

“Sleep choice and time-of-day effects on p -beauty contest outcomes.”

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ABSTRACT

Sleep data are gathered prior to administration of the well-known p -beauty contest game. Additionally, using a validated morningness-eveningness preference measure, morning-type and evening-type subjects are identified and randomly matched or mismatched into morning or evening experiment sessions. This design allows examination of the effects of voluntary sleep restriction and optimal/suboptimal times-of-day on behavioral outcomes. Subject responses display significantly lower levels of iterative reasoning when ‘sleep deprived’ or at non-optimal times-of-day. However, repeated play shows that sleep loss and suboptimal times-of-day do not affect learning/adaptation in response to information feedback. Our results apply to environments where anticipation is important (e.g., coordination games, stock trading, driving, etc.), with important implications for sleep deprived individuals or those operating at suboptimal times-of-day (e.g., shift workers, new parents).

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Introduction

Recent surveys from the *National Sleep Foundation* indicate that the average American adult now sleeps less than 7 hours per night, causing concern that as many as 50 million American adults are chronically sleep deprived.¹ Research has shown reduced cognitive performance at 7 hours sleep per night relative to 8 or 9 hours per night in controlled laboratory settings (Van Dongen et al., 2003; Belenky, et al, 2003), though Horne (2004) argues that 7-7.5 hours per night is satisfactory for a healthy adult. However, even the loss of just one-hour following the Spring Daylight savings shift leads to both increased traffic fatalities (Coren, 1996b) and non-vehicular accidental deaths (Coren, 1996c).² Additionally, in many professions public safety is at issue due to more severe and chronic sleep restriction. For example, U.S. and Canadian truckers average about 5 hours sleep per night (Mitler et al., 1997), and medical residents make significantly more medical errors when sleeping less than 5 hours per night, which is not uncommon (Baldwin et al., 2004; see also, Weinger and Ancoli-Israel, 2002). Sleep loss is also estimated to cost the U.S. economy \$40 billion annually in terms of lost U.S. labor productivity—based on a conservative 4% reduction in labor productivity for sleep-deprived adults (Stoller, 1997).

Not surprisingly, sleepiness increases with one's wake time in what is referred to as the homeostatic drive for sleep. Superimposed upon this is the body's natural daily cycle of alertness: the circadian rhythm.³ An adverse point in one's circadian rhythm, or what we call "circadian mismatch", can explain one's drowsiness in the afternoon even when sleeping adequately every night. Similarly, more favorable points in one's circadian rhythm can lead to periods of relative alertness even after more than 24 hours of sleep deprivation. Thus, sleep loss

¹ Recent data also show that 60% of adults surveyed reported driving while drowsy, and 36% reported falling asleep or nodding off at some point while driving. These data are from the *National Sleep Foundation's* 2005 and 2008 'Sleep in America' polls of adults and working adults, and can be accessed at www.sleepfoundation.org.

² In one of the few economics studies considering sleep effects on measurable economic outcomes, Kamstra et al., (2000) find that the daylight savings shift, which causes a short-term sleep desynchronization, leads to significant financial market losses each year on the first trading day following the shift.

³ The circadian rhythm is influenced by core body temperature and correlated with melatonin secretion, which peaks in the middle of the night. Light/dark queues help set and reset the circadian rhythm as is illustrated by one's adjustment to jet lag after changing time zones.

and circadian mismatch both produce a strong biological need for sleep, resulting in sleepiness. Researchers have found decreased performance at adverse circadian phase times—such as what shift-workers might experience—in the areas of recall memory, subjective alertness, visual attention (Wright et al., 2002), and reaction times (Wright, et al., 2002; Horowitz et al., 2003). In an early study, Bjerner et al., (1955) examined about 175,000 ledger entries over a 3-shift (24 hours a day) gasworks factory in Sweden. Two distinct peaks in entry errors were found: a major peak at about 3 a.m., and a secondary minor peak at about 3 p.m. This is consistent with evidence summarized in Coren (1996a) that shows a major nighttime and minor afternoon peak in single-vehicle automobile accidents.

This paper takes a novel look at naturally-occurring sleep loss and circadian influences on rationality and learning. Iterative reasoning, anticipation, and adaptation are crucial skills towards successful performance in many professions and decision environments: financial market trading, military combat decisions, marketing and entrepreneurial decisions, and driving, to name a few. Behavioral outcomes are often the product of many inputs (e.g., cognition, motor-skills, risk attitude, etc), and so we focus our study of sleep and circadian effects on a higher-level decision task that engages iterative reasoning and has been of interest to economists. The goal of this research is to help shed light on relatively hidden decision effects of sleep in a setting where sleep habits closely match those in the naturally-occurring world.

We find that both naturally occurring sleep restriction and circadian mismatch lead to lower levels of iterated reasoning or “rationality” in subjects’ initial decisions. Interestingly, we find that decisions are closest to the equilibrium predictions (i.e., most “rational”) at about 7 hours of sleep per night, *ceteris paribus*. That is, nonlinear sleep effects estimates indicate that both too little *and* too much nightly sleep lead to reductions in iterative reasoning. Subjects who are most circadian mismatched (e.g., extreme evening-type subject in an 8 a.m. experiment session) also make more rational initial choices than those moderately mismatched, perhaps indicating that extreme mismatch also produces awareness of the mismatch and the use of compensatory efforts. However, adaptation and convergence towards equilibrium with repeated play indicate no difference in these learning effects as a result of sleep loss or circadian mismatch. Our results therefore hold implications for decisions in one-shot interactions or initial performance in novel environments (i.e., same group but new game parameters) that value

decision-maker anticipation skills, or in environments engaging deliberate thought processes more than automatic or unconscious processes.

The p -Beauty Contest (Guessing) Game

The interest in p -beauty contest games stems from a desire to understand environments where anticipation is valued. Such games are straightforward. Subjects in a group are asked to submit a number from a designated interval $X=[x_{\min}, x_{\max}]$, and let \bar{x} be the average of all guesses. The guess closest to $p \cdot \bar{x}$ times the average guess wins a prize, where $p > 0$ is a common knowledge parameter. John Maynard Keynes (1936) considered newspaper competitions where entrants were asked to pick out the six most “pretty” faces (from a series of photographs), and a prize went to the person whose pick corresponded most closely with the average preferences of all respondents. Related environments can be captured by differing whether the prize goes to the person exactly matching others’ choices ($p=1$, the newspaper competition game mentioned by Keynes or coordination games) or whether the prize goes to the person whose choice deviates from the group average in a specified way ($p \neq 1$).

Thus, the beauty contest captures many important features of higher-level thinking that are useful outside the lab. Ho et al., (1998) describe the Keynes stock market analogy as a p -beauty contest game where $p < 1$ in the sense that selling a rising stock before others yields the highest payoff. Games involving network externalities would be another example of a $p=1$ beauty contest. In such games, the payoff is higher to those correctly anticipating the choice of others, such as in guessing which new technology standards will be adopted.⁴ Individuals may even engage in a guessing game each morning if they select between alternative commuting routes to work, or if an entrepreneur must anticipate rival firm decisions. Importantly, the literature has evaluated such games experimentally (e.g., Nagel, 1995; Stahl, 1996; Duffy and Nagel, 1997; Ho et al, 1998, Bosch-Domenech et al, 2002; Weber, 2003; Costa-Gomes and Crawford, 2006; Grosskopf and Nagel, 2007) in efforts to explore bounded rationality or iterative dominance in initial guesses, as well as learning and adaptation across multiple rounds of play with or without information feedback.

⁴ Our thanks to Mike McKee for suggesting the example of network externalities.

Our specific hypotheses relate to initial round play and to learning in subsequent round play. Details on the experiment design are in the next section, but we have already summarized the key sleep-related variables we will use as independent variables in this study: voluntary sleep loss and circadian mismatch. Existing research directly supports the hypothesis that the prefrontal cortex (PFC) is disrupted following acute total sleep deprivation (Chee and Chua, 2008), and the PFC is well-known as a critical brain region in higher level decision-making. Existing psychological research also indirectly supports the hypothesis that circadian mismatch reduces cognitive resources and makes individuals more likely to utilize simple heuristics such as stereotyping (Bodenhausen, 1990) and transference (Kruglanski and Pierro, 2008). While heuristics need not be *per se* inaccurate, our interest lies in the fact that circadian mismatch is hypothesized to deplete cognitive resources in a way similar to sleep loss. Thus, because the initial round guessing game decision requires iterative reasoning, a high-level decision process, we have:

Hypothesis 1 (iterative reasoning): Voluntary sleep loss and circadian mismatch will both lead to initial decisions farther from the (perfectly) rational equilibrium prediction.

With respect to learning, one might assume that depleted cognitive resources will harm learning, we highlight that such a conclusion may be premature. Specifically, given that “learning” can take on a variety of meanings, we note that our design will employ a full-information feedback protocol that makes it relatively simple for a subject to adapt one’s decision during repeated play. An important stream of research in psychology has shown that learned tasks require little conscious thought and rely more heavily on automatic-unconscious processing whereas novel tasks rely to a greater extent on deliberate-conscious processing (e.g., Ferreira et al., 1996, among others). Further, this stream of research shows that depletion of cognitive resources (i.e., remembering a string of numbers) greatly affects deliberate-conscious thought but has little effect on automatic-unconscious processing. Therefore, when decisions rely more on automatic processing, behavioral outcomes are predicted to be more resilient to the depletion of cognitive resources. On the other hand, decisions relying on deliberate-conscious processes are predicted to be adversely affected by such depletion in cognitive resources. Thus, we have:

Hypothesis 2 (simple learning): Simple learning (or adaptation) will be unaffected by sleep loss and circadian mismatch.

We note that hypothesis 2 is not a global hypothesis regarding learning. Rather, we consider it a sensible hypothesis in the context of basic learning (e.g., adaptation, reinforcement learning) with low cognitive requirements. Of course, it is subjective to state that equilibrium convergence in the guessing game involves “basic” learning, but our experiments utilize a protocol that easily allows all subjects to observe the winning guess in each round. Our view is supported by recent Guessing Game research has concluded that convergence patterns are due to mimicking others’ choices, rather than self-initiated rationality (Grosskopf and Nagel, 2007).

Experimental Design

We control for both objectively measured sleep quantities and circadian mismatch in our unique design. In order to manipulate circadian mismatch in our design, we need an objective and validated measure of each subject’s sleep personality, or chronotype. A validated short-form survey instrument is given in Adan and Almirall (1991), which is a reduced form of the original morningness-eveningness survey instrument given in Horne and Ostberg (1976). The reduced-form instrument, henceforth rH&O, consists of 5 items and ranks each respondent to this morningness-eveningness questionnaire (MEQ) on a scale of 4-25, with extremes of the scale representing extreme evening- and morning-type subjects. From the rH&O subjects are classified as follows: 4-11 Evening Type, 12-17 Intermediate Type, 18-25 Morning Type. One could administer this instrument to each recruited subject after recruitment, but this complicates obtaining a balanced sample of morning- and evening-types because of the rarity of morning-type young adults. Young adult estimates from college students find that only about 7% are morning-types, whereas 48% are evening-types based on the rH&O (Chelminski et al., 2000).

The alternative approach we take is to first administer an online survey, which includes demographic questions, the rH&O instrument, and screening questions for depression, anxiety, and any diagnosed sleep disorder.⁵ A wave of this survey went out to University email lists

⁵ Screening questions for anxiety and depression were not included until after about 25% of the sample had already been acquired. For the majority of the sample, however, we explicitly screen out survey respondents who are at risk

(mostly students, although a small number of faculty and staff responded as well) in each of the Spring, Summer, and Fall semesters during an academic year. Each survey wave generated close to 1000 responses, and a random prize drawing was offered as incentive to complete the 5-10 minute online survey. It was also indicated that completing this survey was required for eligibility to participate in a special set of upcoming cash-compensated research experiments involving sleep and decisions. Figure 1 shows the chronotype profile of survey respondents in the representative summer wave, which roughly correspond to Chelminski et al. (2000). From the survey respondents, we then score the rH&O questions to identify morning- and evening-type subjects, randomly assign them to an evening or morning session time slot, and contact them for recruitment for the main experiment. In this way, a subject is randomly assigned to either be in a morning (8:00 a.m.) or evening (8:00 p.m.) experiment session, and if they cannot or choose not to sign up, they are **not** allowed the option of the other time session. We mostly eliminate intermediate-type subjects from recruitment to the main experiment because circadian match/mismatching is not as stark with intermediate-types.

Subjects are recruited to the main phase of the experiments to attend two 1-hour sessions, separated by one week (using only Tuesdays, Wednesday, and Thursdays to avoid weekend confounds), at their randomly assigned morning or evening time slot. During Session 1, subjects signed Consent forms, complete 3 short surveys,⁶ and were assigned an actigraphy (sleep watch) to wear for the next week. The actigraphy, which looks much like a wrist watch, continuously measures G-forces and generates “activity-count” data for each time epoch of a specified size (e.g., 30 seconds in our study). Subjects wear the watch 24 hours a day over the course of the actigraphy week, with few exceptions.⁷ The resulting data from each subject looks much like ‘seismographic’ data of the subject’s wrist movements. The basic idea is that periods of low to no activity are scored as sleep and, in conjunction with use of subjective data from sleep diaries that subjects also complete, the actigraphy-derived measure of total sleep time does not differ

for depression or anxiety from participating in the main experimental phase, given the known correlation between these and sleep difficulty. For the entire sample, we do not include subjects with known sleep disorders.

⁶ These include a socio-economic status survey, a brief instrument assessing numeric abilities, and the Need for Cognition Scale (Cacioppo and Petty, 1982), which scores a subject’s preference towards and enjoyment of thinking and cognitive engagement.

⁷ Exceptions include taking the watch off for contact sports, or whenever the watch may be in danger. Subjects note such instances in the sleep diaries, and these periods are scored as wake periods by default.

significantly from what one gets with the intrusive alternative of polysomnography (Kushida et al., 2000). Figures 3a and 3b show examples of the scored actigraphy data from two of our subjects. Subjects are compensated a flat fee of \$30 for providing the week's worth of sleep watch and sleep diary data. This compensation is independent of their incentive-pay in the decision experiment that occurs at the end of their week during Session 2 of the experiment (the decision experiment session).

Session 2 occurs one week after Session 1, again at the randomly assigned time of day (8 a.m. or p.m.). Session 2 includes the decision experiment, a short instrument to assess current sleepiness and caffeine use⁸, removal of the actigraphy, and payment of all compensation in cash and private. It is important to note that while sleep quantities are objectively measured, they are not manipulated in our design. Subjects are instructed to behave as they normally would throughout the week of actigraphy data acquisition. A subjective cutoff of 6.5 hours sleep per night is used to score subjects as sleep-deprived (SD) or well-rested (WR) in Table 1. Nightly sleep average between the morning- and evening-types in our sample is not significantly different (Mann-Whitney test, $p > .10$), indicating no confounding correlation between chronotype and sleep levels.

As a validation of our circadian mismatch protocol, for the majority of our sample ($n=78$) we administer the well-known Karolinska Sleepiness Scale (KSS) both prior to and just after the decision experiment session. We then average the two ratings to get a subjective measure of a subject's sleepiness at the time of the decision experiment. The KSS runs from 1=extremely alert to 9=extremely sleepy (fighting sleep). Our circadian mismatch protocol is validated in the sense that average KSS scores are significantly higher for circadian mismatched (MM) subjects (4.56) compared to circadian matched (CM) subjects (3.73) ($p=.04$ Wilcoxon unmatched two-sample test).⁹ However, morning mismatched subjects—evening subjects in an 8 a.m. experiment (18 of the 42 mismatched subjects) reported average KSS scores of 6.19. It appears, therefore, that a morning mismatch is a more serious mismatch, as indicated by higher subjective sleepiness ratings, but these sleepier subjects are *not* necessarily less rational in terms of their

⁸ The state-level sleepiness and caffeine questions were added after the first 3 groups (24 subjects) as a validity check on the circadian mismatch protocol. So, these data are available on 78 out of 102 subjects.

⁹ The result holds if one instead compares KSS sleepiness and the continuous *Mismatch Scale* variable introduced in the Results section.

behavioral choices in the guessing game, as we will see below. This increased subjective sleepiness is likely due to evening-type subjects making decisions when normally asleep in a morning session, which is not the case for the morning-types in an evening (8 p.m.) session (see average bed times in Table 1). It should be noted however, that the subjective sleepiness rating does not significantly predict behavioral outcomes in the analysis below, and therefore we consider it useful primarily as a casual indication that our circadian mismatch protocol was successful. This is true in spite of the fact that our design is deliberately uncontrolled with respect to the use of coping mechanisms to combat sleepiness.¹⁰

During Session 2 we administer the well-known guessing game experiment studied first in the lab by Nagel (1995). Following the parameterization in Ho et al (1998), we employ a treatment with a treatment of $p=.7$, $X=[0,100]$ (treatment 1), and another treatment with $p=1.3$, $X=[100,200]$ (treatment 2). The order of the treatments is reversed for half of the 12 total sessions, for both morning and evening experiment sessions. Ho et al, (1998) note that average guess levels can be categorized into levels of iterated reasoning by elimination of dominated strategies. For example, in treatment 1, even if all guesses are at the upper bound $x_{\max}=100$, then $.7*100=70$, and so guesses in the range $[70,100]$ describe zero-level rational subjects, $R(0)$, whereas rational $R(1)$ subjects have guesses in the $[0,70]$ interval. $R(2)$ subjects consider all others obey $R(1)$ reasoning and so $R(2)$ subjects guess in the $[0,49]$ interval. Thus, we would classify a subject with guess $x \in [49,70]$ as an $R(1)$ subject. The unique equilibrium in treatment 1 is a guess of 0, which requires infinite depth of reasoning (i.e., $R(\infty)$ application of iterated dominance). In treatment 2, application of iterated dominance leads to the equilibrium guess of $x=200$ at two levels of iterated reasoning.¹¹ The choice of the Ho et al. (1998) parameters was

¹⁰ We do not, however, find any significant differences in caffeine consumption in the 2 hours prior to the decision experiment based on circadian mismatch, and only one subject took a nap during the afternoon prior to the evening experiment session time.

¹¹ Application of iterated dominance does not predict clusters of initial guesses around specific points without further assumptions. Costa-Gomez and Crawford (2006) highlight the success in Nagel's (1995) approach to categorize initial disequilibrium choices, but the difference between approaches is not substantive for our purposes. Either approach implies infinite reasoning to reach equilibrium in treatment 1, but finite depth of reasoning to reach equilibrium in treatment 2.

therefore of interest for the reason that treatment 2 presents subjects with a p -beauty contest that is notably more cognitively simple than treatment 1.¹²

The objective of the present paper is not to portray a detailed categorization of levels of iterated rationality, nor is our objective to discriminate between alternative models of iterative reasoning. The common feature of alternative categorizations is that higher levels of iterated reasoning correspond to lower initial round guesses in our treatment 1 but higher initial round guesses in treatment 2. Simply put, we will interpret initial round guesses that are closer to the equilibrium prediction as reflecting a higher level of reasoning, or a more rational response. Strictly put, the equilibrium guess assumes rationality as well as the belief that others are rational, indicating a potential confound in interpreting non-equilibrium responses. However, recent results with 2-person guessing games, which make the Nash equilibrium a dominant strategy equilibrium, still reveal a prevalence of non-equilibrium guesses (Grosskopf and Nagel, 2007). Thus, we feel it reasonable to interpret non-equilibrium guesses in our environment as consistent with bounded rationality, as opposed to belief alteration.

Our experiments utilize a full information framework where subjects are informed of the guesses of all other group members (as well as the target guess) at the end of each round. Thus, converge towards equilibrium in multi-round play will be interpreted as type of simple adaptation (i.e., mimicking others' behavior), rather than as a fundamental change in subjects' state-level rationality. Our experiment groups range in size from 8-10 subjects, which we feel adequate to eliminate concerns for group size effects as studied in Ho et al (1998)—they examined groups of 3 and 7 subjects.

In short, our design includes both experimentally manipulated circadian match/mismatch for the decision session time-of-day as well as objective data generation on voluntary sleep choices captured by actigraphy. Whereas in a controlled sleep lab study, subject coping mechanisms against sleepiness are strictly controlled and/or eliminated (e.g., no caffeine or nicotine use, no physical activity, etc), they are uncontrolled in our design. We therefore consider that any significant behavioral effects we find are truly a conservative measure of sleep and circadian effects in this decision environment.

¹² The experiments are computerized and administered via the Veconlab guessing game program at <http://veconlab.econ.virginia.edu/admin.htm>.

Results

The data are from 102 subjects (46 female), average age 23.2 ± 8.4 years of age (\pm refers to standard deviation). Payoffs averaged a total of \$52.55 for each subject: \$30 for the actigraphy week, and then $\$22.55 \pm \8.84 from the guessing game experiments. Average nightly sleep quantities over the 7 nights prior to the decision experiment were 380 ± 59 minutes, or just under 6.5 hours of sleep per night. Daily sleep time is increased by an average of 14 minutes if we include naps that subjects took, but doing so does not provide any additional predictive power (results available upon request). Thus, we utilize the traditional nightly sleep variable in our analysis. Figure 2 presents the probability distribution of the chronotypes recruited based on MEQ score with traditional cutoffs highlighted. Due to the difficulty in identifying and recruiting morning-types in our study, we recruited individuals with MEQ scores of 16 and 17, although these fall below the traditional (subjective) cutoff point for a morning type. For ease of exposition, we still refer to these subjects as morning-types. In the end, the evening-types we recruit are, on average, strong evening-types. Thus, our sample still includes a clean separation along the sleep personality dimension. Table 1 shows the design cells for circadian match/mismatch with our roughly equal numbers of matches and mismatches for both morning- and evening-types. We also include summary statistics on various sleep parameters for each design cell in Table 1.

As we proceed, we first present analysis by separating the data into subjectively-defined groups of well-rested (WR), sleep-deprived (SD), circadian matched (CM), and circadian mismatched (MM) subjects. However, given that both sleep quantity and MEQ score provide continuous measures of sleep quantity and chronotype, we will also present analysis utilizing these continuous variables as regressors. We define sleep-deprived as any subject having a nightly sleep time average of less than 6.5 hours. This generates a sample of 55% SD subjects, 45% WR subjects. Figures 3a and 3b show the actigraphy data from a subject scored as SD and one scored as WR; one is a morning-type, the other an evening-type subject.

The p -beauty contest results are first shown in summary form in Figures 4a and 4b, where we plot the pooled (across groups) average guesses for each round within a treatment. From these figures it does not appear that there are any noticeable differences in the evolution of

average guesses across rounds (learning). We will examine subject learning in the next section. Initial round guesses offer a way to examine subject choice prior to the onset of learning or prior to any adaptation in response to feedback information. Our initial hypothesis is that sleep loss and circadian mismatch lead to reduced rationality (i.e., reduced application of iterative reasoning). Thus, we can employ one-tailed tests of the null hypotheses that initial round guesses do not differ by sleep state (SD or WR) or time-of-day matching (MM or CM) against the alternative hypotheses that guesses are farther from equilibrium for SD and MM subjects. The data constitute a (non-matched) pair of samples for the initial round guesses, and we use the non-parametric Mann-Whitney two-sample test. Results are highlighted in Table 2.

The results offer support for our hypotheses that both sleep deprivation and circadian mismatch result in responses farther from equilibrium, though the result only holds in treatment 1 for circadian mismatch. Table 3 shows subject categorization based on levels of iterated dominance for these treatments highlighted in Ho et al., (1998). The general indication is that subjects apply higher levels of iterated dominance when well-rested rather than sleep-deprived, or when at their more peak time-of-day rather than at their off-peak time of day.¹³ In treatment 1, subject initial guesses are significantly closer to equilibrium when they are well-rested, or when they are matched to a circadian peak point-in-time. Table 2 shows that average guesses of 60.15 (SD) and 61.15 (MM) correspond to categorizing the average sleep-deprived and circadian mismatched subjects as having iterated reasoning level R(1), whereas well-rested and circadian matched subjects would be at level R(2) (average guesses at about 48). The results are qualitatively similar for treatment 2, although initial round guesses are only statistically significantly closer to equilibrium (i.e., *higher* guesses, in this case) for WR compared to SD, and not for the circadian match/mismatch test.

Because our sleep and chronotype data are continuous, we waste information to a large extent by restricting analysis to dichotomous variables based on subjective cutoffs. We can

¹³ If one examines experience in the *p*-beauty contest game, then initial guesses in the first treatment administered (round 1) would constitute inexperienced play, whereas initial guesses the second treatment administered (round 11) would constitute experienced play in a different *p*-beauty contest. Our data show that there is an apparent anchoring effect of guesses from the initial treatment when making round 11 guesses, which differs from results in Ho et al., (1998). That is, more subjects display *lower* levels of iterated dominance (i.e., higher initial round guesses) in treatment 1 when it follows treatment 2, irrespective of sleep or circadian state. This anchoring does not seem to occur in treatment 2 when it follows treatment 1. These data are available from the authors on request.

alternatively model initial round guesses as a function of the (continuous) sleep quantity variable and a circadian mismatch scale we generate. Recall that a subject's chronotype is indicated by her morningness-eveningness questionnaire (MEQ) score, which lies in the interval [4,25], with lower (higher) scores indicating more evening-types (morning-types). Define the variable Mismatch Scale as follows:

$$Mismatch\ Scale = \begin{cases} \frac{25 - MEQscore}{21} & \text{if morning session} \\ \frac{MEQscore - 4}{21} & \text{if evening session} \end{cases}$$

This variable takes on values in the [0,1] interval, with larger values indicating a larger degree of circadian mismatch. For example, the most extreme circadian mismatch (*Mismatch Scale*=1) in our design is either an extreme morning-type subject with MEQ=25 in an evening session, or an evening-type subject with MEQ=4 in a morning session. Our sample includes circadian mismatch values within the full range or [0,1], including the endpoint extremes.¹⁴ While the experimental design was initially conceived with 12-hours separating morning and evening sessions for symmetry, it is likely the case that the greater circadian mismatch occurs with evening subjects in our 8 a.m. session as opposed to morning subjects in the 8 p.m. session. Curiously, however, when focusing the mismatch analysis on these morning mismatches alone, we find no significant differences in initial round guesses in either treatment. This indicates that the results are driven by evening mismatches—morning subjects in our evening sessions—which seems paradoxical given that evening mismatched subjects reported lower KSS sleepiness scores compared to morning mismatched subjects. We will further address this curiosity below.

Consider the following model of initial round guesses (N=102):

$$Guess_i = \alpha + \beta_1 * SleepQ_i + \beta_2 * SleepQ_i^2 + \beta_3 * MS_i + \beta_4 * MS_i^2 + \varepsilon.$$

We estimate the model separately for treatments 1 and 2, and the results are shown in Table 4.¹⁵ Table 4 indicates that both nightly sleep quantity over the prior week and circadian mismatch are statistically significant predictors of initial round guesses. Most interestingly, the squared terms

¹⁴ The extreme *Mismatch Scale* values = 1 in our sample are all due to extreme evening-type subjects (MEQ=4 scores) in morning sessions. As shown in Figure 2, the most extreme morning-type in our sample are those with MEQ score=22.

¹⁵ Estimation of the model with an interaction term yields an insignificant coefficient on the interaction term and does not change our results (estimation available upon request). Our results are also unchanged by a group-specific fixed effects modeling of the data.

to allow for nonlinear effects are both statistically significant. Figures 5a-5d show the models' predictions in each treatment with respect to one's average nightly sleep quantity (Fig. 5a, 5b) and Mismatch scale (Fig. 5c, 5d). With respect to sleep quantity, the model predicts guesses closer to equilibrium as one gets more nightly sleep *up until* about 6.8 hours per night (about 7 hours per night in treatment 2). Average nightly sleep beyond that is predicted to push one's initial round guess farther from equilibrium. The prediction is that there is an optimal level of nightly sleep, but rationality is *not* monotonically increasing in nightly sleep.

We also estimate a non-linear pattern of the effect for the degree of circadian mismatch on initial round guesses. Just as the estimations in Table 4 do not indicate that more sleep is always better, the forecast of initial round guess with respect to circadian mismatch (holding sleep constant) is intriguing. In a *local* (as opposed to global) sense, initial round guesses are closest to equilibrium at minimum and maximum circadian mismatch. In treatment 1, the globally optimal level of circadian mismatch is zero, though in treatment 2 the forecasted difference in initial round guess for zero versus complete circadian mismatch is negligible. The basic flavor of this result is that, controlling for sleep loss, optimal perform may occur both at one's optimal time of day as well as at their complete off-time. We estimate that it is the intermediate levels of circadian mismatch that are farthest from equilibrium. This is a curious result that one might hypothesize is due to our design's uncontrolled nature with respect to strategies subjects may employ to combat sleepiness—most mismatched subjects would be most sleepy and therefore most likely to use coping strategies to combat sleepiness. Our results do not, however, indicate increased use of caffeine at high levels of circadian mismatch (*Mismatch Score* > .70) compared to low levels of mismatch (*Mismatch Score* < .30).

The estimates in Table 4 can also be used to forecast one's guess if both sleep deprived and at a suboptimal circadian mismatch point. The forecast guess in Treatment 1 for nightly average sleep of 5 hours per night and circadian mismatch level=.65 is a guess=78. This contrasts with the forecast Treatment 1 guess of 23 for 7 hours sleep per night with low circadian mismatch level=.05—the difference between an R(0) and an R(3) subject. In Treatment 2, forecast guesses are 166 (7 hours sleep, mismatch scale=.05) and 140 (5 hours sleep and mismatch scale=.65). In short, our model estimates indicate differences in iterative reasoning

that are both statistically and economically significant, even for within sample levels of relatively mild sleep loss and for decisions at still reasonable times of day.

While we do not have an explanation for this nonlinear effect of circadian mismatch on levels of iterated reasoning, we do offer a hypothesis. Subjects report increased subjective sleepiness levels the higher the degree of circadian mismatch ($p=.00$ on the OLS $\beta=2.54$ coefficient estimate from $KSS=\alpha + \beta * Mismatch\ Score + \epsilon$). An increased awareness of one's sleepiness may facilitate compensatory effort. For example, Drummond et al. (2005) report both increased subjective sleepiness *and* significantly higher self-reported effort to complete a verbal learning task following an admittedly more extreme 36 hours of total sleep deprivation. Our subjects' KSS scores do **not**, however, vary with nightly average sleep time ($p=.69$ on the OLS $\beta=.001$ coefficient estimate from $KSS=\alpha + \beta * SleepQ + \epsilon$). We hypothesize that SD subjects do not, but MM subjects do, report increased sleepiness because sleep loss is voluntary in our design, but circadian mismatch is manipulated (and subjects are aware of this).

Increased subjective sleepiness may be the trigger to engage compensatory effort, but voluntarily sleep restricted subjects may be biased towards reporting that they are not sleepy. Theories of cognitive dissonance (e.g., Festinger, 1957) would predict this type of self-rationalization for our SD subjects, thus explaining the difference in sleepiness ratings we find resulting from circadian mismatch versus sleep loss. Van Dongen et al. (2003) also highlights a particular concern regarding partial sleep loss—individuals may experience significant behavioral deficits similar to those suffering from shorter-term total sleep deprivation, but self-reported sleepiness may not be nearly as affected under partial sleep loss. This may constitute a behavioral trap that is magnified when sleep restriction is voluntary, because our natural tendency in such cases may be to rationalize that our voluntary choice to restrict sleep does not have any harmful effects.

Learning and Adaptation

An overview of the pattern of guesses across all 10 rounds of the p -beauty contest game is in Figures 6 and 7. For each treatment, we separate the data by WR v. SD, and by MM v. CM. The scatter-plots show the relationship of the difference in a subject's current round guess and her guess in the previous round compared to the difference between the optimal guess (the

“target”) and the subject’s guess in the previous round. Each plot also includes the simple OLS fit of the equation: $Guess_t - Guess_{t-1} = \alpha + \beta^*(Target_{t-1} - Guess_{t-1})$, for each subset of data indicated.¹⁶

What is apparent from Figures 6 and 7 is that subjects generally respond rationally to deviations from the winning guess in the previous round, as indicated by the upward slopes of all scatter-plot relationships. In other words, the more the subject’s guess in the previous round was above (below) the target, the more likely the subject was to decrease (increase) her guess in the following round. The concentration of points on the horizontal axis in the treatment 2 plots (Fig. 6b, 7b) are due to the significantly higher number of equilibrium guesses in treatment 2—for this reason most guesses are below the “target” in treatment 2, because as long as the average guess is at least 154, then $p=1.3$ times the average guess is 200, making it impossible to have guesses above the target in such cases.

These Figures 6 and 7 indicate similar patterns of guess response to feedback regardless of one’s sleep condition or time-of-day. Following Nagel (1995), we can more specifically examine the data’s conformity to a qualitative learning model that assumes subjects adjust their guess in the direction of (ex post) the optimal adjustment factor: the learning-direction theory. Nagel (1995) defines subject i ’s adjustment factor and the optimal adjustment factor as

$$(1) \quad a_{it} = \frac{x_{it}}{(mean)_{t-1}}$$

$$(2) \quad a_{opt,t} = \frac{x_{opt,t}}{(mean)_{t-1}} = \frac{p^*(mean)_t}{(mean)_{t-1}}$$

where $(mean)_{t-1}$ is set equal to the midpoint of the guess interval for the first round of the treatment. A “good” adjustment, as defined by this qualitative learning model, is one where a subject changes her adjustment factor to correct the direction of the previous round’s error. That is, if $a_t > a_{opt,t}$ then $a_{t+1} < a_t$ represents a good adjustment (and $a_t < a_{opt,t}$ implies $a_{t+1} > a_t$). She restricts her analysis to the subsample of the data where the subject did *not* win or share in the

¹⁶ The OLS fit is meant to be a suggestive description of the scatter-plot relationship. It is not meant to be a proper modeling of the data.

prize in the previous round, as such rounds present subjects with distinct feedback.¹⁷ By doing so, we have a sample of $N=787$ treatment 1 and $N=297$ treatment 2 guesses in response to a no-win outcome in the previous round.

We find that in the pooled data 75% of subject guesses in treatment 1 are consistent with learning-direction theory, which is similar to proportions reported in Nagel (1995) for $p < 1$. In treatment 2, the proportion is just 56%, though this is still statistically different from random adjustment factor alterations based on a coin flip (binomial test: $p = .03$ for the one-sided test against the null hypothesis that $p = .50$). Table 5 shows the results of evaluating the learning-direction theory compared to an even more naïve rule-of-thumb adjustment process—*equilibrium guess adjustment*—where subjects simply adjust their guess in the direction of the predicted equilibrium, independent of what the winning guess was in the previous round. For the most part, there are no statistically significant differences between the proportion of guesses conforming to the learning-direction model across the subsamples of sleep deprived versus well-rested, or circadian matched versus mismatched subjects (two-sample proportions test: p -value $> .10$ in all cases). A marginal result is that learning-direction may be utilized more often in treatment 2 when a subject is well-rested compared to sleep-deprived (significance of which depends on the test used and the subjective cutoff for coding SD). Though not a robust result, this is suggestive that a further examination of learning effects should be on the agenda for future research. A use of the continuous sleep and circadian mismatch scale variable reveals that neither is a significant predictor of the probability that a subject utilizes the learning-direction rules (results available on request). With respect to use of the naïve adjustment model, we also find no differences in use of either learning rule as a function of sleep or circadian effects.

Finally, for a given sleep state (SD or WR, MM or CM) we examine whether a subject is more likely to use the more sophisticated learning-direction model or the naïve equilibrium guess adjustment model. In treatment 1, we fail to reject the hypothesis that the proportion of guesses conforming to learning-direction is equal to the proportion conforming to equilibrium guess adjustment for SD or WR subjects (two-sample proportions test: p -value $> .10$). We find the same result for treatment 1 comparing the MM and CM subsamples. So, the various sleep sub-

¹⁷ The data suggest that following a round where the subject win's or shares in the prize (14% of the total subject rounds), adjustments are much less likely to follow the learning-direction theory—only 41% do so compared to the 75% of subject-rounds reported above who respond to no-win feedback.

groups have no significant effect on the propensity to use one type of simple learning model versus the other. For treatment 2, in all comparisons we find that subjects are more likely to use the more simple equilibrium guess adjustment model than the learning-direction model, which is not surprisingly the less complex decision environment of the two treatments. Though other learning models may be compared using our data, the purpose of our paper is not a comprehensive comparison of learning models. Most all learning models utilize some type of reinforcement learning based on previous round outcomes or payoffs, and in the context of the Guessing Game, subject learning involves mimicking others' winning guesses. As such, Figures 6 and 7 seem to highlight what our simple analysis concludes—subject guesses adjust towards the previous round's target (i.e., winning) guess, but this adjustment process does not appear to differ when a subject is sleep-deprived or circadian mismatched. These results are consistent with our *Hypothesis 2*, which is based on the notion that adaptation in our experiments requires relatively little deliberative thought.

Conclusions

We replicate the well-known p -beauty contest experiment with a unique but relevant behavioral twist. Subjects are objectively monitored for a one-week period prior to the experiment to generate a measure of their average nightly hours of sleep. Thus, sleep is not manipulated. Rather, we utilize the cross-sectional variation in voluntary sleep choice to estimate behavioral sleep quantity effects. Because sleepiness and wakefulness are also known to follow a circadian rhythm, we utilize morningness/eveningness preferences generated from a first-stage survey to then randomly assign subjects to either a morning (8:00 a.m.) or evening (8:00 p.m.) experiment session. The rH&O biological sleep preference instrument allows us to randomly assign half the subjects to more versus less optimal times-of-day for each subject chronotype. The result is a design that allows us to examine the effects of voluntary sleep restriction and circadian mismatch on iterative reasoning and learning/adaptation in a repeated p -beauty contest. This is a behavioral treatment with important implications for a modern society that employs shift work, is more globally integrated in real time, functions increasingly 24/7, and has millions of Americans sleeping an average of less than 7 hours per night.

Our main results indicate that both voluntary sleep restriction and circadian mismatch produce statistically significant effects on initial round guesses in two distinct guessing game treatments. Specifically, they lead to guesses farther from equilibrium. In other words, our evidence indicates that sleep loss and circadian mismatch lead to inexperienced guesses that display lower levels of iterated reasoning. The effects seem most robust in treatment 1, which is cognitively more challenging and requires infinite depth of reasoning to reach equilibrium. We also estimate an apparent “optimal” level of nightly sleep at about 7 hours of sleep per night, which is quite close to estimated sleep levels in young adults.¹⁸ This is roughly consistent with recent commentary from sleep researchers that suggests that 7-7.5 hours of good-quality sleep per night is reasonable (Horne, 2004). With respect to circadian mismatch, we also estimate nonlinear effects that imply that moderate levels of mismatch may be more detrimental to iterative reasoning than more extreme levels. We speculate that this results from compensatory effort due to increased subjective sleepiness when constrained (experimentally) into an extreme mismatch time slot.

While we find significant behavioral effects on initial round guesses, voluntarily sleep-deprived and circadian mismatched subjects converge towards equilibrium similar to well-rested and circadian matched subjects. That is, the proportion of subject decisions that conform to Nagel’s (1995) simple learning-direction theory, as well as a more naïve rule of adjustment towards equilibrium, do not differ based on one’s sleep or circadian state. Given the full information feedback that subjects receive after each round of our guessing games, it is perhaps not easy to disentangle the effects of subject learning, feedback, and adaptation. Weber (2003) documents introspection-type learning in the guessing game with no information feedback, though much of the literature has examined reinforcement or feedback-based learning. Grosskopf and Nagel (2007) attribute equilibrium convergence in 2-player guessing games, though strategically different from $n > 2$ -player guessing games, to adaptation-based learning. Because we do not manipulate information feedback in our design, it would be inappropriate to interpret our results as if sleep and circadian timing have no effect on *any* dimension of subject learning. But, with full information feedback in groups of 8-10 subjects, adaptation or reinforcement-based learning may be relatively simple and effective in our experiments.

¹⁸ See data reported by the *National Sleep Foundation*, which can be accessed at www.sleepfoundation.org

As a number of theoretical propositions in psychology would seem to suggest (e.g., Kahneman and Frederick, 2002; Sloman, 1996; Stanovich and West, 1998), when people perform a task that is well learned or requires little thought, they tend to rely on automatic/unconscious processing, whereas for novel tasks or those requiring deliberate or effortful thought they tend to rely on more conscious processing (e.g., Ferreira et al., 2006; Jacoby & Kelley, 1987; Jacoby et al., 1989). This distinction may emerge when individuals perform a task or engage in a strategic environment repeatedly. It is likely that reliance on conscious and unconscious processing will vary depending upon whether the person is in the initial round or engaged in subsequent rounds. That is, initial task performance should be seen as novel and individuals should rely more on conscious/deliberate processing. However, experienced play in subsequent rounds implies that the task is learned and should require less effortful thinking, resulting in more dependence upon unconscious processing (Jacoby and Kelley, 1987). Therefore, it seems likely that a “shift” will occur from conscious to more unconscious processing of the decision depending upon the phase of the game play.

Our results are consistent with such arguments that highlight the conscious vs. unconscious processing differences in novel and learned tasks. Homeostatic and circadian influences on the biological need for sleep, along with the extant literature of (mostly) controlled sleep studies, led us to hypothesize that sleep loss and circadian mismatch would deplete one’s cognitive resources. For example, total sleep deprivation is known to particularly disrupt prefrontal cortex function (e.g., Chee and Chuah, 2008). It then follows that we hypothesize that higher-level thinking, which requires greater cognitive resources, would be disproportionately affected by sleep loss and circadian mismatch. If subjects use simple adaptation processes in the guessing game, then these simple processes may require less deliberate thought, and therefore be less affected, than the more cognitively challenging initial decision. Of course, this is a bit speculative given that we do not have direct evidence on whether subjects are using more deliberative processes in the initial round compared to subsequent rounds. Nevertheless, it is an area worth further exploration, and our results may be an indication that the type of learning utilized in the guessing game may be quite basic. At the very least, our results are not consistent with the hypothesis that sleep loss will damage *all* types of decisions.

Our findings have important implications for our modern society functioning on increasing levels of voluntary sleep loss and circadian mismatching due to shift work. Average nightly sleep levels in our sample, which are close to typical young adult levels and close to our estimated optimal level in terms of iterative reasoning, might suggest that individuals can identify their optimal level of sleep. It must be noted, however, that this result is conditional on low levels of circadian mismatch, which is not always possible. Out of sample forecasts from our results indicate very large effects on iterative reasoning for the sleep deprived who are also at high circadian mismatch levels—differences of up to 3-4 levels of iterative reasoning. Because a full 1/3 of our subjects do not even sleep 6 hours per night during the study period, our results have implications relevant to a large segment of the young adult population. Given our examination of relatively mild levels of sleep loss and decision making at reasonable times of day, the behavioral effects we find should send an important message to those operating regularly at more adverse states of sleep loss or circadian mismatch.

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Table 1: Chronotype and Time Session assignments

Time Session for Decision Experiment		
Summary statistics (N, averages, standard deviations)		
Chronotype	8:00 a.m. (morning)	8:00 p.m. (evening)
Morning type	N=24 (15 female) Age=23.9 ± 9.4 years old Avg. MEQ score= 17.42 ± 1.5 Avg. nightly sleep=374 ± 65 min Avg. wake time=8:12 a.m. ± 73 min Avg. bed time=12:21 a.m. ± 73 min Avg. sleep efficiency*=82% ± 5.0%	N=26 (5 female) Age=26.9 ± 12.1 years old Avg. MEQ score=18.07 ± 1.8 Avg. nightly sleep=379±61 min Avg. wake time=7:37 a.m. ± 60 min Avg. bed time=12:03 a.m. ± 77 min Avg. sleep efficiency*=80%±6.7%
Evening type	N=27 (10 female) Age=20.7 ± 2.5 years old Avg. MEQ score=7.15 ± 2.2 Avg. nightly sleep=389 ± 49 min Avg. wake time=10:04 a.m. ± 72 min Avg. bed time=1:46 a.m. ± 66 min Avg. sleep efficiency*=81% ± 7.1%	N=25 (16 female) Age=21.4 ± 5.4 years old Avg. MEQ score=6.56 ± 1.32 Avg. nightly sleep=380 ± 64 min Avg. wake time=9:59 a.m. ± 94 min Avg. bed time=2:03 a.m. ± 61 min Avg. sleep efficiency*=84% ± 4.8%

*sleep efficiency is the percentage of the time within the subjects nightly attempted sleep intervals that is scored as actual sleep. That is, sleep efficiency takes into the time taken to fall asleep as well as any bouts of wakefulness during the night as measured by the actigraphy.

Note: ± indicates standard deviation.

Table 2: Initial round guesses (round 1 or 11)

Treatment 1		Mann-Whitney ranks-sum test (one-tailed tests)
Guess _{SD} = 60.15	Guess _{WR} = 48.36	Guess _{SD} > Guess _{WR} (p=.02)
Guess _{MM} = 61.15	Guess _{CM} = 48.01	Guess _{MM} > Guess _{CM} (p=.02)
Treatment 2		Mann-Whitney ranks-sum test (one-tailed tests)
Guess _{SD} = 150.80	Guess _{WR} = 160.62	Guess _{SD} < Guess _{WR} (p=.03)
Guess _{MM} = 152.25	Guess _{CM} = 157.98	Guess _{MM} = Guess _{CM} (p>.10)

Table 3: Levels of Iterated Dominance by Sleep State (initial round data)

Level of iterated dominance [guess interval]	Percentage reported	Percentage reported		Percentage reported	Percentage reported
TREATMENT 1	SD (n=56)	WR (n=46)		MM (n=53)	CM (n=49)
R(0) [70,100]	50.00	28.26		49.06	28.57
R(1) [49,69]	8.92	19.57		13.21	14.29
R(2) [34,48]	21.42	23.91		16.98	28.57
R(3) [24,33]	7.14	8.70		9.43	6.12
> R(3) [0,23]	12.5	19.57		11.32	20.41
TREATMENT 2*	SD (n=56)	WR (n=46)		MM (n=53)	CM (n=49)
R(0) [100,130]	28.57	13.04		16.98	26.53
R(1) [131,169]	29.29	41.30		45.28	34.69
R(2) [170,200]	32.14	45.65		37.74	38.78

*In treatment 2, a maximal guess of x=200 implies level of iterated dominance R(2), so we are unable to identify higher-level reasoners in treatment 2.

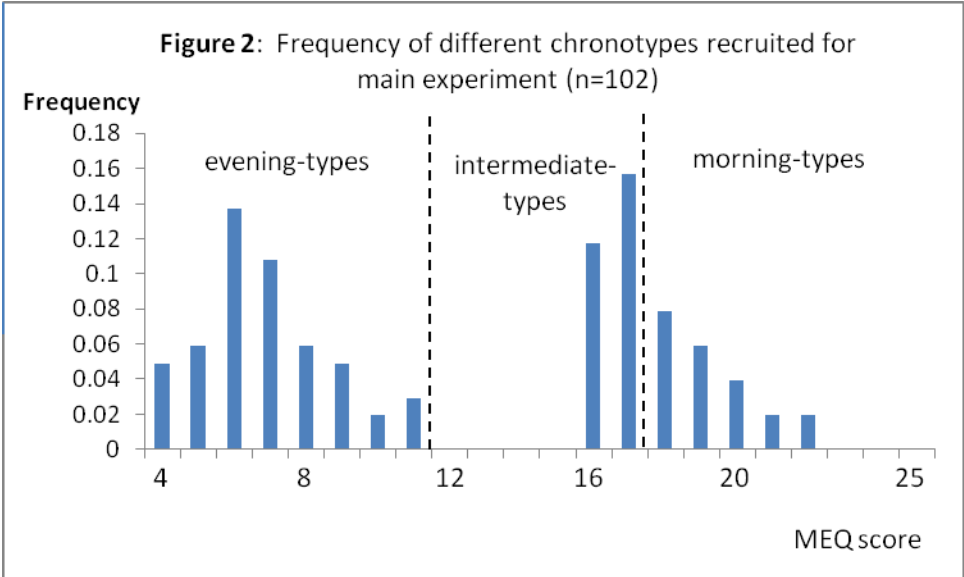
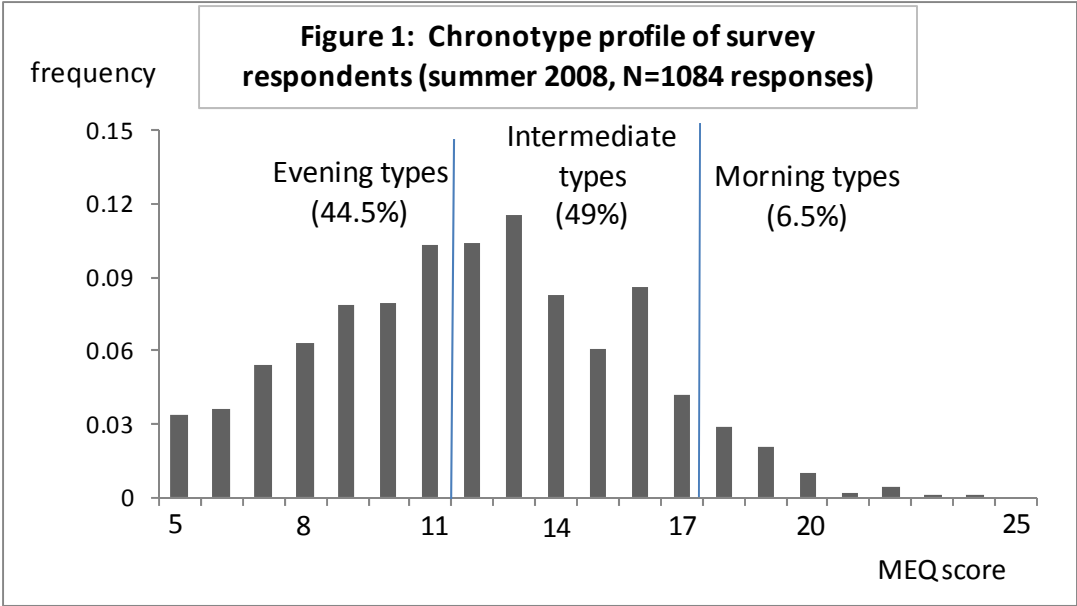
Table 4: OLS estimation of initial round *Guess* (st. errors in parenthesis)

<i>Variable</i>	Treatment 1	Treatment 2
Constant	395.77 (82.98)***	-32.42 (79.82)
Sleep Quantity	-1.92 (.44)***	.93 (.42)**
Sleep Quantity-squared	.0024 (.00057)***	-.001 (.00055)**
Mismatch Scale	129.74 (36.09)***	-57.97 (34.72)*
Mismatch Scale-squared	-103.03 (34.95)***	64.51 (33.62)*
R ²	.26	.14

*, **, *** indicate significance at the .10, .05, and .01 levels, respectively for the two-tailed test.

**Table 5: Summary of Learning Model Performance
(subset of data following no-win feedback)**

<u>Learning-Direction</u>	<u>SD=1</u>	<u>SD=0</u>	<u>MM=1</u>	<u>MM=0</u>
Treatment 1 (N=787)	75% (N=422)	75% (N=365)	75% (N=412)	75% (N=375)
Treatment 2 (N=297)	53% (N=176)	60% (N=121)	55% (N=164)	56% (N=133)
<u>Equil. Guess Adj.</u>				
Treatment 1 (N=787)	73% (N=422)	72% (N=365)	71% (N=412)	74% (N=375)
Treatment 2 (N=297)	80% (N=176)	83% (N=121)	80% (N=164)	83% (N=133)



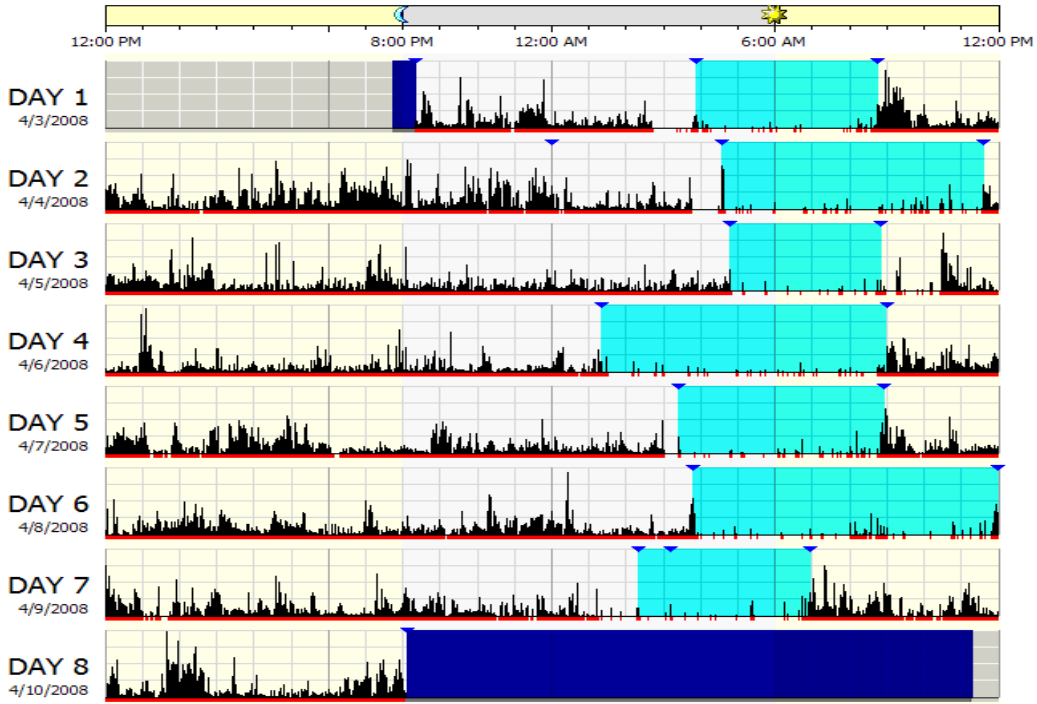


Figure 3a: Subject 25=SD—Evening-type, 5 hours average sleep per night
 (note: average bed/wake times for evening-types given in Table 1)

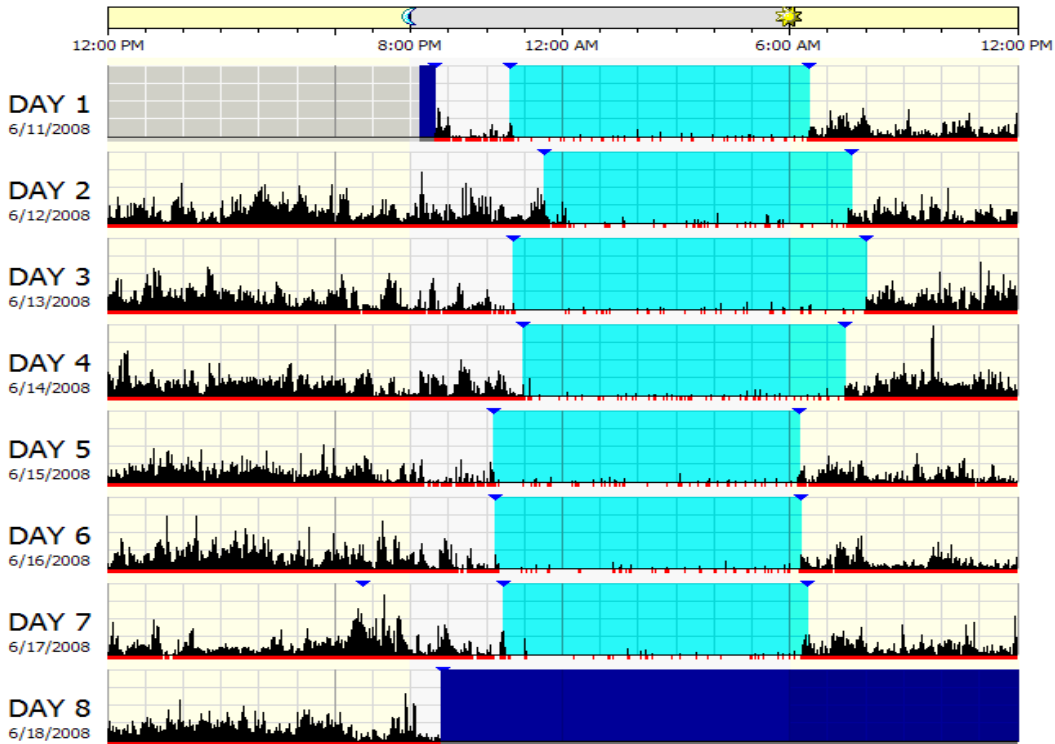
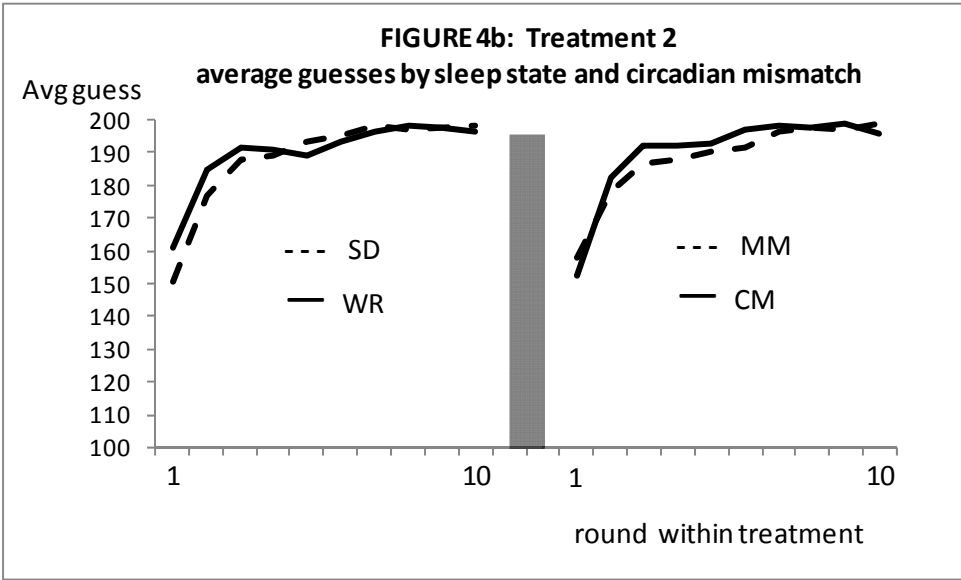
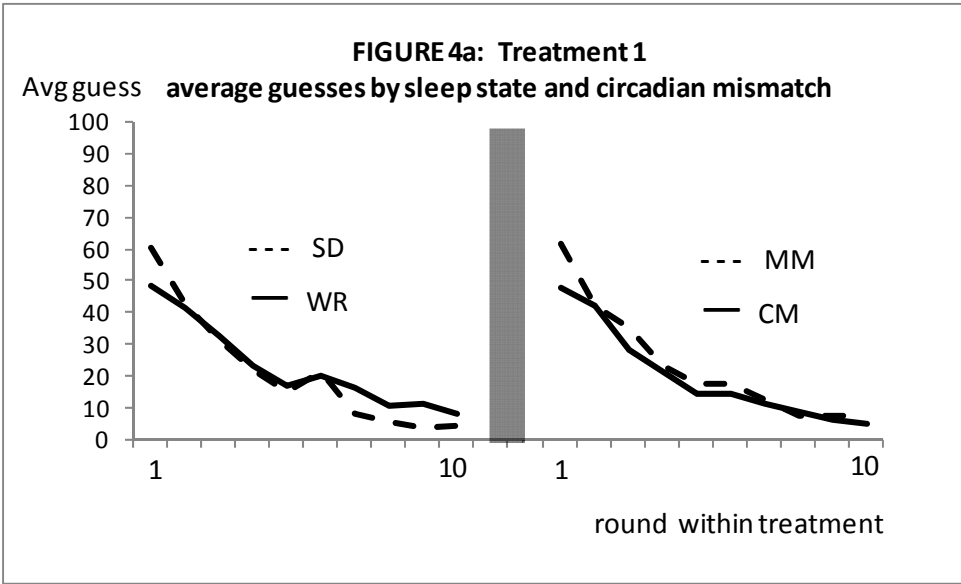
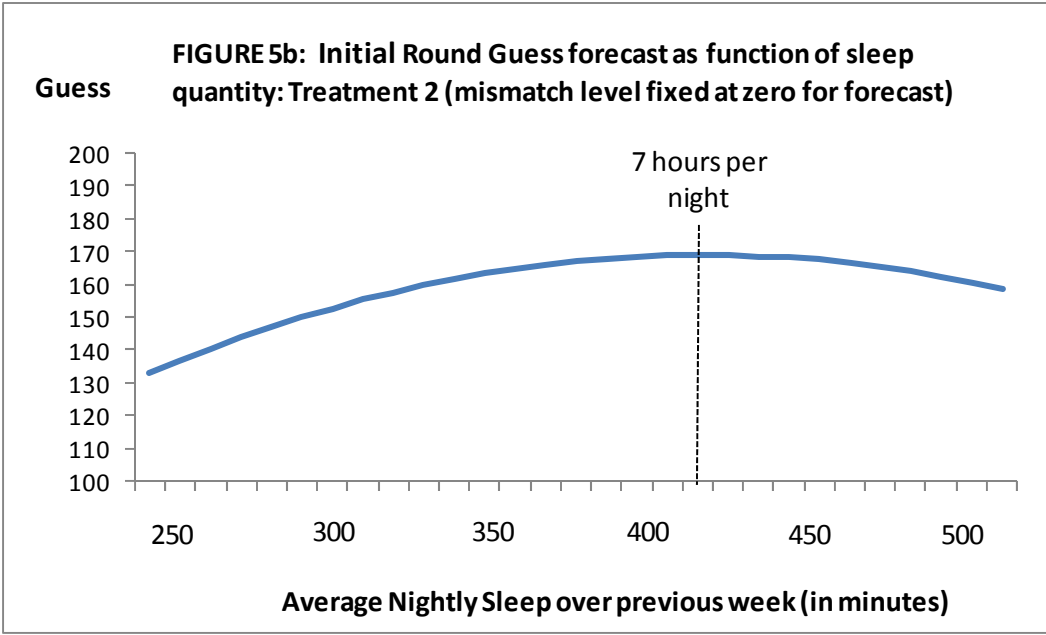
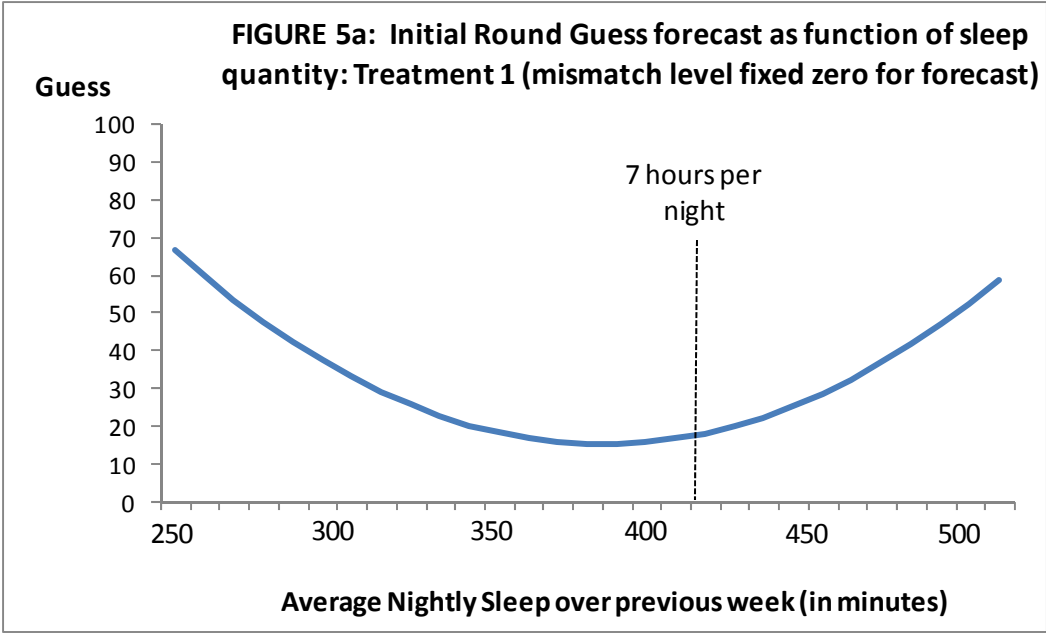
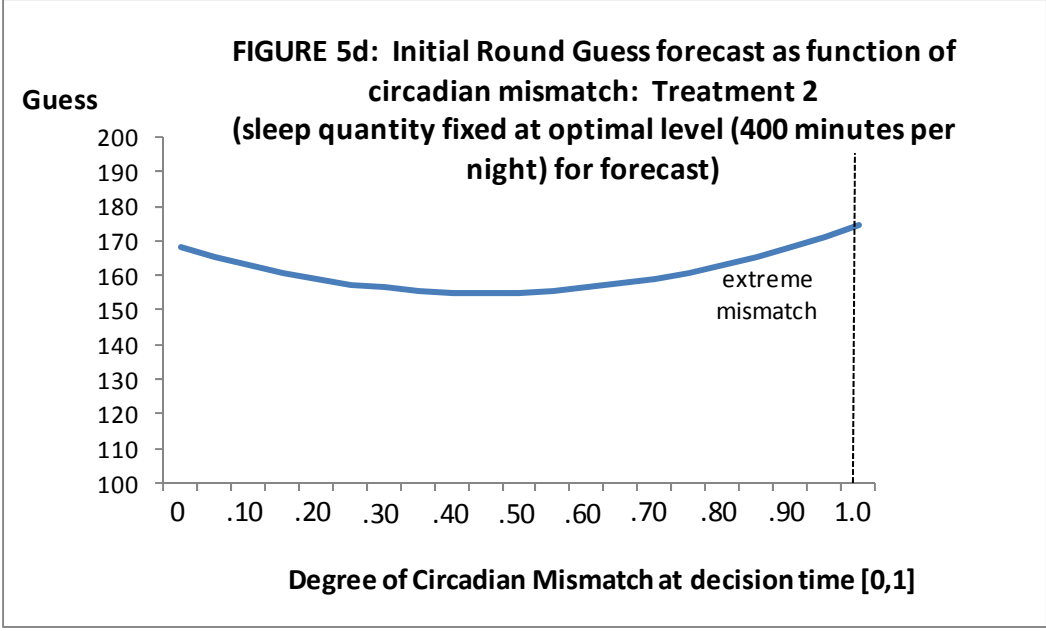
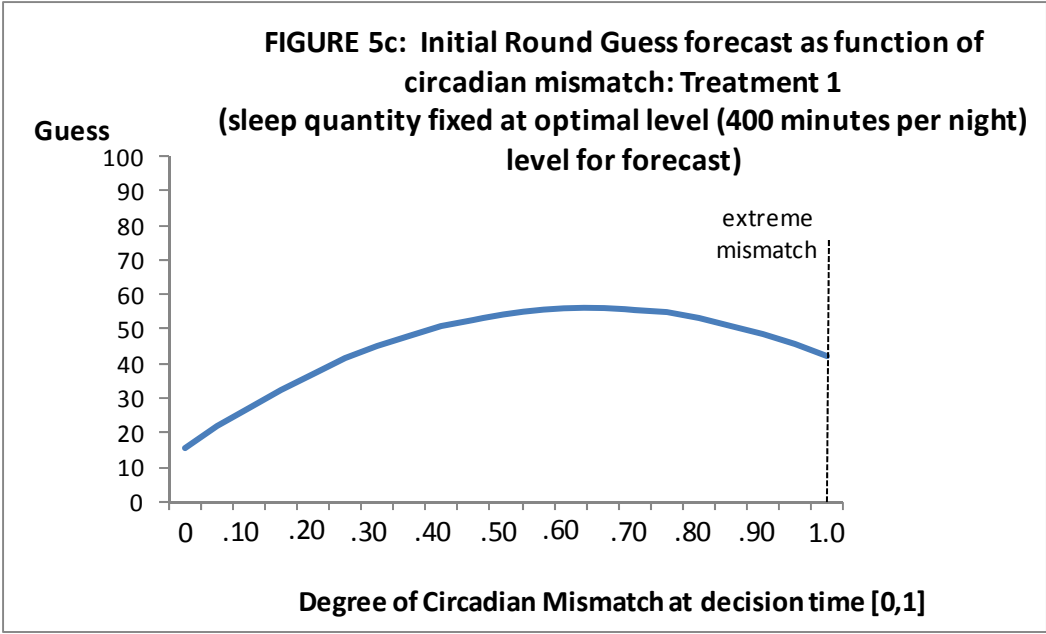


Figure 3b: Subject 35=WR—Morning-type, 7.5 hours average sleep per night
 (note: average bed/wake times for morning-types given in Table 1)







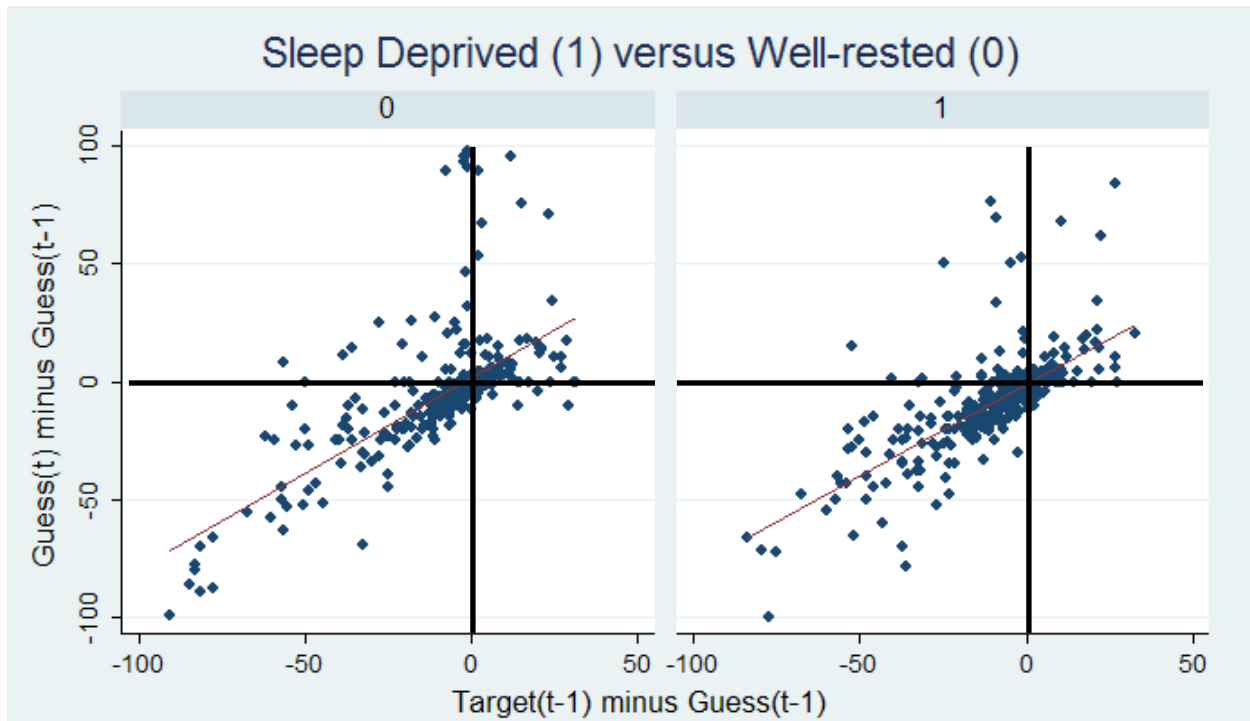


FIGURE 6a: Treatment 1 guess sensitivity to distance from target in previous round (OLS prediction overlaid)

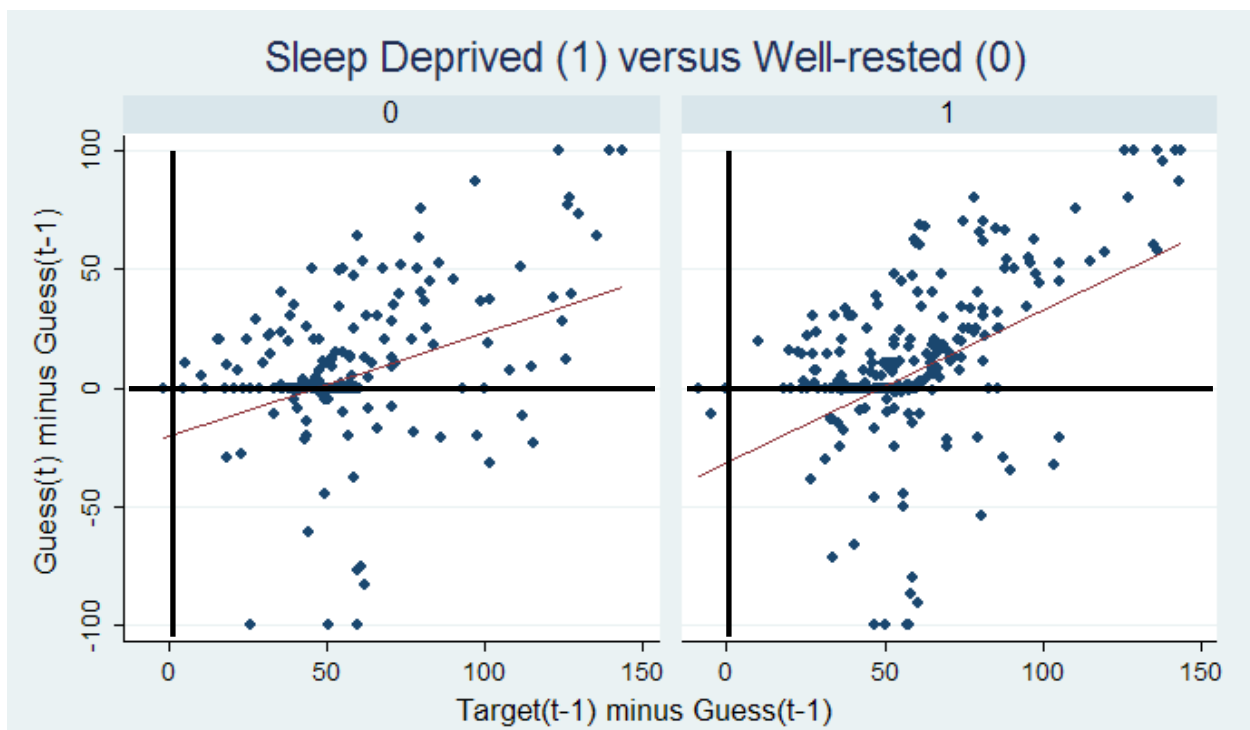


FIGURE 6b: Treatment 2 guess sensitivity to distance from target in previous round (OLS prediction overlaid)

