep. We obtain this data from Google Trends, which provides monthly search intensity for these terms from May 2017 through April 2023.[10] The search intensity index for each term is normalized to equal 100 in the month when the term was most popular within the sample. Accordingly, a value of 25, for instance, in another month m indicates that the term's popularity in that month was one-quarter of its peak popularity during the full sample period.

We aggregate the daily residuals from equation (3) to the monthly frequency by computing their average value within each month. We denote the monthly value of this residual by $\varepsilon_t^{(M)}$. Such aggregation is necessitated by the fact that Google only provides search intensity data over long time periods at the monthly frequency. The association between the monthly

[10] See the Google Trends website for further details on this dataset.

measure of abnormal sleep quality and Google search volume (GSV) is estimated via:

$$\Delta\varepsilon_t^{(M)} = \phi_0 + \phi_1 \Delta GSV_t + \eta_t, \tag{4}$$

where $\varepsilon_t^{(M)}$ denotes the monthly-aggregated residuals from equation (3) obtained when SleepQuality_t is proxied using either the proportion of deep sleep or sleep efficiency, and GSV_t is the monthly value of the Google Trends index related to one of the three terms: "bad sleep," "can't sleep," or "insomnia." We estimate projection (4) using the first difference of each variable, such that a positive change in $\varepsilon_t^{(M)}$ represents an improvement in sleep quality between month $t-1$ and t and a positive change in GSV_t represents increased interest over the same time period. We standardize both the dependent and independent variables, such that ϕ_1 represents the correlation between the two.

Figure 1 presents the results using scatterplots. The top (bottom) row displays the results when sleep quality is measured using abnormal deep sleep (sleep efficiency), while the first, second, and third columns report the results when the search terms are "bad sleep," "insomnia," and "can't sleep," respectively. Each scatterplot also shows the best linear fit for the association between these variables, with a slope of ϕ_1.

The figure reveals a clear negative relation between innovations in abnormal sleep quality and the popularity of sleep-related searches. Months characterized by heightened search activity for terms such as "can't sleep" and "insomnia" among U.S. households coincide with abnormally low levels of deep sleep. Similarly, sleep efficiency is unusually low in months when households search more intensively for "bad sleep." The correlations (slope coefficients) are uniformly negative, and the corresponding t-statistics strongly reject the null hypothesis of no relationship in four out of the six panels. Notably, the correlation between sleep efficiency and insomnia is rather weak. This is expected, as insomnia refers to a chronic clinical condition, whereas sleep efficiency could capture pure transitory shifts in sleep. The analysis stresses the advantage of biometric data: since it is available at a greater frequency (daily or minute-level) compared to survey or search-based data, it is able to capture both high- and low-frequency oscillations in sleep .

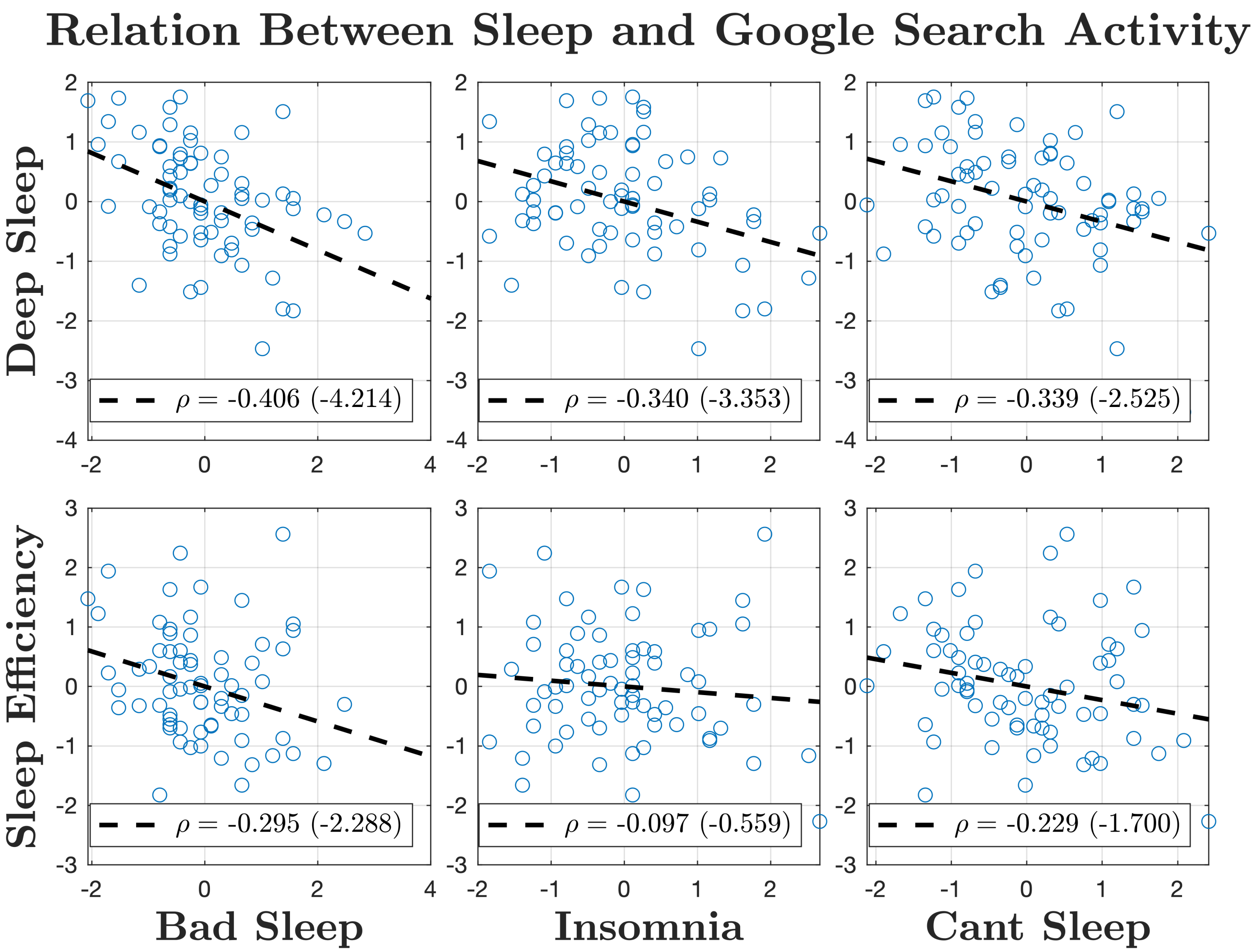

Figure 1: Association with internet search activity

The figure shows how abnormal sleep quality comoves with Google search interest in "Bad sleep," "Insomnia," and "Can't sleep." We obtain these results by (i) filtering each measure of sleep quality through equation (3) to obtain our proxy for abnormal sleep, (ii) averaging daily abnormal sleep in each month to construct measures of abnormal sleep at the monthly frequency, and (iii) relating monthly changes in abnormal sleep to monthly changes in search intensity via equation (4). Each subpanel plots the scatterplot of monthly changes with the fitted OLS line and reports the slope (in standardized units), the Pearson correlation coefficient, and its Newey and West (1987) t-statistic. The top row measures sleep quality via the proportion of deep sleep (equation (1)), while the bottom row measures sleep quality via sleep efficiency (equation (2)). Columns correspond to the three keywords, and the sample ranges from May 2017 through April 2023.

2 Wake-and-See: The Imprint of Uncertainty on Sleep

In this section, we demonstrate that uncertainty shocks leave a real-time imprint on sleep quality, making abnormal sleep an *implicit barometer of economic uncertainty.* In Section 2.1 we employ an event study methodology, showing that large and arguably exogenous events that raise geo-political uncertainty deteriorate sleep quality instantaneously. In Section 2.2 we employ projection analysis, showing that policy uncertainty systematically lowers sleep, and the economic magnitude is as large as that of other environmental factors. In Section 2.3 we use recursive identification to extract uncertainty shocks, showing the dynamic persistent effect of uncertainty on sleep quality. Lastly, in Section 2.4 we study the heterogeneity in the imprint of uncertainty on sleep, depending on several demographic dimensions.

2.1 Event Study

We demonstrate that part of the variation in abnormal sleep quality is driven by individuals' physiological reactions to large exogenous shocks that, beyond any first-moment effects, also elevate uncertainty regarding social, political, and economic conditions. We disentangle the reaction to first- versus second-moment shocks in later subsections.

Specifically, we study how sleep quality fluctuates around a set of dates with the most prominent domestic and global geopolitical news—relevant for households in the United States—between May 2017 and April 2023. We ask ChatGPT 5 to deliver this set of dates, along with an explanation of why each date is selected. This yields a list of 40 events displayed in Table IA.B.2 of the Internet Appendix. The events range from incidents of disasters, violence, and terror (e.g., the Grenfell Tower fire that killed 72 individuals in London in June 2017, the Parkland school shooting in February 2018, and the assassination of former Japanese Prime Minister Shinzo Abe in July 2022) to financial and political events (e.g., the collapse of Silicon Valley Bank in March 2023, the United States Capitol attack of January 2021, and the midterm elections of November 2022). Other prominent events include the outbreak of the COVID-19 virus in early 2020, the murder of George Floyd in May of the same year, and the Russian invasion of Ukraine in 2022.

We examine how the residuals from equation (3) evolve in the 11-day window surrounding each event. Specifically, we treat each event date as time zero and track the residuals from

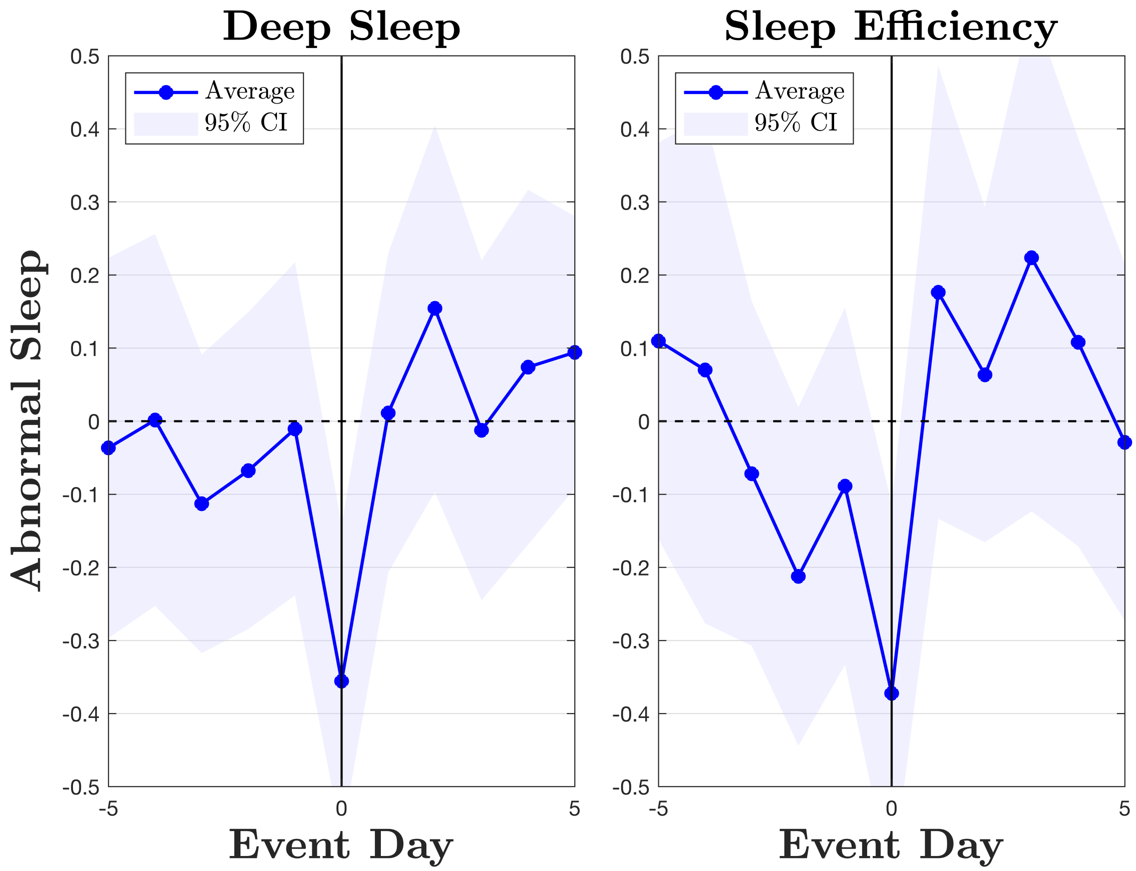

Figure 2: Event study
The figure reports the results of event studies in which the average value of abnormal sleep quality, obtained by filtering each measure of sleep quality through equation (3), are displayed around forty prominent domestic and geopolitical news days that are relevant for U.S. households between May 2017 and April 2023. A list of these 40 events is provided in Table IA.B.2 of the Internet Appendix. We record how each measure of abnormal sleep quality behaves in the 11-day window centered around each event (e.g, from five days before the event to five days after). The solid blue line then reports the average value of abnormal sleep on each event date, while the blue-shaded region represents the 95% confidence interval associated with this cross-event average. The standard errors underlying this confidence interval are computed in accordance with White (1980). The left panel reports the results obtained when sleep quality is measured using the proportion of deep sleep from equation (1), while the right panel reports the results obtained using the measure of sleep efficiency from equation (2).

five days before to five days after the event. Finally, we compute the average value of the residual across all events and plot the resulting values in Figure 2 alongside the 95% confidence intervals.

The results in both panels of Figure 2 indicate that both deep sleep and sleep efficiency drop sharply on days with pertinent national and geopolitical news. As the residuals underlying equation (3) have a standard deviation of about 0.80, the point estimates in these figures suggest that abnormal sleep quality declines by about half a standard deviation across these 40 event days. This sharp decline in sleep quality on the event date is statistically significant at the 5% level but is relatively short-lived, as both deep sleep and sleep efficiency rebound to their pre-event value of zero in the days following the typical event. Nonetheless, in Section 2.3 we use impulse-response analysis to show that the effect of *uncertainty* shocks persists for several days. The lack of persistence in our event study could either reflect the fact that the sample of events is small or the fact that it blends the reaction to both first- and second-moment variation, whereas only the latter induces a significant effect on abnormal sleep (see Section 2.2). In all, the analysis reaffirms that the residuals underlying equation (3) reflect the unexpected components of sleep quality and that large geo-political shocks register in individuals' sleep in real-time and without a lag.

2.2 Projections

Motivated by the evidence that large geo-political events induce a large impact on abnormal sleep, we hypothesize that sleep quality continuously and systematically reacts to changes in macroeconomic and financial uncertainty. The focus on uncertainty is driven by two notions. First, unlike the actual realization of large first-moment shocks—which is either backward-looking or infrequent—uncertainty is highly persistent and forward-looking by nature. The prospects of large future shocks (governed by greater jump intensity or a spike in the conditional volatility of Gaussian shocks) have a large economic impact (see, e.g., Bloom, 2009; Ludvigson, Ma and Ng, 2021; Anschukov, Bhamra and Kuehn, 2024). Second, if economic shocks affect individuals' sleep, it is tantamount to affecting their sentiment. Uncertainty and sentiment interact and reinforce one another: Garcia (2013) finds that the sensitivity of investors to news is highest during recessions, characterized by enhanced volatility; Dicks and Fulghieri (2021) show that investor sentiment depends on uncertainty on the fundamentals; Birru and Young (2022) show that higher uncertainty enhances the role of sentiments in affecting asset prices.

Uncertainty has many facets, each having potentially different implications for the macroeconomy. For our benchmark analysis, we consider the prevalent measure of economic policy uncertainty of Baker, Bloom and Davis (2016), a widely adopted measure of economic uncertainty based on textual analysis of news content. In robustness, we also consider forms of financial uncertainty: VIX, equity market volatility (Baker, Bloom, Davis and Kost, 2026),

Table 2: Projection results

The table reports the results of estimating equation (5) when sleep quality is measured using the proportion of deep sleep from equation (1) (Panel A) or sleep efficiency from equation (2) (Panel B). The projection includes combinations of the following predictor variables: the logarithmic daily value of the Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), the total amount of sunlight per day, the average daily temperature and amount of rainfall, the number of newly diagnosed COVID-19 cases per one million residents, the amount of physical activity, the daily value of the Hedonometer of Dodds *et al.* (2011), referred to as "Happy," and the standard deviation of the typical individual's heart rate. In the final column of each panel, we also control for the excess market return on each trading day, which is denoted by MKTRF. A complete definiton of each variable is provided in Section IA.A of the Internet Appendix. Each variable is standardized by its unconditional standard deviation and the t-statistic aassociated with each slope coefficient, reported in parentheses, is constructed using Newey and West (1987) standard errors. The regression is estimated using daily data that begins on April 26, 2017 and runs through May 26, 2023.

Variable	Panel A: Deep Sleep				Panel B: Sleep Efficiency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EPU	-0.09		-0.15	-0.20	-0.22		-0.18	-0.12
	(-2.28)		(-5.64)	(-6.40)	(-6.46)		(-5.89)	(-2.79)
Sunlight		-0.41	-0.40	-0.42		0.45	0.44	0.63
		(-7.57)	(-7.86)	(-7.83)		(7.92)	(8.01)	(7.91)
Temperature		0.85	0.84	0.89		-0.69	-0.67	-0.94
		(17.45)	(19.45)	(17.68)		(-12.80)	(-12.80)	(-13.42)
Rainfall		-0.15	-0.15	-0.18		-0.04	-0.05	-0.05
		(-7.82)	(-8.20)	(-7.55)		(-1.87)	(-2.36)	(-1.52)
COVID-19		-0.22	-0.17	-0.22		-0.09	-0.07	-0.05
		(-4.99)	(-4.11)	(-4.60)		(-1.89)	(-1.55)	(-0.77)
Activity		0.13	0.13	0.05		0.09	0.09	0.09
		(3.32)	(3.59)	(1.17)		(1.81)	(2.02)	(1.28)
Happy		0.23	0.19	0.20		0.29	0.25	0.29
		(6.37)	(5.84)	(5.80)		(10.12)	(9.17)	(7.87)
HRV		-0.41	-0.43	-0.53		0.02	-0.06	0.08
		(-11.04)	(-13.29)	(-13.98)		(0.56)	(-1.37)	(1.23)
MKTRF				0.02				0.00
				(1.26)				(0.22)
N	2221	2221	2221	1533	2221	2221	2221	1533
R^2	0.01	0.46	0.48	0.53	0.05	0.22	0.24	0.38

and macroeconomic uncertainty (Bekaert *et al.*, 2022), obtaining similar results.

To verify our hypothesis, we start with the following contemporaneous projection:

$$\text{SleepQuality}_t = \beta_0 + \beta_1 \text{EPU}_t + \boldsymbol{x}_t' \boldsymbol{\beta} + \varepsilon_t \tag{5}$$

where EPU_t denotes the natural logarithm of the Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016) on day t, SleepQuality refers either to the aggregate DeepSleep or SleepEfficiency, as constructed in Section 1.4.1, and all other controls follow the structure and definitions provided alongside equation (3). We standardize all variables entering this equation to have a unit standard deviation. As such, each slope coefficient can be interpreted as representing how many standard deviations each measure of sleep quality changes for a one-standard-deviation change in a predictor of interest. Table 2 provides the results.

Columns (1) and (5) in Table 2 report univariate regressions that document the association between the EPU index and each proxy of sleep quality. Column (1) shows that a one-standard-deviation increase in economic uncertainty is associated with a 0.09 standard-deviation reduction in the median individual's proportion of deep sleep. Similarly, Column (5) shows that the same change in EPU results in a 0.22 standard-deviation reduction in sleep efficiency (i.e., more time spent awake in bed).

Together, these results provide preliminary support for our hypothesis. They point out a new welfare tax of uncertainty: whereas extant literature discusses the welfare loss in terms of reduced economic growth due to "wait-and-see" effects (McDonald and Siegel, 1986), the projection points to a complementary welfare loss in terms of economic agents' health due to a "wake-and-see" effect—the loss of restorative sleep due to economic-based stressors—which could be converted to productivity losses as in Gibson and Shrader (2018).

Next, Columns (2) and (6) report how the control variables in equation (3) are related to each outcome variable. Longer daylight hours reduce the share of deep sleep but improve sleep efficiency. Higher temperatures have the opposite effect, enhancing deep sleep but lowering sleep efficiency. Increased rainfall, newly diagnosed cases of the COVID-19 virus, and heart rate variability have a negative and statistically significant effect on deep sleep, and non-positive effect on sleep efficiency. In contrast, physical activity and general happiness tend to have a positive and statistically significant effect on both measures of sleep quality.

Columns (3) and (7) show the results of including the EPU index alongside all the controls mentioned above. The results show that increases in the EPU index remain negatively associated with both measures of sleep quality, even after accounting for the full set of physiological and environmental controls. What is perhaps even more surprising is that the economic magnitude of the effect of EPU remains economically sizable. Column (3) shows that a one-standard-deviation increase in policy uncertainty is associated with a 0.15

standard-deviation reduction in the median deep-sleep share. In absolute value, this is about the same magnitude as the effects on deep sleep from rainfall (i.e., seasonality), the prevalence of COVID, or general happiness. Column (7) shows that a one-standard-deviation increase in policy uncertainty is associated with a 0.18 standard-deviation reduction in the median individual's sleep efficiency. In absolute value, this is about four times as large as the effects of rainfall, three times as large as the effects of heart-rate variability, and about twice as large as the effects of physical activity.

Focusing on the effect of large uncertainty shocks, as in Bloom (2009), a two-standard-deviation shock to uncertainty reduces sleep efficiency by 0.30 standard deviations and deep-sleep share by 0.36 standard deviations. Given the unconditional volatility of sleep efficiency (deep-sleep share) is 1.8% (3.6%) per day, the loss is about 2.59 minutes of total sleep and 5.80 minutes of deep sleep just for *one* night, assuming eight hours of sleep per day.[11] We emphasize, as stated above, that these effects are of a similar size to those induced by other prominent environmental factors. When scaled to a cohort of 59,020 individuals, or by means of extrapolation, the entire adult population in the US, these micro-level effects aggregate to thousands of hours of sleep loss at the macro-level. Furthermore, the effect of EPU on sleep quality is not merely contemporaneous, as shown in the next subsection.

Finally, Columns (4) and (8) of the table show that the negative effects of uncertainty on sleep quality continue to persist if we control for fluctuations in equity market returns, a common proxy for shocks to the level of economic activity. Although including market returns restricts our sample to trading days only, thus reducing the total number of observations by about 700 days, we continue to find an economically large and negative association between increases in economic uncertainty and reductions in sleep quality. In fact, the association between uncertainty and deep sleep becomes stronger when we condition on market returns. While the effect of uncertainty on sleep efficiency is slightly attenuated in magnitude, it remains economically large and statistically significant at the 1% level. This bolsters the claim that sleep quality is particularly sensitive to changes in economic uncertainty, not first-moment market shocks.

[11] These estimates are based on a two-standard-deviation shock to uncertainty, reducing sleep efficiency by $0.30 \times 0.018 = 0.0054$. Given eight hours of sleep, this reduced sleep efficiency translates into $0.0054 \times (8 \times 60) = 2.59$ fewer minutes of sleep. Similarly, as the average sleep efficiency ratio is 0.875 and the average deep sleep ratio is 0.152, post-shock deep sleep duration is $[(0.875 - 0.0054) \times (8 \times 60) \times (0.152 - (0.36 \times 0.036)] = 58.03$ minutes. This is in contrast to a baseline of $0.875 \times (8 \times 60) \times 0.152 = 63.84$ minutes of deep sleep per night.

Robustness. We verify that the negative relation between economic uncertainty and sleep quality persists even after (i) considering several methodological variations in how we construct our time series of aggregate sleep quality and (ii) considering alternative proxies for economic uncertainty. For instance, IA.B.3 in the Internet Appendix shows that the results continue to persist if we do not apply a linear time trend to our aggregate measures of sleep (Panel A), consider the cross-sectional average individual each day rather than the median individual (Panel B), do not remove day-of-the-week seasonality (Panel C), and do not winsorize the sleep data to account for outlier observations (Panel D).

Similarly, Table IA.B.4 in the Internet Appendix shows that we obtain similar results when we use other proxies for economic uncertainty in place of the EPU index. Most notably, we continue to observe a negative relation between uncertainty and sleep quality if we measure uncertainty using the risk-neutral VIX index (Panel A), the equity market volatility index (Panel B), or the daily measure of economic uncertainty from Bekaert *et al.* (2022) (Panel C). Similarly, we continue to find that first-moment shocks do not explain dynamic variations in sleep quality. For example, fluctuations in neither the investment-minus-consumption spread of Papanikolaou (2011) in Panel E nor the intermediary factor of He, Kelly and Manela (2017) in Panel F can explain changes in sleep quality.

2.3 Structural VAR and Impulse Response Functions

The former analysis was confined to static effects. We now aim to establish a causal and dynamic link between policy uncertainty and sleep quality, using recursive identification in a vector autoregression (VAR) system. Specifically, we assume that these variables satisfy the following autoregressive law of motion:

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \boldsymbol{u}_t. \tag{6}$$

Here, $\boldsymbol{y}_t$ denotes a $(K \times 1)$ vector that includes all the variables of interest, described below, $\boldsymbol{c}$ is a $(K \times 1)$ vector of intercept terms, $\boldsymbol{A}_1$ is a $(K \times K)$ matrix of autoregressive coefficients, and $\boldsymbol{u}_t$ is a $(K \times 1)$ vector of reduced-form innovations with $\mathbb{E}[\boldsymbol{u}_t] = \boldsymbol{0}$ and a symmetric, positive definite covariance matrix $\boldsymbol{\Sigma}_u = \mathbb{E}[\boldsymbol{u}_t \boldsymbol{u}_t']$. These properties of the covariance matrix allow us to express $\boldsymbol{\Sigma}_u = \boldsymbol{P}\boldsymbol{P}'$, where $\boldsymbol{P}$ is a lower triangular matrix with positive diagonal elements obtained through Cholesky factorization.

On each day t of the sample period, $\boldsymbol{y}_t$ includes the following nine variables that are placed in the following order: the duration of sunlight, the average daily temperature, the amount of precipitation, the number of newly diagnosed cases of the COVID-19 virus, the level of the Hedonometer of Dodds *et al.* (2011), the value of the EPU index, the amount of physical activity, the quality of sleep measured using either DeepSleep or SleepEfficiency as constructed in Section 1.4.1, and within-day heart rate variability.

Placing the variables in this order provides us with structural (orthogonal) shocks to each variable in equation (6) via $\boldsymbol{\epsilon}_t = \boldsymbol{P}^{-1}\boldsymbol{u}_t$. Our identifying assumptions are that (i) meteorological variables are contemporaneously exogenous to the rest of the system; (ii) COVID-19 cases can contemporaneously respond to weather, but not to happiness, EPU, or physiological outcomes on the same day; (iii) happiness and economic uncertainty can react to environmental shocks but not to health outcomes; and (iv) physiological outcomes can respond instantaneously to all preceding shocks but do not contemporaneously influence those earlier variables.[12]

The dynamic system described by equation (6), along with the identifying assumptions outlined above, allows us to trace impulse response functions (IRFs) that examine how a structural shock to economic uncertainty propagates through this dynamic system and impacts the quality of sleep.[13]We obtain these IRFs by estimating (6) on an equation-by-equation basis using OLS. We then compute the Cholesky decomposition of $\hat{\boldsymbol{\Sigma}}_u$, and use estimates of $\boldsymbol{A}_1$ and $\boldsymbol{P}$ to construct the impulse responses for $h = 0, \ldots, 15$ days ahead. Statistical inference associated with these IRFs is conducted using a residual bootstrap with 1000 draws from the estimated values of $\hat{\boldsymbol{u}}_t$.

Figure 3 displays the IRFs from the baseline specification. The panels show how a one–standard-deviation structural shock to economic policy uncertainty (EPU) affects deep sleep (left) and sleep efficiency (right). In the left panel, higher uncertainty is associated with a 0.05–standard-deviation reduction in the median proportion of time spent in deep sleep, which is about 0.2% of the average individual's deep sleep time. The same shock

[12]Figure IA.C.7 in the Internet Appendix shows that our results are essentially unchanged if we augment this VAR by placing the excess market return, investment-minus-consumption spread of Papanikolaou (2011), and the intermediary capital factor of He *et al.* (2017) before EPU, so that uncertainty shocks are orthogonal to the contemporaneous first-moment effect.

[13]The $(K \times K)$ matrix of impulse responses for forecast horizon $h = 0, \ldots, H$ is denoted by $\boldsymbol{\Theta}_h$. Column j of this matrix records how a structural shock to each element of $\boldsymbol{y}_t$ at time 0 propagates to variable j at horizon h. The IRF for forecast horizon h can be found via $\boldsymbol{\Theta}_h = \boldsymbol{P}$ for $h = 0$ and $\boldsymbol{\Theta}_h = \boldsymbol{A}_1^h\boldsymbol{P}$ for $h \geq 1$.

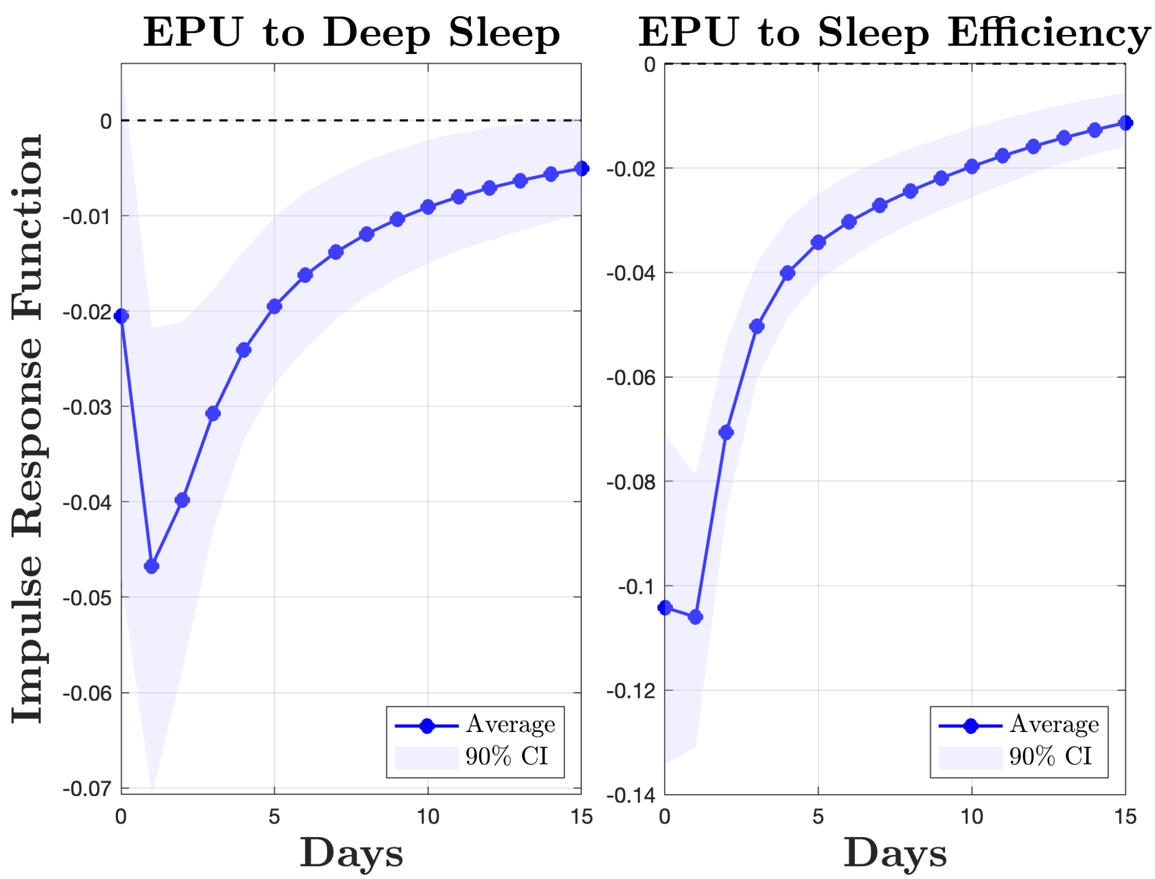

Figure 3: Impulse response functions: baseline
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). These IRFs are obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

implies a 0.1–standard-deviation decline in sleep efficiency, corresponding to roughly a 0.2% increase in time spent awake in bed.[14] Although these one-day effects are modest, they are statistically significant and persist for several subsequent nights. As a result, the *cumulative* impulse-response over a span of one week is quite substantial, amounting to about a 0.21

[14] We obtain each of the magnitudes outlined above by multiplying the point estimate of each impulse response function by the standard deviation reported in Panel B of Table 1. For example, a one-standard-deviation increase in economic policy uncertainty is associated with an approximately $-0.10 \times 0.018 = -0.002$ decline in sleep efficiency.

standard deviation reduction for deep sleep and a 0.46 standard deviation reduction for sleep efficiency. For instance, a two-standard-deviation shock to uncertainty reduces total sleep time by about 56 minutes over the next week and reduces deep sleep by about 52 minutes over the same horizon.[15]

2.3.1 Robustness

We implement a battery of robustness checks to verify that the IRFs presented in Figure 3 are not driven by specific identification assumptions or methodological choices. These tests confirm that the baseline IRFs are not materially affected by (i) the order of variables in (6) that drive the Cholesky decomposition associated with equation (6); (ii) using local projections (Jordà, 2005) rather than a VAR to estimate the IRFs; (iii) using an alternative measure of economic uncertainty in place of the EPU index; and (iv) considering several methodological variations in how the sleep quality measures are constructed in the data.

First, we consider the *generalized* IRFs described by Pesaran and Shin (1998). These IRFs do not depend on the order of variables included in $\boldsymbol{y}_t$. These generalized IRFs are defined by $\boldsymbol{\Theta}_h^{(G)} = \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{D}^{-1/2}$ for $h = 0, \ldots, H$, where $\boldsymbol{\Psi}_h$ represents the matrix of moving-average (MA) coefficients for the h^{th} lag from the MA representation of equation (6) and $\boldsymbol{D} = \operatorname{diag} \boldsymbol{\Sigma}$ represents a $(K \times K)$ matrix that retains the diagonal elements of $\boldsymbol{\Sigma}$. While these GIRFs retain the observed contemporaneous correlation among innovations and do not admit a structural interpretation of shocks, they provide a means to assess the sensitivity of the IRFs to variable ordering. Figure IA.C.5 in the Internet Appendix shows that these generalized IRFs are almost identical to the baseline (orthogonalized) IRFs considered above.

Second, we estimate the IRFs using the Smooth Local Projections (SLPs) of Barnichon and Brownlees (2019). This approach is based on the local projection framework of Jordà (2005) that, for each forecast horizon, estimates a regression of a future outcome on current covariates. Unlike typical local projections, however, SLPs require that the IRFs be a smooth function of the horizon. In finite samples, IRFs from local projections and VARs occupy opposite positions on the tradeoff between bias and variance: the former typically exhibit lower bias but higher variance, whereas the latter are more efficient but may be biased (Olea, Plagborg-Møller, Qian and Wolf, 2025).

Figure IA.C.6 in the Internet Appendix reports the IRFs obtained via the SLP method-

[15] Footnote 2 on Page 3 contains the calculations underlying these figures.

ology and shows that they are similar to those obtained in the baseline analysis. That is, a one-standard-deviation increase in EPU is associated with a decline in both deep sleep and sleep efficiency, with even greater persistence compared to the benchmark.

Third, Figure IA.C.8 in the Internet Appendix repeats the analysis using daily stock return volatility in place of the EPU index of Baker *et al.* (2016), as inspired by Leahy and Whited (1996). The results indicate that a structural shock to uncertainty continues to display a negative, persistent, and statistically significant association with both deep sleep and sleep efficiency.

Finally, Section IA.C in the Internet Appendix shows that the negative and persistent effects of uncertainty on sleep quality persist if we (i) compute the daily average value of sleep quality across individuals in the *All of Us* data instead of the daily median (see Figure IA.C.9; (ii) do not linearly detrend the aggregate measures of sleep quality (see Figure IA.C.10; (iii) do not winsorize the aggregate measures to reduce the impact of outlier days, such as the start of Daylight Saving Time (see Figure IA.C.11; and (iv) do not remove day-of-the-week fixed effects to account for intra-week variation in sleep quality (see Figure IA.C.12.

2.4 Cross-Sectional Heterogeneity

We examine how the impact of uncertainty on sleep quality differs across demographics of interest. Namely, we examine the extent to which the estimated effects are larger or smaller among wealth, age, race, sex, and education.

We obtain each individual's characteristics through surveys completed as part of the onboarding process to join the *All of Us* Research Program. While age, race, and sex are individual-specific traits, the remaining demographic characteristics (e.g., income and education) are collected as part of the Census Bureau's annual ACS initiative and are not individual-specific. Rather, these statistics reflect survey responses from households in the same three-digit ZIP code location as the individuals in the *All of Us* Research Program.

We analyze *relative* heterogeneity along each dimension by estimating the IRFs implied by the VAR represented by equation (6). Instead of measuring sleep quality using the median person's deep sleep or sleep efficiency on a given day t, we consider the *difference* in sleep quality on day t between (i) individuals with a high level of a given characteristic, such as income, and (ii) individuals with a low level of the same characteristic. This captures how sleep quality on a given day changes between the two populations of interest. For the sake of this analysis, we do not remove individual fixed effects from the underlying cohorts' time series, as these would eliminate the source of intra-individual variation examined. When the characteristic of interest is continuous, such as age or income, we use the 80^{th} and 20^{th} percentiles of the cross-sectional distribution of that characteristic to delineate members of the high and low groups. When the characteristic is defined in a binary manner (e.g., "white" or "non-white"), we split individuals into two groups on the basis of this binary variable. The results are reported in Figures 4 and 5.

Figure 4 shows how sleep quality differentially reacts to structural economic uncertainty shocks across the wealth distribution. We proxy for wealth in one of four ways. The top row of the figure divides individuals into groups based on the median household income in their residential area. The second row compares the differential sleep response between individuals living in areas with lower use of income assistance (wealthier locations) and areas with higher use of income assistance (less wealthy locations). The third row splits individuals based on an area's deprivation index. This composite index combines several variables in the ACS into a single metric of a location's socioeconomic conditions, with higher values indicating greater hardship. The final row reports the differential response between individuals living in areas with low poverty rates (i.e., fewer households in the same three-digit ZIP code living below the federal poverty line) versus those living in areas with high poverty rates.

By and large, the figure indicates that wealthier individuals tend to have more negative sleep-quality reactions to economic uncertainty shocks than less wealthy households. In particular, the future impact of uncertainty on either deep sleep or sleep efficiency is more sizable for wealthier households. Wealthier households tend to experience a 0.05-standard-deviation *excess* reduction in sleep quality, suggesting that the overall impact on their sleep is twice as large as that of the median household, as reported in Figure 3. These effects tend to be statistically significant at the 10% level and persist for multiple days.

In contrast to the wealth-related results, Figure 5 shows relatively muted differential effects associated with age, race, gender, and education (as proxied by the percentage of residents in a given three-digit ZIP code location who have completed high school or a higher level of education). The top row shows that individuals in the top quintile of age (i.e., those around 70 years and older) tend to sleep slightly better after an uncertainty shock than those in the bottom quintile of age (i.e., those around 35 years and younger). This

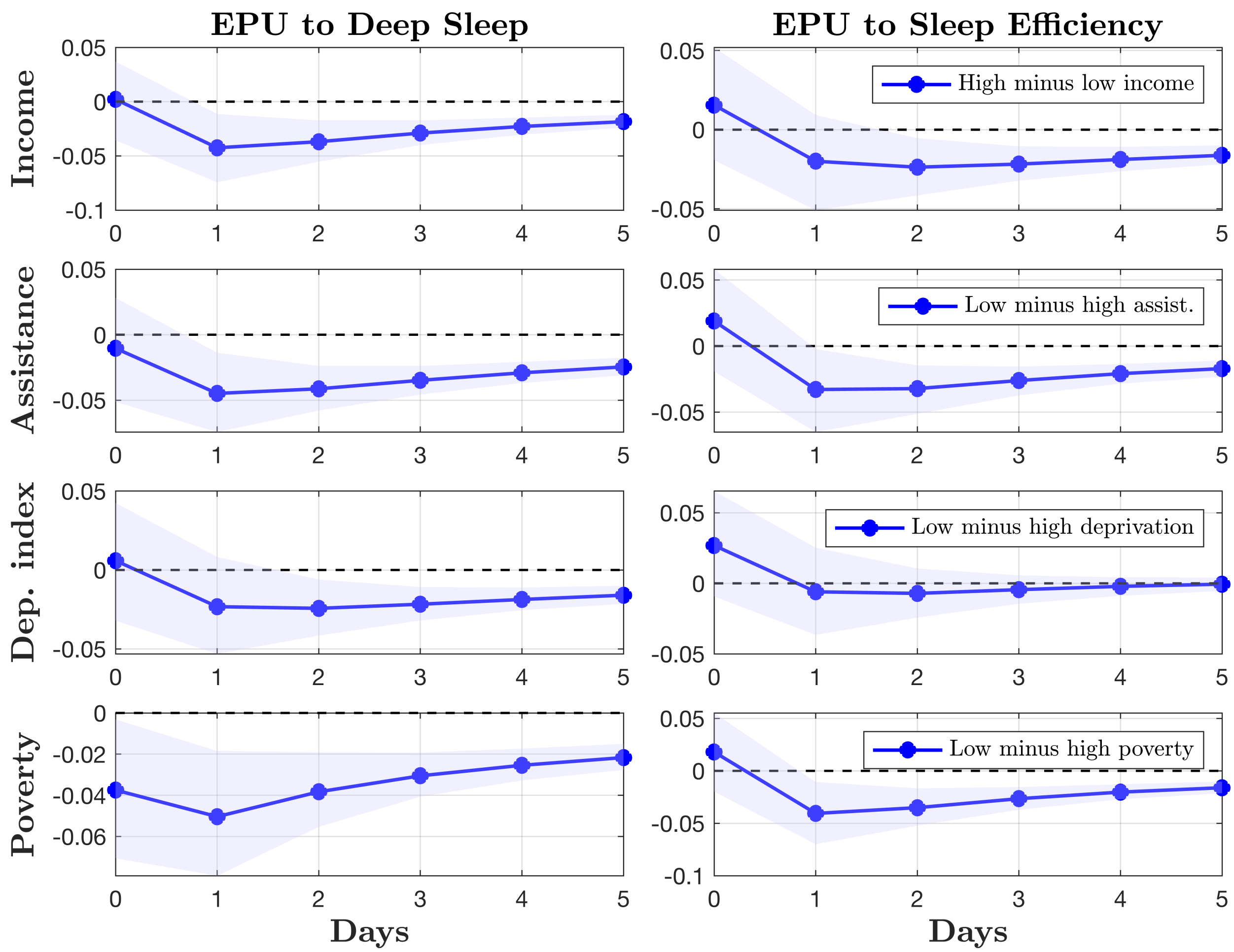

Figure 4: Impulse response functions: Heterogeneity by wealth

The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the difference in one of the two measures of sleep quality between two populations of interest. In the left panel, we measure sleep quality using the proportion of deep sleep, obtained via equation (1), while the right panel focuses on efficiency (right panel), obtained via equation (2). The first row looks at the difference in sleep quality between individuals living in areas with the top versus bottom quintile of household income. The second row looks at the difference in sleep quality between individuals living in areas in the bottom versus top quintile of income assistance. The third row looks at the difference in sleep quality between individuals living in areas in the bottom versus top quintile of the deprivation index of McInerney *et al.* (2013). The bottom row looks at the difference in sleep quality between individuals living in areas in the bottom versus top quintile of poverty rates. A definition of each of these variables is provided in Section IA.A of the Internet Appendix. IRFs are obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

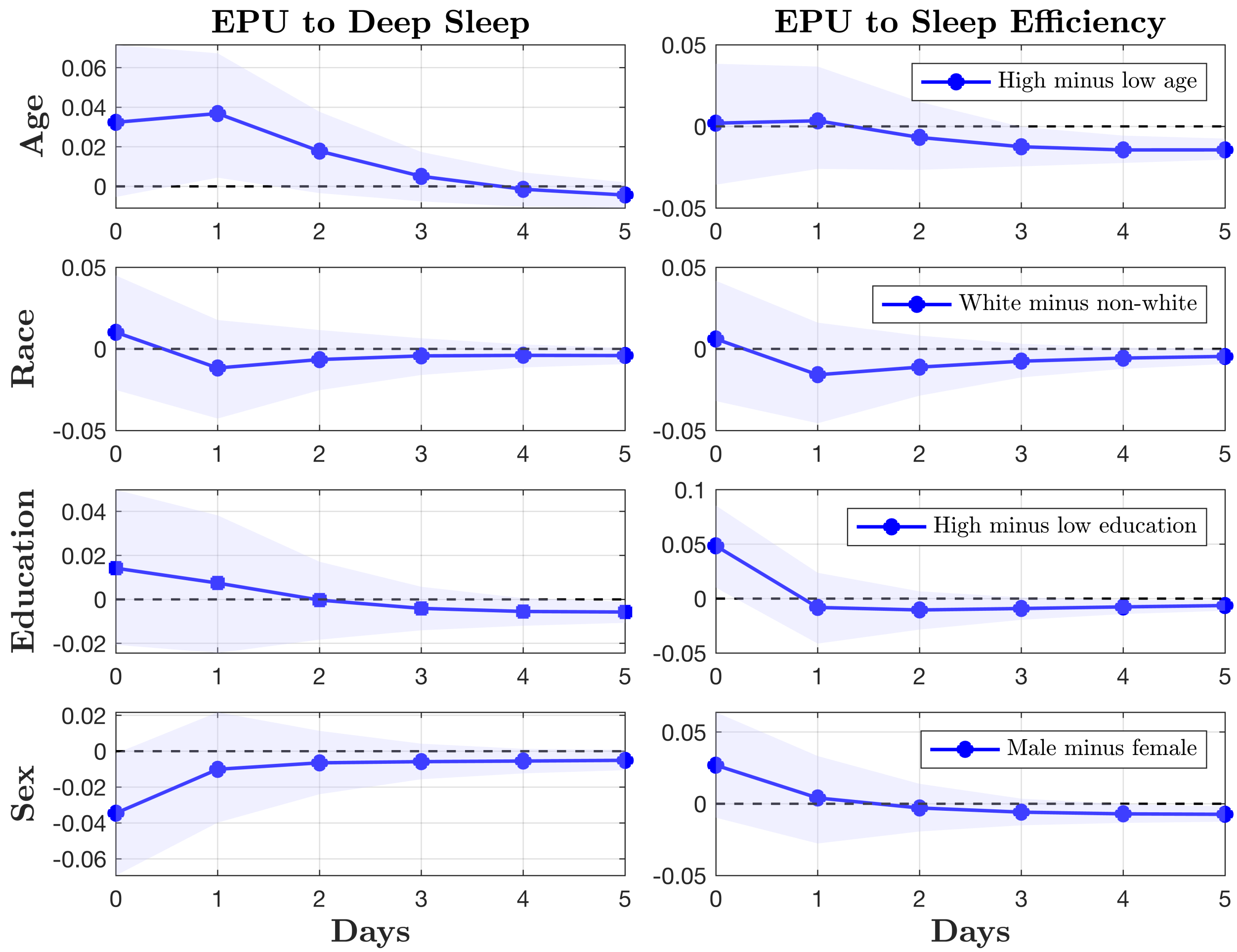

Figure 5: Impulse response functions: Heterogeneity by age, race, education, and sex
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the difference in one of the two measures of sleep quality between two populations of interest. In the left panel, we measure sleep quality using the proportion of deep sleep, obtained via equation (1), while the right panel focuses on efficiency (right panel), obtained via equation (2). The first row looks at the difference in sleep quality between individuals in the top versus bottom quintile of age. The second row looks at the difference in sleep quality between white versus non-white individuals. The third row looks at the difference in sleep quality between individuals living in areas in the top versus bottom quintile of high school completion rates. The bottom row looks at the difference in sleep quality between male versus female individuals. A definition of each of these variables is provided in Section IA.A of the Internet Appendix. IRFs are obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

is consistent with the notion that uncertainty shocks are likely to have a bigger effect on working individuals rather than on retired individuals. This age-related effect is, however, only mildly statistically significant. The middle two panels show almost no differences in the effect between racial and gender groups, and the bottom panel shows no effects based on education rates.[16]

3 The Imprint of Sleep on Equity Markets

In this section, we examine the reverse relation—the effects of sleep quality on financial markets. We examine whether poor sleep spills over into equity markets through two channels:

Hypothesis 1. *Given sleep quality affects cognitive performance, better sleep enhances investors' capacities to process and act on information, leading to higher liquidity and more efficient price adjustments.*

Hypothesis 2. *As Section 2 shows that aggregate abnormal sleep quality can serve as a nightly population-level physiological metric that responds to non-economic sentiment, such as population-level mood and cultural events, improvements in abnormal sleep may positively predict short-run market returns.*

Section 3.1 provides empirical evidence supporting these conjectures, while Section 3.2 refines the analysis by examining how the sleep–market relation varies with the prevailing level of economic uncertainty and the release of good and bad macroeconomic news.

3.1 Projections

We examine the implications of abnormal sleep quality in night $t-1$ on intra-day market quality on day t by running the following projection:

$$y_{\text{open}_t \to \text{open}_{t+\tau}} = \beta_0 + \beta_1 \text{AbnormalSleep}_{t-1} + \boldsymbol{x}'_{t-1}\boldsymbol{\beta} + \epsilon_t. \tag{7}$$

Here, $y_{\text{open}_t \to \text{open}_{t+\tau}}$ denotes a market-level outcome computed from the market open on day t to minute $t+\tau$ of the same trading day, where $\tau \in \{30, 60, 90, 120, 150, 180\}$ minutes. This

[16]This muted effect of education is consistent with the lack of variation in high school education rates across the United States. The typical three-digit ZIP code sees around 88% of individuals complete high school, and 50% of locations in the United States see between 86% and 92% of individuals graduate from high school.

variable refers to either (i) the cumulative intraday return of the market or (ii) the Amihud (2002) illiquidity measure. We construct each of these variables by using the returns and dollar-trading volume of the SPDR S&P 500 ETF, commonly referred to as the SPY ETF, as our proxy for the aggregate equity market's returns and liquidity. $\text{AbnormalSleep}_{t-1}$ denotes abnormal sleep quality on day $t-1$ and is obtained by filtering either the aggregate deep-sleep share or sleep efficiency through equation (3), and $\boldsymbol{x}_{t-1}$ is a vector of lagged control variables that includes the previous day's (open to close) return and overnight (close to open) return. All variables entering equation (7) are standardized by their unconditional standard deviation. The sample period underlying the regression runs from April 26, 2017, through May 26, 2023. Details on the construction of all variables are provided in Section IA.A of the Internet Appendix.

Table 3: Sleep Quality and Intraday Market Responses
This table reports regressions in which the dependent variables are intraday market responses from the market open of day t through to minute τ of the trading day, where $\tau \in \{30, 60, 90, 120, 150, 180\}$ minutes. The dependent variables include (i) the Amihud illiquidity measure, which is computed as the absolute return divided by dollar volume, and (ii) the cumulative market return over the same windows. The key explanatory variables are the abnormal components of deep sleep and sleep efficiency on day t, which are obtained by filtering deep sleep, defined in equation (1), and sleep efficiency, defined in equation (2), through equation (3). All regressions control for the previous trading day's open-to-close return and the previous day's overnight return. All variables are standardized. The sample covers March 26, 2017 through May 26, 2023. t-statistics based on Newey and West (1987) standard errors are reported in brackets. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Panel A: Deep Sleep						Panel B: Sleep Efficiency					
Minutes (τ)	30	60	90	120	150	180	30	60	90	120	150	180
Amihud	-0.09***	-0.07**	-0.07**	-0.07**	-0.07**	-0.06**	-0.13***	-0.11***	-0.11***	-0.09***	-0.09***	-0.10***
	[-2.96]	[-2.37]	[-2.23]	[-2.31]	[-2.35]	[-2.14]	[-4.50]	[-3.63]	[-4.02]	[-3.13]	[-2.85]	[-3.25]
$\bar{R}^2$	0.01	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.01	0.01	0.01
Return	0.02	0.05**	0.06***	0.05**	0.04*	0.03	0.02	0.03	0.02	0.02	0.01	0.01
	[1.14]	[2.21]	[2.59]	[2.11]	[1.66]	[1.17]	[1.05]	[1.05]	[0.93]	[0.96]	[0.31]	[0.20]
$\bar{R}^2$	0.04	0.01	0.03	0.02	0.01	0.01	0.04	0.01	0.02	0.02	0.01	0.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553	1553

Table 3 reports the results. Both panels show that improvements in sleep quality are associated with improvements in liquidity across all horizons considered. More restorative sleep corresponds to a smaller price impact per dollar traded in at least the first three hours of the typical trading day, consistent with Hypothesis 1. While the slope coefficients are modest and indicate that a one-standard-deviation improvement in sleep quality corresponds to an approximately 0.10 standard-deviation reduction in illiquidity, the results are likely to provide a lower bound on the effects of sleep on market quality. After all, we examine the illiquidity of the SPY ETF, one of the most actively traded assets in the equity markets.

Improvements in the deep-sleep share also predict higher cumulative returns during early trading hours. The coefficients are significant at the 10% level for the 60- to 150-minute windows and fade thereafter. A one-standard-deviation increase in deep sleep raises the opening-hour returns by roughly 0.05 standard deviations, or 2.03 basis points per hour, which is equivalent to about 13.1 basis points per day. The slope coefficients for sleep efficiency are positive but statistically insignificant. Overall, these findings support Hypothesis 2 by showing that restorative sleep predicts moderately higher early-day returns.

3.2 Conditional Predictability

3.2.1 High versus Low Aggregate Uncertainty

Section 2 shows that higher policy uncertainty leads to lower sleep quality. Because uncertainty itself is typically associated with lower stock returns (see, e.g., Bansal and Yaron, 2004; Boguth and Kuehn, 2013), a natural concern is whether the relation documented in Section 3.1, whereby worse sleep predicts lower subsequent returns, might simply reflect periods of elevated aggregate uncertainty rather than a sleep-induced sentiment channel.

We address this concern by examining whether the relation between sleep quality and intraday market dynamics varies with the level of uncertainty. Each trading day t is assigned to a group that depends on the value of the EPU index on day $t-1$. The high EPU subsample includes all days for which the lagged value of the EPU index is above the 70^{th} percentile of its distribution, while the low EPU subsample includes days for which the lagged value of the EPU index is below the 30^{th} percentile of its distribution. Intermediate observations are excluded from the analysis. Equation (7) is then estimated separately for each subsample. Because the lagged value of the EPU index is observed on day $t-1$, while sleep quality is typically measured between the night of day $t-1$ and the morning of day t, equation (7) effectively serves as a predictive regression of market outcomes on sleep quality.

Table 4 shows that abnormal sleep quality improves market liquidity in both high- and

Table 4: Sleep Quality and Intraday Market Dynamics: Split by Uncertainty
This table reports regressions in which the dependent variables are intraday market responses from the market open of day t through to minute τ of the trading day, where $\tau \in \{30, 60, 90, 120, 150, 180\}$ minutes. These regressions are estimated separately for subsamples that are split on the basis of the lagged value of the Economic Policy Uncertainty (EPU) index. Days in which the lagged value of the EPU index is above (below) the 70^{th} (30^{th}) percentile of its distribution are denoted as high (low) EPU days. The results for high and EPU days are reported in Panels A and B, respectively. The dependent variables include (i) the Amihud illiquidity measure, which is computed as the absolute return divided by dollar volume, and (ii) the cumulative market return over the same windows. The key explanatory variables are the abnormal components of deep sleep and sleep efficiency on day t, which are obtained by filtering deep sleep, defined in equation (1), and sleep efficiency, defined in equation (2), through equation (3). All regressions control for the previous trading day's open-to-close return and the previous day's overnight return. All variables are standardized. The sample covers March 26, 2017 through May 26, 2023. t-statistics based on Newey and West (1987) standard errors are reported in brackets. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: High EPU												
	Deep Sleep						Sleep Efficiency					
Minutes (τ)	30	60	90	120	150	180	30	60	90	120	150	180
Amihud	-0.09	-0.13**	-0.11**	-0.10**	-0.12**	-0.12**	-0.13**	-0.10**	-0.12**	-0.13**	-0.12**	-0.13**
	[-1.43]	[-2.40]	[-2.06]	[-2.03]	[-2.53]	[-2.57]	[-2.56]	[-1.97]	[-2.28]	[-2.29]	[-2.18]	[-2.51]
$\bar{R}^2$	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.02
Return	0.03	0.06	0.08*	0.07	0.07	0.05	-0.01	-0.02	-0.01	-0.01	-0.02	-0.04
	[0.78]	[1.48]	[1.86]	[1.52]	[1.33]	[0.92]	[-0.33]	[-0.34]	[-0.29]	[-0.22]	[-0.44]	[-0.74]
$\bar{R}^2$	0.10	0.03	0.07	0.05	0.03	0.01	0.10	0.03	0.06	0.05	0.02	0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	465	465	465	465	465	465	465	465	465	465	465	465
Panel B: Low EPU												
	Deep Sleep						Sleep Efficiency					
Minutes (τ)	30	60	90	120	150	180	30	60	90	120	150	180
Amihud	-0.12***	-0.10**	-0.13***	-0.16***	-0.12**	-0.09*	-0.12***	-0.11**	-0.12***	-0.09**	-0.06	-0.08*
	[-2.92]	[-2.38]	[-2.94]	[-3.24]	[-2.42]	[-1.93]	[-2.98]	[-2.45]	[-3.03]	[-2.31]	[-1.33]	[-1.67]
$\bar{R}^2$	0.01	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
Return	-0.01	0.09**	0.12***	0.11**	0.08*	0.07	0.03	0.04	0.03	0.04	0.00	0.02
	[-0.28]	[2.11]	[2.68]	[2.49]	[1.87]	[1.49]	[0.61]	[0.92]	[0.59]	[0.87]	[0.03]	[0.41]
$\bar{R}^2$	-0.00	0.01	0.01	0.01	0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	466	466	466	466	466	466	466	466	466	466	466	466

low-uncertainty periods. In contrast, the predictive power of deep sleep for subsequent returns is concentrated in low-uncertainty periods, which is inconsistent with the notion that elevated uncertainty drives the results from Section 3.1. The evidence supports the interpretation that when background volatility is low, the signal-to-noise ratio in sentiment-based variables rises, allowing deep sleep to serve as a sharper predictor of next-day returns.

3.2.2 Good versus Bad Macroeconomic News

Finally, we examine whether the relation between sleep quality and intraday market dynamics varies with the release of macroeconomic news, which typically occurs before the market opens. We focus on four regularly scheduled U.S. macroeconomic indicators: the monthly unemployment rate (UNRATE), weekly initial jobless claims (ICSA), quarterly real GDP (GDPC1), and monthly industrial production (INDPRO). For each release, we collect both the *actual* print and the pre-announcement *consensus forecast*.[17] Surprises are classified with economically consistent signs. For "negative" indicators where a lower value is better (i.e., UNRATE and ICSA), an actual value that exceeds (falls short of) the consensus forecast constitutes a bad (good) surprise. For "positive" indicators where higher is better (i.e., GDPC1 and INDPRO), an actual value that falls short of (exceeds) the forecast is deemed a bad (good) surprise. We label these pre-open surprises on each announcement day t so that they align with the corresponding intraday outcomes. Regression (7) is then re-estimated separately for days with good macroeconomic news and bad macroeconomic news. We exclude the few days with mixed macroeconomic news from the analysis.

Table 5 reports the results. On mornings when *bad* macroeconomic news is released, better deep sleep is associated with more negative early-session returns and higher liquidity (lower Amihud illiquidity). This pattern suggests that better-rested investors react more rapidly and fully to adverse information, thereby improving the efficiency of price discovery. In contrast, the relationship between sleep quality and market outcomes largely disappears on *good* news days: returns show no systematic response, and liquidity effects are muted. This asymmetry echoes the evidence in Garcia (2013) and related studies showing that investor sensitivity to sentiment is heightened during bad times. Overall, the findings support Hypothesis 2 by showing that sleep quality shapes the market's ability to absorb and transmit

[17] We collect these consensus forecast values from the Investing.com Economic Calendar, which aggregates expectations from major data providers (e.g., Bloomberg, Reuters, and Dow Jones) into a market consensus.

Table 5: Sleep Quality and Intraday Market Dynamics: Split by Macroeconomic News

This table reports regressions in which the dependent variables are intraday market responses from the market open of day t through to minute τ of the trading day, where $\tau \in \{30, 60, 90, 120, 150, 180\}$ minutes. These regressions are estimated separately for subsamples that are split on the basis of whether macroeconomic news released on a given announcement day exceed or fall short of consensus estimates for the release. The results of regressions estimated using good news days are reported in Panel A, while the results associated with bad news days are reported in Panel B. The dependent variables include (i) the Amihud illiquidity measure, which is computed as the absolute return divided by dollar volume, and (ii) the cumulative market return over the same windows. The key explanatory variables are the abnormal components of deep sleep and sleep efficiency on day t, which are obtained by filtering deep sleep, defined in equation (1), and sleep efficiency, defined in equation (2), through equation (3). All regressions control for the previous trading day's open-to-close return and the previous day's overnight return. All variables are standardized. The sample covers March 26, 2017 through May 26, 2023. t-statistics based on Newey and West (1987) standard errors are reported in brackets. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Good Macroeconomic News Days												
	Deep Sleep						Sleep Efficiency					
Minutes	30	60	90	120	150	180	30	60	90	120	150	180
Amihud	-0.02	0.00	0.01	0.03	0.04	0.04	-0.13**	-0.09	-0.10	-0.09	-0.09	-0.15**
	[-0.28]	[0.04]	[0.10]	[0.41]	[0.49]	[0.47]	[-2.05]	[-1.39]	[-1.47]	[-1.32]	[-1.44]	[-2.16]
$\bar{R}^2$	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.00	0.00	0.00	0.01
Return	-0.03	0.06	0.07	0.09	0.09	0.06	-0.01	-0.01	0.00	0.01	-0.01	-0.01
	[-0.48]	[1.33]	[1.14]	[1.44]	[1.54]	[1.12]	[-0.25]	[-0.12]	[-0.01]	[0.16]	[-0.18]	[-0.11]
Adj. R^2	0.08	0.02	0.01	-0.00	0.00	0.00	0.08	0.01	0.01	-0.00	-0.00	-0.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	233	233	233	233	233	233	233	233	233	233	233	233
Panel A: Bad Macroeconomic News Days												
	Deep Sleep						Sleep Efficiency					
Minutes	30	60	90	120	150	180	30	60	90	120	150	180
Amihud	-0.14*	-0.14*	-0.10	-0.14**	-0.20***	-0.17**	-0.17**	-0.17	-0.13	-0.09	-0.11	-0.15*
	[-1.87]	[-1.94]	[-1.47]	[-2.12]	[-3.07]	[-2.28]	[-2.14]	[-1.60]	[-1.33]	[-1.27]	[-1.56]	[-1.76]
$\bar{R}^2$	0.01	0.01	0.01	0.01	0.03	0.03	0.02	0.02	0.02	-0.00	0.00	0.03
Return	-0.07	-0.06	-0.04	-0.07	-0.12*	-0.14**	-0.05	0.01	0.00	0.06	-0.04	-0.05
	[-1.11]	[-0.91]	[-0.57]	[-1.00]	[-1.79]	[-2.30]	[-0.72]	[0.20]	[0.07]	[1.21]	[-0.66]	[-0.77]
$\bar{R}^2$	0.01	0.06	0.07	0.02	0.04	0.07	0.01	0.05	0.07	0.02	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	193	193	193	193	193	193	193	193	193	193	193	193

information.

4 Conclusion

Economic uncertainty leaves traces not only on macroeconomic aggregates and asset prices but also on nightly physiology. Using novel minute-level sleep data for a national cohort, we show that spikes in uncertainty reduce deep sleep and sleep efficiency for several nights—a "*wake-and-see*" response that is robust to environmental and behavioral controls, more tightly linked to second-moment risk than to first-moment market moves, and economically meaningful in the aggregate. We then close the loop by demonstrating that population-level sleep quality helps forecast next-day market quality. Poor sleep foreshadows weaker opening-hour returns and higher Amihud illiquidity, with effects concentrated early in the trading day, stronger when policy uncertainty is low, and consistent with a more complete incorporation of bad pre-open macro news when sleep is better. Taken together, the evidence shows a bidirectional link between uncertainty and physiological restoration, and that these physiological changes can propagate to price discovery through better rest.

Our broader contribution is to show how biometric time series can be harnessed for economic analysis. Because uncertainty is difficult to observe cleanly, our approach complements traditional indicators with a continuous, objective biomarker that is naturally tied to attention, learning, and productivity. In doing so, we provide evidence of a novel non-pecuniary channel through which uncertainty shocks impose costs: lost deep sleep and reduced sleep efficiency that accumulate across nights and individuals and plausibly map into foregone output. The evidence motivates integrating biometric "biofeedback" effects into macro-finance analysis—not as a substitute for standard measures, but as a high-frequency indicator of risk and its human-capital consequences.

The study opens up several avenues for future research. First, it is plausible to treat sleep as a state variable that shifts risk-bearing capacity or the capacity to acquire new information: models with state-dependent risk aversion or information-processing frictions can be disciplined with our daily series and the intraday patterns in returns and liquidity. Second, nightly restoration can be embedded directly in preferences or in the accumulation of cognitive capital to model how uncertainty propagates to consumption and investment when restorative resources are depleted. Third, as biometric time series in *All of Us* lengthen and coverage deepens, it would be promising to test whether population sleep can directly forecast lower-frequency macro outcomes—productivity, labor supply, and spending. Each of these steps would connect human physiology more tightly to the macro-finance cycle and help quantify the welfare costs of risk beyond pecuniary margins.

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Internet Appendix

IA.A Variable Descriptions

Activity. Data on activity is obtained from the NIH's *All of Us* Research Program. Specifically, we use data on each individual's number of "very active minutes" per day of the sample period. These are the number of minutes the individual engaged in activities with metabolic equivalents (METs) of six or greater, where METs are defined in line with Jetté, Sidney and Blümchen (1990). After obtaining this data, we remove individual fixed effects before calculating the cross-sectional average value of active minutes across all individuals in the data. This provides us with a daily time series of activity that ranges from January 5, 2013 through October 1, 2023.

Age. The age of an individual is calculated by computing the number of years between (i) the individual's date of birth, as reported through the onboarding process of the *All of Us* Research Program and (ii) the date of each sleep event associated with the individual.

Amihud illiquidity. The Amihud illiquidity measure is computed as the absolute value of the cumulative return divided by dollar-trading volume within each intraday window. Specifically, for each trading day t and minute horizon $\tau \in \{30, 60, 90, 120, 150, 180\}$,

$$\text{Amihud}_{t,tau} = \frac{|\text{CumRet}_{t,\tau}|}{\text{DollarVolume}_{t,\tau}}.$$

Both cumulative returns and trading volumes are constructed for the SPY ETF from the NYSE Trade and Quote (TAQ) database, which aggregate trade and quote information at the one-minute frequency during regular trading hours (9:30 a.m.–4:00 p.m. EST). This variable captures the immediate price impact per dollar traded and serves as an inverse proxy for market liquidity.

COVID-19. The number of new COVID-19 cases diagnosed each day per one million people in the United States between January 22, 2020 and March 9, 2023 is obtained from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University at the following link: https://github.com/CSSEGISandData/COVID-19/.

Cumulative return. Cumulative market returns are computed from one-minute log returns measured from the market open on day t through to each intraday minute horizon

$\tau \in \{30, 60, 90, 120, 150, 180\}$. That is, for each day t and trading interval τ,

$$\text{CumRet}_{t,\tau} = \sum_{j=1}^{\tau} r_{t,j},$$

where $r_{t,j}$ denotes the one-minute log return of the SPY ETF in minute j of trading day t. The one-minute price series used to construct these returns are obtained from the NYSE Trade and Quote (TAQ) database, which aggregate trade and quote information at the one-minute frequency during regular trading hours (9:30 a.m.–4:00 p.m. EST).

Deep Sleep. Data on deep sleep is constructed using data provided by the *All of Us* Research Program. The construction of this variable is provided in the discussion related to equation (1) in the main text.

Deprivation index. The Nationwide Community Deprivation Index is constructed by following Brokamp *et al.* (2019) and is disseminated through the *All of Us* Research Program. This variable is constructed from responses to the annual American Community Survey (ACS) administered by the United States Census Bureau and reflects the first principal component of six measures of socioeconomic conditions captured by the ACS. This principal component, which explains about 50% to 60% of the variation in the underlying measures, is referred to as the "Deprivation index" and is scaled to take values between zero (low deprivation) and one (high deprivation). The *All of Us* Research Program reports the value of this index that corresponds to the three-digit ZIP code associated with an individual's location in the United States.

Education. Education refers to the fraction of the population at the three-digit ZIP code level that are 25 years of age or older with an educational attainment of at least high school graduation or equivalent (e.g., have successfully completed the General Educational Development (GED) test). This variable is constructed from responses to the annual American Community Survey (ACS) administered by the United States Census Bureau. The *All of Us* Research Program reports the value of this variable that corresponds to the three-digit ZIP code associated with an individual's location in the United States.

Ethnicity. Ethnicity refers to the self-reported ethnicity of an individual included in the *All of Us* Research Program. Selections include "Hispanic, Latino, or Spanish," and "Non-Hispanic," among other possible selection (including choosing not to answer). Complete information on the coding of this variable is available online via the *All of Us* documentation.

Happy. Happiness is measured using the daily language-based hedonometer index that is made available on hedonometer.org. This index is constructed following the methodology described by Dodds *et al.* (2011) and Dodds *et al.* (2015).

HRV. Average heart rate variability (HRV) is constructed using data from the NIH *All of Us* Research Program. Specifically, on each day of the sample period, we compute the standard deviation of each individual's heart rate using minute-level heart rate data. We then take the average heart rate volatility across all individuals in the data on the given day. Finally, we project HRV on both sleep quality and daily physical activity, as both of these margins can induce predictable changes in HRV. This provides us with a daily time series of heart rate volatility that ranges from January 21, 2015 through October 1, 2023.

Income. Income refers to the median household income in the past 12 months in 2015 inflation-adjusted dollars. This variable is constructed from responses to the annual American Community Survey (ACS) administered by the United States Census Bureau. The *All of Us* Research Program reports the value of this variable that corresponds to the three-digit ZIP code associated with an individual's location in the United States.

Income assistance. Income refers to fraction of households in a three-digit ZIP code area that have received public assistance income or food stamps or Supplemental Nutrition Assistance Program (SNAP) benefits in the past 12 months. This variable is constructed from responses to the annual American Community Survey (ACS) administered by the United States Census Bureau. The *All of Us* Research Program reports the value of this variable that corresponds to the three-digit ZIP code associated with an individual's location in the United States.

Poverty. Poverty refers to the fraction of households in a three-digit ZIP code area that have a household income in the last 12 months that is below the federal poverty level. This variable is constructed from responses to the annual American Community Survey (ACS) administered by the United States Census Bureau. The *All of Us* Research Program reports the value of this variable that corresponds to the three-digit ZIP code associated with an individual's location in the United States.

Race. Race refers to the self-reported race of an individual included in the *All of Us* Research Program. Selections include "White," "Black," and "Asian," among other possible selections (including choosing not to answer). Complete information on the coding of this variable is available online via the *All of Us* documentation.

Rainfall. Data on the average daily rainfall, measured in millimeters, is obtained from Meteostat (https://meteostat.net/en/), one of the largest vendors of open climate and weather data. Meteostat aggregates weather data from a variety of sources, including the NOAA, to provide data on the weather at each of the thousands of weather stations located in the United States. We then compute the average amount of rainfall across all of these weather stations on each day between January 1, 2024 and December 3, 2024.

Sex. Sex refers to the self-reported sex of an individual included in the *All of Us* Research Program. Selections include "Male" and "Female" among other possible selections (including choosing not to answer). Information on the coding of this variable is available online via the *All of Us* documentation.

Sleep Efficiency. Data on sleep efficiency is constructed using data provided by the *All of Us* Research Program. The construction of this variable is provided in the discussion related to equation (2) in the main text.

Sunlight. Data on the average amount of sunlight each day, measured in hours, is provided by the National Oceanic and Atmospheric Administration (NOAA) agency of the U.S. Department of Commerce. This data, which is collected and disseminated by NOAA's Global Monitoring Laboratory, reports the daily average sunlight duration across 21 U.S. main cities from January 1, 2024 through December 31, 2023. The data are available via the following link: https://gml.noaa.gov/grad/solcalc/.

Temperature. Data on the average daily temperature is obtained from Meteostat (https://meteostat.net/en/), one of the largest vendors of open climate and weather data. Meteostat aggregates weather data from a variety of sources, including the NOAA, to provide data on the weather at each of the thousands of weather stations located in the United States. We then compute the average temperature, recorded in degrees Celsius, across all of these weather stations on each day between January 1, 2024 and December 3, 2024.

Table IA.B.1: Summary statistics: Other variables

The table reports summary statistics for the control variables used in the main analyses: the natural logarithm of the daily Economic Policy Uncertainty (EPU) index (Baker *et al.*, 2016); daylight duration (hours), which is referred to as "Sunlight;" average daily temperature (degrees Celsius); and average daily precipitation (millimeters). We also report the daily number of newly diagnosed COVID-19 cases per million people and the Hedonometer's daily happiness score (Dodds *et al.*, 2011). Finally, we construxt two additional variables from using *All of Us* data: daily physical activity (measured in minutes) and heart-rate variability, proxied by the within-day standard deviation of an individual's one-minute heart rate. For each variable, the table reports the mean, median, standard deviation, and the 5th, 10th, 25th, 75th, 90th, and 95th percentiles. Complete variable definitions appear in Section IA.A of the Internet Appendix. The sample ranges from April 26, 2023 to May 26, 2023.

	Mean	Std	p5	p10	p25	Median	p75	p90	p95
EPU	4.80	0.62	3.89	4.07	4.40	4.75	5.16	5.63	5.96
Sunlight (Hours)	12.23	1.96	9.37	9.51	10.33	12.28	14.13	14.85	14.97
Temperature (Celsius)	12.82	8.35	0.14	1.90	5.57	12.95	21.16	23.57	24.16
Rainfall (mm)	2.31	1.45	0.51	0.69	1.21	2.03	3.04	4.33	5.21
COVID	1.49	2.17	0.00	0.00	0.00	0.64	2.08	4.88	6.51
Activity (Mins)	17.60	1.99	14.26	15.04	16.34	17.69	18.94	19.99	20.61
Happy	5.98	0.06	5.88	5.92	5.96	5.99	6.02	6.04	6.06
HRV (BPM)	12.52	0.46	11.86	11.96	12.15	12.46	12.92	13.15	13.23

IA.B Additional Tables

Table IA.B.2: Key domestic and geopolitical news days

The table presents a set of 40 prominent domestic and geopolitical news events that are relevant for U.S. households between May 2017 and April 2023. This set of dates is obtained by prompting GPT 5 to deliver a set of dates, alongside an explanation for why each date is selected.

Number	Date	Event Description
1	2017-06-01	Trump announces U.S. withdrawal from Paris Climate Agreement
2	2017-06-14	Grenfell Tower fire in London kills 72, prompts safety overhaul debate
3	2017-07-04	North Korea launches its first ICBM (Hwasong-14)
4	2017-10-01	Las Vegas shooting becomes deadliest in modern U.S. history
5	2017-11-15	Military moves against Mugabe signal end of 37-year rule in Zimbabwe
6	2017-12-22	Trump signs $1.5 tn Tax Cuts and Jobs Act into law
7	2018-02-14	Parkland school shooting reignites U.S. gun-control debate
8	2018-03-04	Nerve-agent attack on Skripals strains U.K.–Russia relations
9	2018-04-14	U.S., U.K., France launch missile strikes on Syrian regime sites
10	2018-06-12	First Trump–Kim denuclearisation summit in Singapore
11	2018-07-16	Trump–Putin Helsinki summit triggers bipartisan criticism
12	2018-10-02	Saudi journalist Jamal Khashoggi murdered inside Istanbul consulate
13	2018-11-06	U.S. midterm elections flip House control to Democrats
14	2018-11-25	Russia seizes Ukrainian vessels in Kerch Strait
15	2019-03-22	Mueller delivers Russia-probe report to U.S. Attorney General
16	2019-05-10	U.S. hikes tariffs on $200 bn of Chinese goods—trade-war apex
17	2019-06-20	Iran shoots down U.S. RQ-4 drone over Strait of Hormuz
18	2019-07-24	Boris Johnson becomes U.K. Prime Minister
19	2019-09-14	Drone/missile attack cripples Saudi Aramco oil facilities at Abqaiq
20	2019-10-09	Turkey launches offensive against Kurdish forces in Syria
21	2020-01-23	Wuhan locks down as novel coronavirus spreads globally
22	2020-03-11	WHO declares COVID-19 a global pandemic
23	2020-03-27	CARES Act injects $2.2 tn stimulus into U.S. economy
24	2020-04-12	OPEC+ finalises historic oil-production cuts
25	2020-05-25	Murder of George Floyd sparks worldwide protests
26	2020-06-30	China imposes sweeping national-security law on Hong Kong
27	2020-07-22	U.S. orders closure of China's Houston consulate; Beijing retaliates
28	2021-01-06	U.S. Capitol insurrection shocks American democracy
29	2021-01-20	Joe Biden inaugurated 46th President of the United States
30	2021-03-23	Ever Given blocks Suez Canal, halting global trade
31	2021-06-24	Surfside condominium tower collapses in Florida
32	2022-03-16	Airstrike destroys Mariupol theatre sheltering civilians
33	2022-04-14	Ukraine sinks Russia's Black Sea flagship Moskva
34	2022-06-24	U.S. Supreme Court overturns Roe v. Wade
35	2022-07-08	Former Japanese PM Shinzo Abe assassinated
36	2022-11-08	U.S. midterm elections produce a divided Congress
37	2022-12-07	Peru's President Castillo ousted after failed self-coup
38	2022-12-22	Historic Arctic blast cripples U.S. infrastructure and travel
39	2023-02-06	Magnitude-7.8 earthquake devastates Turkey and Syria
40	2023-03-10	Silicon Valley Bank collapse triggers banking turmoil

Table IA.B.3: Projections: Robustness to aggregation

The table presents a series of robustness tests related to the projection analysis associated with equation (5), described in Section 2.2. Specifically, the table reports robustness to aspects of the aggregation procedure described in Section 1.4.1. The top row of the table displays the baseline results from Columns (1), (3), (5), and (7) of Table 2 for the purpose of comparison. Next, Panels A and B report the results obtained after reconstructing the aggregate measures of sleep quality without detrending the data and by taking the cross-sectional average rather than median each day, respectively. Similarly, Panels C and D report the results obtained after constructing the aggregate-level sleep quality measures without applying day-of-the-week fixed effects and winsorizing the data, respectively. Odd-numbered columns report the results of univariate regressions, while even-numbered columns also include the comprehensive set of control variables underlying equation (5). Finally, t-statistics, reported in parentheses, are constructed using Newey and West (1987) standard errors, and the sample period runs from April 26, 2017 through May 26, 2023.

Variable	Deep Sleep		Sleep Efficiency	
	(1)	(2)	(3)	(4)
Baseline				
EPU	-0.09	-0.15	-0.22	-0.18
	(-2.28)	(-5.64)	(-6.46)	(-5.89)
R^2	0.01	0.48	0.05	0.24
Panel A: No time trend				
EPU	-0.27	-0.24	-0.34	-0.16
	(-7.40)	(-8.33)	(-12.30)	(-6.01)
R^2	0.07	0.40	0.12	0.34
Panel B: Cross-sectional average				
EPU	-0.11	-0.14	-0.22	-0.18
	(-2.48)	(-5.43)	(-5.97)	(-5.43)
R^2	0.01	0.52	0.05	0.24
Panel C: No day-of-week fixed effects				
EPU	-0.18	-0.33	-0.30	-0.30
	(-5.31)	(-11.64)	(-8.59)	(-9.23)
R^2	0.03	0.56	0.09	0.28
Panel D: No winsorization				
EPU	-0.09	-0.15	-0.03	-0.09
	(-2.36)	(-5.74)	(-2.44)	(-3.35)
R^2	0.01	0.47	0.00	0.03
Controls	No	Yes	No	Yes

Table IA.B.4: Projections: Robustness to economic conditions

The table presents a series of robustness tests related to the projection analysis associated with equation (5), described in Section 2.2. Specifically, the table reports robustness to using alternative measures of economic conditions in the projection, in place of the Economic Policy Uncertainty (EPU) index. The top row of the table displays the baseline results from Columns (1), (3), (5), and (7) of Table 2 for the purpose of comparison. Panel A then replaces the daily value of the EPU index with the daily value of the VIX index. Likewise, Panels B and C measure the daily level of uncertainty using the equity market volatility index (VOL) and the Bekaert *et al.* (2022) (BEX) measure of economic uncertainty, respectively. In Panel D, we measure economic conditions using daily excess market returns, while Panels E and F measure the level of economic conditions using the investment-minus-consumption (IMC) spread of Papanikolaou (2011) and the intermediary capital factor (INT) of He *et al.* (2017), respectively. Odd-numbered columns report the results of univariate regressions, while even-numbered columns also include the comprehensive set of control variables underlying equation (5). Finally, t-statistics, reported in parentheses, are constructed using Newey and West (1987) standard errors, and the sample period runs from April 26, 2017 through May 26, 2023.

Variable	Deep Sleep		Sleep Efficiency	
	(1)	(2)	(3)	(4)
		Baseline		
EPU	-0.09	-0.15	-0.22	-0.18
	(-2.28)	(-5.64)	(-6.46)	(-5.89)
R^2	0.01	0.48	0.05	0.24
		Panel A: Implied volatility		
VIX	-0.12	-0.18	-0.20	-0.12
	(-2.26)	(-4.18)	(-4.14)	(-2.49)
R^2	0.01	0.52	0.04	0.38
		Panel B: Equity market volatility index		
VOL	-0.15	-0.15	-0.14	-0.05
	(-3.28)	(-5.33)	(-2.65)	(-1.42)
R^2	0.02	0.52	0.02	0.37
		Panel C: BEX Uncertainty		
UNC	-0.19	-0.23	-0.24	-0.16
	(-4.66)	(-6.58)	(-5.71)	(-3.79)
R^2	0.03	0.55	0.06	0.38
		Panel D: Excess market return		
MKTRF	0.02	0.04	0.03	0.01
	(0.75)	(1.87)	(0.87)	(0.55)
R^2	-0.00	0.50	0.00	0.37
		Panel E: Investment-minus-consumption		
IMC	0.02	0.01	-0.01	-0.01
	(0.89)	(0.71)	(-0.30)	(-0.33)
R^2	-0.00	0.50	-0.00	0.37
		Panel F: Intermediary capital factor		
INT	0.02	0.03	0.02	-0.00
	(0.63)	(1.61)	(0.71)	(-0.21)
R^2	-0.00	0.50	-0.00	0.37
Controls	No	Yes	No	Yes

IA.C Additional Figures

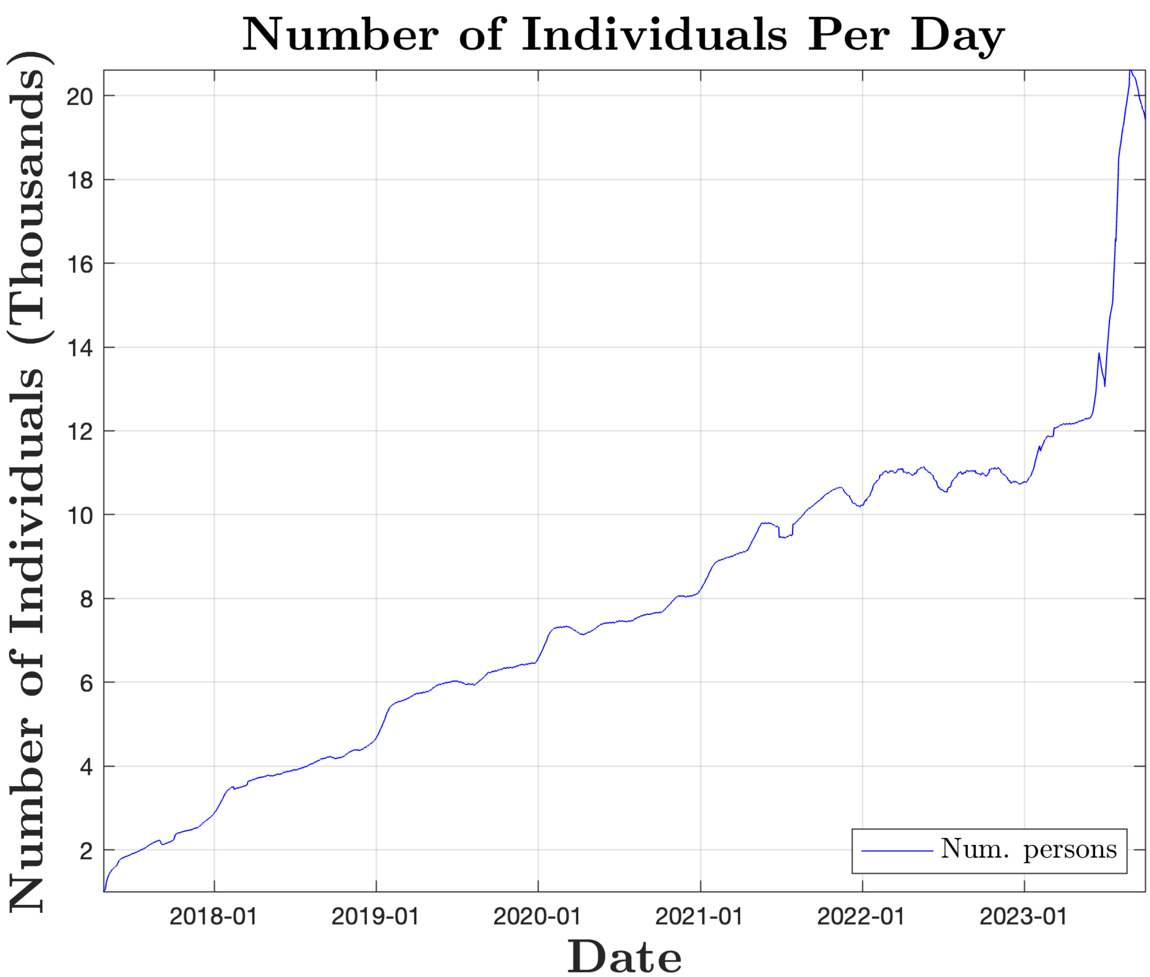

Figure IA.C.1: Unique individuals per day
The figure reports the number of unique individuals in the NIH *All of Us* Research Program on each day of the sample period. We retain only individual–day observations for which the "is_main_sleep" flag in the *All of Us* data is true and drop days with fewer than 1,000 individuals with valid data. For visual clarity, we plot the 30-day moving average of the daily counts. The resulting sample runs from April 26, 2017 through May 26, 2023.

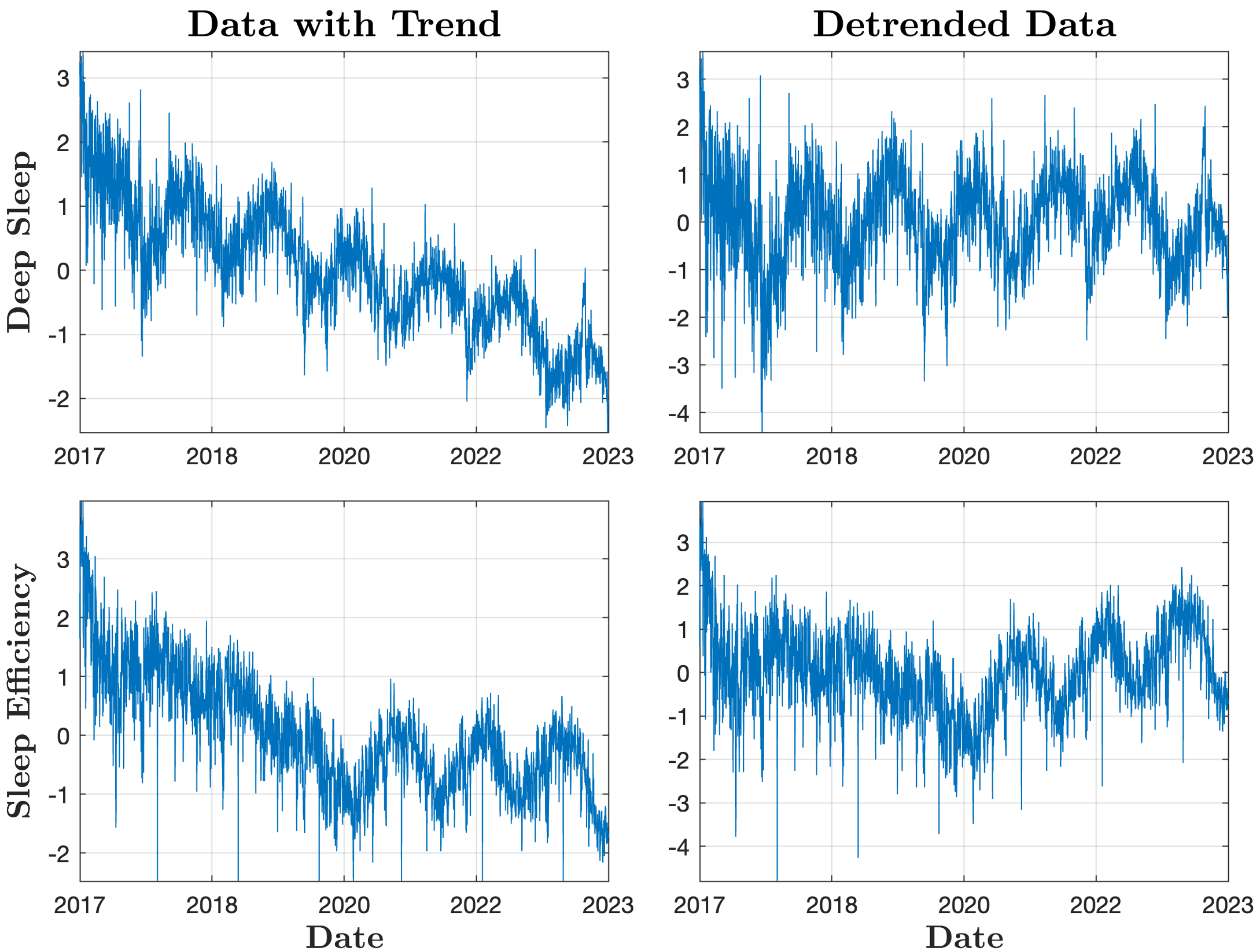

Figure IA.C.2: Aggregate sleep quality with and without linear time trend
The figure provides the daily time series of aggregate sleep quality, defined in Section 1.4.1, with and without removing a linear time trend. The top row of the figure displays the time series of the aggregate deep-sleep share, defined via equation (1), while the bottom row of the figure displays the time series of aggregate sleep efficiency, defined via equation (2). The left column of the figure shows the raw aggregate time series associated with each variable before removing day-of-the-week fixed effects and winsorization. The right column of the figure shows the linearly detrended aggregate time series of each variable. Specifically, the data is detrended by projecting the daily time series of each measure of sleep quality on a time index that takes on a value of one on the first day of the sample period, and is incremented by one on each subsequent day. The detrended series is obtained as the residual of this projection. The data underlying this figure ranges from April 26, 2023 through May 26, 2023.

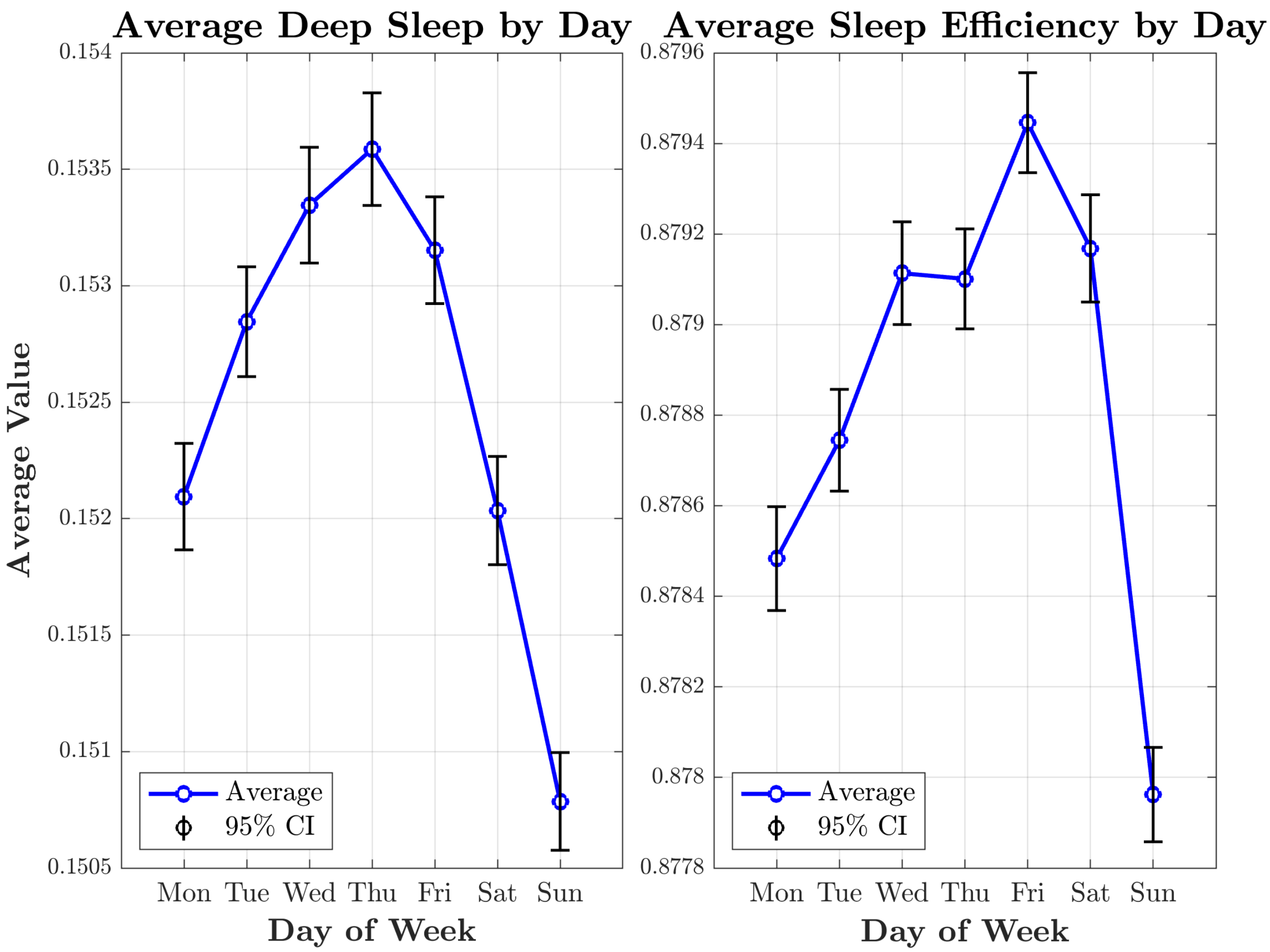

Figure IA.C.3: Aggregate sleep quality and day-of-the-week effects
The figure provides the average value of each measure of aggregate sleep quality, defined in Section 1.4.1, on each weekday of the sample period. The left column of the figure displays the average value of the aggregate deep-sleep share, defined via equation (1), on each day of the week across the entire sample period, while the right column displays the average value of aggregate sleep efficiency, defined via equation (2). Each point on the plot presents the average value on a given day of the week and the black bars present the 95% confidence interval associated with each mean. The data underlying this figure ranges from April 26, 2023 through May 26, 2023.

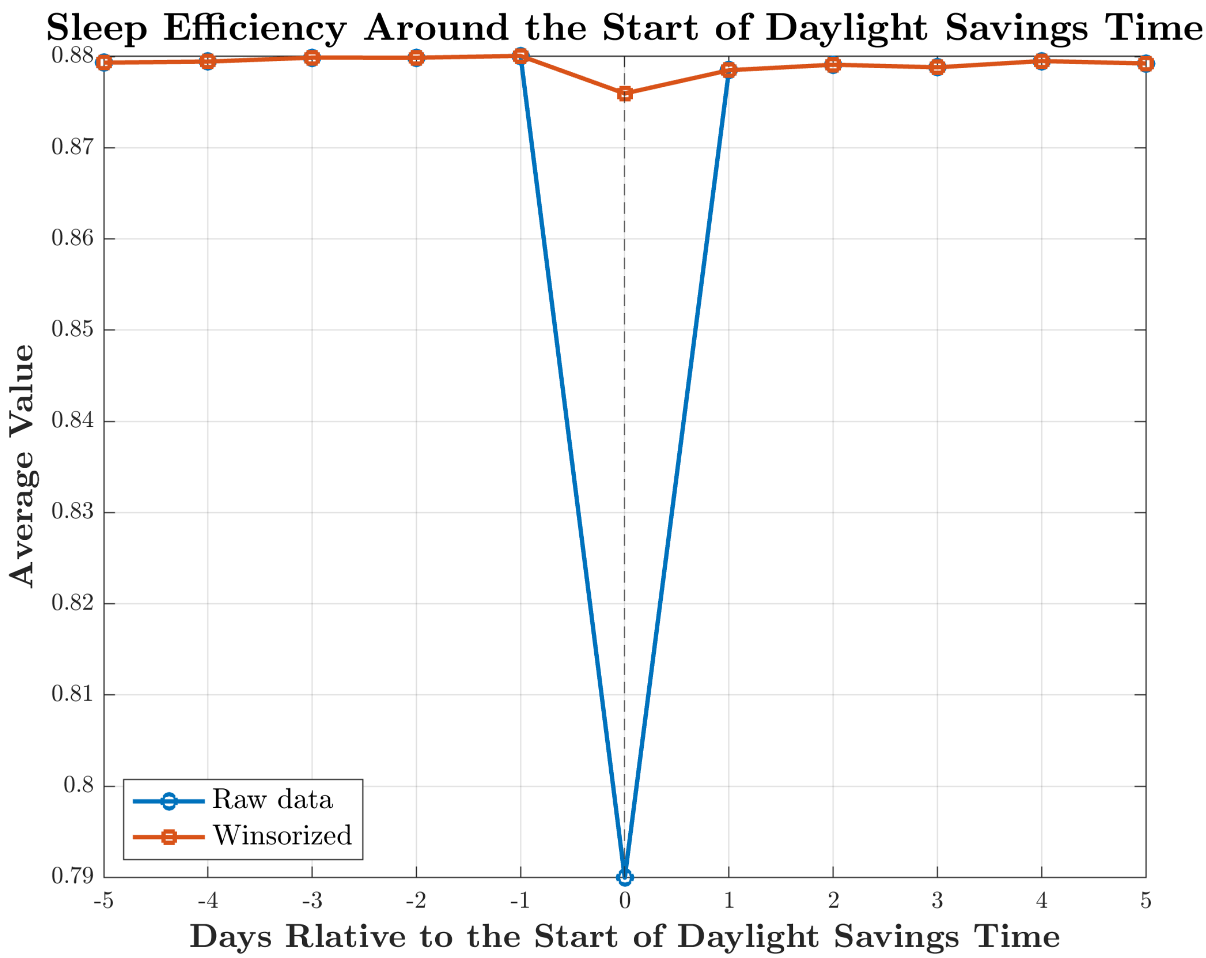

Figure IA.C.4: Aggregate sleep efficiency and the effects of winsorization
The figure provides the average value of aggregate sleep efficiency, defined via equation (2), in the 11-day event window surrounding each year's start of Daylight Saving Time (DST). For each event date, we compute the daily value of aggregate sleep efficiency, and then take the mean value of this time series across all six time changes during our sample period. The blue line reports the results of this analysis when we do not winsorize the sleep data at the 1% level, while the red line reports the results of this analysis after winsorizing the data. The data underlying this figure is daily and includes all changes to DST between 2017 and 2022.

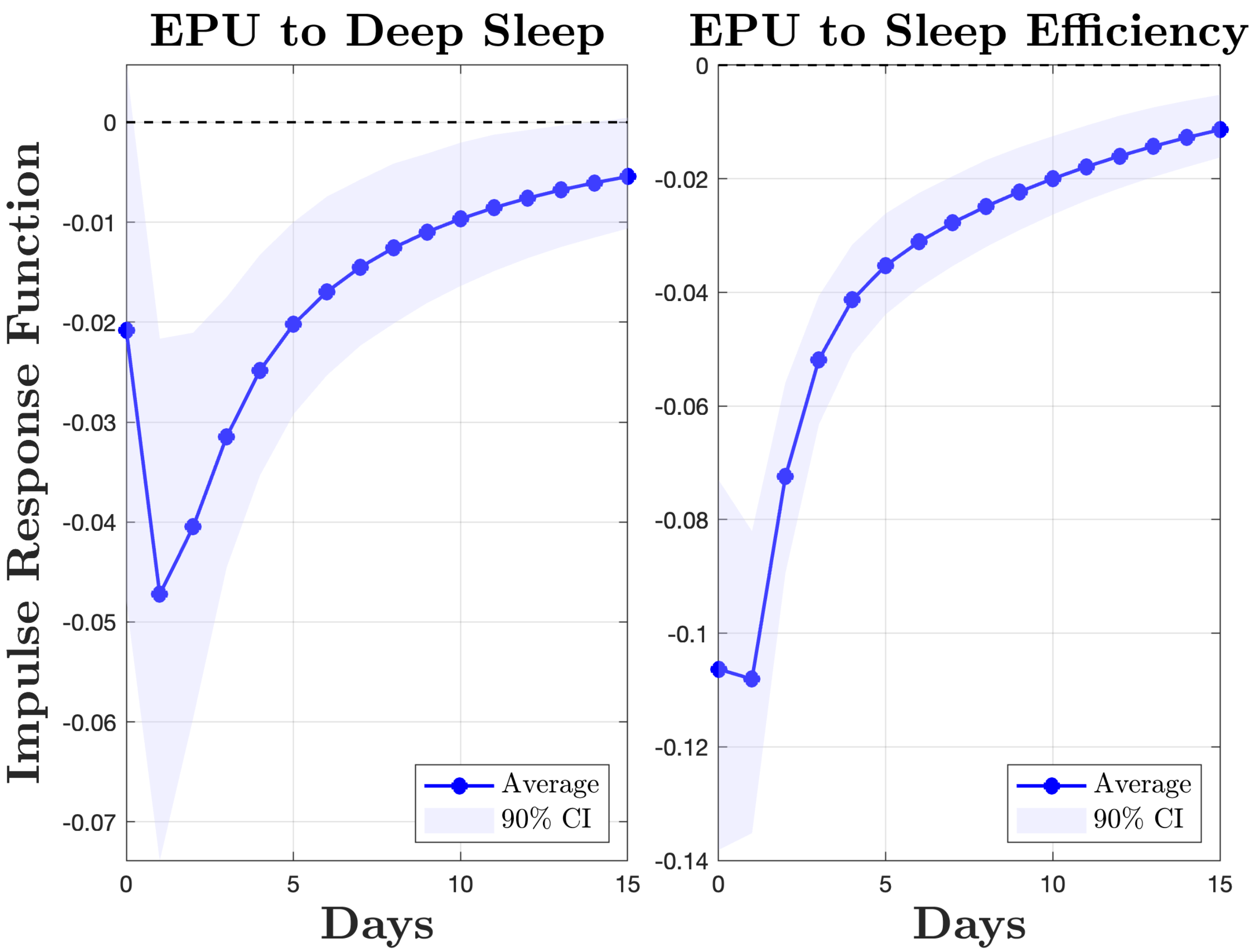

Figure IA.C.5: Impulse response functions: Generalized (order-invariant) responses
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). These IRFs are obtained by estimating the vector autoregression presented by equation (6) and employing the order-invariant generalized IRF identification scheme described by Pesaran and Shin (1998). The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

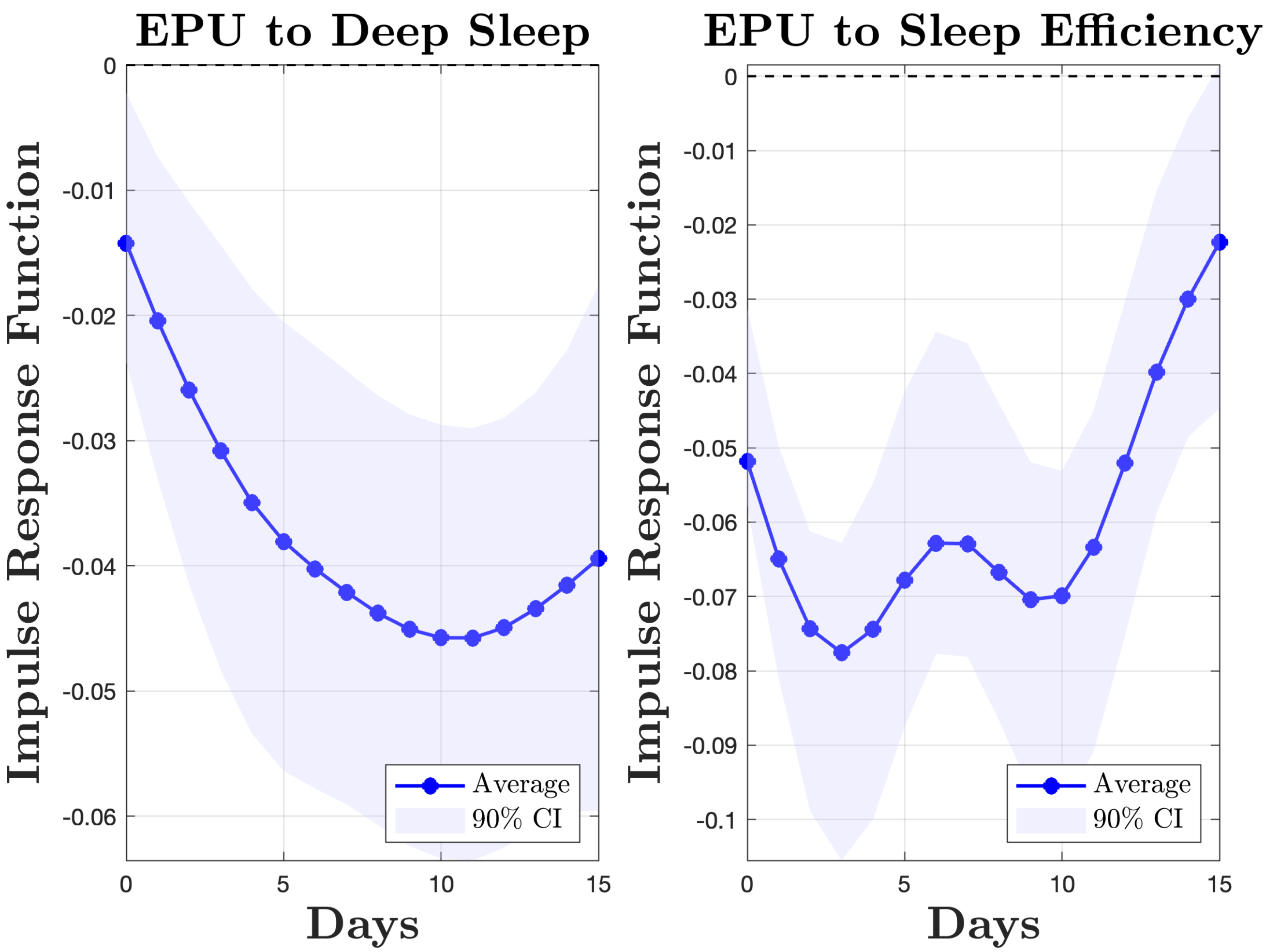

Figure IA.C.6: Impulse response functions: Smooth local projections
The figure reports impulse response functions (IRFs) that display how a shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). These IRFs are obtained by estimating the smooth local projections described by Barnichon and Brownlees (2019), which predict each sleep quality at the $t + h$, for $h \in \{0, \ldots, 15\}$ as a smooth function of the explanatory variables at time zero. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

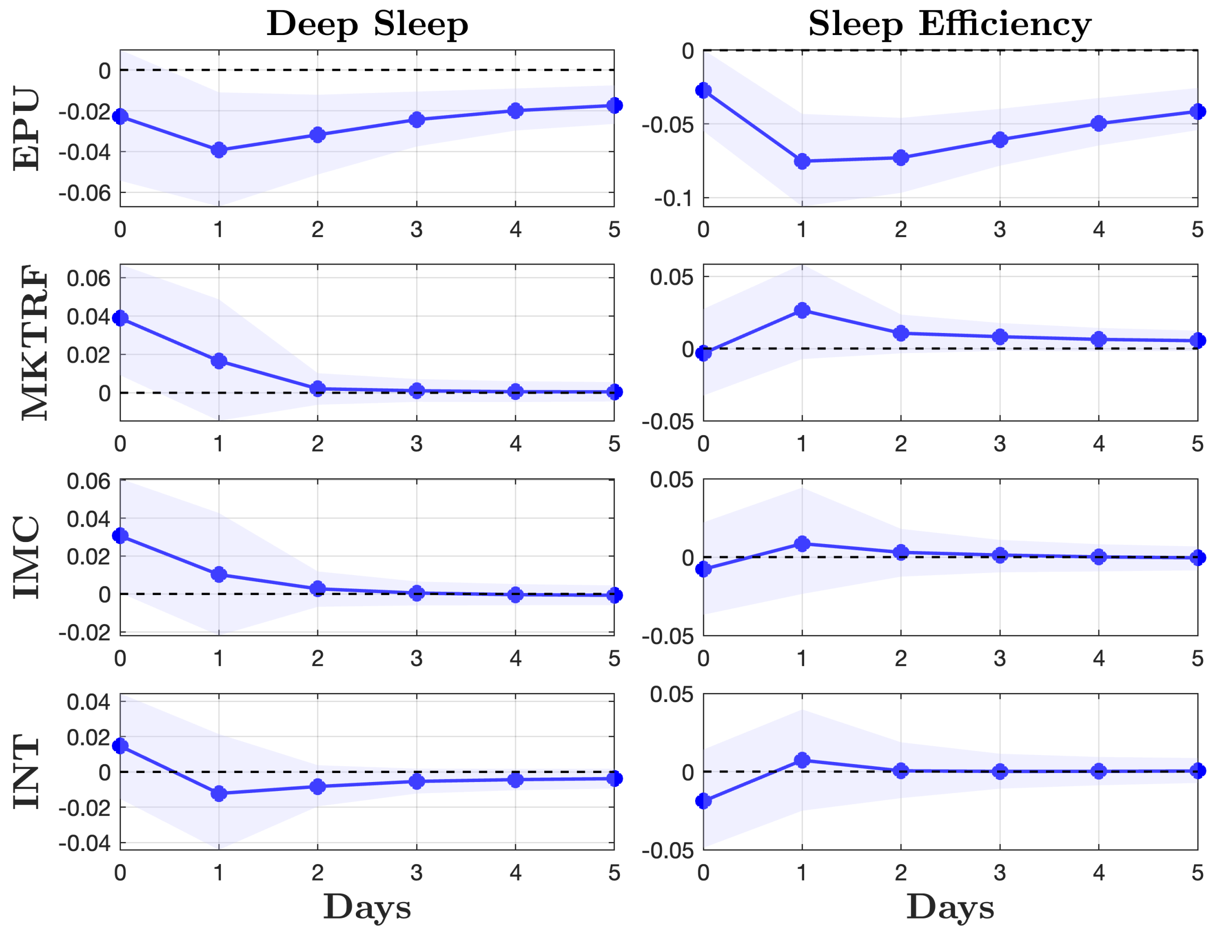

Figure IA.C.7: Impulse response functions: Additional first-moment controls
The figure reports impulse response functions (IRFs) that display how a structural shocks to each of economic variables, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016) and three additional first-moment controls, propagate to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). These IRFs are obtained by first augmenting the vector autoregression presented by equation (6) to include three extra variables. These three additional variables are including in the vector $\boldsymbol{y}_t$ immediately preceding the EPU index. The three variables are the daily excess market return, denoted by MKTRF, the daily return on the investment-minus-consumption spread of Papanikolaou (2011), denoted by IMC, and the daily return on the intermediary capital factor of He *et al.* (2017), denoted by INT. We obtain the IRFs by estimating the vector autoregression and employing the recursive (Cholesky-based) identification of each structural shock. The top row of the figure shows the IRFs associated with EPU, the second row shows the IRFs associated with MKTRF, the third row shows the IRFs associated with IMC, and the final row shows the IRFs associated with INT. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and spans each trading day from April 26, 2017 through May 26, 2023.

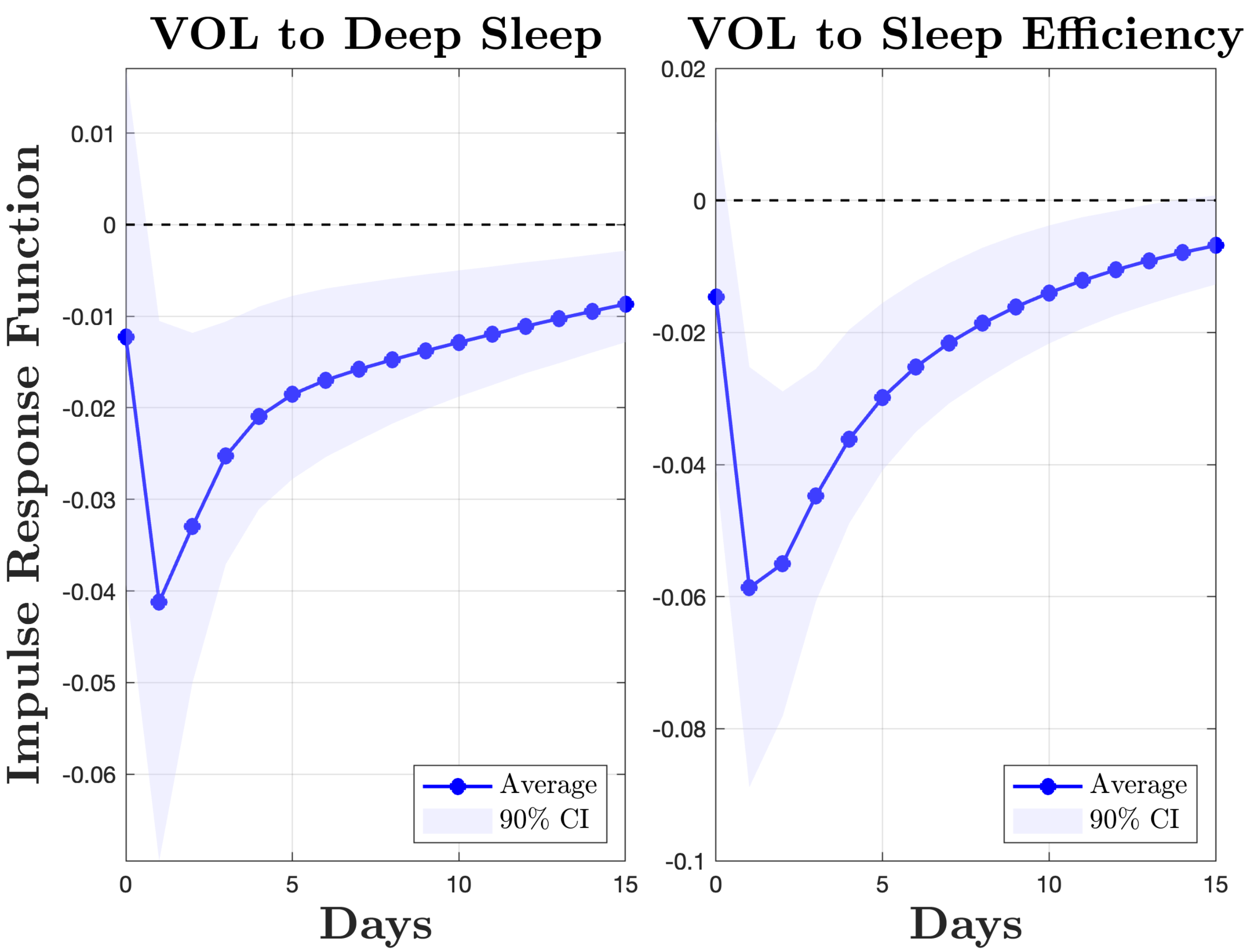

Figure IA.C.8: Impulse response functions: equity market volatility
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the equity market volatility index, propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). These IRFs are obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

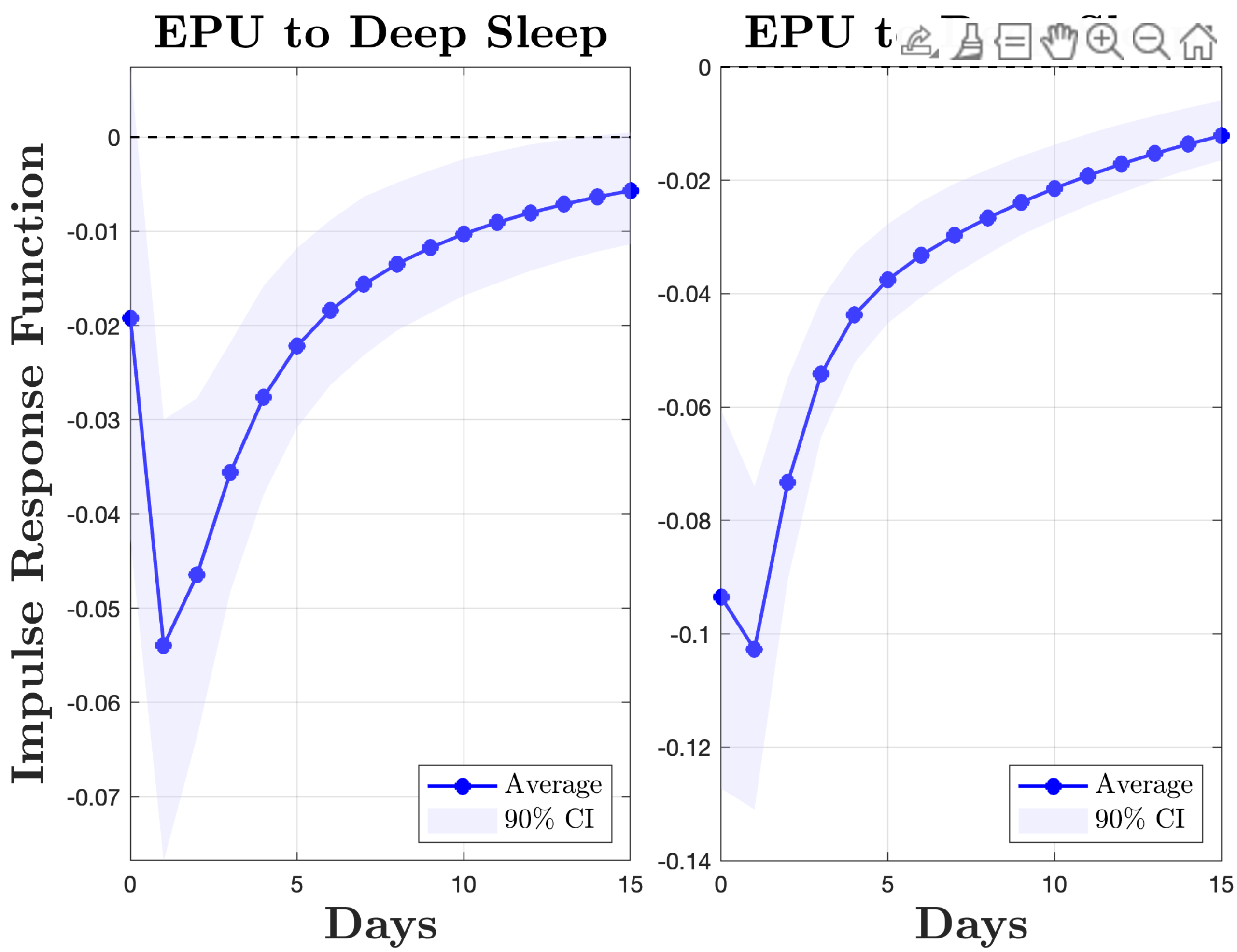

Figure IA.C.9: Impulse response functions: Cross-sectional average
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). Unlike the baseline analysis that aggregates observations across individuals by taking the cross-sectional median value each day, the sleep quality data underlying this figure computes the daily cross-sectional average value. These IRFs are then obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

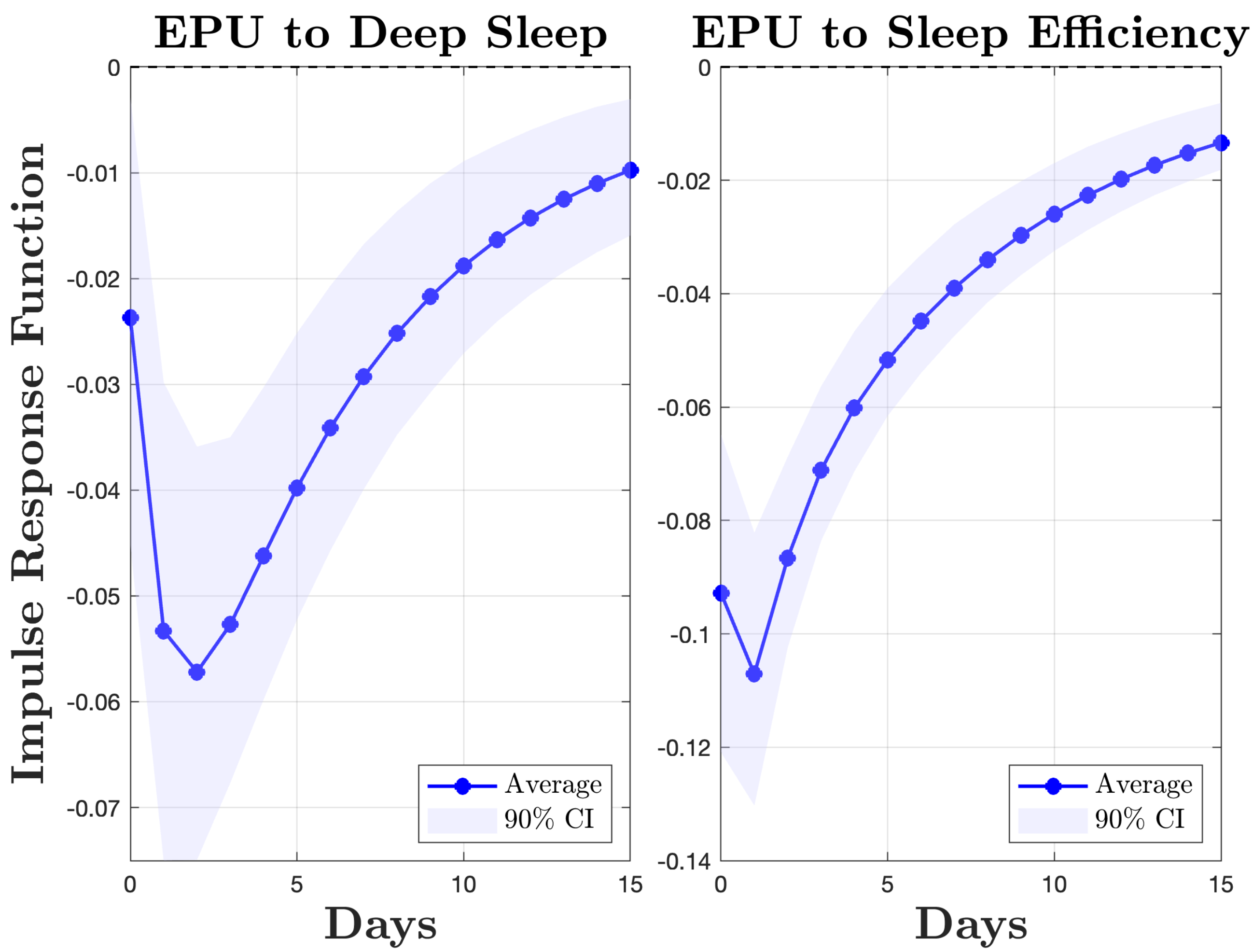

Figure IA.C.10: Impulse response functions: No time trend
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). Unlike the baseline analysis that removes a time trend from the aggregate measures of sleep quality (as discussed in Section 1.4.1 of the main text), the sleep quality data underlying this figure is not detrended. These IRFs are then obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

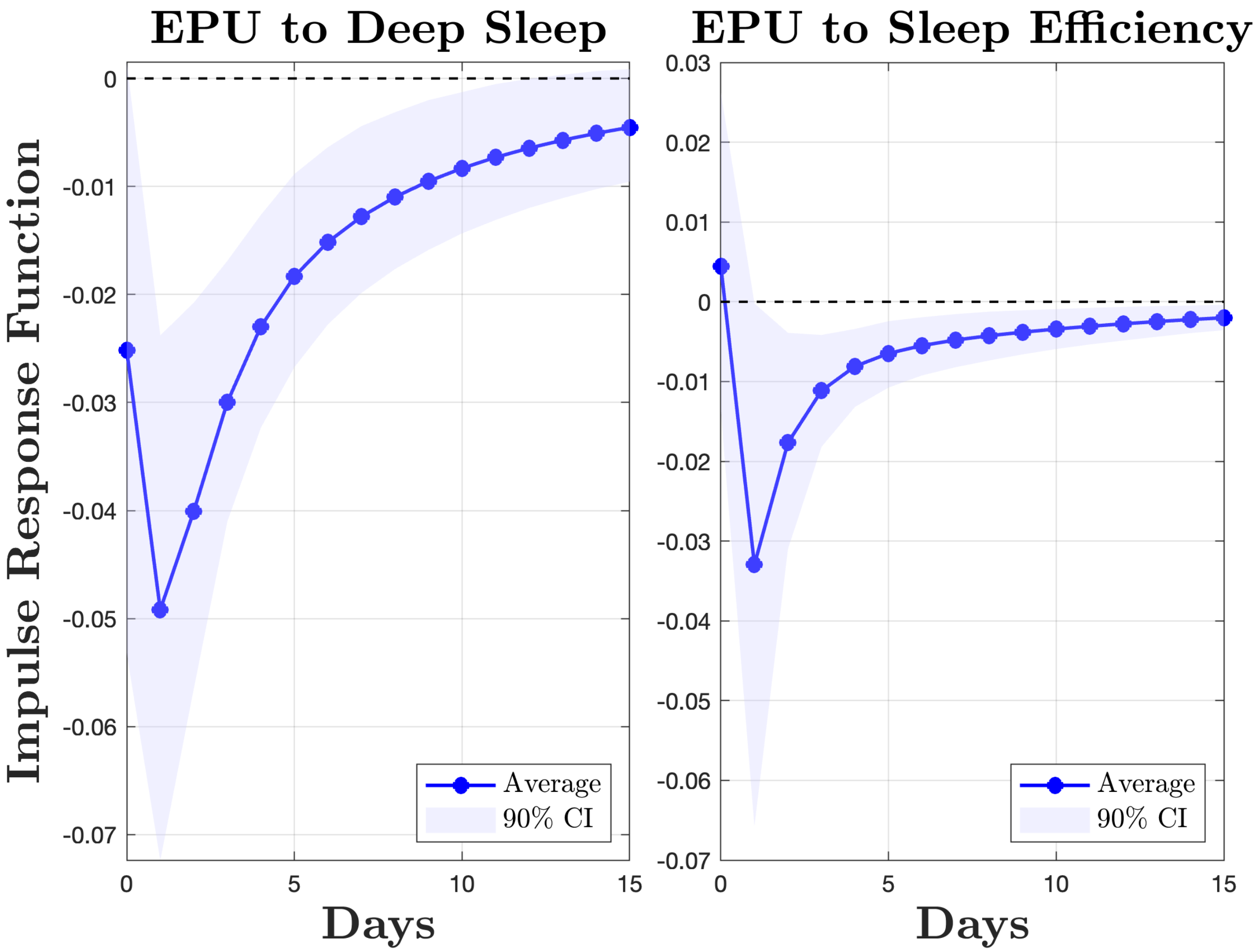

Figure IA.C.11: Impulse response functions: No winsorization
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). Unlike the baseline analysis that winsorizes the sleep quality measures at the 1% level (as discussed in Section 1.4.1 of the main text), the sleep quality data underlying this figure is not winsorized. These IRFs are then obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.

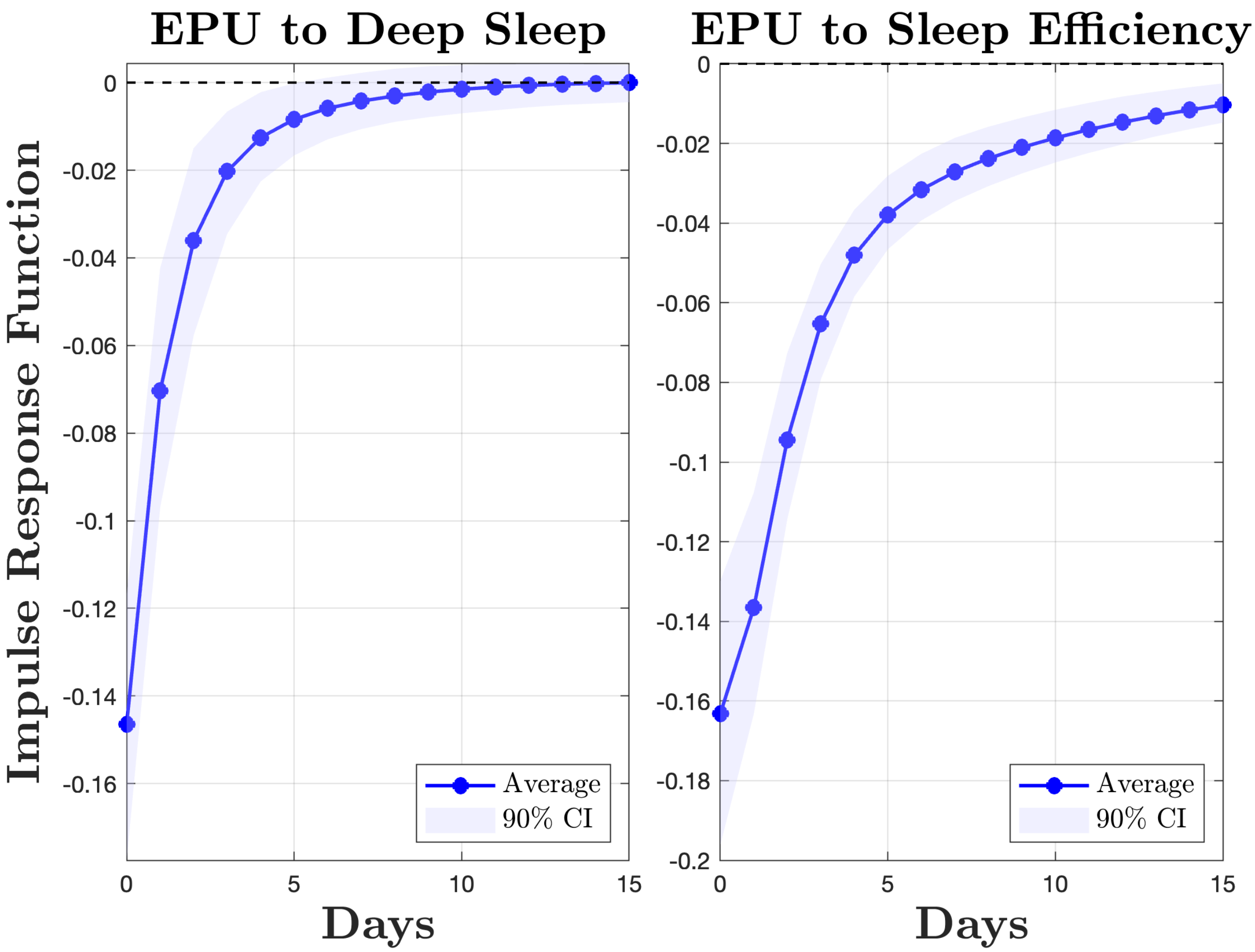

Figure IA.C.12: Impulse response functions: No day-of-the-week fixed effects
The figure reports impulse response functions (IRFs) that display how a structural shock to economic uncertainty, measured using the natural logarithm of the daily Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), propagates to the proportion of deep sleep (left panel), measured via equation (1), and sleep efficiency (right panel), measured via equation (2). Unlike the baseline analysis that removes intra-week variation in sleep quality by applying day-of-the-week fixed effects to the aggregate measures of sleep quality (as discussed in Section 1.4.1 of the main text), the sleep quality data underlying this figure is not adjusted for this intra-week seasonality. These IRFs are then obtained by estimating the vector autoregression presented by equation (6) and employing the recursive (Cholesky-based) identification of structural shocks. The solid blue line in each panel represents the average effect, and the 90% confidence interval represented by the blue-shaded region is obtained using a residual bootstrap with one thousand draws from the estimated residuals. Finally, the data underlying this analysis is daily and runs from April 26, 2017 through May 26, 2023.