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The Cost of Preexisting Heart Conditions on Objective Sleep Quality

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Topic

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Introduction

Sleep quality plays a vital role in people's health outcomes throughout their lives. Preliminary studies on rats have consistently showed that sleep deprivation lowers life expectancy by leading to gradual physical deterioration (Shepard et al. 2005). Among humans, the resulting economic consequences of inadequate sleep have become increasingly apparent, with sleep disorders alone estimated to account for approximately $94.9 billion in yearly health care costs in the United States alone ("Sleep Disorders Tally $94.9 Billion in Health Care Costs Each Year" n.d.). Despite the magnitude of these ever-present issues, it is difficult to identify an all-encompassing solution, as the factors affecting an individual's sleep can be both voluntary (behavioral) and involuntary (medical), the former of which is much more difficult for a clinical practitioner to address directly. Nevertheless, the consequences of inadequate sleep have been shown to have a similar effect on many activities of economic importance, the most cited of which include worker productivity, traffic accidents and demographic disparities.

Unlike other departments of medical science, the study of sleep is a relatively novel field of research, with many notable advances mainly starting to occur over the last 70 years with the discovery of rapid eye movement (REM) sleep (Shepard et al. 2005). Since then, typical measurements of quality of sleep have often relied on approximations derived from people's personal impressions and experiences. The creation and continuous improvement of technologies has allowed for accurate measurements of sleep duration in the form of polysomnography and actigraphy studies, the former of which has been shown to consistently have an accuracy above 80% (Marino et al. 2013). This allowed new studies to not only use more reliable sleep efficiency data, but also to make a distinction between subjective sleep and objective sleep. As a result, an increasing number of academic papers and clinical studies have started to not only pivot more heavily from subjective to objective sleep quality, but also to study the causes in discrepancies between the two measurements (Unruh et al. 2008).

While there is little dispute over the importance of sleep quality on the overall health of an individual, this entire area of study is still missing a lot of crucial information about what determines the level of quality. Objective measurements currently describe it as the interval between sleep onset and sleep offset while the participant is asleep. This metric is then used across a vast array of medical studies to determine the causal relationship with various medical complications (Shepard et al. 2005). However, rather than include sleep as an explanatory variable when studying other traits of individuals, it would be equally insightful to identify the main determinants of sleep quality itself. The multivariate models in the current literature that attempt to build this framework typically draw from a number of economic, behavioral and medical parameters depending on the data available from existing clinical studies ("Multidimensional Sleep and Mortality in Older Adults: A Machine-Learning Comparison With Other Risk Factors | The Journals of Gerontology: Series A | Oxford Academic" n.d.). However, due to the difficulty of taking objective sleep measurements on the same individuals across multiple and lengthy periods of time, the majority of such studies limit themselves to cross-sectional regression analysis. This approach would likely suffer from an inability to properly account for factors such as individuals' health deterioration across time. This particular point cannot be ignored due to the fact that individual choices leading to sleep deprivation directly impact the brain's ability to regulate sleep efficiently. This results in a vicious circle that further accelerates the previously discussed economic and health-related consequences (Schmidt, Peigneux, and Cajochen 2012).

This research paper uses the Sleep Heart Health Study (SHHS) dataset, derived from a multi-center cohort medical trial implemented by the National Heart Lung & Blood Institute to attain two objectives: first, it aims to use patient personal and clinical data to expand on the existing literature by determining whether medical events such as previous strokes and hypertension play a role in influencing objective sleep quality. Second, it constructs a two period panel data model by first differencing the two time periods to determine the change in effects over the two time periods. By achieving the first objective, the paper aims to not only confirm the significance of pre-established determinants of sleep quality, but also to improve the existing frameworks by better accounting for losses of sleep derived from health complications. For instance, while the current assumption is that inadequate sleep increases the risk of heart disease, it is also the case that the development of heart disease further deteriorates the individual's ability to achieve the same resting time under similar conditions. The second objective aims to capture the effect of changes in the determinants of objective sleep quality by removing time-invariant unobserved characteristics that could otherwise affect the estimated effect of our variables of interest.

Literature Review

The approach taken for the methodology and calculations of this paper is informed by prior economic and medical sleep studies in recent years. This literature review will introduce a couple of notable results addressing the relationship between sleep quality and individual health profiles, with a focus on risks of health complications such as cardiovascular disease, dementia, and Alzheimer's disease, as well as the main factors influencing sleep outcomes. In the same context, this paper will outline the multidimensional nature of sleep, condensed into sociodemographic, behavioral, and genetic/physical health, and the rising need to further identify the main determinants of what is classified as objective sleep quality across time. Lastly, the paper will provide an outline of the economic consequences of sleep such as high medical costs, traffic accidents, and lower rates of productivity. The same approaches will then inform this paper's methodology in further assessing similar costs through losses in individuals' overall sleep capacity.

Objective versus Subjective Sleep

The introduction of the first medical instruments used to measure sleep patterns mainly in the form of polysomnography and actigraphy has led to the need to distinguish between subjective and objective sleep, as well as determine the true influencing factors (Shepard et al. 2005). By definition, subjective sleep is understood as the total sleep duration recorded either by the patient himself after waking up, or by a third party in the following morning based on the patient's feedback. However, as the O'Donnell et al. (2009) paper shows, this approach is far less reliable than its objective counterpart, which excludes wake-up times from the total amount. The authors of this paper analyzed both objective and subjective sleep data from 24 healthy adults between 55 and 74 years of age for 32 consecutive days using polysomnographic monitoring. The results pointed towards correlation between objective and subjective sleep latency, as well as a strong significance of duration of premature awakening on individual ratings of sleepiness at wake time. Moreover, the authors were able to determine large inaccuracies in subjective sleep quality assessments for subjects whose sleep patterns and schedules did not change by a high amount across the 32 days.

This result is further strengthened by (Kaplan et al. 2017), which seeks to study how well subjective reports of sleep are correlated with polysomnographic measures. The paper employs data collected from 1483 adults who partook in the Osteoporotic Fractures in Men and Study of Osteoporotic Fractures studies. In both cases, the patients completed a polysomnographic test during one night, followed by a morning survey about the prior night's sleep quality. The authors further incorporated demographic characteristics such as age, sex, and race, as well as clinical characteristics in the form of body mass index and sleep disorders into the model to develop multiple predictive machine learning algorithms of subjective sleep. While polysomnographic measurements emerged as the most highly predictive variables, the models were only able to explain 11-17% in the variance of subjective sleep. As the authors suggest, it is likely that the models suffer from omitted variable bias, as is often the nature with assessing subjective perceptions of reality. As such, they propose the use of additional behavioral and medical records including alcohol and caffeine consumption, as well as preexisting heart conditions. Since the sleep study datasets used by the paper only contain information across one time period, the authors further highlight the importance of future clinical studies across extensive time periods.

The overall underwhelming results presented thus far have used polysomnographic measurements, which are considered to be more accurate, but more intrusive than their actigraphy counterpart (Marino et al. 2013). In trying to determine whether the instrument of choice has any effect on subjective assessments of sleep quality, Van Den Berg et al. (2008) construct similar multivariate models for 969 participants aged 57-97 years and undergoing both diary and actigraphic estimates of sleep duration for six consecutive days. In doing so, the authors were able to analyze variations arising between the two indicators of sleep quality, and possibly determine the main factors influencing the disagreement. Not only was total sleep time shown to vary by more than one hour in the two estimations for 34% of participants, but objective poor sleep measurements were often associated with longer subjective estimates of total sleep time. The importance of this result extends to medical examinations and diagnoses, since it shows varying levels of inconsistencies based on the type of patient. As such, the use of objective sleep quality measurements should always be prioritized for patient treatments whenever such data is available.

Determinants of Sleep Quality

There is currently little dispute over the long-term relevance of sleep quality over individuals' health outcomes and life expectancy (Silva et al. 2009). Given the newfound traction and importance gained by the field of sleep science over the last decades, a majority of research has recently concentrated on studying the main factors of sleep quality itself (Shepard et al. 2005). The presence of sleep disorders such as sleep apnea were among the first to explore by papers such as Newman et al. (2001), which started with a specific investigation into the impact of sleep disorders on cardiovascular disease. The authors use data from the first visit of the Sleep Heart Health Study, which contains moderate levels of sleep-disordered breathing, or Respiratory Disturbance Index (RDI) among a large segment of patients. The results showed a strong relationship between RDI and factors such as age, body mass index and hypertension, particularly among patients above 65 years of age. Overall, the paper demonstrated the importance of demographic and medical characteristics in the modeling of sleep quality.

Complementing the results shown above, Unruh et al. (2008) used the same cross-sectional data to establish whether objective and subjective sleep quality are influenced by age independent of other chronic health conditions. In doing so, the paper was able to introduce behavioral characteristics in the form of alcohol consumption and cigarette use, both of which were found to be statistically significant. The results demonstrate significant sleep deterioration among older adults and men, further emphasizing the importance of demographic characteristics. However, due to the nature of cross-sectional data, the authors were unable to capture the effect of what sleep science refers to as accelerated sleep deterioration, whereby the maximum capacity of sleep of older adults lowers over time (Shepard et al. 2005). Nevertheless, this paper highlighted the importance of behavioral characteristics when modeling sleep quality.

Similar to many economic parameters, disparities in sleep quality have also been shown to be influenced by race. Redline et al. (2004) looks at polysomnographic data of 2685 participants aged

37 to 92 to assess the role played by demographic variability and sleep-disordered breathing on objective sleep quality. The results further strengthen a pattern in which men relative to women and American Indians and blacks suffer from deficiencies in their overall ability to rest. Moreover, these variations were found to have stronger significance than sleep-disordered breathing and obesity. The important differences in sex physiology thus raise further questions regarding overall omitted variable bias, or whether there is a hidden societal effect not accounted for. Nevertheless, the results presented above informed the choices in variables when creating the models.

Consequences and Measurements of Economic Impact

Given the close tie between health and economics, it is not surprising that inadequate sleep would cause negative externalities on a both microeconomic and macroeconomic level. A clear example of such consequences relates to the impact of sleep-related disturbances on employee overall productivity and work performance addressed by Rosekind et al. (2010). The paper conducted questionnaires with sleep-related information for 4188 employees at four US large companies. The respondents were divided into four types, namely insomnia, at-risk, insufficient sleep, and good sleep. The cost incurred by each company from sleep-related work loss was calculated using disclosed salary information and subtracting any productivity losses. The overall results showed an average annual cost of $1967 per employee due to fatigue-related productivity loss. As a result, sleep disturbances, often caused by individual lifestyle choices rather than medical conditions contribute greatly to variations in worker productivities.

Losses in productivity, as well as larger macroeconomic implications of inadequate sleep are further shown by Hafner et al. (2016) in a large cross-country comparative analysis sponsored by Rand Europe. The authors split the calculations of economic costs into two separate studies. The first conducts empirical analysis on workplace productivity losses measured as absenteeism (missing days from work) and presenteeism (time at work unable to focus) as proxies for productivity. The data was collected from the Bureau of Health Workforce for 62,000 UK employees and contains demographic and clinical variables of interest. The authors construct an OLS and fractional response estimator to look at the percentage of work impairment added or reduced for different categories of sleep quality, divided into less than 6 hours, 6 to 7 hours, 7-9 hours and over 9 hours. Among other findings, the results report a 3% increase of work impairment for respondents with a sleep time of less than 6 hours, compared to 7-9 hours. By the same comparison, a respondent with a sleep time larger than 9 hours also displays an increase of 2.4% in work impairment. As the paper suggests, this is due to the fact that individuals who sleep very long hours likely suffer from additional illnesses which prevent them from resting adequately. Using similar data from four other OECD countries, While revealing, the paper uses subjective sleep quality data, which suggests there may be bias in the overall assessments. Given that we make use of polysomnographic data but lack additional context on worker productivity, we will use the average estimates and calculations provided by Hafner et al. (2006) to approximate the cost of preexisting conditions on productivity.

Sleep-disordered breathing, often manifested in the forms of snoring, sleep apnea or obesity hypoventilation syndrome, is generally considered to be a main influencer of sleep quality with long-term costs. Using data collected from the Danish National Patient Registry, Jennum and Kjellberg (2011) investigate both the direct and indirect costs associated with each of the aforementioned ailments. They find a significant impact for each type in the form of increased hospital visits, use of medication and unemployment. As per expectations, the same effects were shown to increase proportionally to the severity of the sleep-disordered breathing. To assess the overall costs quantitatively, the authors devise a combination of company level information on work hours and productivity, as well as total medical costs collected from hospitals, both with a direct and indirect component. The results show that individuals suffering from snoring, sleep apnea or obesity hypoventilation syndrome incur an annual mean social cost of €147, €879 and €3263, respectively. One of the main highlights of this calculation is the importance of incorporating economic and medical costs into one framework that should provide future research with a more informed framework on how to assess the impact of different levels of sleep quality on individuals on a both microeconomic and macroeconomic scale.

Methodology

Dataset

The data used in this paper was collected by the Sleep Heart Health Study (SHHS), a clinical evaluation meant to provide insights regarding the cardiovascular consequences of sleep-disordered breathing, as well as the extent to which sleep-related breathing increases the risk of coronary heart disease, stroke, hypertension, and all-cause mortality (Quan et al. 1997). The sample comprises of 5804 men and women 40 years and older who attended two clinical visits separated by a five year period (referred to as Visit 1 and Visit 2). That being said, a lot of the variables of interest contain missing data for Visit 2, as some of the patients could no longer be contacted due to refusal to participate in future studies, illnesses or death. As a result, we could only use data for 2602 participants for Visit 2, a limitation whose implications will be discussed in further sections of the paper.

Demographic Characteristics

The demographic variables of interest consist of gender, race, age, and education level. male participants of the Visit 1 SHHS represented 48% of the sample, at an average age of 63 years, with the youngest participant at the time of 39 years and oldest participant of 90 years. In terms of race distribution, approximately 91% self-identified as white, and the most represented educational group was between 11 and 15 years of education at approximately 45%, with 6% of male participants who attained more than 20 years of education. The remaining female participants have the same average, minimum and maximum age, but a more acute representation of 11-to-15-year education at 52%, with only 4% attaining more than 20 years of education. Due to missing observations pertaining to education level, 483 observations had to be excluded from the study. Of the excluded participants, 43% were male, with an average age of males and females of 54 and 53 respectively. Table 1 lists the summary statistics of the demographic variables for Visit 1 selected based on the approaches presented in the literature review.

Table 1. Demographic Variables for Clinical Visit 1

	Men		Women		Total	
Variable	**Count (N)**	**Percent (%)**	**Count (N)**	**Percent (%)**	**Count (N)**	**Percent (%)**
Race						
White	2319	90.73%	2459	88.93%	4778	89.80%
Black	168	6.57%	232	8.39%	400	7.52%
Other	69	2.70%	74	2.68%	143	2.69%
Age						
39-50 years	311	12.17%	317	11.46%	628	11.80%
51-60 years	675	26.41%	790	28.57%	1465	27.53%
61-70 years	827	32.36%	741	26.80%	1568	29.47%
71-80 years	609	23.83%	742	26.84%	1351	25.39%
81-90 years	134	5.24%	175	6.33%	309	5.81%
Education						
< 10 years	206	8.06%	229	8.28%	435	8.18%
11-15 years	1147	44.87%	1603	57.97%	2750	51.68%
16-20 years	1043	40.81%	870	31.46%	1913	35.95%
> 20 years	160	6.26%	63	2.28%	223	4.19%
Total Count	2556	48.04%	2765	51.96%	5321	

Before mentioning the notable demographic sample statistics for Visit 2, it should be mentioned that the sample size used across both summary statistics and regression results was lowered significantly as a result of missing observations across the majority of variables of interest. After excluding all the missing data, the total number of participants remained 5321. The consequences and limitations of the ensuing analysis will be discussed further in the results section. Of the remaining sample, male participants for Visit 2 accounted for approximately 47% of the sample, with an average age of 68 years, with the youngest participant at the time of 44 years and oldest participant of 90 years. In terms of race distribution, 94% self-identified as white, and the most represented educational group continued to be between 11 and 15 years of education at approximately 48%, with 7% of male participants who attained more than 20 years of education. Female participants have the same average, minimum and maximum age, but the highest representation of 11-to-15-year education across the two visits at 59%, with only 3% attaining more than 20 years of education. The summary statistics of the demographic variables for Visit 1 can be viewed in Table 2 below.

Table 2. Demographic Variables for Clinical Visit 2

	Men		Women		Total	
Variable	**Count (N)**	**Percent (%)**	**Count (N)**	**Percent (%)**	**Count (N)**	**Percent (%)**
Race						
White	1053	94.35%	1192	92.83%	2245	93.54%
Black	48	4.30%	69	5.37%	117	4.88%
Other	15	1.34%	23	1.79%	38	1.58%
Age						
39-50 years	44	3.94%	63	4.91%	107	4.46%
51-60 years	189	16.94%	239	18.61%	428	17.83%
61-70 years	379	33.96%	420	32.71%	799	33.29%
71-80 years	372	33.33%	397	30.92%	769	32.04%
81-90 years	132	11.83%	165	12.85%	297	12.38%
Education						
< 10 years	77	6.90%	101	7.87%	178	7.42%
11-15 years	539	48.30%	754	58.72%	1293	53.88%
16-20 years	419	37.54%	394	30.69%	813	33.88%
> 20 years	81	7.26%	35	2.73%	116	4.83%
Total Count	1116	46.50%	1284	53.50%	2400	

Polysomnographic and other sleep-related monitoring

Objective sleep quality among the SHHS participants was determined through polysomnography, which included a number of measurements over one night of sleep, the most relevant of which include total time asleep, arousal and wake frequency, sleep efficiency (defined as total minutes actually asleep divided by total time in bed), REM sleep latency (the interval between falling asleep and the first REM sleep excluding wake time), and the apnea-hypopnea index. The latter variable is defined as the number of respiratory events with an oxygen desaturation ≥3% per hour, thus a measure of the breathing quality of the patient(Quan et al. 1997). Given the sufficient availability of measurements of objective sleep across both visits, typical subjective ratings such as individual restlessness, sleepiness and subjective sleep quality post-polysomnography were also included. Table 3 provides descriptive statistics on the used variables, including the dependent variable of objective sleep time measured in minutes. On average, women are shown to sleep approximately 16 minutes longer than their male counterparts, who display the most extreme cases of sleep deprivation. Despite overall having better results of objective sleep quality on average, women appear to perceive their overall restlessness during sleep higher (3.0/5.0 compared to 2.9/5.0 for men), an observation supported by Van Den Berg et al. mentioned in the literature review (Van Den Berg et al. 2008).

Table 3. Sleep Quality Variables for Clinical Visit 1

	Men				Women			
Variable	Mean	(SD)	Min	Max	Mean	(SD)	Min	Max
Objective Sleep								
Sleep Time (minutes)	351.4	(61.1)	34.5	509.0	367.3	(65.1)	104.5	514.5
Time Awake (min)	66.4	(46)	1.5	338.5	57.4	(41.1)	0.0	307.0
Arousal Index	21.6	(11.6)	3.0	110.4	17.2	(9.2)	2.2	69.8
Apnea-Hypopnea Index	18.8	(16.9)	0.0	119.9	11.2	(13.2)	0.0	122.9
REM Sleep Latency	70.6	(39)	0.0	343.0	79.9	(45.2)	0.0	354.0
Subjective Sleep								
Restlessness (1-5)	2.9	(1.1)	1.0	5.0	3.0	(1.2)	1.0	5.0
Sleepiness (0-24)	8.4	(4.5)	0.0	24.0	7.2	(4.2)	0.0	24.0
Sleep Quality (1-5)	3.0	(1)	1.0	5.0	3.1	(1.1)	1.0	5.0

Similar if not more pronounced average discrepancies are observed for the second visit data, despite almost identical subjective sleep assessments. However, women appear to have more concentrated tails in the distribution of objective sleep time. The summary statistics for Visit 2 may be viewed in Table 4 below.

Table 4. Sleep Quality Variables for Clinical Visit 2

	Men				Women			
Variable	Mean	(SD)	Min	Max	Mean	(SD)	Min	Max
Objective Sleep								
Sleep Time (minutes)	362.7	(66.5)	98.0	530.0	383.2	(69.8)	68.0	583.0
Time Awake (min)	87.8	(58.1)	5.0	378.0	73.8	(50.7)	4.0	335.0
Arousal Index	20.8	(11)	4.2	81.4	16.6	(8.9)	2.6	75.3
Apnea-Hypopnea Index	20.5	(17.1)	0.1	90.8	12.9	(13.3)	0.0	109.5
REM Sleep Latency	71.4	(41.4)	0.0	324.0	81.5	(45.6)	0.0	399.0
Subjective Sleep								
Restlessness (1-5)	3.1	(1.1)	1.0	5.0	3.1	(1.2)	1.0	5.0
Sleepiness (0-24)	8.0	(4.2)	0.0	24.0	7.0	(4.1)	0.0	22.0
Sleep Quality (1-5)	3.1	(0.9)	1.0	5.0	3.1	(1)	1.0	5.0

Behavioral and Medical Characteristics

The final component of analysis pertains to individual health status and lifestyle choices with potentially significant impact on sleep patterns. Smoking and the amount of caffeinated drink intake up to four hours before the polysomnographic recording are used as the main influencers of choice-related sleep disruptions. The medical component contains information about the individuals' BMI (body mass index), systolic blood pressure and any history of heart conditions that led to a stroke. The latter variable is of particular interest as it adds an important preexisting condition that could very well limit the body's capacity to achieve the same potential parameters of restful sleep. With an older age range among the study's patients, 4% of men and 3% of women have a history of heart complications in the form of one or multiple strokes for Visit 1 (Table 5), whereas Visit 2 displays 6% of the sample men who have suffered a stroke and 4% of women who have suffered a stroke (Table 6).

The difference in percentages is mainly attributed to two factors: missing observations for Visit 2 and death of 208 participants between the two clinical visits. Of the 208 participants, the SHHS reports the cause of death to be 28% due to heart failure (Quan et al. 1997).

Table 5. Behavioral and Medical Variables for Clinical Visit 1

	Men			Women		
Variable	**%/Mean (N/SD)**	**Min**	**Max**	**%/Mean (N/SD)**	**Min**	**Max**
Behavioral						
Current Smoker	10% (211)			9% (215)		
Caffeinated drinks before bed	0.1 (0.4)	0.0	5.0	0.1 (0.4)	0.0	6.0
Medical						
Body Mass Index	28.3 (4.2)	18.0	50.0	27.8 (5.6)	18.0	50.0
Blood Pressure	128.2 (18.4)	52.0	203.0	126.8 (20)	79.0	214.0
Previous Stroke	***4% (79)***			***3% (74)***		

Table 6. Behavioral and Medical Variables for Clinical Visit 2

	Men			Women		
Variable	**%/Mean (N/SD)**	**Min**	**Max**	**%/Mean (N/SD)**	**Min**	**Max**
Behavioral						
Current Smoker	7% (75)			7% (88)		
Caffeinated drinks before bed	0.1 (0.3)	0.0	5.0	0.0 (0.3)	0.0	3.0
Medical						
Body Mass Index	28.6 (4.1)	18.2	46.0	27.8 (5.5)	18.0	50.0
Blood Pressure	128.8 (16.8)	79.0	210.0	127.0 (18.1)	74.0	210.0
Previous Stroke	***6% (57)***			***4% (53)***		

Regression Analysis

Given the nature of the SHHS, this paper will run two separate cross-sectional analyses on the data described above for each clinical visit. The dependent variable is the polysomnography-determined amount of minutes asleep, while the independent variables contain the aforementioned demographic, sleep-related, behavioral and medical variables. In addition, this paper runs a first difference estimation in the context of a two-period fixed effects panel model. This approach is taken in the context of the usual OLS assumption that the error term is not correlated with the explanatory variables. As such, we address the following model:

$$Y_{it} = X_{it}\beta + \varepsilon_{it} \tag{1}$$

where subscript i refers to the individual observation, while subscript t refers to the time period. One of the assumptions used in the context of panel data is the decomposition of the error term into the following:

$$\varepsilon_{it} = \theta_i + \tau_{it} \tag{2}$$

where θ_i represents a fixed effect that is unaltered over time. By using first-difference estimation, it is possible to relax the OLS assumption of consistency that $E(\varepsilon_{it}|X_{it}) = E(\theta_i + \tau_{it}|X_{it}) = 0$ to a weaker assumption in the form of $E(\tau_{it}|X_{it}) = 0$, which eliminates the fixed effect. Thus, in the context of two time periods, the two separate regressions to use are:

$$Y_{it} = X_{it}\beta + \theta_i + \tau_{it} \tag{3}$$

$$Y_{it-1} = X_{it-1}\beta + \theta_i + \tau_{it-1} \tag{4}$$

Taking first differences gives:

$$Y_{it} - Y_{it-1} = (X_{it} - X_{it-1})\beta + (\theta_i - \theta_i) + (\tau_{it} - \tau_{it-1}) \quad (5)$$

Which simplifies to:

$$\Delta Y_{it} = \Delta X_{it}\beta + \Delta\tau_{it} \quad (6)$$

With the fixed effect eliminated and the assumption that $E(\tau_{it}|X_{it}) = 0$ we are able to obtain consistent estimates of our coefficients. However, this approach also introduces spurious negative correlation between the data observations. With serial correlation present, the OLS coefficients may no longer be efficient, and could be better estimated through GLS. Moreover, the standard errors will not be accurate if serial correlation among the error terms is not addressed. As a result, this model accounts for serial correlation by clustering across the individual i. A couple of new insights may be derived from the two approaches, such as the expected degradation in sleep quality over time, but also the possible effect of new variables such as newly diagnosed heart conditions, strokes or changes in behavior.

Results

Cross-sectional Results

Cross-sectional analysis for Visit 1 shows statistical significance for a number of key variables, including history of previous strokes. For a reported p-value of 0.03, patients who have suffered a stroke prior to the polysomnographic test appear to lose approximately 11.75 minutes of sleep to healthy individuals. However, the variable was found not to be statistically significant for Visit 2, as well as contributing to an average of only 3.57 minutes. Despite the large discrepancy between the two results, it should be noted that the regression for Visit 2 suffers from several limitations, the most important of which is the quality of the data itself. Information for several variables including preexisting heart conditions was gathered from follow-up interim studies conducted by the SHHS, and some of the data took several years to collect. In that time, additional patients may have passed away and thus been excluded from the study. In the case of Visit 1, all medical records were collected prior to the polysomnographic intervention. Moreover, the methodologies for the data collection differed as all relevant qualitative data for Visit 1 was obtained from the patients in person on the morning after the observed night of sleep, whereas for Visit 2 they were obtained through phone communication. Overall, the cross-sectional results for Visit 1 should provide a much more accurate picture due to having more reliable data. Table 7 below summarizes the results for our independent variable of interest:

Table 7: Cross-sectional results for Visits 1 and 2

	Visit 1	**Visit 2**
Variable	Coefficient (t-stat)	Coefficient (t-stat)
Previous Stroke	-11.75* (5.424)	-3.574 (6.592)
Obs	4561	2177
adj. R-sq	0.257	0.266

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Additional factors included in the regression analysis were found to have a large impact on sleep quality. Wake after sleep onset, or the total duration awake from the beginning to the end of sleep displayed the most statistically significant result, showing that an additional minute awake results in an approximate 0.45 minute loss in time asleep, confirming the current literature's remark that individuals are not able to efficiently make up for sleep lost during the same night (Shepard et al. 2005). On the other hand, race was found to have the strongest impact, with white and other participants benefiting from a 16.3 minute and 11.2 minute increase in sleep compared to black participants. Males were further shown to have a negative correlation with sleep quality of approximately 9 minutes compared to females. The demographic results are thus in line with the current research presented in the literature review (Redline et al. 2004). From a socio-economic perspective, the paper also incorporates levels of education as a factor, with the rationale that individuals from lower income and education levels may lack the same healthy background and living conditions that negatively impact their sleep. However, no level of education was shown to be statistically significant.

The inclusion of behavioral variables finds statistical significance for both smoking and caffeine consumption, with the former accounting for 11.2 minutes of sleep loss and the latter accounting for 4.7 minutes lost at a 95% confidence level. While not directly addressed in the literature review, these behaviors are in line with the documented scientific research, especially given that the caffeine consumption variable relates specifically to activities prior to the night's sleep (Shepard et al. 2005). It is also not surprising that physiological measurements such as BMI, blood pressure, and REM sleep latency are strong determinants of sleep quality. Surprisingly, however, the Apnea-Hypopnea Index (AHI) was shown not to be statistically significant, a contentious result in the current literature, and thus a stronger confirmation in favor of Redline et al. (2004). At the same time, the expectation would have been of a negative coefficient, whereas the OLS regression coefficient was positive. The specific inclusion of this sleep-disorder index therefore does not seem to be appropriate in the context of this study.

While less reliable than the results for Visit 1, the Visit 2 outcomes continue to show strong statistical significance for Age and Gender, with one additional year contributing to approximately 1.1 minute loss. What stands out the most, however, is the lack of significance attributed to caffeine consumption and subjective assessments of sleep quality such as individual rating of restfulness and the Epworth Sleepiness Scale ranking the likelihood of dozing off. The lack of consistency among these results may point towards faulty modeling when it comes to combining objective and subjective sleep measurements. Moreover, it suggests there is a small likelihood that patients' beliefs about their overall sleep quality are actually hiding accurate assessments that cannot be captured by objective instruments alone. The full cross-sectional regression results from the two clinical visits may be explored in full in Appendix A.

Multicollinearity and Omitted Variable Bias

Given the nature of the data explored, we test the degree of multicollinearity among the explanatory variables to ensure the standard errors of the coefficients are not inflated. Using the variance inflation factor (VIF), we classify a variable with a VIF higher than 10 or tolerance value lower than 0.1 to have an acceptable degree of collinearity. Table 8 below shows the results for both Visit 1 and Visit 2. We do not find sufficient evidence of multicollinearity among the explanatory variables in either case, as well as a surprising among of consistency among the results.

Table 8. Multicollinearity Test

	Visit 1				Visit 2			
Variable	VIF	SQRT VIF	Tolerance	R-Squared	VIF	SQRT VIF	Tolerance	R-Squared
Age	1.36	1.17	0.7351	0.2649	1.53	1.24	0.6515	0.3485
White	1.46	1.21	0.6830	0.3170	1.48	1.22	0.6748	0.3252
Other	1.46	1.21	0.6863	0.3137	1.46	1.21	0.6837	0.3163
Male	1.15	1.07	0.8727	0.1273	1.14	1.07	0.8796	0.1204
liteduc	2.57	1.60	0.3886	0.6114	2.25	1.50	0.4453	0.5547
mededuc	6.30	2.51	0.1588	0.8412	5.68	2.38	0.1759	0.8241
higheduc	5.93	2.44	0.1686	0.8314	5.36	2.31	0.1867	0.8133
smoker	1.06	1.03	0.9478	0.0522	1.08	1.04	0.9256	0.0744
BMI	1.18	1.08	0.8502	0.1498	1.19	1.09	0.8393	0.1607
restfulness	1.64	1.28	0.6087	0.3913	1.53	1.24	0.6547	0.3453
sleepiness	1.05	1.03	0.9505	0.0495	1.05	1.02	0.9562	0.0438
wake time	1.24	1.11	0.8055	0.1945	1.35	1.16	0.7421	0.2579
AHI	1.72	1.31	0.5803	0.4197	1.69	1.30	0.5910	0.4090
arousal	1.60	1.26	0.6268	0.3732	1.68	1.30	0.5950	0.4050
blood pres	1.10	1.05	0.9081	0.0919	1.15	1.07	0.8715	0.1285
stroke	1.02	1.01	0.9822	0.0178	1.05	1.02	0.9569	0.0431
caffeine	1.03	1.01	0.9738	0.0262	1.05	1.02	0.9554	0.0446
sleep qual	1.61	1.27	0.6217	0.3783	1.52	1.23	0.6585	0.3415
REM slp	1.04	1.02	0.9578	0.0422	1.06	1.03	0.9436	0.0564
Mean VIF	**1.87**				**Mean VIF**	**1.80**		

The issue of heteroskedasticity is addressed through the use of robust standard errors to reduce the influence of outlying cases and improve the overall fit of the models.

To explore the possibility of omitted variable bias, we construct the Ramsey test for the regressions, with the null hypothesis of no omitted variables. As Table 9 below shows, both cross-sectional results conclude the models contain omitted variables, a common issue among sleep clinical studies (Kaplan et al. 2017). Future studies would require additional explorations of better fit models, as well as conducting polysomnography studies collecting the most up to date explanatory variables conducive to research.

Table 9. Omitted Variables Test

```
Ramsey RESET test for omitted variables
Omitted: Powers of fitted values of slpprdp

H0: Model has no omitted variables

F(3, 4538) =    7.91
  Prob > F = 0.0000
```

```
Ramsey RESET test for omitted variables
Omitted: Powers of fitted values of slpprdp

H0: Model has no omitted variables

F(3, 2154) =    8.55
  Prob > F = 0.0000
```

First difference results

The limitations pertaining to the Visit 2 dataset will carry over to the two period panel data. Nevertheless, the previous stroke dummy variable has a p-value of 0.04 and shows an even more negative effect on objective sleep quality than the analysis for Visit 1 suggested. The result suggests that patients who did not suffer a heart attack prior to their first clinical visit, but later did have a stroke before the second clinical visit lost approximately 18.2 minutes of sleep between the two periods. This points towards a significant degree of sleep deterioration that cannot be purely explained by natural physical deterioration.

As expected, additional measurements of objective sleep quality align with the medical literature, showing strong significance in the case of breathing patterns, REM sleep latency, and time awake during the sleep period. A one minute change in time awake during sleep between the two visits appears to a 0.25 minute change in sleep time. Changes in arousal index and REM sleep latency also appear to lead to a 0.77 minute reduction and 0.12 minute increase, a much smaller impact than our variable of interest. However, behavioral characteristics such as caffeine intake prior to the night's sleep showed a negative, but statistically insignificant result. One possible explanation may be related to the already built-in deficiencies of prior choices made over a long range of years. As a result, if drinking caffeinated beverages close to sleep time used to be a common behavior, but the individual chose to change their behavior, the deterioration already caused would continue to persist regardless.

Interestingly, subjective assessments on quality of sleep also show statistical insignificance, which adds further proof to existing studies analyzing the link between subjective and objective sleep assessments (Van Den Berg et al. 2008). The only variable of interest is the next morning subjective rating, which shows that patients who rated their quality of sleep as improving by one additional unit of measurements see an improvement in objective sleep time by 17.9 minutes. The full regression results are shown in Table 10 below:

Table 10: First difference results

Variable	Coefficient (t-stat)
Age	1.862 (0.61)
Body Mass Index	-1.517* (-2.11)
Epworth Sleepiness Scale	-0.876 (-1.71)
Time Awake	-0.252*** (-7.57)
Apnea-Hypopnea Index	0.385* (2.51)
Arousal Index	-0.772*** (-3.51)
Blood Pressure	-0.0486 (-0.58)
Previous Stroke	***-18.24**** ***(-2.05)***
Caffeine Intake	-6.051 (-1.68)
Subjective Quality of Sleep	17.88*** (12.66)
REM Sleep Latency	0.118*** (3.61)
Constant Term	0.528 (0.03)
Obs	1953

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Economic Cost Approximations

To assess general costs associated with sleep loss, we use the framework of Hafner et al. (2016) outlined in the literature review section with regards to US lost total working time and distribution of working adults into sleep time categories. Due to the low natural rate of occurrence of strokes, there was a sample of six eligible participants who suffered a stroke between the two clinical visits. Of the six participants, one displayed a decline in total objective sleep from 6-7 hours to less than 6 hours, and one participant showed a decline from 7-8 hours to 6-7 hours. The remaining participants stayed within the same sleep range. However, using the results from Visit 1 cross-sectional data for working age participants reveals a total of four participants who, when applying the 11.7 minutes sleep loss, would factor into a less than 6 hour sleep category, and 3 participants who fall into the less than 7 hours category out of a total of 45 individuals. Translated into the methodology presented by Hafner et al. (2016), this results in a 0.8% share of working adults contributing to productivity losses of approximately 4147 days lost annually and another 0.4% share of working adult contributing to productivity losses of approximately 1883 days lost annually from incurred heart conditions. This would result in a total of 6030 days lost annually.

Conclusion

The analysis conducted in this paper found that preexisting heart conditions displayed through instances of previous strokes have a significant impact on individual objective sleep quality. The overall impact is seen through both multivariate comparisons of sleep patterns between individuals enrolled in the Sleep heart Health Study and the differences occurring across two time periods. In addition, variations in sleep quality between the two clinical visits are used to show an approximate 6030 work days lost annually in the United States from 1.2% share of working adults using the framework presented in Hafner et al. (2016). The construction of this paper's cross-sectional models reinforces the results on the significance of demographic characteristics documented in Redline et al. (2005) with regards to polysomnographic measurements, the importance of introducing a behavioral element to estimations akin to Unruh et al. (2008), as well as the consistent discrepancies between objective and subjective sleep quality highlighted in Kaplan et al. (2017).

The results presented in this paper further highlight the need to address important hurdles still faced in today's recording of sleep-related economic and clinical studies. With regards to the recording of company level losses in productivity, the so far overreliance on subjective sleep data is likely to continue to affect data accuracy. Instead, researchers should strive to incorporate polysomnographic or actigraphic sleep monitoring over extended periods of time. The Sleep Heart Health Study demonstrated the importance of collecting patient information across multiple time periods across multiple years rather than several days or weeks. Such data would be far more conducive for time series analysis and machine learning algorithms. The predictive power of these models would likely not only provide additional insight into the nature of sleep, but also aid medical professionals in providing adequate medical care to patients suffering from sleep-related deficiencies. This outcome would further lead to healthcare personalization, an achievement with many economic and overall societal benefits.

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Vpr2108

Appendix A

Cross-sectional Regression Results for Visit 1

```
Linear regression                               Number of obs     =      4,561
                                                F(19, 4541)       =      87.51
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2597
                                                Root MSE          =     54.017
```

slpprdp	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age	-.4074951	.0910521	-4.48	0.000	-.5860016	-.2289887
White	16.31814	3.755651	4.34	0.000	8.955236	23.68104
Other	11.2054	6.220542	1.80	0.072	-.9898892	23.40069
Male	-8.954625	1.706533	-5.25	0.000	-12.30026	-5.608989
liteduc	4.428321	4.908134	0.90	0.367	-5.19401	14.05065
mededuc	3.48995	3.809515	0.92	0.360	-3.978553	10.95845
higheduc	.3011563	3.824424	0.08	0.937	-7.196576	7.798889
currentsmoker	-11.24857	2.926539	-3.84	0.000	-16.98601	-5.511134
bmi_s1	-.6618747	.1829948	-3.62	0.000	-1.020634	-.3031157
rest10	-3.474551	.9469732	-3.67	0.000	-5.331079	-1.618023
ess_s1	-.1396708	.1921041	-0.73	0.467	-.5162884	.2369468
waso	-.447387	.0213997	-20.91	0.000	-.4893408	-.4054332
ahi_a0h3	.0672157	.0705435	0.95	0.341	-.0710838	.2055153
ai_all	-.2268954	.1006854	-2.25	0.024	-.4242878	-.029503
nsrr_bp_systolic	-.2825822	.0440774	-6.41	0.000	-.3689953	-.196169
stroke_dummy	-11.75066	5.424318	-2.17	0.030	-22.38496	-1.116356
coffee10	-4.748172	2.177025	-2.18	0.029	-9.0162	-.4801433
shlg10	17.49074	1.057665	16.54	0.000	15.4172	19.56428
remlaiip	.1072681	.0192586	5.57	0.000	.0695117	.1450244
_cons	410.5176	10.5751	38.82	0.000	389.7852	431.2499

Cross-sectional Regression Results for Visit 2

```
Linear regression                               Number of obs     =      2,177
                                                F(19, 2157)       =      39.50
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2719
                                                Root MSE          =     57.042
```

slpprdp	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Age	-1.08553	.1542342	-7.04	0.000	-1.387994	-.7830672
White	2.134767	7.519405	0.28	0.777	-12.61127	16.8808
Other	-3.151023	11.67928	-0.27	0.787	-26.05484	19.75279
Male	-12.96279	2.608463	-4.97	0.000	-18.07816	-7.84743
liteduc	-1.491322	7.23691	-0.21	0.837	-15.68337	12.70072
mededuc	-2.381999	4.796772	-0.50	0.620	-11.78878	7.024779
higheduc	-4.164591	4.883152	-0.85	0.394	-13.74077	5.411585
currentsmoker	-20.15828	4.989793	-4.04	0.000	-29.94358	-10.37297
bmi_s1	-.5688122	.2703536	-2.10	0.035	-1.098993	-.0386314
rest10	-1.439538	1.431936	-1.01	0.315	-4.247656	1.368581
ess_s1	-.5932349	.3123843	-1.90	0.058	-1.205841	.0193709
waso	-.3174363	.0289973	-10.95	0.000	-.3743019	-.2605707
ahi_a0h3	.1014714	.1070493	0.95	0.343	-.1084591	.3114019
ai_all	-.3169612	.1767084	-1.79	0.073	-.6634977	.0295753
nsrr_bp_systolic	-.0977622	.0782984	-1.25	0.212	-.2513104	.0557861
stroke_dummy	-3.574372	6.591516	-0.54	0.588	-16.50076	9.352014
coffee10	-2.024318	3.631101	-0.56	0.577	-9.145141	5.096506
shlg10	19.18697	1.719956	11.16	0.000	15.81403	22.55992
remlaiip	.1625495	.0307436	5.29	0.000	.1022593	.2228398
_cons	452.2291	17.75543	25.47	0.000	417.4095	487.0486

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