"Naturally-occurring sleep choice and time of day effects on *p*-beauty contest outcomes."

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ABSTRACT

We explore the behavioral consequences of sleep loss and time-of-day (circadian) effects on a particular type of decision making. Subject sleep is monitored for the week prior to a decision experiment, which is then conducted at 8 a.m. or 8 p.m. A validated circadian preference instrument allows us to randomly assign subjects to a more or less preferred time-of-day session. The well-known *p*-beauty contest (a.k.a., the guessing game) is administered to examine how sleep loss and circadian mismatch affect subject reasoning and learning. We find that the subject responses are consistent with significantly lower levels of iterative reasoning when 'sleep deprived' or at non-optimal times-of-day. A non-linear effect is estimated to indicate that too much sleep also leads to choices consistent with lower levels of reasoning, with an apparent optimum at close to 7 hours sleep per night. However, repeated play shows that sleep loss and non-optimal times-of-day do not affect learning or adaptation in response to information feedback. Our results apply to environments where anticipation is important, such as in coordination games, stock trading, driving, etc. These findings have important implications for the millions of adults considered sleep deprived, as well as those employed in shift work occupations.

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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] Some argue that 7-7.5 hours per night is satisfactory for the a healthy adult (Horne, 2004), though others document reduced cognitive performance when even 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). No one doubts that, in many professions and activities, public safety is at issue for an increasingly sleep-deprived society. For example, U.S. and Canadian truckers average about 5 hours sleep per night (Mitler et al., 1997), and medical residents significantly more medical errors when sleeping less than 5 hours per night (Baldwin et al., 2004; see also, Weinger and Ancoli-Israel, 2002). Even minor loss of sleep following the Spring Daylight savings shift leads to both increased fatal traffic accidents (Coren, 1996b) and accidental deaths unrelated to traffic accidents (Coren, 1996c).[2] 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. However, superimposed upon this is the body's natural daily cycle

[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 measureable economic outcomes, Kamstra et al., (2000) find that the daylight savings shift, which causes an short-term sleep desynchronosis, leads to significant financial market losses each year on the first trading day following the shift.

of alertness: the circadian rhythm.[3] An adverse point in one's circadian rhythm, or what we will 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 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) examine about 175,000 ledger entries over a 3-shift (24 hour 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, marketing and entrepreneurial decisions, and driving, to name a few. Because behavioral outcomes are often the product of many different components (e.g., cognition, motor-skills, risk attitude, etc) we aim to examine only the sleep and circadian effects of certain higher-level decision skills in this paper. Any potential interventions aimed at reducing traffic accidents or stock market losses that result from sleep deprivation would be misdirected if one failed to

[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.

understand whether the root cause was slowed reaction times, motor skill decrements, lapses in vigilance, failure to reason or anticipate, or a combination of effects. This research will 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 in subjects' initial decisions. Interestingly, we find that subject "rationality" appears optimized in initial round decisions when the subject averages about 7 hours of sleep per night, ceteris paribus. That is, nonlinear sleep effects are estimated to indicate that both too little *and* too much nightly sleep may 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 use of compensatory efforts. However, adaption and convergence towards equilibrium with repeated play indicate no difference in these learning effects as a result of sleep loss or circadian mismatch. Thus, in our environment sleepy subjects are able to learn much like nonsleepy subjects. Our results therefore hold implications primarily for initial performance in new environments (i.e., same group but new game parameters) and for one-shot interactions.

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 $p*\bar{x}$ times the average guess wins a prize, where p>0 is a common knowledge parameter. John Mayard Keynes (1936) considered newspaper competitions where entrants are asked to pick out the six most "pretty" faces (from a series of photographs), and a prize goes to the person whose picks correspond 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 rivals firm decisions on short notice. 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-Gomez 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.

Experimental Design

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

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 simply administer this instrument to each recruited subject after recruitment, but this greatly complicates obtaining a balanced sample of morning- and evening-types. The reason is that, in young adults, morning-type individuals are significantly more rare than evening types. 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 (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

[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 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 include no subjects with known sleep disorders.

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 experiment time slot, and then 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 an "activity-count" for each time epoch of a specified size. For our study, we utilize 30-second time-epochs. Subjects wear the watch 24 hours a day over the course of the actigraphy week, with few exceptions.[7] That is, the resulting data from each subject looks much like 'seismographic' data of the subject's wrist movements. The basic idea is

[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.

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 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 starts at 8:00 a.m. or 8:00 p.m. one week after Session 1, which starts at the same time. Session 2 includes the decision experiment, a short instrument to assess current sleepiness and caffeine use[8], removal of the actigraphy, and payment of all compensation in cash and private. It is important to note that while sleep quantities are observed, 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 designate 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 that there is no confounding correlation between chronotype and sleep loss.

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

[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).

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 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 purposefully 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

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

[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.

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. For example, 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 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 present 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.

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,

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[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.

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

converge towards equilibrium in multi-round play will be interpreted as learning or adaptation, rather than as a fundamental change in subjects' level of rationality. All our groups range from 8-10 subjects, which we feel adequate to eliminate any concern for group size effects as studied in Ho et al (1998)—they examined groups of 3 and 7 subjects.

Our design is a hybrid of experimentally manipulated circadian match/mismatch for the decision session time slot and uncontrolled sleep choices captured objectively 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 a conservative measure of sleep and circadian effects in this decision environment.

Results

The data are from 102 subjects (46 female), average age 23.2 ± 8.4 years of age. Payoffs averaged a total of $52.55 for each subject: $30 for the actigraphy week, and then $22.55 ± $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 including 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, we still sample subjects with good separation in the sleep personality dimension. The design cells for circadian match/mismatch are shown in Table 1, showing 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:

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

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 our validation instrument showed these same subjects seemed less

[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.

circadian mismatched based on KSS sleepiness reports. We further address this curiosity in the analysis below.

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

$Guess_i = \alpha + \beta_1*\text{SleepQ}_i + \beta_2*\text{SleepQ}_i^2 + \beta_3*\text{MS}_i + \beta_4*\text{MS}_i^2 + \varepsilon.$

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 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 none, though in treatment 2 the forecasted difference in initial round guess for zero versus complete circadian mismatch is negligible. The

[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.

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. It is the intermediate levels of circadian mismatch that we estimate will generate initial round guess that are farthest from equilibrium. This is a curious result, but we highlight that our design is uncontrolled with respect to strategies subjects may employ to combat sleepiness. Circadian mismatch may also display distinct effects when one holds MEQ score constant while varying the time of day along a continuum, as opposed to fixing two time points as we have done and examining mismatch resulting from the range of MEQ scores. It is of interest that the highest levels of circadian mismatch may be better than lesser mismatch levels if they are more likely to promote explicit coping strategies. 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. 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 of the potential behavioral effects of voluntary sleep loss and circadian mismatch 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 β=2.54 coefficient estimate from $KSS=\alpha + \beta * Mismatch\ Score + \varepsilon$). 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. Subjects' KSS scores do **not**, however, vary with nightly average sleep time (p=.69 on the OLS β=.001 coefficient estimate from $KSS=\alpha + \beta * SleepQ + \varepsilon$). It may be that SD subjects in our experiments do not indicate increased sleepiness yet MM subjects do because sleep loss is voluntary in our design, but circadian mismatch is manipulated (and subjects are aware of this).

Perceived sleepiness may explain why extreme circadian mismatch may engage a subject during the relatively short-term guessing game task. That moderate sleep loss in our environment does not lead to increased subjective sleepiness is consistent with findings in the literature on laboratory-controlled partial sleep deprivation. Van Dongen et al, (2003) show that partial but chronic sleep deprivation over the course of 1-2 weeks harms working memory performance and behavioral alertness to an extent similar to one night of total sleep deprivation, but subjective sleepiness reported is significantly lower in the case of chronic partial sleep deprivation. Thus, the existing research and findings in our study highlight a particular concern regarding partial sleep loss—individuals may experience significant behavioral deficits similar to those 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 in a rational direction to their 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 seem to indicate similar patterns of guess response to feedback regardless of one's sleep condition or time-of-day. Following Nagel (1995), we can examine the data's conformity to a qualitative learning model that posits that subjects adjust their guess 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.

direction of what would have been the optimal adjustment factor: the learning-direction theory. Nagel (1995) defines subject *i*'s adjustment factor and the optimal adjustment factor as

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

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

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 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.

Similar to proportions in Nagel (1995) for *p* parameters less than 1, we find that in the pooled data 75% of subject guesses in treatment 1 are consistent with learning-direction theory. 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 a more naïve rule-of-thumb adjustment process by which subjects just continue to adjust their guess in the direction of the predicted equilibrium, independent of

[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.

what the winning guess was in the previous round, *equilibrium guess adjustment*. 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. While the result is statistically insignificant (p=.12) with the two-sample proportion test, it is marginally significant (p=.09) using the binomial test. Alternatively, by sliding the subjective cutoff for coding of SD=1 to nightly average sleep of 6 hours or less (instead of 6.5 hours or less), the result is significant using the two-sample proportions test (p=.09). Though weak, this marginal result 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-based on sleep or circadian effects.

For a given sleep state (SD or WR, MM or CM) we can also 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-groups have no significant effect on the propensity to use one type of learning model versus the other. For treatment 2, in all comparisons we find that subjects are more likely to use the naïve equilibrium guess adjustment model than the learning-direction model, which is not surprisingly the less complex decision environment of the two treatments. Though a variety of 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. As such, Figures 6 and 7 seem to highlight what our simple analysis concludes—subject guesses seem to adjust in a rational way to deviations from the target in the previous round, but this adjustment process does not appear to differ when a subject is sleep-deprived or circadian mismatched.

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 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. Thus, subjects are matched or mismatched to more versus less optimal times-of-day, given their biological sleep preferences. The result is a design allowing 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, 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 6.5-7 hours of sleep per night, which is the range of estimated average nightly sleep 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. This is perhaps due to compensatory effort when manipulated (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 effects, and adaptation. Weber (2003) documents introspection-type learning in the guessing game with no information feedback, though much of the literature has examined feedback-learning. Grosskopf and Nagel

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

(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. With full information feedback in groups of 8-10 subjects, adaptation may be relatively simple in our experiments. A more comprehensive examination of sleep and learning seems warranted.

Our knowledge of the homeostatic and circadian influences on the biological need for sleep, and the extant literature of (mostly) controlled sleep studies, led to the hypotheses of 1) reduced application of iterative reason, and 2) adverse effects on learning. Though our data support only the first of these hypotheses, our findings have important implications for our modern society of increasing levels of voluntary sleep loss and circadian mismatching due to shift work. And, 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

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

Variable	**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)

Learning-Direction	**SD=1**	**SD=0**	**MM=1**	**MM=0**
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)
Equil. Guess Adj.				
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)

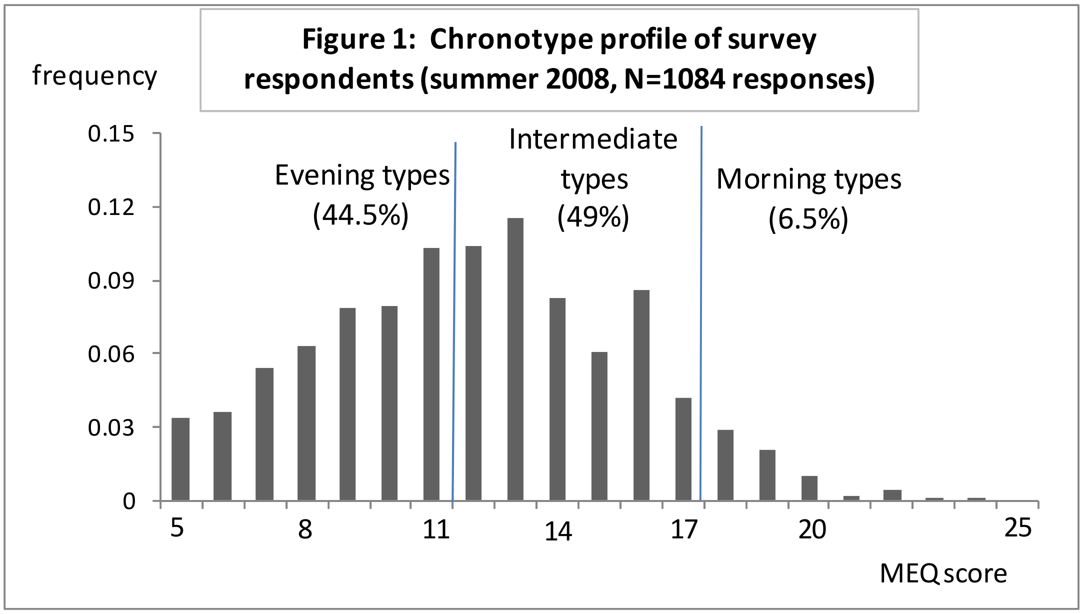


Figure 1: Chronotype profile of survey respondents (summer 2008, N=1084 responses)
frequency
0.15
0.12
0.09
0.06
0.03
0
Evening types (44.5%)
Intermediate types (49%)
Morning types (6.5%)
5
8
11
14
17
20
25
MEQ score

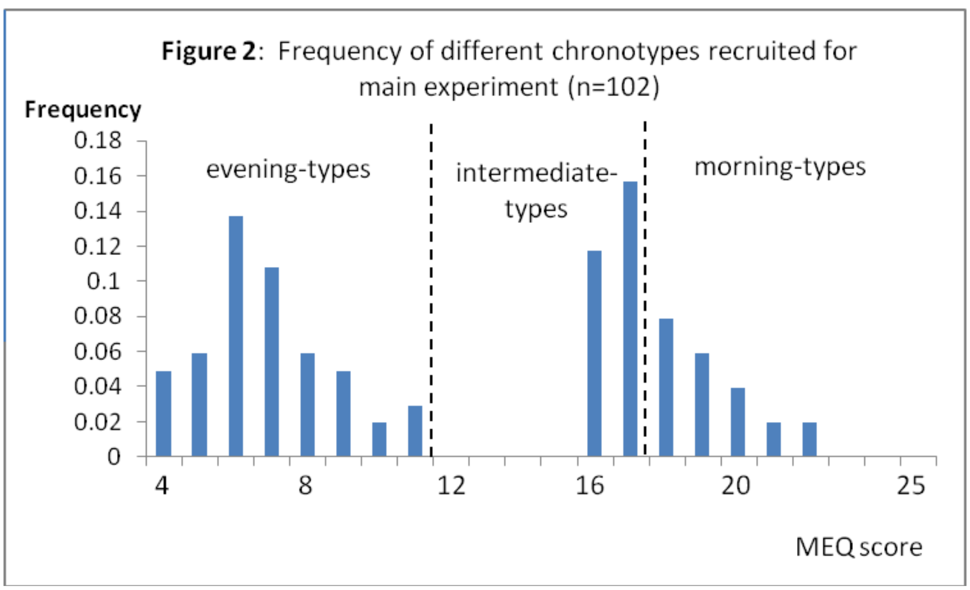


Figure 2: Frequency of different chronotypes recruited for main experiment (n=102)
Frequency
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
evening-types
intermediate-types
morning-types
4
8
12
16
20
25
MEQ score

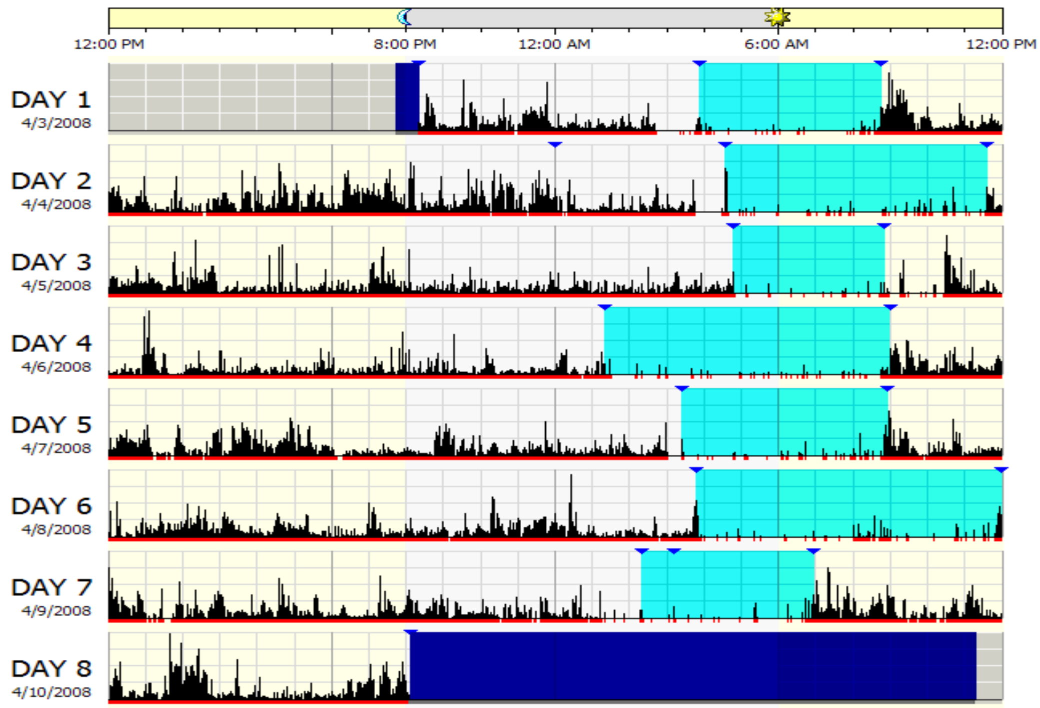


Figure 3a: Subject 25=SD—Evening-type, 5 hours average sleep per night
(note: average bed/wake times for evening-types given in Table 1)

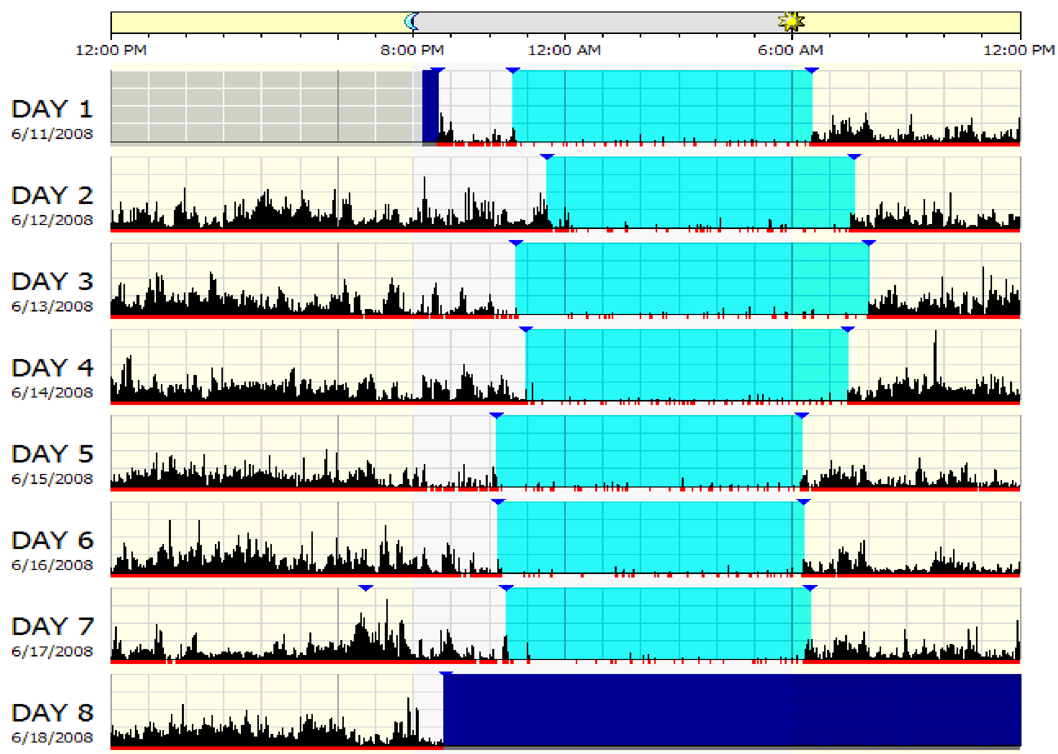


Figure 3b: Subject 35=WR—Morning-type, 7.5 hours average sleep per night
(note: average bed/wake times for morning-types given in Table 1)

FIGURE 4a: Treatment 1
average guesses by sleep state and circadian mismatch

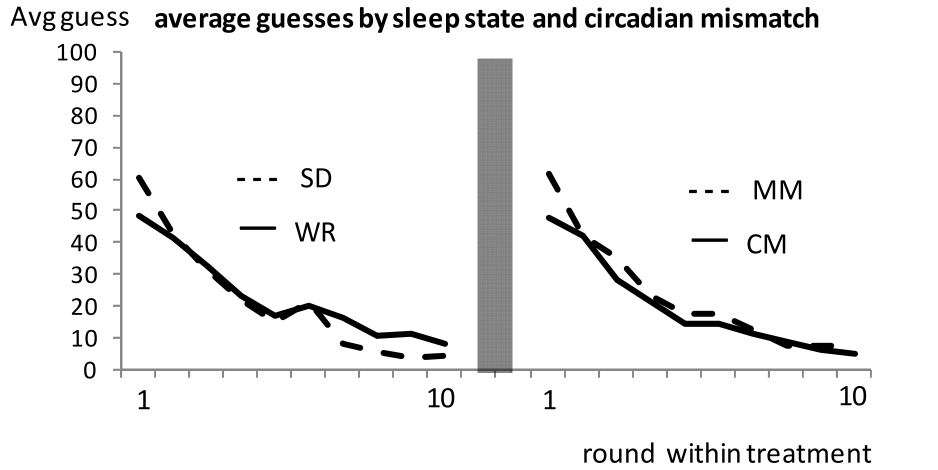
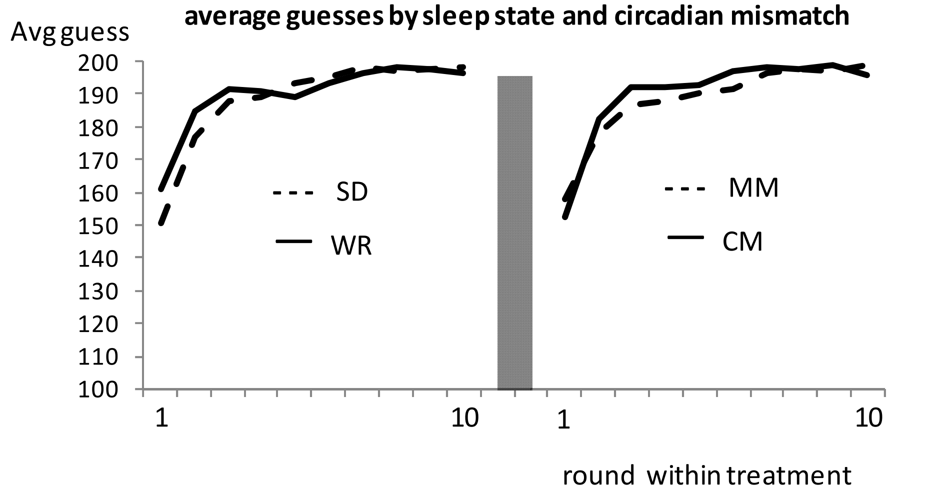


FIGURE 4b: Treatment 2
average guesses by sleep state and circadian mismatch



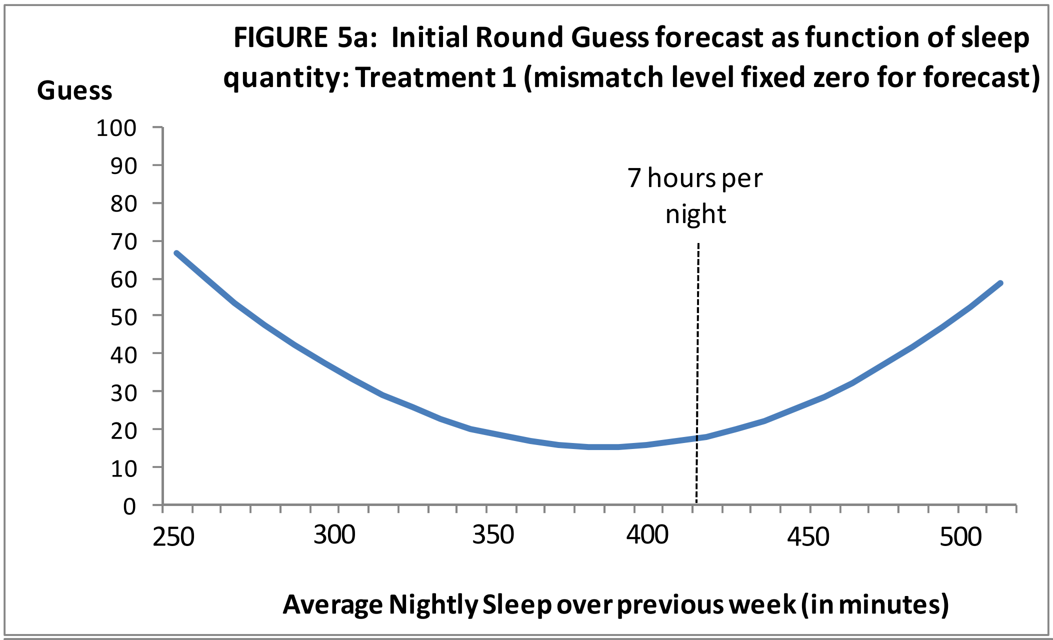


FIGURE 5a: Initial Round Guess forecast as function of sleep quantity: Treatment 1 (mismatch level fixed zero for forecast)
Guess
100
90
80
70
60
50
40
30
20
10
0
7 hours per night
250
300
350
400
450
500
Average Nightly Sleep over previous week (in minutes)

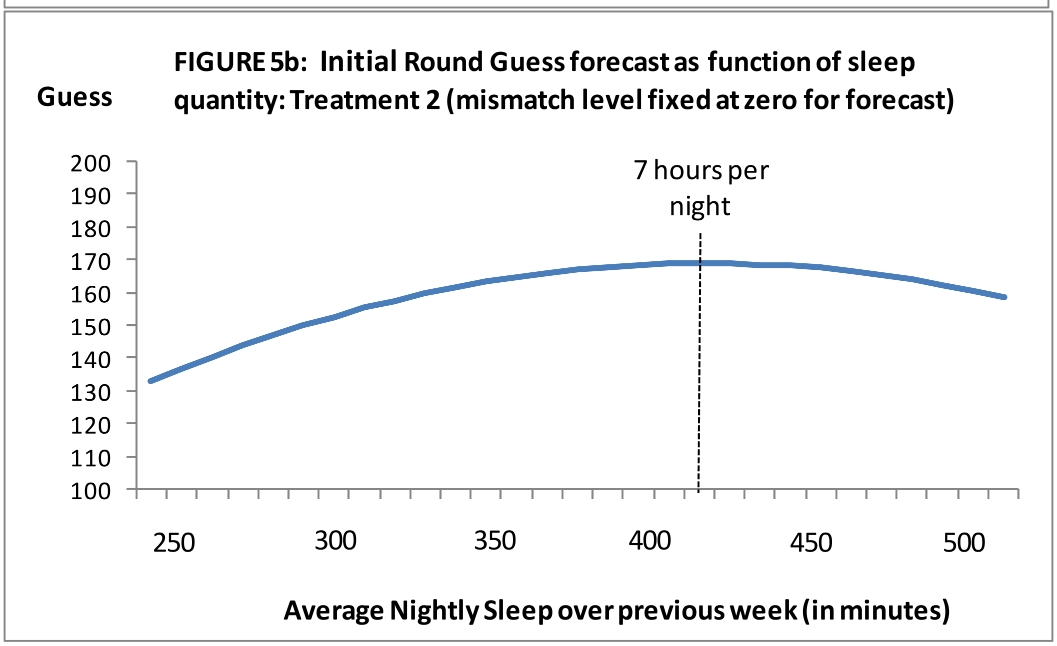


FIGURE 5b: Initial Round Guess forecast as function of sleep quantity: Treatment 2 (mismatch level fixed at zero for forecast)
Guess
200
190
180
170
160
150
140
130
120
110
100
7 hours per night
250
300
350
400
450
500
Average Nightly Sleep over previous week (in minutes)

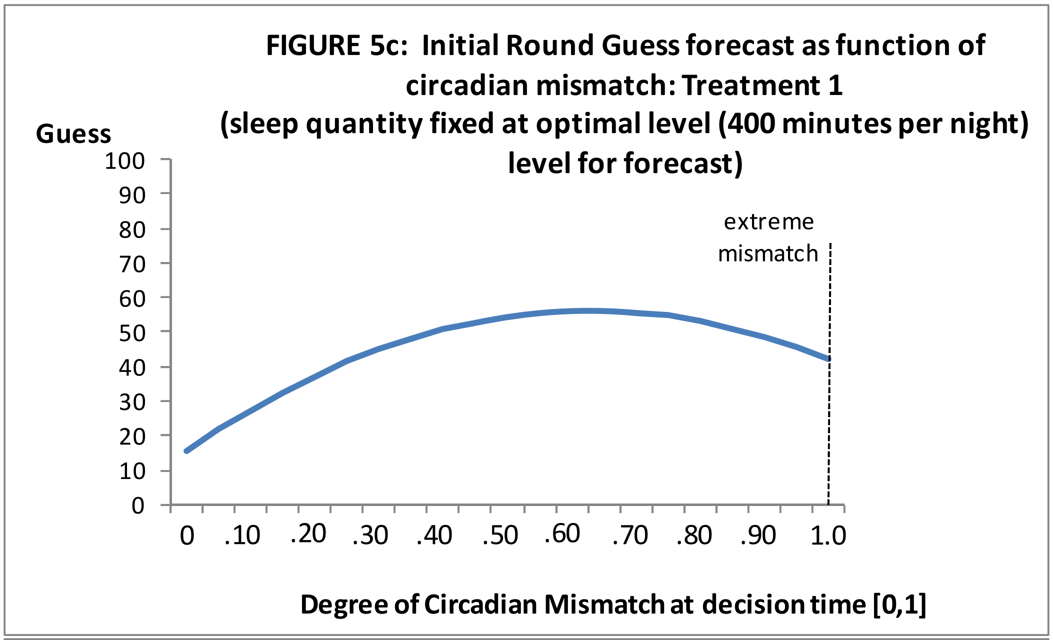


FIGURE 5c: Initial Round Guess forecast as function of circadian mismatch: Treatment 1
(sleep quantity fixed at optimal level (400 minutes per night) level for forecast)
Guess
100
90
80
70
60
50
40
30
20
10
0
extreme mismatch
0
.10
.20
.30
.40
.50
.60
.70
.80
.90
1.0
Degree of Circadian Mismatch at decision time [0,1]

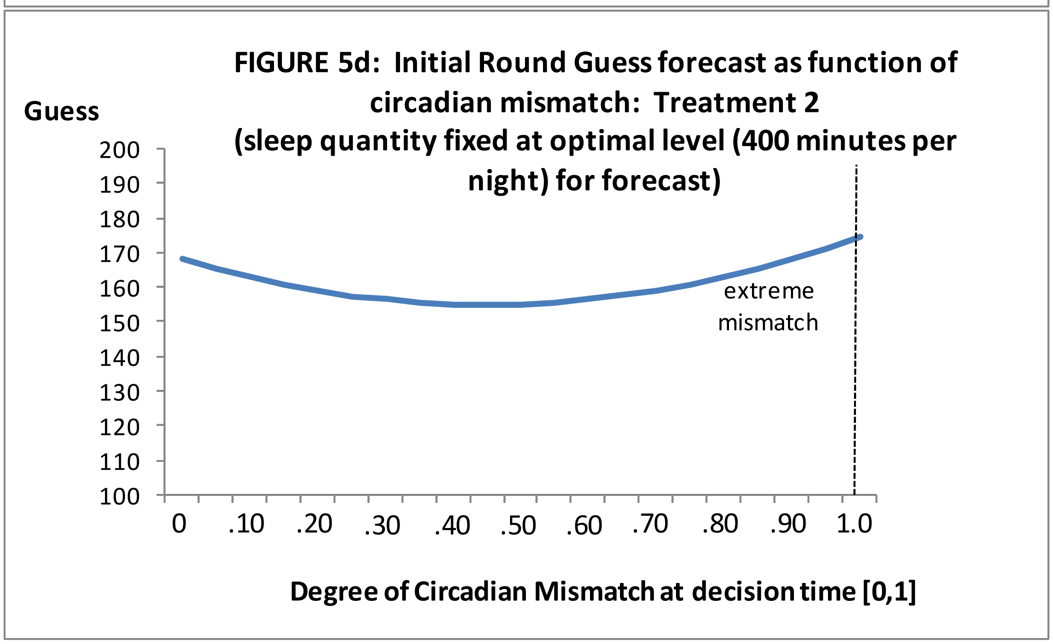


FIGURE 5d: Initial Round Guess forecast as function of circadian mismatch: Treatment 2
(sleep quantity fixed at optimal level (400 minutes per night) for forecast)
Guess
200
190
180
170
160
150
140
130
120
110
100
extreme mismatch
0
.10
.20
.30
.40
.50
.60
.70
.80
.90
1.0
Degree of Circadian Mismatch at decision time [0,1]

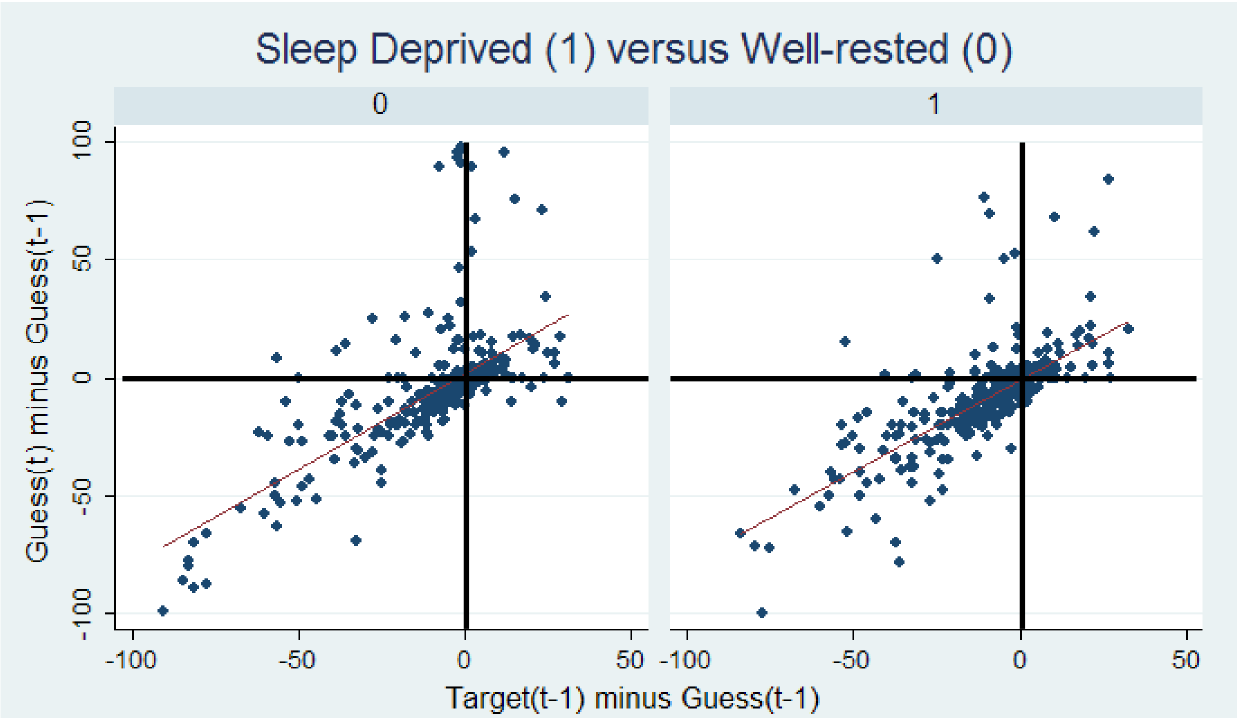


FIGURE 6a: Treatment 1 guess sensitivity to distance from target in previous round (OLS prediction overlaid)

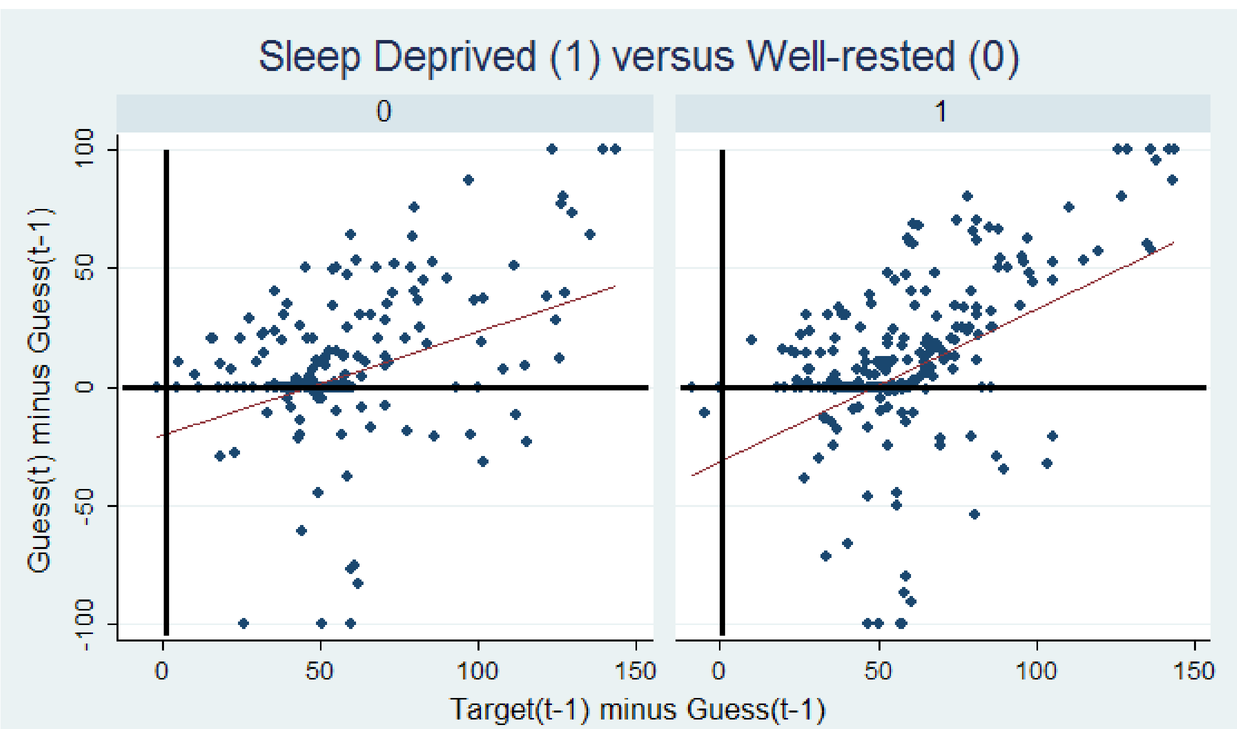


FIGURE 6b: Treatment 2 guess sensitivity to distance from target in previous round (OLS prediction overlaid)

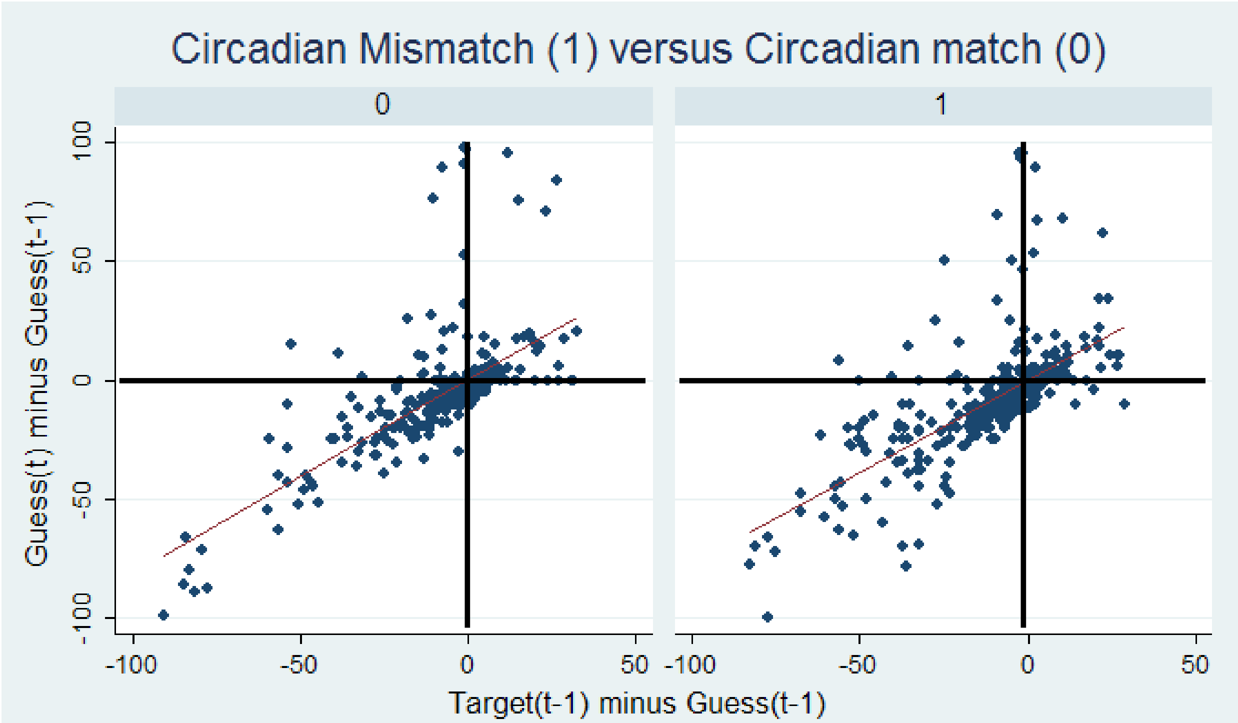


FIGURE 7a: Treatment 1 guess sensitivity to distance from target in previous round (OLS prediction overlaid)

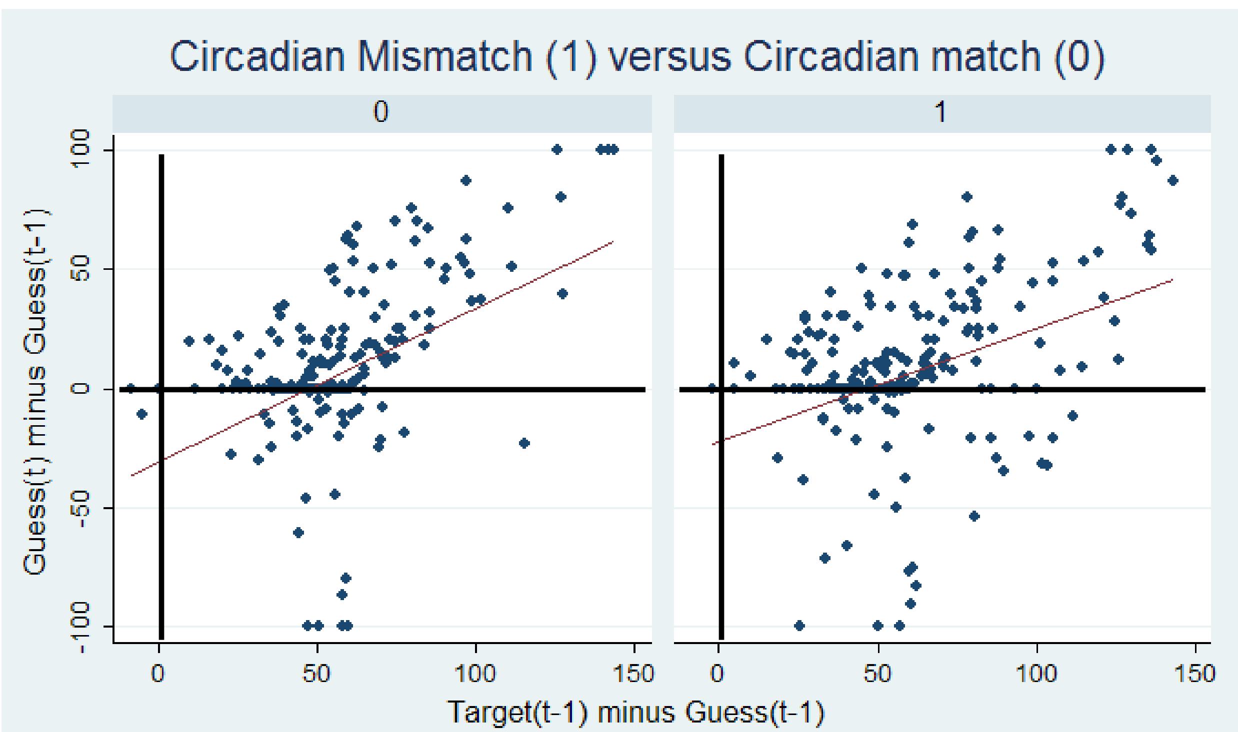


FIGURE 7b: Treatment 2 guess sensitivity to distance from target in previous round (OLS prediction overlaid)