NBER WORKING PAPER SERIES

THE VARIABILITY AND VOLATILITY OF SLEEP: AN ARCHETYPAL BEHAVIOR

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Working Paper 29658
http://www.nber.org/papers/w29658

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2022

We thank Richard Baillie, Jeff Biddle, Patrick Button, Joan Costa-Font, Yonah Hamermesh, Albert Meijer, Aaron Pancost, Cody Tuttle, and participants in seminars at several universities for helpful comments, the Centre for Time Use Research for providing the time-use data, Jagriti Tanwar for clarifying the characteristics of those data, and the Data Archiving and Network Service of the Netherlands for the OSA data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 29658
January 2022
JEL No. C22,I14,J22

ABSTRACT

Using Dutch time-diary data from 1975-2005 covering over 10,000 respondents for 7 consecutive days each, we show that individuals' sleep time exhibits both variability and volatility characterized by stationary autoregressive conditional heteroscedasticity: The absolute values of deviations from a person's average sleep on one day are positively correlated with those on the next day. Sleep is more variable on weekends and among people with less education, who are younger and who do not have young children at home. Volatility is greater among parents with young children, slightly greater among men than women, but independent of other demographics. A theory of economic incentives to minimize the dispersion of sleep predicts that higher-wage workers will exhibit less dispersion, a result demonstrated using extraneous estimates of earnings equations to impute wage rates. Volatility in sleep spills over onto volatility in other personal activities, with no reverse causation onto sleep. The results illustrate a novel dimension of economic inequality and could be applied to a wide variety of human behavior and biological processes.

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I. Introduction

Economists have analyzed how time spent sleeping is partly determined by the incentives that people face, beginning with Biddle and Hamermesh (1990), followed up by others, including recently Asgeirsdottir and Olafsson (2015) and Sedigh *et al*. (2017). No economic research has considered differences among individuals in the inter-temporal variability of sleep, although the impact of sleep variability on the behavior of one prominent individual, Donald Trump, has been considered (Almond and Du, 2020).

Biomedical researchers have expended much effort studying day-to-day variations in sleep time among individuals, typically examining the determinants of the amount of variability in small samples within narrowly defined demographic groups. None of the biomedical studies considers the extent of dispersion across adjacent days—volatility as defined by econometricians. Instead, they typically study how the coefficient of variation of sleep time over some limited time period differs across subjects. While interpersonal differences in the variance of sleep are important for understanding individuals' behavior and thus merit studying broad nationally representative samples, there are good reasons to believe that differences in the volatility of sleep are also important.

We know, for example, that lower average earnings are positively correlated with adverse labor market shocks. Thus, additional educational attainment, for example, reduces earnings volatility in the short and long run (except among older men, Delaney and Devereux, 2019). Labor-market shocks may spill over onto shocks to sleep time, even after adjusting for hours of paid work time. Another possibility, which we use to motivate a theory of the dispersion of sleep, is that higher-wage individuals may have greater incentives to reduce it. Both ideas are consistent with interpersonal variations in sleep being yet one more avenue along which inequality in well-being is exacerbated.

The simplest econometric characterization of volatility, autoregressive conditional heteroscedasticity (ARCH), has been a central focus of time-series econometrics since its proposal by Engle (1982). It is a pillar of financial econometrics (Linton, 2019), underlying research on financial time series and on the behavior of financial markets.[1] The econometric approach to volatility in time series that it addresses appears never to have been applied to any aspect of individual choices about time use or spending. Yet ARCH behavior, which implies that periods of tranquility and stability are sometimes replaced by episodes of unrest, may be a good characterization of histories of people's daily sleep activity.

We focus on sleep, the largest use of time by the overwhelming majority of people in wealthy countries. But the central idea—applying this time-series econometric approach to short panels of data describing individuals' behavior—should be relevant to many other human activities that could be observed each day. Daily caloric intake is one example. Many basic activities that are purely biological can be and perhaps are measured on a daily or even hourly basis.

In what follows we first discuss what the biomedical literature shows about the variability of sleep time (often, but mistakenly in terms of econometric distinctions, presented as volatility) and in Section III present the data used. Section IV demonstrates the existence and demographic correlates of sleep time and its variability and shows that sleep exhibits volatility independent of its variability. Section V derives predictions about the economic determinants of variability and volatility and examines their empirical validity, while Section VI examines possible spillovers of sleep volatility onto other uses of time, and vice-versa.

II. Volatility and Variability in the Biomedical Literature

Volatility and variability are different concepts. Variability describes the change in the quantity of sleep, and volatility describes the change in its variability. Hence, they imply different temporal patterns in sleep time, with volatility explicitly linking sleep on adjacent days and variability measuring the average variation across all days within some multi-day period. Greater variability is associated with higher but constant variance through time. Volatility occurs haphazardly; its incidence is unpredictable, stationary, but

[1]Searches on December 17, 2020, of articles in print from 1982 onward showed 399 articles in *EconLit* that included "ARCH" and 12,231 that included "Volatility" in the title. In the *Web of Science* 196 published articles included "ARCH" in the title; and 8,118 that were classified in the areas of economics, finance, or the social sciences included "Volatility" in the title. The original article, Engle (1982), had received a remarkable 8,293 citations in the *Web of Science*.

not constant through time. If it occurs, it will disappear after some time period, and it implies more unrest over short periods of time.

Consider two hypothetical individuals, A and B, whose daily sleep times over a week are shown in Figure 1. Each person's sleep averages 7.71 hours per night. Each person's variance of sleep time is:

$$(1) \qquad \hat{\sigma}^2 = \tfrac{1}{7}\sum_{d=1}^{7}([S_d - S.]^2),$$

where S_d is sleep on day d, $S.$ is average sleep during the week, and *d* is a day in the week depicted in Figure 1. Individuals A and B exhibit the same coefficient of variation of sleep time, $\hat{\sigma}_A/7.71 = \hat{\sigma}_B/7.71 = 0.12$. Denote volatility over the week as:

$$(2) \qquad \hat{\upsilon}^2 = \tfrac{1}{6}\sum_{2}^{7}\left|([S_d - S.]^2 - [S_{d-1} - S.]^2)\right|,$$

Person A's sleep volatility is $\hat{\upsilon}_A^2 = 0.33$, but Person B's is $\hat{\upsilon}_B^2 = 0.83$.[2] The individuals' sleep times are identical on average and equally variable; but Person B's sleep exhibits much greater volatility. There is no reason to think, other things equal, that the two individuals are equally well off (equally satisfied with their sleep). Indeed, we venture that most people would prefer Person A's sleep pattern to Person B's, although some people might prefer greater volatility in this biological activity.[3]

Much of the substantial and burgeoning biomedical literature has focused on the impact of sleep variability on outcomes among groups of children and teenagers, with samples in the hundreds of subjects. For example, Kjeldsen *et al*. (2014) examined the correlation of the mean daily variation in sleep with various blood markers. Zhang *et al*. (2019) studied how such characteristics as gender, age, BMI, and the socio-economic status of their households are related to the standard deviation of toddlers' sleep time over a week, implicitly viewing the relationship as causal. Moore *et al.* (2011) examined very similar questions using a sample of teenagers. Fuligni *et al*. (2018) related differences in teenagers' sleep time between non-

[2]The squared terms measuring $\hat{\upsilon}^2$ link this presentation to the subsequent discussion of ARCH estimates. The same implication—the difference between variability and volatility—would result if we took absolute values.

[3]The point is related to Anscombe's Quartet (Anscombe, 1972), except that we concentrate on the time dimension of the data, specifically on their autocorrelation.

school and school nights to such outcomes as academic achievement and self-assessed measures of behavioral problems, demonstrating that those teens with less variable sleep time performed better in school and felt better about themselves (and the reverse too in this correlational study).

Buysse *et al*. (2010) showed that individuals who report being chronic insomniacs exhibit greater sleep variability. Lemola *et al*. (2013) show that greater sleep variability is negatively correlated with subjective well-being. Some subsequent research on sleep variability among adults concentrates on its relationship with cardio-vascular health and mortality. Thus Häusler *et al*. (2020) use a large random sample of older Swiss citizens, calculate several measures of variability in sleep time over a 14-day period, and demonstrate a positive correlation with obesity but no significant relationship with the incidence of diabetes or hypertension. Other studies, e.g., Suh *et al*. (2012), use samples of individuals seeking treatment for insomnia and show that the treatment reduced sleep variability.

Only variability has been analyzed extensively in the biomedical literature and typically using small non-random samples. One study, however, demonstrated the existence of ARCH-type volatility in breathing during sleep apnea (Hu and Tsoukalas, 2006); another related stress to gut microbial activity and demonstrated volatility in the latter, suggesting the stress/unrest link that we propose (Bastiaanssen *et al*., 2021). In the following sections we establish the presence of day-to-day sleep variability and volatility, examine their magnitudes, show how the exogenous determinants of variability differ from those of sleep volatility, and use the results to motivate a theory of their determinants.

III. Daily Sleep Patterns: The Dutch Time Diaries

To distinguish variability from volatility we need at least three observations on sleep time, with at least two of them being of consecutive nights. Beginning in 1975 and quinquennially thereafter, the Netherlands has collected daily time diaries of large random samples of individuals. We use those for 1975-2005, which are available from the Centre for Time Use Research. The surveys—the *Tijdbestedingsonderzoek* (*Tbo*)—are by far the most extensive worldwide in terms of the number of respondents who kept diaries for one complete week, in this case, Sunday midnight through Saturday, 11:59PM, with the surveys fielded in October or November.[4] (In most years separate samples were collected in each of two weeks.[5]) The sampling frame consists of individuals ages 12 or older, with only one person in each household (thus preventing examining spousal spillovers of sleep time on variability or volatility).[6]

The biomedical literature shows that there is a substantial correlation between answers to questions about how much someone slept and measures of their non-active time during the night based on motion-generated recording devices—actigraphs (Buysse *et al*., 2010, which collected both measures from a small group of subjects).[7] The reports of sleep used here, based on detailed diaries of how time was spent on the previous day with reported time use constrained to total 24 hours per day, are likely to provide more accurate measures than subjective responses to questions about total sleep time in the previous night. Nonetheless, in the end, no method allows inferring exactly how much sleep actually takes place. And while time-diary based reports of sleep time pervade the small economics literature, they have been used sparingly in the biomedical literature.

To avoid including youths, teens, and people who could retire, we restrict the samples to individuals ages 22-64 when they completed the time diary. Also, we exclude respondents who did not provide complete information on all the demographic and behavioral measures used in the analysis, including gender, educational attainment, marital status, age of the person's youngest child at home, and the previous

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[4]See https://www.scp.nl/over-scp/data-en-methoden/onderzoeksbeschrijvingen/tijdsbestedingsonderzoek-tbo.

[5]In 1990, one of the two weeks in which the survey was fielded included the Sunday when the Netherlands went off summertime, so that on that day the time diaries covered 1500 rather than the usual 1440 minutes. We exclude observations from that week.

[6]The restriction to one person per household is regrettable, as it would be desirable to analyze the extent of complementary/substitutable volatility, thus analogizing volatility in this aspect of human behavior to the jointness of labor supply demonstrated in several studies (Rogerson and Wallenius, 2019, describing retirement decisions; and Goux *et al*., 2014, describing paid work time of working-age partners).

[7]This correlation should be encouraging to social scientists using time diaries to examine the determinants of sleep; and the technology has now been used by economists in a small sample in a developing country (Bessone, 2022).

week's paid workhours.[8] With these restrictions the usable sample consists of 71,814 diaries of reported sleep time by 10,259 individuals.

The average daily amount of sleep over the diary week in the sample is 497 minutes/day (8-1/4 hours), with the 10th-percentile person averaging only 430 minutes (7-1/4 hours) and the 90th-percentile person averaging 564 minutes (9-1/2 hours) per night over the survey week. There is substantial intra-week variation even in average sleep time, from 471 minutes on Fridays to 560 minutes on Sundays. As a check on the consistency of reported sleep time with results in the literature, we estimate its demographic determinants and its relation to work time, modeling the specifications after those in Biddle and Hamermesh (1990). The results are presented in Table 1, for the entire sample and then separately by gender. In addition to the variables listed in the Table, each equation also includes indicators of the year of the survey and the day of the week for which the time diary was kept.

The impact of an extra minute of paid work on a diary day is about what has been found previously. With paid work averaging 422 minutes—29 percent of the day—if a person performs work for pay on the diary day, about twelve percent of work time comes from reduced time sleeping. Since men perform more paid work on days when they work, it is not surprising that this relationship is stronger among them. These results underscore the desirability of accounting for inter-day differences in market work time when measuring the variability and volatility of sleep and examining their determinants.

While men sleep less on average than women, the difference is due entirely to gender differences in their other characteristics, in particular market work time. Once these are accounted for, on average men sleep slightly but statistically significantly more, 4.4 minutes per day (one-half hour per week). The sleep-age relationship is described by a statistically significant U-shaped relationship, with a minimum at age 50.

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[8]We included the 70 days (fewer than 0.1 percent) on which the time-diarist recorded no sleep time, an inclusion that had no qualitative effects on the estimates reported here. Most of the exclusions due to item non-response resulted from missing information on the previous week's workhours. Throughout this study the statistics and estimates are computed using sampling weights. The standard errors of the parameter estimates are clustered on individuals. In the tables and calculations, the number of observations is slightly less than the full sample, because in the *Tbo* 0.6 percent of the usable days were assigned a sampling weight of zero. Including these observations and not using sample weights also had no qualitative impact on the estimates.

Additional education reduces sleep time, while the presence of children also lowers time spent sleeping, with the effect diminishing as the youngest child ages, and with much greater negative effects of younger children on women's than on men's sleep time. Other things equal, there are no significant differences in sleep time by marital status. Taken together, the results corroborate those of previous work and suggest that it is valid to move to examining the variability and volatility of sleep.

IV. Variability and Volatility

To study volatility and variability in a unified framework, we first adjust for differences in each person's average weekly sleep time, $S_{i,t}$, and remove deviations resulting from daily variations in paid work time by estimating:

$$(3) \qquad S_{idt} = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{Z}_{idt} + \boldsymbol{\beta}_2 S_{i.t} + \mu_{idt},$$

where $\boldsymbol{Z}_{idt}$ is a vector of variables that includes minutes of work by person *i* on day *d* in year *t*, usual weekly hours of paid work, and indicators of the day of the week and the year of the survey.[9] (Appendix Table A1 presents estimates of (3).) Apparent volatility is automatically induced by market work being concentrated on certain days of the week, but we treat that here as mechanical, not behavioral. Equation (3) removes that mechanical factor by including the vector *Z*. This specification also means that we are abstracting from interpersonal differences in average sleep time over the week by including $S_{i.t}$.[10] We are thus concentrating solely on the variability and volatility of inter-temporal patterns of sleep independent of differences in average sleep, hebdomadal differences, and day-to-day variations in paid work time.

To estimate both measures, we assume that $\mu_{idt} \sim ARCH(1)$, such that:

$$(4) \qquad \mu_{idt}^2 = \zeta_{00} + \zeta_{10}\mu_{idt-1}^2 + \varepsilon_{idt}, \qquad d = 2, \ldots, 7, \text{and } 0 < \zeta_1 < 1,$$

[9]This adjustment is especially important when using Dutch data, since paid work in the Netherlands is more heavily concentrated on weekdays than in most other wealthy countries (Hamermesh and Stancanelli, 2015).

[10]Note that we are not regressing deviations from average sleep against $\boldsymbol{Z}$, since there is no reason to constrain the effect of average weekly sleep on daily sleep to be +1. Indeed, the results in Appendix Table A1 show that constraint would be rejected.

where the μ_{idt}^2 are the squared estimated residuals in (3), and the i.i.d. innovation ε_{idt} has an unconditional constant variance, but a conditional variance that changes over time. The equation also includes indicators of the year of the survey and the day of week d. ζ_{00} measures the residual variability of sleep, while ζ_{10} measures its volatility. Equation (4) is the ARCH(1) specification pioneered by Engle (1982) to analyze macroeconomic time series (and later by many others to study high-frequency financial time series). Note that in this case the data generating process of sleep itself must be stationary AR(1) with positive autocorrelation and with μ_{idt} having fat tails (kurtosis > 3).[11]

In the finance/macro literature the data offer many observations on a single series, allowing the analysis of changing volatility over the period during which the time series is observed. Here we have only seven observations per time series, but over 10,000 time series (weeks of individuals' sleep time).[12] To fix ideas about this different context, think of the observations on an individual's week of sleep times as picking randomly from all possible seven-day time series describing that person's sleep over an adult lifetime. We cannot analyze changing variability or volatility for an individual within the ARCH framework given the nature of the data, since we do not observe any individual over a long period of time. Rather, what we observe is a seven-day snapshot of each person's variability and volatility, allowing measuring their averages and using the snapshots of individuals' sleep patterns to infer the determinants of interpersonal differences in them. The specification in (4) is the simplest possible way of considering these characteristics of sleep together.

ARCH-type behavior may differ by demographic group, allowing us to measure the determinants of variability and volatility. We thus re-write (4) as:

(5) $\mu_{idt}^2 = \zeta_{00} + \sum j\, \zeta_{0j} X_{ijt} + \zeta_{10}\mu_{idt-1}^2 + \sum j\, \zeta_{1j} X_{ijt} \bullet \mu_{idt-1}^2 + \epsilon_{idt},\qquad d = 2, \ldots, 7$; j = 1, ... , K,

[11]With these very short time series, using estimators more complicated than the simple ARCH specification is not feasible.

[12]No data set provides nearly so many seven-day samples of sleep time. None provides a large longitudinal sample of time diaries on consecutive days either, although a few (Juster and Stafford, 1991; Gershuny, 2003) do provide data on small samples of individuals observed in several years.

where X_j is the vector of K demographic characteristics included in Table 1, defined over individuals i in year t, and $\epsilon_{idt} \sim N(0, \lambda^2)$.

The implication of applying ARCH analysis to this large sample of individuals' short time series of sleep is that we can only investigate the probability of observing an ARCH process in a person's sleep pattern. The higher ζ_{00}, the greater the residual variability of sleep over the week; and the variance may be identified as differing across demographic groups, as indicated by the components of the vector of estimates of the ζ_{0j}. The higher ζ_{10}, the longer the process of unrest lasts. In our observational study a higher ζ_{10} thus implies that the likelihood of volatile sleep is higher in the sample. Stated differently, the higher ζ_{10}, the more the data indicate that episodes of unrest are occurring in this sample. Volatility may also differ by demographic characteristics, as indicated by the estimates of the vector ζ_{1j}.

The processes generating the seven-day snapshots of sleep time that we observe conform to the assumptions underlying the ARCH(1) model. Daily sleep time is autocorrelated AR(1), with a first-order autocorrelation coefficient of +0.394. The ARCH(1) process in (4) must also have $0 \leq \zeta_{10} < 1$, $\zeta_{10}^2 < 1/3$. Table 2 lists the estimates of (4). The estimated ζ_{10} satisfies the assumptions needed to characterize residual sleep as an ARCH(1) process. With that justification, we see that there is statistically significant volatility in sleep—the greater the squared deviation in sleep from its predicted value (based on the individual's average sleep and his/her paid work time) on a given day, the greater will be the squared deviation on the next day.[13]

The degree of volatility is, however, low compared to that found in the typical financial time series, e.g., the Standard & Poor Index. This should not be too surprising: People cannot easily substitute sleep time on one day for that on an adjacent day. While a person may have a week with relatively little sleep

[13]The observed volatility is not an artifact from observing people of different ages from different birth cohorts over the 30-year sample. If we restrict the sample to individuals ages 22-31 in 1975, 27-26 in 1980, through 52-61 in 2005, thus creating an artificial birth cohort, the estimated ARCH(1) parameter becomes 0.171 (s.e.=0.03), close to that shown in Column (1) of Table 2 for the much larger main sample.

compared to her sleep during other weeks, our short time series cannot pick up volatility defined across weeks (or longer intervals).[14]

Remembering that the estimates adjust for inter-day differences in paid work time and in society-wide norms about sleep time over the days of the week, we note that ARCH(1) behavior characterizes the whole sample. It also holds for both men and women separately, although the extent of volatility differs by gender and is greater among men, although not statistically significantly so.[15]

Table 3 presents the estimates of (5), with the first column in each pair of equations (for the entire sample, and then for men and women separately) showing the estimated ζ_{0j} and the second column listing the estimated ζ_{1j}. In each case an estimate is bolded if it, or the vector of indicators or interactions of which it is a component, is statistically significantly nonzero. Consider first Column (1): Except for differences by gender and marital status, the residual variance of sleep differs significantly across demographic characteristics. It decreases with age over the entire sample range (at a decreasing rate); it decreases with educational attainment; and it decreases if the youngest child in the household is younger. Moreover, the variance of sleep time is higher on weekends than on weekdays.[16]

While the entire vector of ζ_{1j}, j = 0, …, K, is statistically significant, the age and presence of children comprise the only vector in the set of X variables that significantly alters volatility, with pre-school children adding to the volatility of their parents' sleep, and older children reducing it relative to households without children at home.[17] With young children having the opposite effect on the variability

[14]The observed volatility in sleep does not arise from volatility in work time: Adding the squared residuals from an equation relating daily deviations in work time from average daily work time to the same variables used to create the μ_{idt}^2 hardly changes the estimate of ζ_{10}.

[15]If we account for sleep variability in a simplistic way by adding the coefficient of variation of each individual to the estimates of (4), the ARCH(1) terms in the estimating equations remain statistically significant.

[16]The same results are observed in simple regressions of the coefficient of variation of sleep time across individuals on these demographic characteristics.

[17]We obtained data on weather in Amsterdam for each survey date, including the low and high temperatures and the amount of precipitation. Including each, or day-to-day changes in each, in (5) barely changed the estimates of the ζ_{1j}, and no parameter estimate on any of the weather variables had a t-statistic greater than 1.0 in absolute value. Similarly,

of their parents' sleep, this distinction underscores the importance of considering volatility along with variability: They are not the same, nor, as these results imply, are their determinants necessarily the same.

Moving to the estimates for men and women separately, the conclusions about the determinants of variability and volatility remain essentially the same. The variability of sleep time decreases with age among both men and women, and it is lower if a young child is present in the household. As in the aggregated data, among both men and women having young children raises the volatility of sleep, while the presence of older children reduces it.

We cannot directly refute the possibility that the results on variability arise because more educated, middle-aged respondents complete their daily time diaries more carefully than other respondents, so that there is less randomness in their responses. There is, however, no reason to assume that this happens; and it seems more likely that being more careful would lead them to be more precise about the amount of sleep that they obtain, with other, younger, and less educated respondents simply providing the same answers each day and thus exhibiting less measured volatility. This latter interpretation is consistent with the observation that more educated time-diarists exhibit more day-to-day variation in the timing of the non-work activities that they undertake (Hamermesh, 2005, based on data from Australia, Germany, the Netherlands, and the U.S.) and that they list more different activities in their diaries (Gronau and Hamermesh, 2008, based on data from Australia, Israel, and Germany).

V. Rationalizing Sleep Variability and Volatility

To rationalize the results, note that, assuming variability and volatility are undesirable, they are consistent with evidence on demographic differences in preferences (Falk *et al.*, 2018). The results in Table 3 show, however, that the estimated impacts of the demographic characteristics also present a pattern consistent with their known correlations with the value of time: Less variability with age (in this sample of

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including indicators for each unique date in the surveys (thus implicitly interacting day of week with year) had only very small effects on the estimates of ζ_{10}.

people 22-64), and a decrease with additional education. These correlations suggest thinking about how economic incentives could affect the variability and volatility of sleep.

The crucial assumption is that additional sleep is productivity- and hence utility-enhancing, as suggested by most of the biomedical literature and implied by several economic studies (e.g., Gibson and Shrader, 2018; Giuntella and Mazzona, 2018). The small specialized samples used in the biomedical literature also suggest that variability is detrimental to people's well-being.[18] A rationalization of sleep patterns presented here must answer the questions: Why does sleep variability decrease with full income—the value of a person's time—(one novel finding in this study), and why are there no demographic differences (other than by age of children) in the novel finding of sleep volatility?

Absent shocks to sleep, the agent will set sleep at some optimal S^* each day, with S^* being the deterministic part of (3). We know from Biddle and Hamermesh (1990) and from the substantial subsequent *oeuvre* on sleep that $\partial S^*/\partial w < 0$ –- the substitution effect of a higher wage rate w on sleep time exceeds the income effect. Presumably, each person's choice of S^* is based on weighing the utility-increasing impact on the value of home production and on productivity against the loss of income when sleep time increases, given unobservable biological differences.

Assume that the agent is confronted with a random shock θ_d that is independent of the wage rate, so that, absent any reaction to the shock, sleep would be $S^* + \theta_d$. A positive shock might arise from having gone to a relaxing classical concert, having done Pilates exercises in the evening (Albraki *et al.*, 2021), or being able to rise later due to a Covid lockdown. A negative shock might arise from unusual street noise, worries about some family difficulty, or a physical problem, for examples.

Let the individual's daily productivity P depend on his/her daily sleep time, S_d, so that:

(6) $P = F(S_d)$, $F' > 0$, $F'' < 0$.

[18]A field study based on a natural experiment examining the impact of the variable timing of a different daily activity, students' class time, found no negative impact on their academic achievement (Lusher *et al.*, 2019).

Assume too that the agent can react to the shock θ_d by altering sleep to some extent, choosing a partly offsetting adjustment s_d to mitigate the impact of the shock, and move $S_d = S^* + \theta_d + s_d$ closer to S^*. One might, for examples, counterbalance a positive shock by setting the alarm clock earlier, or offset a negative shock by taking a sleeping pill or having an alcoholic drink.

We assume that the physical **ability** to reduce the impact of a shock is independent of the wage rate (and S^*). The **incentive** to do so, however, will vary with the wage, because of the shape of the productivity function F.[19] With $S^* + \theta_d$ lower among higher-wage individuals for a given $\theta_d < 0$, the productivity gain to setting $s_d > 0$—to reducing the departure from S^* -- will be greater for them. Higher-wage individuals thus have a greater incentive to minimize a negative departure of actual from desired sleep time. Vice-versa, a higher wage individual has a greater incentive to reduce the departure from S^* in case of a positive shock, $\theta_d > 0$, and wants to counterbalance that shock, because of a productivity gain to setting $s_d < 0$. Assuming no differences by wage rate in the ability to do so, we will thus observe a smaller deviation of S_d from S^*, less variability of sleep around its average, among high-wage individuals. This model says nothing about the economic determinants of volatility, which, in any case, differs significantly across individuals only along the dimension of the presence and ages of children.

When shocks θ_d arrive according to a Poisson process with rate λ_θ, and responses s_d occur with a Poisson intensity λ_s, the joint arrival distribution of shocks and responses $\theta_d + s_d$ is independent of time and is jointly Poisson with rate $\lambda_d = \lambda_\theta + \lambda_s$. The stochastic error of sleep in (3) then becomes $\mu_{idt} + \lambda_d$. In the simplest case, when shocks and responses are independent of μ_{idt}, such that $E[\mu_{idt}\lambda_d] = 0$, the expected variation under ARCH becomes:

(7) $$E\left[\mu_{idt}^2\right] = \zeta_{00} - \lambda_d^2 + \zeta_{10}(\mu_{idt-1} + \lambda_d)^2$$

This shows that the randomness of the shock process and the consequent responses induce changes (not necessarily equal) in both the variability and the volatility of sleep.

[19]Relative income is a strong predictor of health and other differences related to individual differences in inequality (Furnée and Pfann, 2010).

We cannot examine this prediction directly using the *Tbo*, since the survey never collected information on participants' wage rates (or earnings). In some sense this is beneficial, as using such information would create concerns about reverse causality between sleep variability/volatility and wages. Instead, we use extraneous estimates of the determinants of earnings in the Netherlands to impute wages to each participant in the time-use surveys.

The "Labor Supply Panel" of the Organization for Strategic Labor Market Research (OSA) contains variables that can be matched exactly to the demographic variables used in Tables 1 and 3. To do that, we estimate separate equations describing the monthly earnings of men and women, pooling the OSA data on workers ages 22-64 for most years from 1985 (the first available year) through 2006.[20] The estimates for both genders include as independent variables the indicators of age, educational attainment, marital status, and ages of youngest children that are also in the *Tbo*. Also included are the year of the survey and a quadratic in the person's weekly hours of work.

The results of estimating these models are shown in Table A2. Unsurprisingly, they all accord very well with intuition: The age-earnings profile peaks later among men, at age 56 compared to age 50 among women; the returns to additional education are greater among men; and there is a marriage premium among men, a marriage penalty among women. We use these estimates to impute monthly earnings in the time-use data under the assumption that weekly hours would be 40, the same for all workers, thus obtaining a measure of their prices of time.

To check on the reasonableness of using these imputations, we re-estimated the equations in Table 1, replacing age, education, gender, ages of youngest children, and marital status with the imputed wage rate, and excluding the possibly endogenous measures of weekly work hours and daily paid work. The estimates can thus be viewed as including an instrumental variable technique for the wage rate. Despite the endogeneity that pervades earlier estimates, the estimates of sleep-wage elasticities are consistent with the

[20]Ter Weel (2003) uses these data to estimate wage equations over random samples of Dutch workers in 1986, 1988, …, 1998, based on years of schooling, a quadratic in age, citizenship status, and gender.

previous literature, with an elasticity of sleep time with respect to the imputed wage rate of -0.034 (s.e. = 0.008) in the full sample, -0.013 (s.e.= 0.14) among men, and -0.102 (s.e. = 0.013) among women. Particularly encouraging is the greater elasticity among women, consistent with prior evidence on sleep and with the general empirical finding of more elastic responses of various aspects of time use, including labor supply, by women.

Table 4 presents the estimates of (5), substituting ln(*w**) for the several demographic variables (and including the vectors of indicators of the survey year and day of week). The first column in each pair includes only the estimates of ζ_{10} and ζ_{00}, while the second adds ζ_{11}, the coefficient on the interaction of the lagged squared residual and the imputed wage rate.

The residual variance of sleep time is lower among those respondents whose price of time (whose imputed wage rate) is higher.[21] A ten percentage-point higher wage rate is associated with 3.7 percent less variability in the entire sample, 7.7 percent less among men, and 3.9 percent less among women. The lesser response among women may result from their much greater incidence of part-time work (fewer than 35 weekly hours), with 69 percent of female workers in the OSA data compared to 9 percent of male workers recording so few hours per week. Even though Equation (3) adjusted for differences in work time, it is quite reasonable to conclude that the adjustments do not fully account for the extent of spillovers to non-work time, including sleep time. Just as the results in Table 3 showed that, except for the presence of young children, volatility did not differ significantly by demographic characteristic, so too there is no evidence that it varies with a person's potential wage rate.

Although the imputed wage has significant negative impacts in these estimates of volatility, the fits (adjusted R^2) of these equations are slightly below those shown in Table 3. The imputed wage is a linear combination of the vectors of demographic characteristics, making it impossible to determine whether the economic incentives that we have modeled affect sleep volatility or simply that, for whatever reason,

[21]We stress that we do not know which respondents would be working for pay—the imputations are based only on those people in the extraneous data set used here who had chosen to work. This selectivity problem induces errors in the imputations, but it is unclear whether and, if so, how they bias the estimated impact of the imputed wage rates.

demographic differences (perhaps preferences, perhaps social norms, perhaps differences in individuals' locus of control over their private lives, or institutional constraints) determine sleep variability or volatility. At this point the best inference is that both are important.

VI. Spillovers from Sleep

On some days, an individual's paid work time will exceed the time spent sleeping; but sleep is by far the most time-consuming activity engaged in by nearly all people over a typical week.[22] As such, one might expect its volatility to alter the volatility of other biological activities, with time spent eating, washing up, using the toilet and having sex comprising the group of "other personal activities" recorded in the Dutch time diaries.[23] Using the *Tbo*, we can then examine whether volatility in sleep spills over onto volatility in this other set of miscellaneous biological activities.

We restrict the sample to those diary-days when some positive amount of eating, and of personal care, is reported, since there are some zeroes in time spent in eating or personal care on a given day. These exclusions reduce the sample used in Sections IV and V by 8 percent. On the average diary-day in this sub-sample, respondents spent 2-1/4 hours in these other activities. We first estimate a version of (3) over this group of activities, then estimate (4) defined over the current and lagged residuals from that re-estimation of (3). The results of this estimation are shown in Column (1) of Table 5. Like sleep, other personal activities are volatile, but to a much lesser degree—only half as volatile in this (slightly restricted) sample.

To examine whether the volatility of these other activities is causally determined by volatility in the much more important category of time use, sleeping, we add the lagged squared residual of sleep time to the specification in Column (1). The results of this addition are shown in Column (2) of Table 5. This term is positive and statistically significant: Volatility in sleep—observing a person whose week of sleeping exhibits greater unrest—is associated with the person exhibiting greater unrest in eating and other personal

[22]Assuming, as is standard in the Netherlands, that very few people perform paid work on weekends, only 5 percent of respondents in the *Tbo* spent more weekly time working than sleeping. Of these, 83 percent were men.

[23]This analysis is analogous to the examination of spillovers in the volatility of commodity prices (e.g.,Trujillo-Barrera *et a*l., 2012).

activities on the next day. Given the extent of volatility in each series, however, its impact accounts for only a small part of the volatility in time spent in these other activities.

What if volatility in any activity is related to volatility in each other activity? We cannot examine most other short time series of activities in the *Tbo*, as for most large aggregates no time is spent in that aggregate on a large fraction of days. (For example, the next most common aggregate, television/radio watching/listening, is only engaged in on 80 percent of the diary-days underlying Table 5.) We can, however, examine whether the volatility that we observe in other personal activities causally affects volatility in sleep. To do so we re-estimate Equations (3) and (4) for sleep time in the slightly reduced sample used in the first two columns of Table 5, and then re-specify (4) by adding in the lagged squared residual of time spent in eating and other personal activities.

The re-estimate of (4) on this sample (which excluded zeroes in eating/drinking and self-care), shown in Column (3) of Table 5, does not alter the estimated volatility of sleep. The test of whether volatility in this other set of activities might be affecting sleep volatility is embodied in the estimates in Column (4), in which we have added the lagged squared residual of eating/personal care to the equation in Column (3). The causal effect of an increase in the volatility of eating/care time is a reduction, albeit small and statistically insignificant, in the volatility of sleep. We can infer from these results that the volatility of sleep may Granger-cause greater volatility of other personal activities, but that there is no evidence that volatility in those activities Granger-causes reductions in the volatility of sleep (Granger, 1969; Chang and McAleer, 2017).

VII. Conclusions and Implications

Analysis of a unique data set that provides seven-day time diaries of large random samples of the Dutch population demonstrates unsurprisingly that sleep exhibits intra-week variability, but also day-to-day volatility, as defined in the econometrics literature. This volatility is distinct from the variability of sleep. Implicitly the results suggest that people go through periods where for several days their sleep departs greatly or little from its longer-term average, and other where it fluctuates more. The extent of variability differs across individuals in predictable ways. More educated individuals and those at prime age exhibit less variability than others, demographic differences that are consistent with the incentive effects of differences in the value of time. That the impact of children on the volatility of their parents' sleep differs by the age of the child is an unexplained additional result.

Whether variability and volatility are partly determined by economic incentives or demographic differences *per se* cannot be determined with the data used here. Distinguishing between their importance awaits examination of the issue based on data sets that include respondents' wage rates and that allow accounting for possible reverse causation between sleep and wage rates. The correlates of the variability of sleep time suggest that it is an additional aspect of human behavior that is associated with lower income and lower social standing, one more type of behavior that indicates greater inequality defined broadly. With sleep accounting for one-third of people's days, and with it being by far the most time-consuming activity that most individuals undertake, more attention to this characteristic of time use that appears to have been previously unnoticed would be very worthwhile.

The idea of volatility has been developed very extensively in econometrics and has been widely applied to time series of national price levels, financial instruments, and other prices. The idea, and ARCH and more complex methods of accounting for it, do not appear to have been applied previously to time series of indicators of human behavior, such as the sleep that is analyzed here. One would expect that such volatility exists in numerous other aspects of how people use time and in their other activities. Daily patterns of caloric intake might be an example. So might daily screen time. These merit empirical investigation.

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Table 1. Determinants of Sleep Time, the Netherlands, 1975, 1980, …, 2005 (minutes/day)*

Dep. Var:	**Sleep time/day**		
Ind. Var.:	**All**	**Men**	**Women**
Paid work (mins./day)	-0.143	-0.169	-0.136
(176.4; 266.7; 103.2)	(0.003)	(0.005)	(0.004)
Weekly work hours	0.068	0.275	-0.054
(29.6; 33.7; 26.3)	(0.038)	(0.065)	(0.054)
Male	4.40	-------	-------
(0.45; 1; 0)	(1.27)		
Age	-2.92	-2.23	-3.42
(39.6; 40.1; 39.1)	(0.47)	(0.70)	(0.63)
Age^2	0.029	0.025	0.031
	(0.006)	(0.008)	(0.008)
Secondary school	-6.09	-7.44	-5.63
(0.42; 0.37; 0.46)	(1.43)	(2.21)	(1.85)
> secondary school	-8.03	-7.97	-8.87
(0.25; 0.31; 0.21)	(1.63)	(2.30)	(2.29)
Youngest child:			
Age 0-4	-20.92	-8.76	-31.70
(0.25; 0.24; 0.25)	(1.61)	(2.38)	(2.26)
Age 5-12	-15.95	-5.93	-23.95
(0.18; 0.17; 0.19)	(1.73)	(2.54)	(2.38)
Age 13-17	-6.72	-8.61	-5.05
(0.08; 0.08; 0.09)	(2.18)	(2.85)	(3.19)
Married/partnered	1.21	0.47	0.99
(0.82; 0.83; 0.80)	(1.68)	(2.58)	(2.26)
R^2	0.198	0.245	0.156
N =	71,376	31,980	39,396
Mean	496.64	486.55	504.83

*Also includes year of survey and day of week. Standard errors (in parentheses below the estimates) are clustered on individuals. Means for the whole sample, males, and females are in parentheses below the variable names.

Table 2. Sleep Volatility –ARCH Estimates Based on Residuals in (3), Dep. Var. μ^{*2}_{dt-1}*

Ind. Var.:	**All**	**Men**	**Women**
μ^{*2}_{dt-1}	0.141	0.161	0.129
	(0.015)	(0.032)	(0.017)
R^2	0.051	0.058	0.049
N =	61,180	27,408	33,772

*In all equations the standard errors, in parentheses below the parameter estimates, are clustered on individuals. Equations also include indicators of the survey year and day of the week.

Table 3. Estimated ζ_{0j} and ζ_{1j} in (5), Dep. Var. μ^{*2}_{idt}*

	All		Men		Women	
	ζ_{0j}	ζ_{1j}	ζ_{0j}	ζ_{1j}	ζ_{0j}	ζ_{1j}
Ind. Var.:						
Main effect	**6296.40**	0.019	6934.01	0.233	**5699.44**	0.033
	(1237.46)	(0.154)	(1985.50)	(0.352)	(1643.65)	(0.168)
Male	191.19	0.052	-------	-------	-------	-------
	(166.13)	(0.030)				
Weekend	**2701.02**	0.054	**3042.56**	0.090	**2310.01**	0.044
	(151.36)	(0.031)	(229.37)	(0.050)	(196.63)	(0.037)
Age	**-97.48**	0.004	**-133.03**	0.002	**-68.11**	0.0014
	(63.94)	(0.008)	(102.29)	(0.017)	(83.26)	(0.010)
Age^2	**0.30**	-0.00005	**0.73**	-0.00003	**-0.03**	-0.00001
	(0.73)	(0.00010)	(1.17)	(0.00019)	(0.96)	(0.00011)
Secondary school	**-439.34**	-0.009	-417.21	**-0.113**	-208.37	0.021
	(179.66)	(0.029)	(283.49)	(0.047)	(226.42)	(0.037)
>Secondary school	**-470.52**	-0.013	-408.91	**-0.084**	-390.02	0.038
	(236.30)	(0.041)	(331.38)	(0.060)	(313.02)	(0.049)
Youngest child:						
Age 0-4	**-1178.39**	**0.057**	**-1159.11**	**0.023**	**-1196.28**	0.071
	(236.31)	(0.041)	(419.81)	(0.084)	(295.18)	(0.043)
Age 5-12	**-381.87**	**-0.057**	**504.25**	**-0.181**	**-906.83**	0.004
	(251.57)	(0.036)	(435.98)	(0.064)	(302.35)	(0.044)
Age 13-17	**-459.02**	**-0.054**	**-520.97**	**-0.161**	**-318.31**	-0.002
	(258.85)	(0.048)	(310.31)	(0.049)	(374.29)	(0.060)
Married/partnered	-354.09	-0.066	-577.89	0.036	-358.24	**-0.103**
	(222.73)	(0.040)	(327.33)	(0.056)	(290.54)	(0.052)
R^2	0.059		0.074		0.056	

*In all equations the standard errors, in parentheses below the parameter estimates, are clustered on individuals. Equations also include indicators of the survey year and day of the week. Parameter estimates are bolded if the single indicator of a characteristic or the vector of indicators describing a characteristic have effects that are statistically significant at least at the 95-percent level.

Table 4. Estimated ζ_{0j} and ζ_{1j} in (5) Using Imputed Wages, Dep. Var. μ^{*2}_{idt} *

	All		Men		Women	
	Simple	Variable ζ_1	Simple	Variable ζ_1	Simple	Variable ζ_1
$\boldsymbol{\zeta_{10}}$	0.140	0.023	0.160	0.445	0.129	-0.060
	(0.015)	(0.263)	(0.031)	(0.679)	(0.017)	(0.328)
$\boldsymbol{\zeta_{01}}$	-1935.84	-2121.28	-3915.22	-3464.65	-1986.47	-2322.47
	(499.43)	(492.44)	(803.70)	(977.93)	(841.77)	(881.44)
$\boldsymbol{\zeta_{11}}$	-------	0.039	-------	-0.091	------	0.064
		(0.087)		(0.214)		(0.111)
R^2	0.052	0.052	0.059	0.060	0.049	0.049

*In all equations the standard errors, in parentheses below the parameter estimates, are clustered on individuals. Equations also include indicators of the survey year and day of the week.

Table 5. ARCH Estimates of Spillovers/Causation Between Sleep and Eating/Personal Care (N=53,371)*

	Dep. Var.:			
	$\mu^{*2}_{EatCareidt}$		$\mu^{*2}_{Sleepidt}$	
Ind. Var.:				
$\mu^{*2}_{EatCareidt-1}$	0.108	0.106	-------	-0.007
	(0.012)	(0.013)		(0.015)
$\mu^{*2}_{Sleepidt-1}$	-------	0.0050	0.218	0.218
		(0.0023)	(0.028)	(0.028)
R^2	0.023	0.023	0.061	0.061
Mean	1693.68		3944.20	

*In all equations the standard errors, in parentheses below the parameter estimates, are clustered on individuals. Equations also include indicators of the survey year and day of the week.

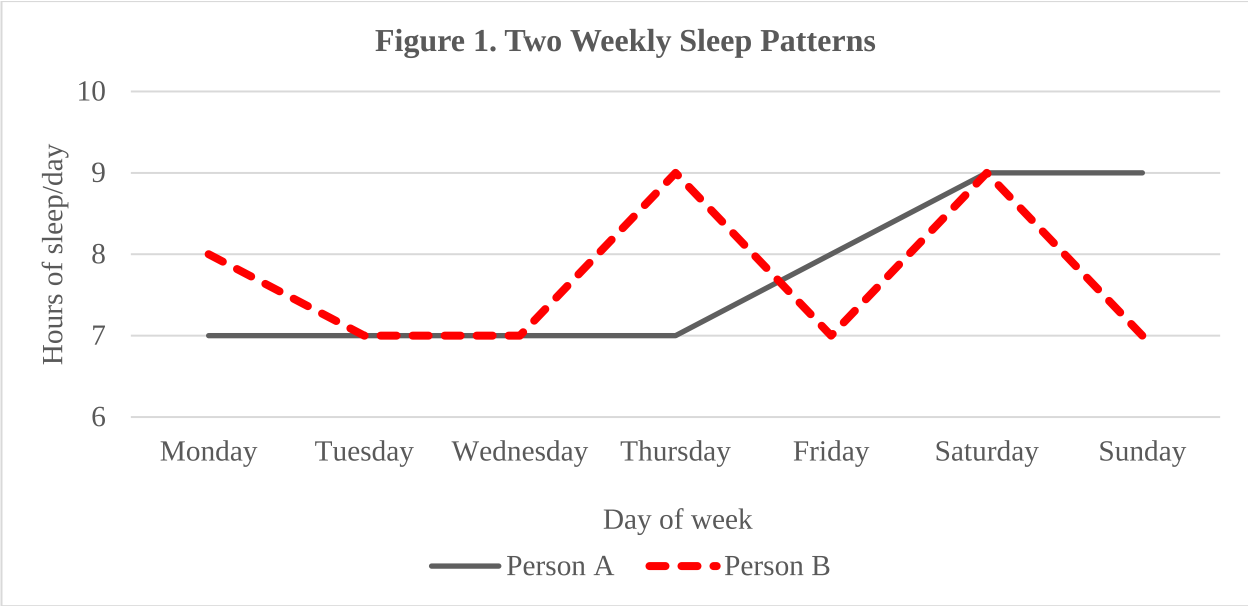

Figure 1. Two Weekly Sleep Patterns
10
9
8
7
6
Hours of sleep/day
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of week
Person A
Person B

Table A1. Estimates of the Impacts of Average Sleep and Day-varying Measures on Daily Sleep Time*

Ind. Var.:	All	Men	Women
Minutes of paid work	-0.075	-0.095	-0.074
	(0.001)	(0.003)	(0.002)
Average weekly sleep	0.868	0.847	0.890
	(0.010)	(0.015)	(0.013)
R^2	0.512	0.528	0.496

*The estimates also include indicators of the survey year and day of the week. The standard errors, in parentheses below the parameter estimates, are clustered on individuals.

Table A2. Ln(monthly earnings) Estimates from *OSA Panel*, 1985-2006*

Ind. Var.	Men	Women
Age	0.0340	0.0375
	(0.0023)	(0.0033)
$Age^2/100$	-0.0301	-0.0368
	(0.0028)	(0.0040)
Secondary school	0.1293	0.1301
	(0.0058)	(0.0088)
>Secondary school	0.3534	0.3187
	(0.0062)	(0.0096)
Youngest child:		
Age 0-4	0.0173	0.0368
	(0.0076)	(0.0117)
Age 5-12	0.0191	0.0405
	(0.0076)	(0.0119)
Age 13-17	0.0179	0.0016
	(0.0084)	(0.0124)
Married/partnered	0.0738	-0.0560
	(0.0068)	(0.0086)
R^2	0.563	0.760
N in sample	12,354	7,720

*Standard errors in parentheses below the parameter estimates. Each equation also includes a quadratic in weekly hours of work and indicators of the survey year.