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Sleep and Student Achievement

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We explore the relationship between sleep and student performance on standardized tests. We model test scores as a nonlinear function of sleep, which allows us to compute the hours of sleep associated with maximum test scores. We refer to this as "optimal" hours of sleep. We also evaluate how the sleep and student performance relationship changes with age. We use the Panel Study of Income Dynamics-Child Development Supplement, which includes excellent control variables that are not usually available in sleep studies. We find a statistically significant relationship between sleep and test scores. We also find that optimal hours of sleep decline with age.
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INTRODUCTION

The topic of sleep has received relatively little attention in economics despite the fact that nearly a third of a person's life is spent in slumber. Research done outside of economics suggests that quantity and quality of sleep can have major impacts on the development of human and health capital. For example, sleep disorders have been found to affect absenteeism, productivity, and injury rates among adults [Hillman et al. 2006]. In this paper, we focus on the relation between the amount of sleep adolescents receive and their performance on standardized tests. We allow for a nonlinear relation between sleep and test scores, and thus we are able to estimate the "optimal" hours of sleep that maximize student test score performance.

There has been substantial work done outside of economics on how academic performance is affected by sleep, especially for children and teens. Wolfson and Carskadon [2003] is an excellent summary of the medical research in this area. One group of papers they review examines sleep-wake patterns and grades. They note that a cause and effect relationship has not been established, but that some patterns do emerge when considering these studies collectively. They find that self-reported sleep quantity, delayed and/or erratic sleep schedules, late weekend rise times, and daytime sleepiness are associated with poor school performance for children and adolescents.

Another group of papers reviewed by Wolfson and Carskadon compare academic performance for early *vs* later starting schools, and for students who are "larks" (morning-type phase preference) *vs* "owls" (evening-type phase preference). These studies suggest that self-reported "owls," delayed sleep schedules, and early school start times may be associated with daytime sleepiness, dozing in class, attention difficulties, and poorer academic performance. Wolfson and Carskadon urge caution in interpreting these findings because of differences in the details of these studies, particularly in the measurement of sleep and academic performance and in the omitted factors.

Taras and Potts-Datema [2005] also review several studies on the relation between sleep and student performance. Many of the studies focus on how sleep disorders and habits among adolescents are correlated with educational outcomes. For example, studies find that sleep-related obstructive breathing is associated with reduced attention, memory, intelligence, and increased problematic behavior. The studies also show improvement in academic performance among children with disordered breathing problems after corrective measures are taken.

While few studies in economics examine the relation between sleep and student performance, two recent studies take on this issue, both from the perspective of school start times. Carrell et al. [2011] identify the causal effect of school start time on academic achievement by using two policy changes in the daily schedule at the US Air Force Academy along with the randomized placement of freshman students to courses and instructors. Results show that starting the school day 50 minutes later has a significant positive effect on student achievement, which is roughly equivalent to raising teacher quality by 1 standard deviation. Hinrichs [2011] studies whether moving school start times later in the morning improves academic performance. He first focuses on the Twin Cities metropolitan area, where Minneapolis and several suburban districts have made large policy changes, but St. Paul and other suburban districts have maintained early schedules. He uses individual-level ACT test score data on all individuals from public high schools in this region who took the ACT between 1993 and 2002 to estimate the effects of school starting times on ACT scores. He then employs school-level data on starting times and test scores on statewide standardized tests from Kansas and Virginia in order to estimate the effects of school start times on achievement for a broader sample of students. The results do not suggest an effect of school starting times on achievement.

The causes of sleeplessness among children and teenagers can come from a variety of sources, both behavioral and physiological, which are described in Mitru et al. [2002]. Parental involvement in setting sleep and wake times can be important for establishing sleep patterns among younger children. Older children and teens often have more control over their sleep schedule, and are more likely to engage in unsupervised night time activities than younger children. Older students may stay up later doing homework and wake up earlier for school. Many teenagers work part-time after school, which may push back bedtime as they stay up later in order to complete homework, socialize with friends and family, or relax. Some children suffer from sleep-disordered breathing such as sleep apnea and respiratory disturbances such as asthma, which can also cause sleep problems.

How sleep affects the development of human capital for elementary and secondary students is a complex and fascinating topic. This research question fits into a broader emerging area of research in economics, which examines the connection between health and education outcomes. The early theoretical work in this area was put forth by Grossman [1972], with more recent contributions to theory provided by Becker [2007]. The empirical research estimating the relation between education and health is rapidly growing. Eide and Showalter [2011] provide a review of recent research examining how education may affect health outcomes, and vice versa.

In this paper, we explore the relationship between sleep and student performance for youth ages 10 through 19, with a focus on estimating the optimal hours of sleep that maximize test score performance. We rely on the well-developed theoretical link between health, human capital, and productivity and assume that sleep affects health. We use standardized math and reading test scores as our measure of human capital. Our regression approach uses a quadratic term in sleep, interacted with age, which then allows us to determine age-adjusted optimal sleep hours. This contrasts sharply with the bulk of previous work, which assumes a simple linear relationship between sleep and test scores.

We also use nationally representative data — the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID) — which contrast with previous work that typically uses information from individual schools and districts, and is often based on small sample sizes. The CDS/PSID data also includes a rich set of socioeconomic variables for the household and the child that allows us to control for confounding variables; these variables have often been unavailable in previous research on sleep. Much of the work examining the relation between sleep and student performance is based on data from controlled environments, for example when a child's sleep is regulated or restricted in some way in order to examine how performance changes under different sleep conditions [Sadeh et al. 2003]. The few papers that use regression analysis use outcomes such as grades, tardiness, or problem behavior. Our regression approach of modeling standardized test scores as a nonlinear function of sleep based on a large sample adds new evidence to the body of knowledge on the relation between academic performance and sleep.

Key to our paper is the idea of optimal sleep. The way in which we think about this idea is based on how much sleep a student needs to maximize test score performance. The medical literature has conceptualized optimal sleep in a different way [Carskadon et al. 1980; Sadeh et al. 2003]. The seminal research characterizing optimal sleep from a medical perspective comes mainly from a longitudinal study completed at the Stanford University sleep camp during the 1970s [Carskadon et al. 1980]. The participants enrolled at 10–12 years of age and their sleep was monitored every year for 5–6 years. Researchers found that regardless of age, when adolescents were allowed to control the amount of sleep they obtained between 10 p.m. and 8 a.m., all children slept about 9.25 hours. Hence, 9.25 is the generally accepted hours of sleep that is considered optimal for adolescents, and which is cited in sleep policy recommendations [National Sleep Foundation 2000].

Our results show a statistically significant and relatively large effect of sleep on test scores, with the quadratic results suggesting negative effects on test scores beyond the optimal level. Results are similar across the four academic tests administered in the CDS. Optimal hours decline with age and tend to be lower than the 9.25 hours, which is suggested by medical research and which is promoted in sleep policy guidelines.

DATA

The data for this study come from the CDS of the PSID, administered by the Survey Research Center at the University of Michigan (http://psidonline.isr.umich.edu/). The CDS is a nationally representative sample added to the PSID to explore sociodemographic, psychological, and economic aspects of childhood. We use the second wave, CDS-II, that interviewed 2,019 families in 2002–2003, providing data on 2,907 children and adolescents aged 5–19. These data were designed to collect information concerning the development of human capital in children and adolescents and contain a rich set of variables for both the child and the family.

The outcomes of interest are math and reading scores from the Woodcock-Johnson Psycho-Educational Battery-Revised test (WJ-R). These scores are commonly used measures of learning. The CDS includes results from three subtests from the WJ-R: the Letter-Word, the Passage Comprehension, and the Applied Problems (math) tests. We also use a combined score, Broad Reading, which combines the Letter-Word and Passage Comprehension tests. We report results using the CDS-provided age-adjusted scoring and normalize for our sample. This normalization provides an easy interpretation for the regression output [Woodcock and Johnson 1989]. The age restriction lowers the sample to 1,724 observations.

The sleep variable, which is our primary variable of interest, is a self-reported answer to the question: "How many hours of sleep do you usually get a night?" asked of respondents age 10 and older.[1] Unfortunately, the questionnaire did not specify weekday *vs* weekend sleep. But the preceding question answered by the student is "What time do you usually go to bed on weeknights?" which likely framed the question in a way to answer it as if it were a weekday [Converse and Presser 1993]. Research on the accuracy of survey questions suggests that measurements for adolescents closely match more objective methodologies (actigraphy or polysomnography) for weekday measurements [Wolfson et al. 2003]. We drop outliers whose reported typical hours are <4 or >12 (33 observations are dropped due to this restriction). As seen in Table 1, average hours of sleep is 7.98 hours with a standard deviation of 1.45 hours. Table 2 looks more specifically at the distribution of sleep by age group. Average hours of sleep decreases from 8.84 hours for 10–11-year-olds down to 7.35 hours for 16–18-year-olds. Figure 1 shows the distribution of sleep hours by age groups.[2] There is a clear shift to lower hours of sleep as age increases.

The PSID/CDS has an unusually rich set of socioeconomic variables that are often unavailable for sleep research. Research in the social sciences, and in particular

Table 1 Descriptive statistics

Variable	*Observation*	*Mean*	*Standard Deviation*	*Min*	*Max*
Test scores (normalized)					
Letter-Word	1,678	0.00	1.00	−3.48	4.16
Passage Comprehension	1,671	0.00	1.00	−4.58	5.54
Broad Reading	1,668	0.00	1.00	−4.04	5.14
Applied Problems	1,674	0.00	1.00	−3.28	4.27
Youth demographics					
Hours of sleep	1,691	7.98	1.45	4	12
Age	1,691	14.31	2.55	10	19.3
Female	1,691	0.51	0.50	0	1
Race/ethnicity					
Black	1,691	0.42	0.49	0	1
Hispanic	1,691	0.07	0.25	0	1
Asian/Pacific	1,691	0.01	0.11	0	1
Other	1,691	0.04	0.19	0	1
Family background					
Income (US$1000s)	1,682	67.69	92.51	1.2	1,366
Education of head of household (years)	1,583	13.00	2.69	0	17
Cognitive ability of caregiver	1,381	0.00	1.00	−4.9	2.2
Region					
North Central	1,691	0.14	0.35	0	1
South	1,691	0.24	0.43	0	1
West	1,691	0.44	0.50	0	1

Table 2 Descriptive statistics of hours of sleep by age

Age group	*N*	*Mean*	*Standard Deviation*	*Percentiles*				
				10th	*25th*	*Median*	*75th*	*90th*
10–11	409	8.84	1.34	7	8	9	10	10
12–13	369	8.25	1.36	6.5	7.5	8.5	9	10
14–15	387	7.68	1.33	6	7	8	8.5	9
16–18	524	7.35	1.29	6	6.5	7	8	9

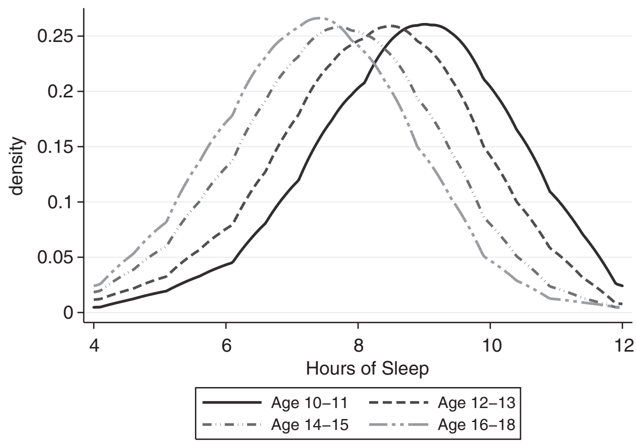

Figure 1. Distribution of sleep by age.

the economics of education, has consistently demonstrated the importance of family background and socioeconomic status in affecting student achievement [Reardon and Robinson 2008]. Studies implementing the "education production function" approach to explaining variations in student achievement have been careful to include as rich a set of variables related to these factors as possible [Brewer et al. 2008]. The control variables used in our study are standard and widely accepted in the economics of education literature, although they are less frequently available in sleep studies. We include variables for family income and education level of the head of household to control for financial resources available in the home, and the extent to which education is emphasized and supported. Test scores have been shown to vary by gender and race/ethnicity, and thus we control for those factors as well with dummy variables. We include age because educational progression is a function of age, and we also use this variable to examine variations in the sleep-test score relationship at different ages. Per pupil spending and education systems can vary across the country, and thus we control for the region of the country where the child lives.

To be included in the regression, each child must have non-missing data on the test score and the sleep variable. Some of the control variables have missing values for some observations (family income, education level, and state of residence). Rather than delete those observations entirely, we use multiple imputation to generate estimated values. The descriptive statistics for all variables are given in Table 1.

METHODS AND RESULTS

The regression results are given in Table 3, with each of the four tests listed in a separate column. We experiment with a variety of regression specifications. Given work from previous research, we expect that sleep patterns would vary with age [Carskadon et al. 1980; Wolfson and Carskadon 1998]. We also want to test for an optimal amount of sleep, motivated by the notion that test scores might be lowered by too much or too little sleep. The simplest regression structure that accomplishes these two goals is a specification with hours of sleep and its square, interacted with age, which allows for variation in sleep pattern by age. This is the specification that we report. We use standard errors that account for heteroskedasticity and clustering at the family level in all regressions and statistical tests.[3]

With this statistical specification, the appropriate way to measure the effect of sleep on test scores is to evaluate all four coefficients jointly — sleep, sleep-squared, sleep∗age, and sleep-squared∗age. In all four regressions, the joint test of significance on the four variables is statistically significant at the 1 percent level. Importantly, the squared terms — sleep-squared and sleep-squared∗age — are also statistically important (at least one of the two is statistically significant) suggesting that the effect of sleep has a nonlinear pattern. The coefficient on sleep is statistically significant in all four regressions and of roughly the same magnitude, ranging from 0.285 for the Letter-Word test up to 0.593 for the Applied Problems test.[4]

Optimal sleep

One interesting aspect of this data and empirical specification is that it allows us to estimate an age-specific optimal amount of sleep — the level of sleep that results in the highest value of the predicted test score, conditioning on other observable characteristics.[5] Estimated optimal hours of sleep for each test for ages 12 and 16 are given at the bottom of the table, with the associated standard errors. The estimated optimums are quite similar across the four tests. Optimal hours of sleep for 12-year-olds is estimated to be 8.34 hours on the Letter-Word test, 8.34 hours with the Passage Comprehension test, 8.43 hours for the Broad Reading test, and 8.38 hours for the Applied Problems test. The estimated optimums for 16-year-olds are substantially lower, ranging from 7.02 to 7.35 hours. These estimates are lower than the 9.25 hours that is typically recommended in sleep policy guidelines.

In Figure 2, we plot the implied optimal amount of sleep and how it varies by age, given the coefficient estimates from Table 3. Two consistent patterns arise. First is that optimal sleep declines substantially by age: optimal sleep for 10-year-olds is about 9.0–9.5 hours, while for 18-year-olds it is slightly under 7 hours. The second pattern is that there is higher variation in the estimate for younger children: the estimated standard error for 10-year-olds' optimal sleep is about 0.6, while it is about 0.3 for 18-year-olds.[6]

We next compute the implications on predicted test score of moving away from the optimal number of hours of sleep. For students age 12, a 1 hour deviation from the optimum (about 7.3 hours on the low side and 9.3 hours on the high side) implies predicted test scores that average 0.035 standard deviations lower across the four tests. For students age 16, scores average 0.045 standard deviations lower for a 1 hour deviation. To put this in perspective, using the regression estimate of 0.152 from the Letter-Word test for the marginal effect of household income, it

Table 3 Regression results

Variable	*Letter-Word*	*Passage Comprehension*	*Broad Reading*	*Applied Problems*
Hours of sleep	0.285**	0.408***	0.347**	0.593***
	(0.138)	(0.145)	(0.135)	(0.119)
Sleep squared	0.00453	−0.00428	0.00303	−0.0190*
	(0.0117)	(0.0119)	(0.0114)	(0.0107)
Sleep∗age	0.0222***	0.0129*	0.0205***	0.00384
	(0.00705)	(0.00729)	(0.00719)	(0.00640)
Sleep squared∗age	−0.00313***	−0.00245***	−0.00318***	−0.00159**
	(0.000827)	(0.000856)	(0.000847)	(0.000748)
Youth demographics				
Female	0.154***	0.151***	0.168***	−0.111***
	(0.0448)	(0.0456)	(0.0446)	(0.0420)
Race/ethnicity				
Black	−0.465***	−0.490***	−0.526***	−0.671***
	(0.0657)	(0.0634)	(0.0650)	(0.0569)
Hispanic	−0.129	−0.294***	−0.207**	−0.240**
	(0.0978)	(0.0978)	(0.0980)	(0.0993)
Asian/Pacific	0.182	−0.0958	0.0517	0.358
	(0.245)	(0.180)	(0.196)	(0.228)
Other	−0.183	−0.250	−0.217	−0.451***
	(0.161)	(0.173)	(0.172)	(0.142)
Family background				
Income (log(US$1000s))	0.152***	0.137***	0.161***	0.144***
	(0.0303)	(0.0371)	(0.0324)	(0.0308)
Education of head of household (years)	0.0646***	0.0706***	0.0740***	0.0660***
	(0.0110)	(0.0109)	(0.0108)	(0.0110)
Region				
North Central	0.00368	0.120	0.0572	0.177**
	(0.0785)	(0.0754)	(0.0772)	(0.0828)
South	−0.0157	0.0741	0.0298	0.0692
	(0.0753)	(0.0744)	(0.0742)	(0.0727)
West	0.165**	0.127*	0.175**	0.105
	(0.0757)	(0.0740)	(0.0764)	(0.0704)
Constant	−3.543***	−3.533***	−3.851***	−3.562***
	(0.538)	(0.583)	(0.554)	(0.429)
N	1,678	1,671	1,668	1,674
R^2	0.18	0.22	0.24	0.30
Adjusted R^2	0.18	0.21	0.23	0.29
Optimum hours of sleep: age 12	8.34	8.34	8.43	8.38
	(0.29)	(0.31)	(0.29)	(0.24)
Optimum hours of sleep: age 16	7.02	7.06	7.05	7.35
	(0.26)	(0.28)	(0.24)	(0.21)

Notes: *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Values in parentheses are standard errors that have been corrected for heteroskedasticity and clustering at the family level. Missing values for income, education, and region were accounted for by multiple imputation and the R^2 and adjusted R^2 numbers are the average from the imputations.

would require a decrease in household income from US$48,200 (the sample median household income) to US$38,291 to generate a similar 0.035 decline for 12-year-olds; for 16-year-olds, it is comparable to an income decrease to US$35,771. When

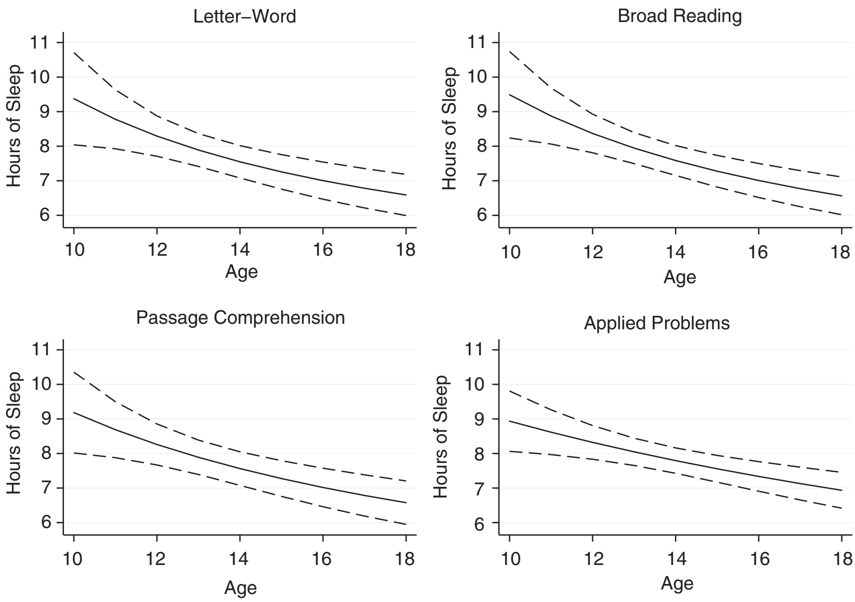

Figure 2. Optimal sleep by age for various tests.
Note: Estimates based on regression coefficients from Table 3. Dashed lines represent 95 percent confidence intervals.

compared with parental (head-of-household) education levels, a 1 hour deviation is equivalent to 50–65 percent of a year of parental schooling.

Nonparametric effects of sleep

Although parsimonious, the quadratic measure of sleep could be missing important nonlinearities. The simplest test is to use dummy variables for different intervals of sleep. We break sleep into eight categories, each 1 hour wide except for the two tails, <5 hours and >11 hours. We run the regression using <5 hours as the omitted category. The results are given in Table 4. It is somewhat easier to see the pattern graphically. Figure 3 shows the results for the four exams. Each of the regressions reveals an inverted U pattern consistent with our findings using the quadratic specification.[7]

We also experiment with estimating the effects by age group. We divide the sample into 3-year age intervals: 10–12, 13–15, and 16–18, and run the regressions for each group separately. Table 5 gives the sleep coefficients and the estimated optimal hours of sleep. We see a consistent decline in the optimal hours of sleep as age increases.

Other variables

Looking at the control variables and other regression statistics, we have the following: the sample size ranges from 1,668 for the Broad Reading test up to 1,678 for the Letter-Word test. The goodness-of-fit measure, R^2, is 0.18 for the Letter-Word test, 0.22 and 0.24 for the Passage Comprehension and Broad Reading, respectively, and 0.30 for the Applied Problems test. The effect of being female raises

Table 4 Regression results using categories for age

Sleep coefficients	*Letter-Word*	*Passage Comprehension*	*Broad Reading*	*Applied Problems*
5–5.99 hours	0.760***	0.860***	0.883***	0.617***
	(0.206)	(0.223)	(0.205)	(0.180)
6–6.99 hours	0.966***	0.966***	1.047***	0.786***
	(0.172)	(0.193)	(0.180)	(0.156)
7–7.99 hours	0.836***	0.897***	0.935***	0.841***
	(0.163)	(0.188)	(0.173)	(0.153)
8–8.99 hours	0.770***	0.827***	0.864***	0.702***
	(0.161)	(0.187)	(0.172)	(0.150)
9–9.99 hours	0.694***	0.761***	0.797***	0.686***
	(0.165)	(0.189)	(0.175)	(0.154)
10–10.99 hours	0.689***	0.719***	0.788***	0.612***
	(0.171)	(0.193)	(0.180)	(0.160)
11 or more hours	0.578***	0.667***	0.672***	0.521***
	(0.208)	(0.240)	(0.224)	(0.189)

Notes: *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Values in parentheses are standard errors that have been corrected for heteroskedasticity and clustering at the family level. Missing values for income, education, and region were accounted for by multiple imputation and the R^2 and adjusted R^2 numbers are the average from the imputations. Also included in the regressions were the variables listed in Table 3: age, gender, race/ethnicity, family income, education of head of household, region, and a constant.

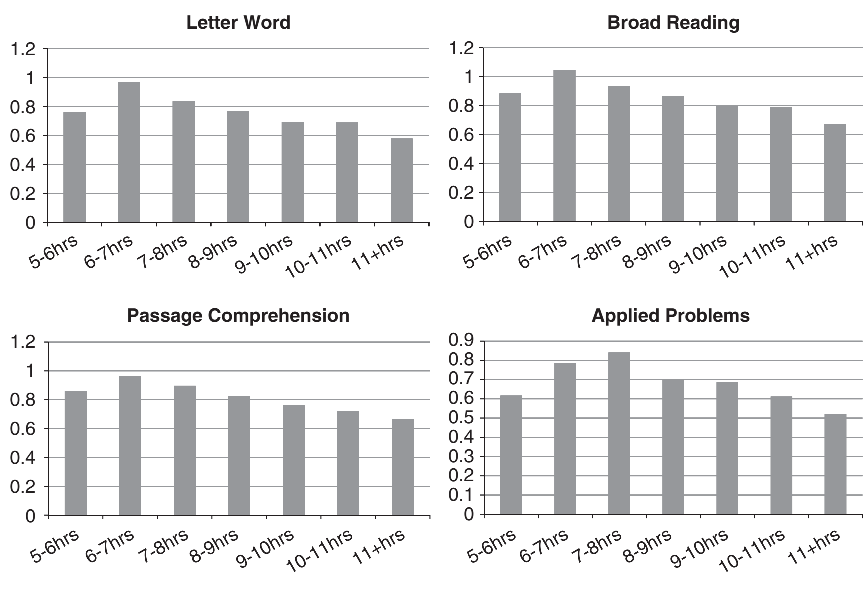

Figure 3. Nonparametric estimates of sleep coefficients.

test scores for the three verbal tests and lowers it for the math test and is statistically significant at the 1 percent level in all four tests. The black coefficient is negative for all four tests and all are statistically significant. Results for other race/ethnicity variables are mixed: the only statistically significant results are for Hispanics (negative coefficients for Passage Comprehension and Applied Problems) and Asian/Pacific for Applied Problems (positive).

Table 5 Regressions by age group

Variable	*Letter-Word*			*Passage Comprehension*		
	Ages 10–12	*Ages 13–15*	*Ages 16–18*	*Ages 10–12*	*Ages 13–15*	*Ages 16–18*
Hours of sleep	0.459**	0.631***	0.493**	0.376*	0.714***	0.443*
	(0.202)	(0.202)	(0.248)	(0.217)	(0.268)	(0.244)
Sleep squared	−0.0276**	−0.0396***	−0.0382**	−0.0224*	−0.0444**	−0.0352**
	(0.0122)	(0.0130)	(0.0163)	(0.0130)	(0.0174)	(0.0158)
Optimum hours	8.33	7.95	6.45	8.39	8.04	6.31
	(0.45)	(0.38)	(0.67)	(0.65)	(0.38)	(0.78)
N	591	562	523	589	559	521
	Broad Reading			*Applied Problems*		
Hours of sleep	0.457**	0.673***	0.527**	0.445**	0.822***	0.547***
	(0.209)	(0.226)	(0.243)	(0.199)	(0.192)	(0.180)
Sleep squared	−0.0270**	−0.0420***	−0.0408**	−0.0256**	−0.0532***	−0.0380***
	(0.0126)	(0.0145)	(0.0161)	(0.0118)	(0.0124)	(0.0119)
Optimum hours	8.46	8.01	6.47	8.71	7.72	7.20
	(0.52)	(0.37)	(0.59)	(0.50)	(0.25)	(0.38)
N	586	559	521	591	561	520

Notes: *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Values in parentheses are standard errors that have been corrected for heteroskedasticity and clustering at the family level. Missing values for income, education, and region were accounted for by multiple imputation and the R^2 and adjusted R^2 numbers are the average from the imputations. Also included in the regressions were the variables listed in Table 3: age, gender, race/ethnicity, family income, education of head of household, region, and a constant.

The family background variables also have strong explanatory power. Income and education of the head of household both have positive and statistically significant effects across all four tests.

LIMITATIONS

Our study is subject to some limitations and caveats. The first issue concerns the non-experimental nature of our data. Because our data were not generated by a controlled experiment, we cannot rule out the possibility that we are measuring a correlation between sleep and test scores rather than a causal relation. However, our results do run counter to some likely alternative explanations. For example, one possible non-causal explanation of our results is that unmeasured innate ability is positively correlated with test scores and negatively correlated with sleep. If innate ability should be in the regression, but is not, then sleep and test scores will exhibit an empirical correlation even if sleep has no causal effect on test scores. But such a story would imply a linear association between sleep and test scores, not the quadratic relationship that actually exists [Wooldridge 2008]. We therefore view this simple alternative explanation with some skepticism.

A second issue also relates to the non-experimental nature of the data. Other studies examining school performance and sleep have used school- and district-level data. These studies generally evaluate the effect of school start times on student performance [Mitru et al. 2002]. Such localized studies by their nature are able to control for factors that we cannot — school and neighborhood attributes — but in turn it is unclear how generalizable their results are. We view our work as complementary to school- and district-level studies. With our nationally representative sample, we implicitly account for a wide variety of school and neighborhood attributes and are able to assess the effects of sleep that are statistically independent of the localized effects possibly contained in the school and district studies.

A third issue is the possibility of measurement error: we use a self-reported measure of "typical" sleep, which might differ from actual sleeping patterns. Under classical measurement error, this would tend to bias our sleep coefficients toward zero, which does not seem to be a problem with our results. However, it is unclear how non-classical measurement error would bias the outcomes, and thus this possibility should be noted in interpreting the results.

A final concern is that our outcome measure is too narrowly defined. Our estimates suggest somewhat less sleep is optimal than what is recommended from the medical research, especially for older teens. But our estimates do not account for overall health and well-being. It is certainly possible that accounting for things other than test scores would suggest higher levels of sleep than what our estimates imply. But as noted in the introduction, the most frequently cited estimates of the amount of sleep that children and adolescents "ought" to get are probably best interpreted as estimates of the amount of sleep that would be obtained without outside stimuli or rewards. It is not clear to us that such recommendations are a good benchmark when sleeping has an opportunity cost in terms of productivity or study time.

CONCLUSION

Our paper contributes to the literature in a number of ways. In contrast to the previous literature that presumes a linear or threshold effect for sleep, we allow for the possibility that too much sleep might reduce test scores. Our nonlinear framework allows us to compute an optimal hours of sleep for test score performance that varies by age. We also have the advantage of a large and nationally representative data source with excellent control variables. Together, these contributions help to fill a gap in the literature on sleep and academic performance.

In summary, our results show a statistically significant relationship between sleep and test scores using nationally representative data on students ages 10 through 19. We are able to statistically determine age-adjusted sleep patterns that are associated with maximum test scores. To the extent that test scores represent the acquisition of human capital in the form of skills and knowledge and are correlated with long run outcomes such as college attendance and labor market success, our results shed light on how non-optimal amounts of sleep during adolescence can have lifelong implications.

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Notes

1. We experimented with using the CDS time diary data in order to check the robustness of the relation between sleep and academic achievement with a second sleep measure, and one that separates sleep into weekday and weekend sleep. A complication with the time diary data is that it includes time spent in bed but not asleep, and therefore the time diary measure overestimates sleep time. The regression estimates were generally insignificant and in some cases the coefficients showed wrong signs. We have more confidence in the self-reported sleep variable and we continue to focus on it in our analysis.
2. There is heaping of sleep hours in the data on 0s and 5s. The distributions are computed with a smoothing parameter of 0.85.
3. There are 6 missing income values, 111 missing education values, and 2 missing region values. We use the MI set of procedures in Stata 11 with 10 imputations [StataCorp 2009]. Results are not materially different when we drop those observations with missing values. Standard errors for all statistical tests account for the imputation procedure.
4. We also experimented with estimating the regressions separately for males and females. With the smaller sample sizes, standard errors increased significantly. We tested for differences between males and females for the sleep and sleep-age variables and could not reject the null hypothesis that the coefficients were the same (10 percent level). With larger sample sizes, closely examining differences between males and females would be an important topic to explore in more detail.
5. The formula is: optimal sleep $= -(B_1 + B_2*\text{age})/(2*(B_3 + B_4*\text{age}))$, where B_1 is the coefficient on sleep, B_2 is the coefficient on sleep*age, B_3 is the coefficient on sleep-squared, and B_4 is the coefficient on sleep-squared*age.
6. We did substantial testing of the quadratic assumption, comparing it with a local polynomial smooth regression. The quadratic did well in all specifications. The results of these additional tests can be obtained by request from the authors.
7. We also interact the sleep dummies with age and find similar patterns by age, although the patterns are not as distinct for the youngest ages and few parameters are significant.

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