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The Variability and Volatility of Sleep: An ARCHetypal Approach

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ABSTRACT

Using Dutch time-diary data from 1975-2005 covering over 10,000 respondents for 7 consecutive days each, we show that sleep time exhibits 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. It is more volatile among men than women, but volatility is independent of other demographic characteristics. A theory of economic incentives to minimize the dispersion of sleep predicts that higher-wage workers will exhibit lesser dispersion, a result demonstrated using extraneous estimates of earnings equations to impute wage rates. Volatility in sleep spills over onto other personal activities, with lesser reverse causation onto sleep. The results illustrate a novel dimension of economic inequality.

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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 Asgeirsdottir and Olafsson (2015), Sedigh *et al*. (2017), and others. 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 variation 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 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] It has usually been applied to much higher-frequency data than those available to scholars examining individuals' behavior. Perhaps for that reason, the econometric approach to volatility in time series 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.

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 volatility in sleep onto other uses of time.

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 not constant through time. If it occurs, it will disappear after some time period, and it is associated with 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]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*.

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

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 have 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) $\hat{v}^2 = \frac{1}{6}\sum_{2}^{7}([S_d - S.]^2 - [S_{d-1} - S.]^2)$,

Person A's sleep volatility is $\hat{v}_A^2 = 0.33$, but Person B's is $\hat{v}_B^2 = 0.83$.[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.

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) examined 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-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 to in this correlational study).

In an "early" study in this literature 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)

[2]The squared terms measuring $\hat{v}^2$ link this presentation to the subsequent discussion of ARCH estimates. The same implication—the difference between variability and volatility—would result if we did not square these terms.

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. While a few studies relate objective measures, such as age or socioeconomic status, to sleep variability, in many cases the analysis is simply correlational, for example, relating sleep variability to BMI, to cardiovascular ailments, or to depression. 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, all day from midnight, through Saturday, 11:59PM, with the surveys fielded in October or November.[3] (In most years separate samples

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

were collected in each of two weeks.[4]) The sampling frame consists of individuals ages 12 or older, one person in each household (thus regrettably preventing examining spousal spillovers of sleep time).[5]

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).[6] 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 week's paid workhours.[7] With these restrictions the usable sample consists of 71,743 diaries of reported sleep time by 10,258 individuals.

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[4]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.

[5]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).

[6]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).

[7]Also excluded were 70 days (fewer than 0.1 percent) on which the time-diarist recorded no sleep time, an exclusion that has tiny effects on the estimates here. Most of the exclusions due to item non-response resulted from missing information on the previous week's workhours. The statistics and estimates are computed using sampling weights throughout this study. The standard errors of the parameter estimates are clustered on individuals. In the tables and

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 431 minutes (7-1/4 hours) and the 90th-percentile person averaging 565 minutes (9-1/2 hours) per night over the survey week. There is substantial intra-week variation even in average sleep time, from 474 minutes on Fridays to 562 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 the first three columns of 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 423 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 effect is larger among them. These results underscore the desirability of accounting for inter-day differences in market work time when measuring the volatility of sleep and examining its 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, 4.5 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. 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

calculations, the number of observations is slightly less than the full sample, because in the *Tbo* 0.6 percent of the usable sampled days were assigned a weight of zero.

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 examine 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*, the previous week's hours of paid work, and indicators of the day of the week and the year of the survey.[8] (Appendix Table A1 presents the 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 $S_{i.t.}$[9] We are thus concentrating solely on the variability and volatility of inter-temporal patterns of sleep independent of differences in average sleep, weekly differences, and day-to-day variations in paid work time.

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

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

where the μ_{idt}^2 are the squares of the 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

[8]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).

[9]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.

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). In that 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).[10]

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, i.e., 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. 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).

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

where X_j is the vector of $j=1,\ldots,K$ 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 immense 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

[10]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.

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 conform to the assumptions underlying the ARCH(1) model. Daily sleep time is autocorrelated AR(1), with a first-order autocorrelation coefficient of +0.39. The ARCH(1) process in (4) must also have $0 < \zeta_{10} < 1$, and $\zeta_{10}^2 < 1/3$. The first column of Table 2 lists the estimates of (4) over the entire sample.[11] 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 substantial 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.[12]

Not only does ARCH(1) behavior characterize the whole sample; it also holds for both men and women separately. Columns (2) and (4) of Table 2 present estimates of equation (4) for men and for women, respectively, who had positive hours of paid work in the week preceding their time diaries. Columns (3) and (5) do the same thing for those who performed no paid work during the previous week nor on any of the days for which they kept time diaries. The estimates show that in both categories men's sleep time is significantly more volatile than women's.

[11]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. Even accounting for differences in variability, men's sleep time exhibits significantly more volatility than women's.

[12]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 0.193 (s.e.=0.03), close to that shown in Column (1) of Table 2 for the much larger main sample.

Comparing groups of respondents within gender, both male and female workers' sleep time is more volatile than that of non-working men or women. Nonetheless, even if one does not work for pay, one's sleep time exhibits some volatility. Moreover, the differences in volatility between workers and non-workers are nearly identical by gender: The double-difference of the estimates of the ζ_{10} = -0.012 (s.e. = 0.045).

Table 3 presents the estimates of (5), with the first column in each pair (for the entire sample, and 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 by demographic characteristic. It decreases with age over the entire sample range; it decreases with educational attainment; and it decreases if the youngest child in the household is younger. Moreover, the variance of sleep is higher on weekends than on weekdays.[13]

While the entire vector ζ_{0j}, j=1, …K, is statistically significant, gender is the only one of the X variables that significantly alters volatility (with, as shown in Table 2, men's sleep being more volatile).[14] Moving to the estimates for men and women separately, the conclusions about the determinants of variability and volatility remain essentially the same. For both genders, volatility is essentially unaffected by other demographic characteristics; and it is the same on weekdays and weekends. The variability of sleep time decreases with age and education among both men and women, is higher on weekends, and it is lower

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

[14]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, 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}.

if a young child is present in the household. Thus, while women's sleep time exhibits less volatility than men's, there are no gender differences in the variability of sleep.

We cannot refute the possibility that 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 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 studied in the biomedical literature also suggests that variability is detrimental to people's well-being.[15] A rationalization of sleep patterns presented here must answer the questions: Why does sleep variability decrease with full income—

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

the value of a person's time—(one novel finding in this study) and why, other than gender, are there no demographic differences other than gender 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 negative shock might arise from unusual street noise, worries about some family difficulty, or a physical problem, for examples. Assume that the individual's daily productivity P depends on his/her daily sleep time, S_d, and that:

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

Assume too that the agent can react to the shock θ_d by altering his/her 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, offset a negative shock by taking a sleeping pill or having an alcoholic drink. We assume that the physical ability to offset 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. 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 the departure of actual from desired sleep time. Assuming no differences by wage rate in the ability to do so, we will thus observe a smaller shortfall of S_d below S^*, i.e., less variability of sleep around its average among high-wage individuals.

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:

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

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.

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 and wages, and sleep variability and 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.[16] 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-

[16]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.

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 the first three columns of 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 previous literature, with an elasticity of sleep time with respect to the wage rate of -0.109 in the full sample, -0.037 among men, and -0.125 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_{01} and ζ_{10}, while the second column in each pair adds the estimate of ζ_{11} (the coefficient on the interaction of the lagged squared residual and the imputed wage rate). The first two columns are estimated over the entire sample, the next two pairs of columns over separate samples of men and women.

The residual variance of sleep time is lower among those respondents whose price of time (whose imputed wage rate) is higher.[17] A ten percent higher wage rate is associated with 4.0 percent less variability in the entire sample, 7.0 percent less among men, and 5.4 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

[17] 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 imputed wage rates.

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 gender, 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 very 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, 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.[18] 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."[19] Using the *Tbo*, we can then examine whether volatility in sleep spills over onto volatility in this other set of miscellaneous biological activities.

As with the analysis of the volatility of sleep, we restrict the sample to those diary-days when some positive amount of eating, and of personal care, is reported, reducing 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

[18]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.

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

activities. We 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. To examine whether their volatility 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 nearly statistically significant: Volatility in sleep—a period of greater unrest in sleep—produces greater volatility in eating and other personal activities. 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 even for other 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 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 slightly reduced sample (which excluded zeroes in eating/drinking and self-care) shown in Column (3) of Table 5 hardly changes 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 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, and that there is weaker 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 migreatly or little from its longer-term average. 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 men's sleep time is more volatile than women's, even after accounting for differences in market work time, 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 increases the extent of 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 does not appear to have been applied previously to time series of indicators of human behavior, such as the sleep that is analyzed here; nor have ARCH models been used in this context. One would expect that such volatility exists in numerous other aspects of how people use time and in other human 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; 266.66; 103.2)	(0.003)	(0.005)	(0.004)
Weekly work hours	0.067	0.268	-0.052
(29.6; 33.6; 26.3)	(0.038)	(0.064)	(0.054)
Male	4.52	-------	-------
(0.45; 1; 0)	(1.26)		
Age	-2.97	-2.35	-3.42
(39.6; 40.1; 39.1)	(0.47)	(0.69)	(0.63)
Age^2	0.030	0.026	0.031
	(0.006)	(0.008)	(0.008)
Secondary school	-6.26	-7.73	-5.71
(0.42; 0.37; 0.46)	(1.42)	(2.16)	(1.85)
> secondary school	-8.17	-8.32	-8.870
(0.25; 0.31; 0.21)	(1.61)	(2.26)	(2.28)
Youngest child:			
Age 0-4	-21.16	-9.01	-31.92
(0.25; 0.24; 0.25)	(1.60)	(2.38)	(2.25)
Age 5-12	-15.93	-5.51	-24.21
(0.18; 0.17; 0.19)	(1.71)	(2.48)	(2.37)
Age 13-17	-6.76	-8.58	-5.19
(0.08; 0.08; 0.09)	(2.16)	(2.81)	(3.19)
Married/partnered	1.15	0.28	1.00
(0.82; 0.83; 0.80)	(1.67)	(2.56)	(2.25)
R^2	0.202	0.249	0.158
N =	71,343	31,961	39,382
Mean	497.50	487.37	505.71

*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} *

	All	Men		Women	
		Workers	Non-workers	Workers	Non-workers
Ind. Var.:					
μ^{*2}_{dt-1}	0.157	0.231	0.203	0.151	0.111
	(0.015)	(0.029)	(0.072)	(0.024)	(0.025)
R^2	0.055	0.073	0.108	0.052	0.044
N =	61,100	22,787	4,038	24,633	8,414

***** 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. Workers are those who reported positive paid hours of work in the week before the time diary was kept. Non-workers reported zero hours during the previous week and no paid work time on their diary days.

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	5290.02	0.118	5048.99	0.277	5467.32	0.146
	(1196.72)	(0.170)	(1868.22)	(0.306)	(1572.74)	(0.195)
Male	54.45	**0.080**	-------	-------	-------	-------
	(161.41)	(0.031)				
Weekend	**2701.98**	0.018	**3343.69**	-0.026	**2208.48**	0.038
	(139.18)	(0.029)	(218.25)	(0.055)	(179.10)	(0.032)
Age	**-67.81**	0.002	**-49.19**	0.0008	**-84.24**	0.0006
	(62.94)	(0.009)	(98.74)	(0.015)	(82.14)	(0.010)
Age^2	**0.097**	-0.00004	**0.071**	-0.00003	**0.276**	-0.00003
	(0.73)	(0.00011)	(1.13)	(0.00018)	(0.96)	(0.00012)
Secondary school	**-381.45**	-0.027	**-761.19**	-0.024	-99.07	-0.028
	(177.68)	(0.032)	(312.27)	(0.061)	(221.07)	(0.039)
>Secondary school	**-669.89**	-0.007	**-698.95**	-0.036	**-618.26**	0.024
	(231.89)	(0.039)	(369.03)	(0.063)	(289.25)	(0.052)
Youngest child:						
Age 0-4	**-1041.85**	0.037	**-1185.97**	0.060	**-1069.36**	0.026
	(231.36)	(0.042)	(416.44)	(0.088)	(293.11)	(0.045)
Age 5-12	**-451.72**	-0.031	**3.78**	-0.092	**-726.15**	-0.017
	(248.49)	(0.038)	(453.14)	(0.076)	(302.84)	(0.045)
Age 13-17	**-284.83**	-0.049	**-510.08**	-0.109	**40.78**	-0.055
	(259.21)	(0.052)	(349.79)	(0.068)	(370.23)	(0.063)
Married/partnered	-316.31	-0.054	-305.37	0.023	-485.92	-0.075
	(224.44)	(0.037)	(335.34)	(0.063)	(302.33)	(0.047)
R^2	0.062		0.078		0.055	

* In all equations the standard errors, in parentheses below the parameter estimates, are clustered on individuals. Equations also include indicators of the survey year. 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. Estimates of (5) Using Imputed Wages, Dep. Var. μ^{*2}_{idt}*

	All		Men		Women	
	Simple	Variable ζ_1	Simple	Variable ζ_1	Simple	Variable ζ_1
$\boldsymbol{\zeta_{10}}$	0.157	-0.014	0.214	0.616	0.132	0.209
	(0.015)	(0.270)	(0.027)	(0.496)	(0.017)	(0.397)
$\boldsymbol{\zeta_{01}}$	-2020.36	-2278.45	-3456.26	-2835.65	-3116.46	-2550.32
	(474.49)	(484.54)	(732.30)	(834.87)	(286.57)	(751.58)
$\boldsymbol{\zeta_{11}}$	-------	0.057	-------	-0.128	------	-0.026
		(0.089)		(0.157)		(0.134)
R^2	0.055	0.056	0.074	0.075	0.048	0.048

* 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 the day of 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.:				
$\mu^{*2}_{EatCareidt-1}$	0.101	0.100	-------	-0.017
	(0.012)	(0.012)		(0.012)
$\mu^{*2}_{Sleepidt-1}$	-------	0.0042	0.203	0.204
		(0.0023)	(0.021)	(0.022)
R^2	0.020	0.020	0.053	0.053
Mean	1688.90		3945.61	

* 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 week.

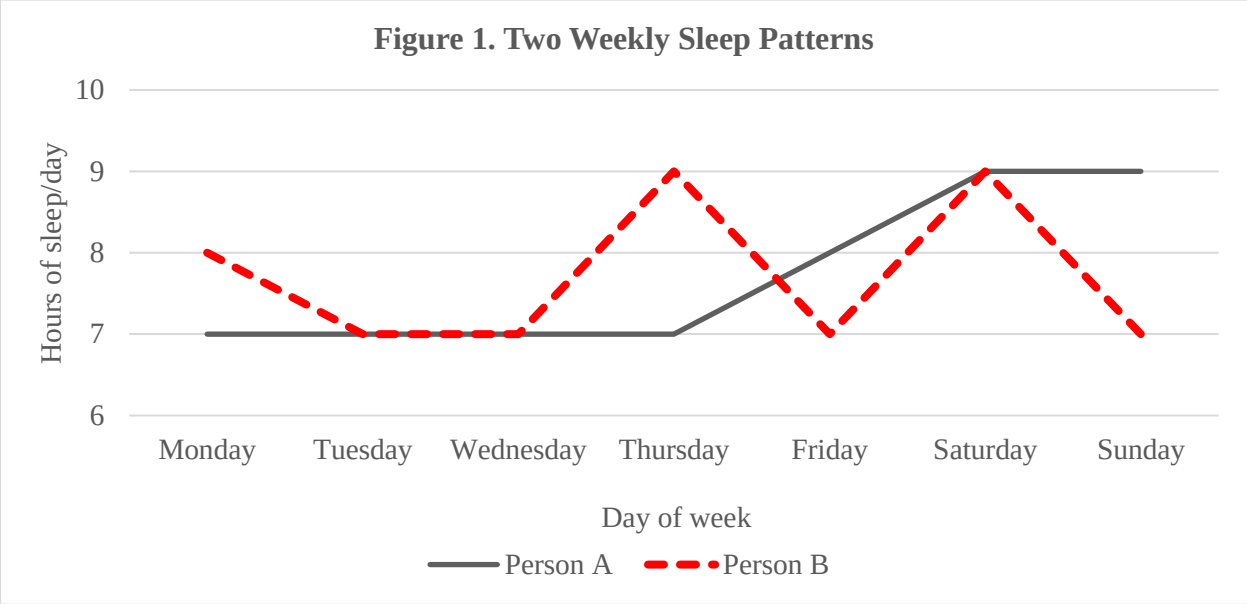
Figure 1. Two Weekly Sleep Patterns
10
9
8
7
6
Hours of sleep/day
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of week
Person A
Person B

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

	All	Men		Women	
		Workers	Non-workers	Workers	Non-workers
Ind. Var.:					
Minutes of paid work	-0.076	-0.116	--------	-0.078	-------
	(0.001)	(0.003)		(0.024)	
Average weekly sleep	0.863	0.847	0.892	0.891	0.895
	(0.010)	(0.018)	(0.018)	(0.016)	(0.024)
R^2	0.514	0.527	0.531	0.490	0.513

*The estimates also include indicators of day of week and of year. In all equations 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 for the year of the survey.