Why Can't a Woman Bid More Like a Man?*

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Abstract

In this study, we investigate gender differences and menstrual cycle effects in first-price and second-price sealed-bid auctions with independent private values in a laboratory setting. We find that women bid significantly higher and earn significantly less than men do in the first-price auction, while we find no evidence of a gender difference in bidding in the second-price auction. At a biological level, we find a sine-like pattern of bidding in the first-price auction throughout the menstrual cycle, with higher bidding in the follicular phase and lower bidding in the luteal phase. Further analysis shows almost all of the variation is driven by contraceptive pill users.

Keywords: gender, menstrual cycle, contraceptive pills, auction, experiment
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1 Introduction

Gender differences in decision-making have long fascinated economists, psychologists and other social scientists. In a recent survey, Croson and Gneezy (forthcoming) synthesize findings from studies of preference differences in both laboratory and field experiments in economics and psychology. Focusing on risk taking, social preferences and reaction to competition, their synthesis indicates that women are more risk averse than men, with a few caveats and exceptions. Furthermore, various studies find that women's preferences for competitive situations are lower than those of men (e.g., Gneezy, Niederle and Rustichini (2003); Niederle and Vesterlund (2007); Gneezy and Rustichini (2004)). These experimental results are consistent with findings from survey data on gender differences in financial decision making (Jianakoplos and Bernasek 1998) and health behavior (Hersch 1996).[1]

However, while both experimental and survey results point towards robust gender differences in various decision-making tasks, it is not clear how much of this difference is due to environmental versus biological differences. Economic research has traditionally focused on environmental causes, examining variations in observable demographics, educational and professional background. In contrast to this approach, we examine the effects of biological processes on behavior. Specifically, we investigate the effects of the menstrual cycle on women's bidding behavior.

The menstrual cycle is "one of the very few biological processes that exhibit a virtually complete dimorphism between male and female members of the human species" (Nyborg 1983). Most women between the ages of 15 and 50 are regularly affected by the hormonal, physiological and psychological changes that are associated with the cyclical process of ovulation and menstruation (Richardson 1992). This is also an age interval when many important life-changing decisions are made. Thus, whether these hormonal and physiological changes affect women's cognitive performance, strategic decision-making, or attitudes towards competition is an important yet open question.

In particular, if the menstrual cycle affects women's strategic decision-making behavior, then it might be beneficial for them to know how their decision-making systematically varies during the cycle, to better time key decisions. This might lead to better decisions in investments, negotiations and other competitive situations, which could improve their earnings and social positions.

Despite the potential importance of the menstrual cycle for economic decision-making and market outcomes, economic research on this topic has so far been scant to our knowledge.[2] In a pioneering study, Chawla, Swindle, Long, Kennedy and Sternfeld (2002) measure lost productivity among women due to the pre-menstrual syndrome (PMS) using a sample of pre-menopausal Californian women. Similarly, Ichino and Moretti (2009) investigate absenteeism using an administrative dataset from a large Italian bank. They find that, below the age of 45, absenteeism

[1] Jianakoplos and Bernasek (1998) examine household holdings of risky assets, and find that, as wealth increases, the proportion of wealth held in risky assets increases by a smaller amount for single women than for single men. In a related study, Hersch (1996) examines data from a large national survey and finds substantial differences by both gender and race in risky behavior such as smoking, seat belt use, preventive dental care, exercise and blood pressure monitoring. Overall, Hersch finds that women make safer choices than men.

[2] Menstrual cycle research in medicine and psychology has found that most menstruating women tend to "experience a variety of physical, psychological and behavioral changes during the period between ovulation and menstruation." (Richardson 1992) Researchers have studied the effects of the cycle on such characteristics as spatial ability (Hampson and Kimura 1992), visual information processing, memory, and mood. However, none of the tasks involves economic decision-making.

of women follows a 28-day cycle, a pattern much more pronounced than that of men, whereas this gender difference is absent among older workers. They interpret this evidence as suggesting that, among pre-menopausal women, the menstrual cycle is a significant determinant of sick-day absenteeism, accounting for as much as one-third of the gender gap in days absent and more than two-thirds of the gender gap in the number of absences. Furthermore, the menstrual cycle can account for about one-seventh of the gender wage gap and the probability of promotion into a managerial position. Yuan, Zheng and Zhu (2006) is another study that indirectly points to a possible effect of the menstrual cycle on economic behavior and market outcomes. The authors investigate the relationship between lunar phases and stock market returns of 48 countries. They find that stock returns are lower on days around a full moon compared to days around a new moon. Citing biological evidence for lunar effects on human body and behavior, the authors note that the most common monthly cycle is menstruation, which is about the same length as the lunar cycle.

While such estimates of menstrual cycle-related effects are interesting and important, field data do not provide sufficient information to infer the extent to which the *phases* of the menstrual cycle affect strategic decision-making or reactions in competitive situations. To address this issue, we use a laboratory experiment to examine gender difference and the menstrual cycle effects in bidding in first-price (FPA) and second-price (SPA) sealed-bid auctions. Theoretically, in the FPA, the Bayesian Nash equilibrium is sensitive to bidders' risk preferences, while in the SPA, bidding one's true value is a weakly dominant strategy regardless of bidders' risk preferences. Thus, these two auction formats provide two distinct competitive situations in which to study gender differences and menstrual cycle effects on decision-making and resulting market outcomes.

This experiment yields three significant findings. First, we find that women bid significantly higher and earn significantly less than men do in the FPA, while we find no evidence of a gender difference in bidding in the SPA. Our second finding relates to menstrual cycle effects in the FPA. Specifically, we find that, while women in all phases of their cycle bid significantly higher than men do, there is a sine-like bidding pattern throughout the cycle, with higher bids in the follicular phase and lower ones in the luteal phase. Lastly, when splitting the sample by usage of contraceptive pills, we find that this variation is driven almost exclusively by women who use the pill, whereas there is little variation in behavior over the cycle among women who do not use the pill. This finding is robust to whether, in addition to the induced value, we control for treatment differences, demographics or risk aversion differences.

Our paper thus presents the first experimental study in economics on how the the menstrual cycle affects economic decision-making and market outcomes. We provide evidence of a systematic variation in bidding behavior in the FPA among women depending on their phase of the cycle and contraceptive pill usage. While the behavioral endocrinology literature has examined the relation between menstrual cycles and cognition, it has not examined the domain of auctions or other competitive tasks. Thus, this paper contributes to the general literature on menstrual cycles and cognition by opening up a new and important domain of investigation. Results in this new domain can provide insights for economic policymakers.

We are aware of three related studies that examine the effects of demographics in auctions. First, in an experimental study of the English, Vickrey and the Becker, DeGroot and Marschak (1964) mechanisms in auctions of a box of gourmet chocolate truffles using home-grown values, Rutstrom (1998) finds both gender and race differences in bidding. In another study, Casari, Ham and Kagel (2007) explore demographic and ability effects in common value auctions, using the induced-value method. They find that women inexperienced in common-value auction experiments bid higher and thus suffer more from the winner's curse than do men, while women experienced at such auctions do at least as well as men. However, while both studies identify gender differences, neither investigates potential biological causes for these differences. Lastly, using our experimental environment and software, Pearson and Schipper (2008) present an experimental study of menstrual cycle effects on bidding in FPA. We comment on the similarities and differences in our measurements and results in Sections 3 and 4.

The rest of the paper is organized as follows. Section 2 discusses the experimental design. We present our results on gender differences in bidding in Section 3, and the effects of menstrual cycle and contraceptive pills on behavior in the FPA in Section 4. Finally, Section 5 concludes.

2 Experimental Design

In this section, we summarize the main features of our experimental design, the post-experiment questionnaire, and additional sources of data that we use. Our data come from two waves of experiments. Dataset 1 contains data on both the FPA and SPA. It is compiled from auction experiments, a post-experiment questionnaire, and additional data on course and major background collected from the University of Michigan Office of the Registrar. We ran these experiments between October 2001 and January 2002, and reported our estimations of bidder risk and ambiguity attitude in Chen, Katuščák and Ozdenoren (2007).[3] The second wave of experiments, contained in Dataset 2, was designed to address concerns about the lack of control for risk aversion and the usage of contraceptive pills in the first wave of experiments, and was conducted in October 2006. In the second wave, we used the same auction environment, restricting attention to the FPA only, and additionally measured subject risk attitudes using the Holt and Laury (2002) lottery instrument. Furthermore, we used a modified version of the questionnaire, which elicited usage of a contraceptive pill and multiple measures of the phases of the menstrual cycle, in addition to questions posted in the first wave.

All sessions were conducted using networked computers at the Research Center for Group Dynamics Laboratory at the University of Michigan. The subjects were recruited from an email list of Michigan undergraduate and graduate students, excluding graduate students in economics. In the first wave, sessions lasted from 40 to 60 minutes, with the average per subject earning being \$13.00 in the FPA and \$19.40 in the SPA. In the second set of experiments, sessions usually took from 60 to 80 minutes due to the presence of the lottery, with the average per subject earning \$12.64 from the FPA and \$10.52 from the lottery (with an average total earning of \$23.16).

2.1 Auctions

The first wave of experiments employs a 2×2 factorial design. In the mechanism dimension, we use the FPA and SPA, while in the information dimension we include treatments with known and unknown distributions. Using both the FPA and SPA enables us to study gender differences in situations with varying strategic complexity. Specifically, while FPA bidding behavior depends on risk attitude, SPA bidding depends on the ability to figure out the dominant strategy. The purpose of the information dimension is to study the impact of ambiguity on bidding, which is the primary

[3]Note that Chen et al. (2007) does not contain any description or analysis of demographic or menstrual cycle effects. It focuses solely on estimations of the structural models of risk and ambiguity.

focus of Chen et al. (2007). The second wave consists of ten independent sessions of the FPA with known distribution.

[Table 1 about here.]

Table 1 summarizes the features of the auction experiments, including mechanisms, number of subjects per session, information conditions, exchange rates, and total number of subjects in each treatment. Each experimental session consists of 8 bidders. This design gives us a total of 30 independent sessions, 20 in Dataset 1 and 10 in Dataset 2, and a total of 240 subjects.

The process within each session is as follows. First, at the beginning of each session, subjects randomly draw a PC terminal number. Then, each subject is seated in front of the corresponding terminal and given printed instructions (Appendix A). After the instructions are read aloud, each subject completes a set of Review Questions to test their understanding of the instructions. The experimenter then checks the responses and answers any questions. The instruction period varies between fifteen to thirty minutes, depending on the treatment.

Each session lasts for 30 rounds, without any practice rounds. In each round, bidders are randomly rematched into groups of two. Bidder valuations are generated as independent draws from either a low value distribution $F^1(\cdot)$ or a high value distribution $F^2(\cdot)$. The support set of these distributions is given by $\{1, 2, \cdots, 100\}$, and the respective densities, f^1 and f^2, are given by:

$$f^1(x) = \begin{cases} \frac{3}{200} & \text{if} \quad x \in \{1, .., 50\} \\ \frac{1}{200} & \text{if} \quad x \in \{51, .., 100\} \end{cases}$$
$$f^2(x) = \begin{cases} \frac{1}{200} & \text{if} \quad x \in \{1, .., 50\} \\ \frac{3}{200} & \text{if} \quad x \in \{51, .., 100\} \end{cases}.$$

In all sessions, we set the probability that bidder value is drawn from $F^1(\cdot)$ at 0.70. In treatments with a known distribution, i.e., in 15 out of 20 FPA and 5 out of 10 SPA sessions, we announce this probability, whereas we do not do so in treatments with an unknown distribution.

Each round of bidding consists of the following stages:

1. For treatments with an unknown distribution only, each bidder is asked to submit his or her estimate of the probability that the valuation of the *other* bidder in the group is drawn from the high value distribution.

2. Next, each bidder is informed of his own valuation. Then each bidder simultaneously and independently submits a bid, which can be any integer between 1 and 100, inclusive.

3. Bids are then collected in each group and the winner is the bidder with the higher bid, using a fair tie-breaking device in case two bids coincide.

4. After each auction, each bidder receives the following feedback on his screen: his valuation, his bid, the winning bid, whether he wins the auction, and his payoff. The payoff is equal to the difference between his value and the price if he wins, and zero otherwise. The price is equal to the winning bid in the FPA, and to the losing bid in the SPA.

2.2 Lottery

In the second wave, we complement the auction experiment with a Holt and Laury (2002) lottery choice experiment to elicit bidder risk preferences. Specifically, subjects make ten choices, each between lotteries A and B, as shown in Table 2. For example, in choice 4, subjects choose between lottery A defined by a 0.4 probability of getting 200 points and a 0.6 probability of getting 160 points, and lottery B defined by a 0.4 probability of getting 385 and a 0.6 probability of getting 10. After the subject has made his choices, one of the ten choices is randomly chosen with equal probability and played. The subject is then paid the realized prize (in points). The exchange rate is the same as that in the auction experiment. To control for order effects, in 5 out of 10 sessions, the lottery precedes the auction, whereas the order is reversed in the remaining sessions.

[Table 2 about here.]

In the lottery choice experiment, an expected utility maximizer should start by choosing lottery A for the first few choices and then switch to lottery B for the remaining choices. By observing when he switches, we can measure his risk aversion. In particular, risk aversion can be measured by the number of times the decision-maker chooses lottery A. A risk neutral decision maker, for example, should switch after four choices of A.

[Table 3 about here.]

Of the 80 subjects in the second wave, 72 display consistent risk preferences in that, once they switch from lottery A to lottery B, they continue choosing lottery B. The remaining 8 subjects show at least one reversal after switching. In this analysis, we measure risk aversion for these subjects by the number of times a subject has chosen lottery A, even if there are some preference reversals. Table 3 lists the distribution of the risk aversion measure separately for men and women. Since there is only one subject with this measure below 4 and only one with this measure above 8, in subsequent analysis we use a doubly-censored measure with categories less than or equal to 4, 5, 6, 7, and more than or equal to 8.

2.3 Survey

At the end of the experiment, all participants complete a survey (Appendix B) to elicit demographic information, as well as a self-described personality assessment and identification of emotions experienced during the experiment. In addition, female subjects provide menstrual cycle information. We do not include the personality or emotion variables in the subsequent analysis, as they are likely to be endogenous to the outcome of the auction (and the lottery).[4] Thus, our variables of interest fall into three categories: demographic, education, and menstrual cycle variables.

For the demographic information, we elicit gender, race, age, and number of siblings.[5] In the first wave, the questionnaire does not contain information on academic majors; therefore we obtain this information from the University of Michigan Office of the Registrar, together with a list

[4]The primary objective of eliciting this information was to study ambiguity attitude in our companion paper (Chen et al. 2007).

[5]If a subject reports two ethnic origins, we set each of the relevant ethnic indicator variables to 0.5.

of courses our subjects took at the University of Michigan prior to participating in the experiment. In the second wave, we elicit academic major information in the questionnaire.

We group academic majors into six different categories: Mathematics and Statistics, Science and Engineering, Economics and Business, Other Social Sciences, Humanities and Other, and Unknown. These categories cluster academic major types with a similar exposure to analytic and strategic reasoning.

[Table 4 about here.]

Summary statistics on survey responses on non-menstrual-cycle variables are contained in Table 4. Of the 240 subjects, 129, or 54%, are women (78 in Dataset 1 and 51 in Dataset 2). The average age is 21.9, and subjects have 1.67 siblings on average. Regarding the racial composition, 48% of subjects are white, 35% are Asian/Asian American, 8% are African American, 5% are Hispanic, and the rest identify themselves as belonging to other racial groups. Because of the relatively low number of non-white or non-Asian subjects, we group all other racial groups into the "Other" category in the analysis. Regarding the academic major, most of our subjects are Science and Engineering majors (31%), followed by Humanities and Other (19%), Economics and Business (12%), Other Social Sciences (9%), and Mathematics and Statistics (3%). We do not have academic major information for 27% of our subjects (all of them in Dataset 1).

Our menstrual cycle information comes from answers to Question 8 in the survey. In the first wave, we elicit the number of days until the next menstrual cycle (*prospective measure*), as well as the presence of premenstrual syndrome (PMS). Since the PMS variable is not statistically significant in any of our results, we exclude it from the analysis presented here. In the second wave, in addition to the prospective measure, we elicit a *retrospective measure* ("What date was the first day of your last menstrual period?"), whether a participant is currently menstruating, number of menstruations per year, the average length of the cycle, the average length of the menstrual period, and most importantly, their contraceptive pill usage. In Appendix C, we report the summary statistics of menstrual cycle information and pill usage. In sum, we have menstrual cycle information on 124 out of 129 female students, and one-third of the female students in the second wave use the pill.

[Figure 1 about here.]

Figure 1 presents the variation in hormonal levels over the course of the cycle, which lasts 28 days on average. The cycle is divided into five phases. During the *menstrual phase* (days 1-5), secretion of estradiol (i.e., the major estrogen produced in the human body) and progesterone ceases, followed by degeneration and expulsion of the uterine lining. Women during this phase have the lowest levels of estradiol and progesterone. During the *follicular phase* (days 6-13), a follicle-stimulating hormone stimulates an ovarian follicle to develop and secrete estradiol. The increased level of estradiol causes reconstruction and proliferation of the uterine lining and stimulates the pituitary to produce the luteinizing hormone. Women during this phase have large amounts of circulating estradiol and very little progesterone. During the *peri-ovulatory phase* (days 14-15), the luteinizing hormone reaches its peak at mid-cycle, which causes the mature follicle to release the ovum through the wall of the ovary. Under the influence of the luteinizing hormone, the original site of the ovum develops into a secretory organ known as corpus luteum. During this phase, estradiol levels somewhat decrease. During the *luteal phase* (days 16-23), estradiol and progesterone are secreted by the corpus luteum to prepare the uterine lining for implantation should fertilization occur. During this phase, progesterone peaks and estradiol levels reach a second peak. Finally, during the *pre-menstrual phase* (days 24-28), sometimes also called the late luteal phase, the levels of both estradiol and progesterone decline drastically.

[Figure 2 about here.]

Since the menstrual cycle has been documented to influence women's cognition (visual information processing, and memory) and mood (Richardson 1992), we are interested in the extent to which the phases of the cycle affect bidding behavior. We measure the phase of the menstrual cycle through self-reports of day counts from the beginning of the last and the beginning of the next cycle. Although day count is not the most reliable method of measuring menstrual cycle phases, it is the most frequently used method in menstrual cycle studies (Sommer 1992). The most reliable method is a direct assay of hormones, which requires invasive procedures such as blood collection. As noted by Sommer (1992), however, day count could be used as a legitimate indicator of hormone levels if the sample size is large. Most menstrual cycle studies in behavioral endocrinology use around 20 subjects, while we have 129 female subjects. We thus believe that our measures enable us to draw useful inferences about the effect of the menstrual cycle on bidding behavior. In Appendix C, we compare the size of the measurement error in the retrospective and prospective measures of the menstrual cycle, both of which have been used in the literature (e.g., Pearson and Schipper (2008)). We find that, while the two measures are highly correlated, the prospective measure is less noisy for our data, which could be due to a larger number of observations. Thus, in all subsequent analyses, we report results using the prospective measure. For robustness checks, we rerun all analyses using the retrospective measure on the data in the second wave, and find that all key findings hold with sometimes larger confidence intervals due to the fact that the retrospective measure is more noisy. Figure 2 plots a histogram of the prospective measure of the menstrual cycle for our subjects.

3 Gender Differences in Bidding

In this section, we present the results on gender differences in competitive bidding, focusing on the FPA. We examine two outcome variables: bids and payoffs. Although the following discussion is framed in terms of bids being the outcome variable, we use the same methodology to analyze payoffs. In the following analysis, we use both non-parametric and parametric methods. While the non-parametric method does not require specification of a functional form, it also does not allow us to control for treatment differences, demographic variables, or risk aversion. Thus, we also conduct parametric analysis to control for these other variables. Details of the non-parametric estimation techniques are described in Appendix D.

Using non-parametric methods, we first estimate the bidding function (bid as a function of value) separately for each gender. We then use the difference in the two predicted bidding functions to estimate the gender difference. We construct 95% confidence intervals for these predictions by bootstrapping with 250 replications, with draws for each replication clustered at the session level to control for bidding interdependence within a session. To investigate the economic consequences of any gender differences in FPA bidding, we conduct a similar non-parametric analysis of gender differences in payoffs.

[Figure 4 about here.]

Figure 4 presents non-parametric estimates of the gender differences in bidding behavior (Panel A) and payoffs (Panel B) in the FPA. Panel A shows that women bid more than men do in the FPA, and this difference is statistically significant for values above 24. Over the 100 different values, women overbid men by a median of 5.73 percentage points of their valuation. Furthermore, Panel B indicates that women's higher bids result in statistically significant lower payoffs for values above 33, with the median gap being 3.61 percentage points of their valuation. Given that the payoff medians for men and women are 18.60 and 14.98 percentage points of their valuations, respectively, this constitutes approximately a one-fifth reduction in the scaled size of payoffs for women.

There are several potential explanations for the gender differences in bidding behavior. One potential explanation is a gender difference in risk aversion (Croson and Gneezy forthcoming). In a symmetric Bayesian Nash equilibrium with known (Riley and Samuelson 1981) or unknown (Chen et al. 2007) distribution of valuations, higher risk aversion increases bids in the FPA. Other likely explanations include differences in strategic reasoning or attitudes toward competition (e.g., Gneezy et al. (2003); Niederle and Vesterlund (2007); Gneezy and Rustichini (2004)). To address these possibilities, we investigate the extent to which risk attitude can explain the gender gap by incorporating the lottery choice data in the second wave of experiments. In addition, we examine any presence of gender difference in bidding behavior in second-price auctions. Lastly, we note that our data do not enable us to differentiate any gender differences in attitudes toward competition.

Using the Holt and Laury measure of risk aversion reported in Table 3, we first check whether, as shown in previous research (Croson and Gneezy forthcoming), women are more risk averse than men. A simple comparison of means shows that even though women are somewhat more risk averse (6.27 vs. 6 on average), the difference is not statistically significant. However, when we control for the order effect and for a set of demographic variables (age, race, academic major and number of siblings), the difference between women and men grows from 0.27 to 0.48, with a p-value of 0.065. As a result, after accounting for observable heterogeneity, the gender difference in risk aversion becomes marginally statistically significant.

To investigate the extent to which the gender differences in bidding can be accounted for by risk aversion, and to test the robustness of the findings from our non-parametric analysis, we conduct a parametric analysis. More specifically, we model the bidding function through a second-order polynomial in value, separating by gender, and controlling for treatment indicators (Dataset 1 and known distribution, Dataset 1 and unknown distribution, Dataset 2 and auction before lottery, Dataset 2 and lottery before auction), demographics (age, race, academic major and number of siblings), and risk aversion indicators, as well their respective interactions with the second-order polynomial in value. We obtain our risk aversion indicator from the lottery choice experiment in the second wave (Table 2). Thus, we model the bidding function as:

$$b_{it} = \beta_0 + \beta_1 v_{it} + \beta_2 v_{it}^2 + \gamma_0 F_i + \gamma_1 F_i v_{it} + \gamma_2 F_i v_{it}^2 + \sum_{s=1}^{S} \left(\delta_0^s X_i^s + \delta_1^s X_i^s v_{it} + \delta_2^s X_i^s v_{it}^2 \right) + \varepsilon_{it}, \quad (1)$$

where b_{it} and v_{it} are the bid and value respectively of subject i in period $t \in \{1, .., 30\}$, F_i is the female indicator, $X_i^s, s \in \{1, .., S\}$, is the set of control variables mentioned above, and ε_{it} is the unobserved disturbance assumed to be uncorrelated with any of the right-hand side variables. We estimate (1) by OLS, adjusting the standard errors and confidence intervals for clustering at the session level.

[Figure 5 about here.]

Figure 5 presents the results of the OLS regressions. Panels A and B show that, accounting for treatment as well as jointly for treatment and demographics, the gender difference now becomes significant for values greater than 23 or 25, respectively, compared to the baseline value of 24 (Figure 4, Panel A). Women still bid higher than men by a median of 5.21 or 4.97 percentage points of their valuation, respectively. In comparison, panels C and D show that, controlling for treatment and risk aversion, without or with controlling for demographics, the gender difference is statistically significant only for values above 39 or 46, respectively. Women now bid higher than men by only a median of 3.63 or 2.98 percentage points of the valuation, respectively. Thus, a gender difference in risk aversion can explain some, but not all, of the gender difference in bidding, especially in the range of high valuations. On the other hand, treatment differences and demographic background can explain relatively little of the gender difference. We now summarize the results in the FPA.

RESULT 1 (Gender)**.** *In the first-price auction, women bid significantly higher than men do, and earn significantly less. Risk aversion can explain some, but not all, of the gender difference in bidding.*

A significant gender difference in bidding in the FPA is also observed in Pearson and Schipper (2008), where they test performance in a FPA with known distributions in the same economic environment as ours, using parametric analysis but without controlling for risk attitudes. In comparison, Casari et al. (2007) find that, in common value auctions, inexperienced women bid substantially higher than men and thus suffer more from the winner's curse, while experienced women do at least as well as men. However, it is not clear how the winner's curse and risk attitudes correlate. Therefore, it is not clear to what extent their gender difference result is due to differences in risk attitudes.

[Figure 6 about here.]

Since all three studies find that women bid higher than men do, one might wonder whether this is a tendency across auctions. We investigate this conjecture using our second-price auction data and find no statistically significant gender differences in bidding, the probability of dominant strategy play or the probability of overbidding. This conclusion holds for both the non-parametric analysis (Figure 6) and for the parametric analysis controlling for treatment and demographics (results not shown). While we do not have data to directly test the extent to which differences in strategic reasoning might account for the remaining gender gap in the FPA, our analysis in the SPA indicates that women do not have a generic tendency to overbid in auctions, nor do they differ from men in dominant strategy play.

4 Effects of the Menstrual Cycle and Oral Contraceptives

Having identified the gender gap in bidding in the FPA in Section 3, we now proceed to investigate whether the menstrual cycle and contraceptive pill usage might influence women's bidding behavior. Using Dataset 1, we also analyze the effect of the menstrual cycle on bidding in the SPA. Unlike in the case of the FPA, however, we do not find any systematic effects in the SPA.[6] We therefore focus on the FPA in this section. We first assume that the bidding function is given by:

$$b_{it} = \beta_0 + \beta_1 v_{it} + \beta_2 v_{it}^2 + \gamma_0 F_i + \gamma_1 F_i v_{it} + \gamma_2 F_i v_{it}^2 + \delta' X_i + f(D_i, P_i) + u_{it}, \tag{2}$$

where, as in (1), b_{it} and v_{it} are the bid and value respectively of subject i in period $t \in \{1, .., 30\}$, F_i is the female indicator, X_i is the set of demographic and risk aversion controls and u_{it} is the unobserved disturbance. In addition, $f(D_i, P_i)$ captures the impact of the day of the menstrual cycle D_i and the indicator for pill usage P_i on bidding, with $f(\cdot, \cdot) \equiv 0$ for all men. We also assume that u_{it} is uncorrelated with the right-hand side variables $v_{it}, v_{it}^2, F_i, v_{it}F_i, v_{it}^2 F_i$, and X_i, and is independent of (D_i, P_i).

There are several possible approaches to estimate the cycle and pill effect, $f(D_i, P_i)$. One approach would be to model $f(D_i, P_i)$ non-parametrically by a set of 56 or 28 indicator variables, depending on whether the pill effect is taken into account. However, given that we have menstrual cycle information for only 73 female subjects in Dataset 1 and 51 in Dataset 2, and pill usage data only for the latter, this approach is infeasible due to the small number of observations. Alternatively, one could attempt to isolate the term $f(D_i, P_i) + u_{it}$ up to a constant as a residual from an OLS applied to (2) with only the observable variables included on the right-hand side and then analyze this residual using a non-parametric method analogous to the one used in Section 3. However, because the pill usage is correlated with age, with older female subjects being more likely to use a pill, this method would lead to a biased estimate of $f(D_i, P_i)$.

Consequently, to best capture the cycle and pill effects, we use a two-stage method that combines these two approaches. In the first stage, we use OLS to estimate the model:[7]

$$b_{it} = \beta_0 + \beta_1 v_{it} + \beta_2 v_{it}^2 + \gamma_1 F_i v_{it} + \gamma_2 F_i v_{it}^2 + \delta' X_i + \sum_{d=1}^{28} \left[\alpha_d^{NP} (1 - P_i) 1_{\{D_i = d\}} + \alpha_d^{P} P_i 1_{\{D_i = d\}} \right] + \widetilde{w}_{it}. \tag{3}$$

Depending on a specification, the set of additional control variables X_i may vary from being empty to including controls for treatment, demographics and risk aversion. We then record the estimated residuals when we set $\widehat{\alpha}_d^{NP} = \widehat{\alpha}_d^{P} = 0$ for all days $d \in \{1, .., 28\}$. In the second stage, focusing on only female observations, we adjust these estimated residuals according to the relevant comparison category. For example, if we are interested in how bidding during the cycle deviates from the women's overall average bidding, we regress the first-stage residuals on a constant and then focus on the residuals from this regression. If we are interested in deviation from the average of a particular subgroup of women (pill users or non-users), we regress the first-stage residuals on a constant and on an indicator for pill users and then focus on the relevant residuals. If we are interested in the deviation from the men's average bidding, we add to the first-stage residuals $\widehat{\gamma}_1 v + \widehat{\gamma}_2 v^2$, where $\widehat{\gamma}_1$ and $\widehat{\gamma}_2$ are the respective estimates of γ_1 and γ_2 from the first stage, evaluated at $v = 80$.[8] The resulting second-stage adjusted residual is then the dependent variable in

[6]The results are available from the authors upon request.

[7]We have also tested whether the approximation of bidding among women by a second-order polynomial in value is significantly different between pill users and non-users, and we cannot reject the null hypothesis of no difference. In the interest of saving degrees of freedom, we therefore proceed to interact the polynomial in value only with gender, and not with pill usage.

[8]It is desirable to choose a value that is high enough since, as shown in Section 3, this is where the gender difference

the non-parametric estimation, as described in detail in Appendix D, with the day of cycle being the explanatory variable.[9] As in Section 3, we construct 95% confidence intervals for these predictions by bootstrapping with 250 replications, clustering at the session level. Note that in some estimations, we do not distinguish between pill users and non-users, in which case we conduct this procedure with the restriction $\alpha_d^{NP} = \alpha_d^P$.

[Figure 7 about here.]

Since the estimates in Figure 7 are based on data from both datasets, they do not consider pill usage. Panel A1 shows that, if we control for values only, female bidding throughout the cycle is a sine-like curve that reaches its maximum in the follicular phase (days 5 to 13) and minimum in the luteal phase (days 16-23) of the cycle. However, the absolute deviation from the women's mean in both extremes is less than one point and the deviation is not statistically significant throughout the cycle. We obtain similar results, with an even smaller magnitude of deviation, in Panel A2 when treatment and demographic controls are included. By contrast, in Panels B1 and B2, we see that women's bids preserve the sine-like curve, yet are now statistically significantly higher than men's bids throughout the cycle. We summarize our analysis below.

RESULT 2 (Menstrual Cycle)**.** *In the first-price auction, throughout their menstrual cycle women bid significantly higher than do men. Furthermore, women's bids throughout their cycle follow a sine-like curve that reaches the maximum in the follicular phase and the minimum in the luteal phase.*

Even though the sine-like variation is not significant when we pool all women together, it becomes significant for pill users, as we see in the second half of this section. This result relates to findings in the extensive behavioral endocrinology literature on the menstrual cycle and cognition, which show that task performance varies across the menstrual cycle. The cognitive tasks in such studies are non-strategic, including "simple arithmetic, short-term memory, verbal skills, visual-spatial, rote speed tasks, motor coordination, frustration tolerance, flexibility, stress responsivity, creativity, dressing behavior, asymmetric hemispheric activity, facial preference, body image and interest in erotica" (Epting and Overman 1998). Sommer (1992) reviews 45 such studies. Epting and Overman (1998) summarize 62 such studies. Among the many studies reporting consistent cognitive changes across menstrual phases, Komnenich (1974) reports a decline in verbal fluency in the post-ovulatory and menstrual phases. Wuttke, Arnold, Becker, Creutzfeldt, Langenstein and Tirsch (1976) find faster performance in simple arithmetic tasks during the luteal phase. Dye (1992) finds significant cycle-related fluctuation in visual information processing, with the best performance in the pre-menstrual phase. Hampson and Kimura (1992) find that women perform better on certain male-oriented tasks (e.g., spatial ability) during menstruation, when estrogen is

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is most prominent in absolute size. On the other hand, due to the boundary problem, any prediction of the second-order polynomial in value becomes less precise for values close to 100 (Figure 5). Note that this particular choice of value affects only the comparisons relative to the male mean, and not the comparisons relative to the female mean or means of pill users or non-users.

[9] Note that the first-stage estimation uses male observations to identify the coefficients on the control variables (if any) and hence results in smaller standard errors and confidence intervals. Using only female data, the estimates are broadly similar to the results when the male data is included, except that the estimates are less precise. The results are available from the authors upon request. Note, however, when there are no additional control variables, the two sets of results are identical.

at its lowest level, than during other phases of their cycle. Conversely, women perform better on certain female-oriented tasks (e.g., articulatory speed and accuracy) during periods of high estrogen levels. This result is confirmed by Hausmann, Slabbekoorn, Goozen, Cohen-Kettenis and Gunturkun (2000), who find a significant cycle difference in spatial ability, with high scores during the menstrual phase and low scores during the luteal phase. In sum, the behavioral endocrinology literature has uncovered that, while women's cognitive performance in non-strategic tasks varies throughout the cycle, the phases when a performance peaks seem to be task-specific.

One study of particular note for us is that of Pearson and Schipper (2008), who use prospective measure of the cycle and find that women during the menstrual or pre-menstrual phase bid significantly higher than men do, while women in other phases do not bid differently from men. We speculate that the partial difference in our results versus theirs could be due to a number of factors, including estimation techniques, retrospective versus prospective measures of the cycle, and subject pool composition (a higher proportion of Asians and lower proportion of Caucasians in Pearson and Schipper).

The observed behavioral variations throughout the menstrual cycle could come from natural hormonal variations or psychological effects related to the cycle. As contraceptive pill usage elevates estrogen and progesterone levels in all but the menstrual phase, we investigate the extent to which pill usage might affect the variations in bidding behavior. Thus, in Dataset 2, we split the female sample into contraceptive pill users and non-users. For each sub-sample, we compare their bids with women's and men's mean bids, respectively. Our results are summarized in the next two figures.

[Figure 8 about here.]

Figure 8 compares pill-users' and non-users' bids with the average bids of their own group. Panels A1 and A2 show that, after controlling for values, the bidding of pill users follows a strong sine-like pattern throughout the cycle, with bids reaching their maximum in the follicular phase (days 6 to 13) and minimum in the luteal phase (days 16 to 23). These results hold regardless of controlling for treatment, demographics, or risk aversion. Although the sine pattern is similar to findings in Figure 7, the bidding deviation from the mean now becomes statistically significant around the maximum and the minimum. In addition, the magnitude of the deviation is larger, reaching close to two points above the mean in the maximum and more than two points below the mean in the minimum. In comparison, Panels B1 and B2 show that the bidding of non-users barely differs from the mean throughout the menstrual cycle.

Figure 8 therefore presents one of the key findings of the paper. The sine-like bidding curve presented in Figure 7 is a weighted average of the bidding behavior of pill users and non-users. As such, it masks the fact that deviation from the mean is almost entirely driven by pill users.

[Figure 9 about here.]

Figure 9 separately compares the bidding behavior of pill users (Panels A1 and A2) and non-users (Panels B1 and B2) to that of men (evaluated at the value of 80). Panels A1 and B1 show that, when we control only for values, non-users bid significantly higher than men do throughout the entire cycle, whereas pill users do so with the exception of part of the luteal phase (days 16-23). When we additionally control for treatment, demographics and risk aversion, the result is preserved for non-users (Panel B2), but the gender difference shrinks somewhat for pill users (Panel A2), which is now significant only in the first half of the cycle (menstrual and follicular phase, plus the beginning of ovulation).

RESULT 3 (The Pill)**.** *In the first-price auction, the sine-like variation in women's bids throughout the cycle is entirely driven by pill users. Pill users on average bid significantly higher than men except in the luteal and pre-menstrual phases, when their bids are statistically indistinguishable from men's bids. In contrast, non-users bid consistently higher than men, with no discernible phasic changes.*

Note that Result 3 depends on evaluation at the value of 80. As shown in Figures 4 and 5, the gender difference in bidding increases with value. Hence the gender difference becomes more (less) pronounced compared to the ones presented in Figure 8 for higher (lower) values. In addition to bids, we have also conducted analyses analogous to Figures 7 to 9 for payoffs and find that the results for payoffs are mirror images of those for bids.[10]

The finding regarding the effect of oral contraceptive use on bidding behavior provides a new insight. To our knowledge, behavioral endocrinology studies have largely focused on the physiological, pharmacological and affective effects of oral contraceptives. For example, while Glick and Bennett (1981) summarize the effects of pill usage on sexuality, mood, and metabolism, Almagor and Ben-Porath (1991) find that users of oral contraceptives experience a higher level of positive affect during the cycle than do non-users. Result 3 indicates that only women with elevated levels of estrogen and progesterone exhibit behavioral variations during their cycle.

Three remarks are in order. First, even though we control for treatment, demographics and risk aversion in our most unrestricted specifications, one may still wonder whether the results based on pill usage are driven by unobservables correlated with pill usage rather than by pill usage itself. Although we cannot reliably rule out such a possibility, there are two sources of indirect evidence against such an explanation. First, there is no qualitative change in results regardless of whether we control for treatment, demographics and risk aversion in the estimation. This suggests that the same may also be true of other (unobservable) variables that we do not control for. Second, when we regress the indicator variable for pill usage on the set of demographic variables and risk aversion indicators (with robust standard errors for heteroscedasticity), the only significant variable is age, with older women being more likely to use the pill. Apart from all other variables being individually insignificant, so is (jointly) the group of academic major indicators and the group of risk aversion indicators.

A second point worth noting is that Result 3 is not driven by the difference in the measurement errors of the menstrual cycle between pill users and non-users. One might conjecture that pill users might have a smaller measurement error in estimating the first day of their next menstrual period, as most pill packages number the pill by the day of the cycle.[11] Using methods discussed in Appendix C (Footnote 15), we find no evidence that pill users have a smaller measurement error than non-users.

Lastly, the day counting method that we use is likely to contain measurement errors. If uncorrelated with the true day of the cycle, this measurement error is likely to attenuate any of the estimated effects toward zero. Therefore, we speculate that sharper results could be obtained with

[10]The results are available from the authors upon request.

[11]We thank Matthew Pearson and Burkhard Schipper for suggesting this possibility (private communication).

a more precise assessment of the cycle. However, as this type of assessment requires a medical procedure, we leave it to future research.

5 Conclusion

While women's and men's average levels of general intelligence are the same, based on the best psychometric estimates (Jensen (1998), chapter 13), economic research has found robust gender differences in risk preference, social preference and reaction to competition (Croson and Gneezy forthcoming). While previous economic research largely focuses on observable environmental causes, such as demographic or educational background, to account for the gender differences, we explore the extent to which menstrual cycle variation can account for observed robust gender differences in competitive bidding behavior.

To study this question, we use experimental data from first- and second-price sealed-bid private value auctions. In the first-price auction, we find that women bid significantly higher than men do and earn significantly less. Although this may seem consistent with findings in other contexts that show women exhibit more risk averse behavior, risk aversion cannot account for all of the bidding gap in our first-price auctions. Furthermore, in the second-price auction, we find no statistically significant gender difference in bidding, the probability of dominant strategy play or the probability of overbidding.

To explore a biological basis for the gender difference in behavior, we examine bidding behavior across the menstrual cycle. Focusing on the first-price auction, we find that women who use oral contraceptives behave differently than those who do not. Specifically, pill users have a much more variable sine-like bidding behavior throughout the menstrual cycle, bidding significantly above the mean in the follicular phase and significantly below the mean in the luteal phase of the cycle. In contrast, non-users' bidding behavior does not exhibit such phasic changes. At higher valuations, the gender difference in bidding is statistically significant throughout the cycle for non-users. For pill users, given their bidding profile throughout the cycle, the difference is significant predominantly in the first half of the cycle, whereas in the luteal phase, pill users bid similarly to men. Together, these results imply that the menstrual cycle influences the bidding behavior of pill users, but has virtually no effect on the bidding behavior of non-users.

Our results imply that an individual's current biological state may be important for economic decisions in strategic as well as non-strategic environments. To the extent that this biological state fluctuates predictably over time and with sufficient knowledge about its effect on behavior, one may be able to optimally time important economic events and decisions such as investment decisions and portfolio allocation, negotiations over job compensation, school exams, and so on. This is the main policy implication of finding a significant variation in behavior based on biological factors that are predictable over time.

One clear limitation of our study is the way we measure the phase of the menstrual cycle. In particular, we use survey self-reports which are likely to suffer from measurement errors. If uncorrelated with the true day of cycle, this measurement error is likely to result in attenuation bias, pushing any estimates toward zero. One way to obtain more accurate results is to measure the phase of the menstrual cycle using blood samples. Joint studies on economics and behavioral endocrinology would be an interesting endeavor to better understand the biological foundations of economic behavior.

Appendix A. Experimental Instructions

The complete instructions for the eight-subject, first-price auction with known distribution treatment are shown here. Instructions for the eight-subject, first-price auction with unknown distribution treatment are identical except that 30% is replaced by x%.

Instructions for the second-price auction are identical to the first-price auction instructions except for "The Rules of the Auction and Payoffs" section and the "Review Questions;" hence only these two parts are provided here. In addition, the complete instructions for the lottery choice experiment are shown at the end of this Appendix.

Experiment Instructions – K1$_8$

Name________ PCLAB __ Total Payoff _____

Introduction

- You are about to participate in a decision process in which an object will be auctioned off for each group of participants in each of 30 rounds. This is part of a study intended to provide insight into certain features of decision processes. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money. You will be paid in cash at the end of the experiment.
- *During the experiment, we ask that you please do not talk to each other.* If you have a question, please raise your hand and an experimenter will assist you.

Procedure

- You each have drawn a laminated slip, which corresponds to your PC terminal number. You will be a bidder for the entire experiment.
- In each of 30 rounds, you will be *randomly* matched with another participant into a group. Each group has two bidders. You will not know the identity of the other participant in your group. Your payoff each round depends ONLY on the decisions made by you and the other participant in your group.
- In each of 30 rounds, each bidder's **value** for the object will be randomly drawn from one of two distributions:
  - **High value distribution**: If a bidder's value is drawn from the high value distribution, then

    * with 25% chance it is randomly drawn from the set of integers between 1 and 50, where each integer is equally likely to be drawn.
    * with 75% chance it is randomly drawn from the set of integers between 51 and 100, where each integer is equally likely to be drawn.

  For example, if you throw a four-sided die, and if it shows up 1, your value will be equally likely to take on an integer value between 1 and 50. If it shows up 2, 3 or 4, your value will be equally likely to take on an integer value between 51 and 100.

  - **Low value distribution**: If a bidder's value is drawn from the low value distribution, then
    * with 75% chance it is randomly drawn from the set of integers between 1 and 50, where each integer is equally likely to be drawn.
    * with 25% chance it is randomly drawn from the set of integers between 51 and 100, where each integer is equally likely to be drawn.

  For example, if you throw a four-sided die, and if it shows up 1, 2 or 3, your value will be equally likely to take on an integer value between 1 and 50. If it shows up 4, your value will be equally likely to take on an integer value between 51 and 100.

  - Therefore, if your value is drawn from the high value distribution, it can take on any integer value between 1 and 100, but it is three times more likely to take on a higher value, i.e., a value between 51 and 100.

    Similarly, if your value is drawn from the low value distribution, it can take on any integer value between 1 and 100, but it is three times more likely to take on a lower value, i.e., a value between 1 and 50.
  - In each of 30 rounds, each bidder's value will be randomly and independently drawn from the high value distribution with 30% chance, and from the low value distribution with 70% chance. You will not be told which distribution your value is drawn from. The other bidders' values might be drawn from a distribution different from your own. In any given round, the chance that your value is drawn from either distribution does not affect how other bidders' values are drawn.

- Each round consists of the following stages:
  - Each bidder will simultaneously and independently submit a bid, which can be any integer between 1 and 100, inclusive.
  - The bids are collected in each group and the object is allocated according to the rules of the auction explained in the next section.

  - You will get the following feedback on your screen: your value, your bid, the winning bid, whether you got the object, and your payoff.

- The process continues.

Rules of the Auction and Payoffs

- In each round,

  - if your bid is greater than the other bid, you get the object and pay your bid:
    Your Payoff = Your Value - Your Bid;
  - if your bid is less than the other bid, you don't get the object:
    Your Payoff = 0.
  - if your bid is equal to the other bid, the computer will break the tie by flipping a fair coin. Therefore,
    * with 50% chance you get the object and pay your bid:
      Your Payoff = Your Value - Your Bid;
    * with 50% chance you don't get the object:
      Your Payoff = 0.

- For example, if bidder A bids 25, and bidder B bids 55, since $55 > 25$, bidder B gets the object. Bidder A's payoff = 0; bidder B's payoff = her value - 55.

- There will be 30 rounds. There will be no practice rounds. From the first round, you will be paid for each decision you make.

- Your total payoff is the sum of your payoffs in all rounds.

- The exchange rate is $1 for ____________ points.

We encourage you to earn as much cash as you can. Are there any questions?

Review Questions: you will have ten minutes to finish the review questions. Please raise your hand if you have any questions or if you finish the review questions. The experimenter will check each participant's answers individually. After ten minutes we will go through the answers together.

1. Suppose your value is 60 and you bid 62.
   If you get the object, your payoff = __.
   If you don't get the object, your payoff = __.

2. Suppose your value is 60 and you bid 60.
   If you get the object, your payoff = __.
   If you don't get the object, your payoff = __.

3. Suppose your value is 60 and you bid 58.
   If you get the object, your payoff = __.
   If you don't get the object, your payoff = __.

4. In each of 30 rounds, each bidder's value will be randomly and independently drawn from the high value distribution with __% chance.

5. True or false:

   (a) __If a bidder's value is 25, it must have been drawn from the low distribution.

   (b) __If a bidder's value is 60, it must have been drawn from the high distribution.

   (c) __You will be playing with the same participant for the entire experiment.

   (d) __A bidder's payoff depends only on his/her own bid.

Experiment Instructions – K2$_8$

Name________ PCLAB __ Total Payoff _____

. . . . . .

Rules of the Auction and Payoffs

- In each round,
  - if your bid is greater than the other bid, you get the object and pay the other bid: **Your Payoff = Your Value - The Other Bid**;
  - if your bid is less than the other bid, you don't get the object: **Your Payoff = 0**.
  - if your bid is equal to the other bid, the computer will break the tie by flipping a fair coin. Therefore,
    - $*$ with 50% chance you get the object and pay the other bid: **Your Payoff = Your Value - The Other Bid**;
    - $*$ with 50% chance you don't get the object: **Your Payoff = 0**.
- For example, if bidder A bids 25, and bidder B bids 55, since $55 > 25$, bidder B gets the object. Bidder A's payoff = 0;
  bidder B's payoff = bidder B's value - bidder A's bid = bidder B's value - 25.
- There will be 30 rounds. There will be no practice rounds. From the first round, you will be paid for each decision you make.
- Your total payoff is the sum of your payoffs in all rounds.
- The exchange rate is $1 for ____________ points.

We encourage you to earn as much cash as you can. Are there any questions?

Review Questions: you will have ten minutes to finish the review questions. Please raise your hand if you have any questions or if you finish the review questions. The experimenter will check each participant's answers individually. After ten minutes we will go through the answers together.

1. Suppose your value is 60 and you bid 62.
   If the other bid is 59, you get the object. Your payoff = __.
   If the other bid is 61, you get the object. Your payoff = __.
   If the other bid is 70, you don't get the object. Your payoff = __.

2. Suppose your value is 60 and you bid 60.
   If the other bid is 55, you get the object. Your payoff = __.
   If the other bid is 60,

   - with __ chance you get the object, your payoff = __;
   - with __ chance you don't get the object, your payoff = __.

   If the other bid is 70, you don't get the object. Your payoff = __.

3. Suppose your value is 60 and you bid 57.
   If the other bid is 55, you get the object. Your payoff = __.
   If the other bid is 58, you don't get the object. Your payoff = __.
   If the other bid is 70, you don't get the object. Your payoff = __.

4. In each of 30 rounds, each bidder's value will be randomly and independently drawn from the high value distribution with __% chance.

5. True or false:

   (a) __If a bidder's value is 25, it must have been drawn from the low distribution.

   (b) __If a bidder's value is 60, it must have been drawn from the high distribution.

   (c) __You will be playing with the same participant for the entire experiment.

   (d) __A bidder's payoff depends only on his/her own bid.

Experiment Instructions – L

Name________ RCGD LAB __ Total Payoff _____

Introduction

- You are about to participate in a decision process in which you will be making choices between a series of two lotteries. This is part of a study intended to provide insight into certain features of decision processes. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money. You will be paid in cash at the end of the experiment.
- *During the experiment, we ask that you please do not talk to each other.* If you have a question, please raise your hand and an experimenter will assist you.

Procedure

- You will be making choices between two lotteries, such as those represented as "Option A" and "Option B" below. The money prizes are determined by the computer equivalent of throwing a ten-sided die. Each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, is equally likely. If you choose Option A in the row shown below, you will have a 1 in 10 chance of earning 200 points and a 9 in 10 chance of earning 160 points. Similarly, Option B offers a 1 in 10 chance of earning 385 points and a 9 in 10 chance of earning 10 points.

Decision	Option A	Option B	Your Choice
1	200 points if the die is 1 160 points if the die is 2 - 10	385 points if the die is 1 10 points if the die is 2 - 10	A or B

- Each row of the decision table contains a pair of choices between Option A and Option B.
- You make your choice by clicking on the "A" or "B" buttons on the right. Only one option in each row can be selected, and you may change your decision as you wish.
- Even though you will make ten decisions, only one of these will end up being used. The selection of the one to be used depends on the "throw of the die" that is the determined by the computer's random number generator. No decision is any more likely to be used than any other, and you will not know in advance which one will be selected, so please think about each one carefully. This random selection of a decision fixes the row (i.e. the Decision) that will be used. For example, suppose that you make all ten decisions and the throw of the die is 9, then your choice, A or B, for decision 9 below would be used and the other decisions would not be used.

Decision	Option A	Option B	Your Choice
9	200 points if the die is 1-9 160 points if the die is 10	385 points if the die is 1-9 10 points if the die is 10	A or B

- After the random die throw fixes the Decision row that will be used, we need to obtain a second random number that determines the earnings for the Option you chose for that row. In Decision 9 below, for example, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff.

Decision	Option A	Option B	Your Choice
9	200 points if the die is 1-9 160 points if the die is 10	385 points if the die is 1-9 10 points if the die is 10	A or B
10	200 points if the die is 1-10	385 points if the die is 1-10	

For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: 200 points for Option A and 385 points for Option B.

- **Making Ten Decisions**: On your screen, you will see a table with 10 decisions in 10 separate rows, and you choose by clicking on the buttons on the right, option A or option B, for each of the 10 rows. You may make these choices in any order and change them as much as you wish until you press the Submit button at the bottom.

- **The Relevant Decision**: One of the rows is then selected at random, and the Option (A or B) that you chose in that row will be used to determine your earnings. Note: Please think about each decision carefully, since each row is equally likely to end up being the one that is used to determine payoffs.

- **Determining the Payoff**: After one of the decisions has been randomly selected, the computer will generate another random number that corresponds to the throw of a ten sided die. The number is equally likely to be 1, 2, 3, ... 10. This random number determines your earnings for the Option (A or B) that you previously selected for the decision being used.

We encourage you to earn as much cash as you can. Are there any questions?

Appendix B. Post-Experiment Survey

[We present questionnaires used in both waves of our experiments. Questions added or modified in the second wave are presented in italics.]

We are interested in whether there is a correlation between participants' bidding behavior and some socio-psychological factors. The following information will be very helpful for our research. This information will be strictly confidential.

1. Gender
   - Male ____
   - Female ____
2. Ethnic origin
   - White ____
   - Asian/Asian American ____
   - African American ____
   - Hispanic ____
   - Native American ____
   - Other ____
3. Age ____
4. How many siblings do you have? ____
5. Would you describe your personality as (please choose one)
   - optimistic ____
   - pessimistic ____
   - neither ____
6. Which of the following emotions did you experience during the experiment? (You may choose any number of them.)
   - anger ____
   - anxiety ____
   - confusion ____

- contentment ____
- fatigue ____
- happiness ____
- irritation ____
- mood swings ____
- withdrawal ____

7. *What is your major field of study?*

8. For female participants only

- How many days away is your next menstrual cycle? ____ [replaced by the following questions in wave 2:]
- *Are you currently menstruating? Yes ____; No ____.*
  - *If yes, how many days have you been menstruating? ____*
  - *If no, how many days away are you from the first day of your next menstrual period? ____*
- *How many times do you menstruate a year?*
  (A drop down menu of 4, 11, 12, 13, > 13)
- *On average, how many days are there between your menstrual cycles?*
  (A drop down menu of <25, 25 to 35 with an increment of 1, > 35)
- *How many days does your menstruation last on average?*
  (A drop down menu of 2, 3, 4, 5, 6, 7, 8 or >8.)
- *Are you on the pill? Yes ____; No ____.*
  - *If yes, what is the name of the pill you are taking?*
    (a) *Name of the pill ____;*
    (b) *I don't remember ____;*
- *What date was the first day of your last menstrual period?*
  (month (September, October), day (1, 2, ..., 31))
- Do you currently experience any symptoms of PMS (Premenstrual Syndrome)? (please choose one)
  - none ____

- mild ____
- severe ____

Thank you very much for your participation!

Appendix C. Menstrual Cycle Measurement

In this appendix, we report in detail our menstrual cycle measurement. This measurement is based on a day count method using subject survey responses. We discuss the likely measurement errors implicit in this method and compare the prospective and retrospective measures based on the size of such measurement error.

In the first wave of our experiment, we elicit from female participants the phase of their menstrual cycle using the question "How many days away are you from the first day of your next menstrual period?" We ask the same question in the second wave, with one modification. In this wave, we first ask each female participant whether she is currently menstruating. If she responds "yes," we then ask her about how many days she has been menstruating. If she responds "no," we ask about the number of days away from the first day of the next menstrual period. In addition, we expand the menstrual cycle part of the questionnaire in the second wave. We ask female subjects about contraceptive pill usage, the average duration of their cycle and the date when the last menstrual cycle began. When combined with the date of the experiment, the latter can be used to compute the number of days from the start of the cycle.

In the second wave, pill usage data is available for all 51 female subjects, duration information for 50 subjects, and the beginning of the last cycle for 47 subjects. The reported cycle duration varies from "less than 25" to "more than 35." Among two-thirds of the women (34 subjects) who do not use the pill, and including only women who report a number between 25 and 35 inclusive (31 subjects), the mean duration of the cycle is 28.87 days, the median is 28 days, and the standard deviation is 2.32 days. Among one-third of the women (17 subjects) who use the pill, 11 report a cycle duration of 28, 2 report a duration of 29, 1 reports a duration of 32, 2 report a duration of "less than 25", and one does not report anything.[12] Apart from these questions, we also ask each female participant about the average number of menstrual cycles per year and the average duration of menstruation. As for the former, 8 subjects report 11 cycles, 39 subjects report 12 cycles and 4 subjects report 13 cycles. The answer to the latter question is available for 50 out of 51 subjects and ranges from 3 to 8 days, with a mean of 5.16, median of 5 and standard deviation of 1.25.

The measure of the phase of the menstrual cycle we use in our analysis is computed as 29 minus the self-reported number of days away from the first day of the next menstrual period, whenever the latter measure is available.[13] By construction, this is a "prospective" measure, assuming a 28-day duration of the cycle. To constrain the measure between 1 and 28, in Dataset 1, we reset the measure to missing for one subject who reports being 60 days away from the next cycle, to 28 for

[12]Of these 17 women, 14 also list the name of the pill they use. Usage information on these brands indicates all are supposed to induce a regular 28-day cycle with minimal cycle-length variation, suggesting a measurement error in the duration variable.

[13]That is, if a female subject reports being one day away, we interpret this as day 28 of the cycle; if she reports being 28 days away, we interpret this as day 1 of the cycle.

four subjects who report being 0 days away, and to 1 for five subjects who report being 30 days away. These adjustments provide menstrual cycle data for 73 out of 78 female subjects in Dataset 1. In Dataset 2, if the number of days away from the next menstrual cycle is not available, we impute the measure to be equal to the number of days the female subject has been menstruating if such information is available and she answered "yes" to the question "Are you currently menstruating?" (11 subjects). In this way, we obtain the measure for 48 out of 51 subjects. In order to maximize the available sample size, for the remaining three subjects we impute the measure to be equal to the computed number of days from the beginning of the last menstrual period plus one.[14] We use these three observations in the analysis presented in the main text, but do not use them in the rest of this Appendix when comparing the prospective and retrospective measures and discussing the measurement error.

As discussed, this prospective measure may suffer from two sources of measurement error. First, female subjects may underestimate or overestimate the true number of days away from the beginning of the next cycle, either because the cycle length may be irregular or because they make a forecast error. Second, we assume that each woman's cycle length is 28 days. However, especially for women who do not use a contraceptive pill, the average cycle duration may differ from 28 and the realized length may vary from cycle to cycle.

[Figure 3 about here.]

In Dataset 2, the severity of the first problem can be evaluated using the retrospective measure based on the number of days from the start of the last cycle. The latter is available for 47 out of 51 female subjects. However, this data also has several issues. In particular, one subject reports the beginning of the last menstrual period to be a date after the date of the experiment. Another five subjects report a past date that is further away from the date of the experiment than their self-declared duration of the cycle. After we exclude these six observations and excluding observations where the prospective measure is imputed by the retrospective one, we have two measures jointly available for 38 observations. Figure 3 presents a cross-plot of the two measures. The correlation coefficient between the two measures is 0.725. In addition, the slope coefficient from the regression of the prospective on the retrospective measure is 0.686 (with the robust standard error of 0.114), whereas the slope coefficient from the regression of the retrospective on the prospective measure is 0.765 (0.146).

Assuming the measurement error contained in either of the two measures is uncorrelated with the true day of the menstrual cycle, and without restricting the correlation between the two measurement errors, these results imply that the variance of the measurement error in the retrospective

[14] That is, if a female subject is one day from the beginning of the last cycle, we interpret this as day 2 of the cycle.

measure is larger than the variance of the measurement error in the prospective measure.[15] Additionally, if we assume that the measurement noise in the two measures is uncorrelated, then we can also quantify the difference in the variance of two measurement errors. In particular, the standard deviation of the measurement error in the prospective and the retrospective measures is 55.4 and 67.7 percent, respectively, of the standard deviation for the true phase of the cycle.[16] The implied signal-to-noise ratios are 3.26 and 2.18, respectively. These observations suggest that, for our data, the prospective measure is less noisy than the retrospective measure.

The severity of the second problem can be evaluated by computing the prospective measure in the same way as before, but using the reported duration of the cycle plus one instead of 29 when doing the subtraction. We then normalize this measure by dividing by the reported average duration of the cycle and multiplying by 28. Using only Dataset 2, we have this measure available for 42 observations. We cannot compute this measure for the remaining observations, either because the reported duration is missing or because it is reported as an interval of "less than 25 days" or "more than 35 days." As the correlation between this measure and our original prospective measure is 0.995, we conclude two measures are equivalent. However, because this alternative prospective measure cannot be computed for Dataset 1, we opt to use the original prospective measure. We also construct a normalized retrospective measure by dividing the original retrospective measure by the reported duration and multiplying it by 28. Again, we exclude observations where the reported duration is less than the number of days from the first day of the last menstrual period, the duration is missing or the duration is reported as an interval of "less than 25 days" or "more than 35 days." The resulting measure is available for 34 observations, its correlation with the original retrospective measure is 0.99, and its correlation with the original prospective measure is 0.6845. We therefore conclude that this normalized retrospective measure is equivalent to the original retrospective measure, and hence inferior to the original prospective measure.

Finally, to check for the robustness of our results to the choice of the menstrual cycle measure, we rerun all the estimations reported in Section 4 using the retrospective measure, constrained to the observations where the day of cycle is positive and does not exceed the reported average duration of the cycle. Under these restrictions, the retrospective measure is available for 41 out of 51 females in Dataset 2, and ranges from 3 to 29 days. We replace the day of cycle in one observation with the value of 29 by the value of 28 in order to constrain the observations to lie in the range 1 through 28. All of the key findings reported in Section 4 are qualitatively robust

[15]To see that, let X^* be the true day of the menstrual cycle and let $X_1 = X^* + \varepsilon_1$ and $X_2 = X^* + \varepsilon_2$ be its two noisy measures, where the measurement errors ε_1 and ε_2 satisfy $Cov(X^*, \varepsilon_1) = Cov(X^*, \varepsilon_2) = 0$. Then the slope coefficient β_{12} from the regression of X_1 on X_2 is given by $[Var(X^*)+Cov(\varepsilon_1, \varepsilon_2)]/[Var(X^*)+Var(\varepsilon_2)]$, whereas the slope coefficient β_{21} from the regression of X_2 on X_1 is given by $[Var(X^*)+Cov(\varepsilon_1, \varepsilon_2)]/[Var(X^*)+Var(\varepsilon_1)]$. As a result, $\beta_{12} \gtreqless \beta_{21}$ as $Var(\varepsilon_1) \gtreqless Var(\varepsilon_2)$.

[16]Assuming that $Cov(\varepsilon_1, \varepsilon_2) = 0$, we see that $\sqrt{Var(\varepsilon_1)/Var(X^*)} = \sqrt{1/\beta_{21} - 1}$ and $\sqrt{Var(\varepsilon_2)/Var(X^*)} = \sqrt{1/\beta_{12} - 1}$.

to using this measure. However, the estimates are less precise and hence the confidence intervals are larger compared to the prospective measure.[17] This is expected as our analysis suggests the retrospective measure is more noisy compared to the prospective measure.

[17] The results are available from the authors upon request.

Appendix D. Non-parametric Estimation Techniques

The non-parametric estimation used in Sections 3 and 4 operates as follows: let y_j be the observations of the outcome variable and x_j the observations of the explanatory variable, where j indexes individual observations across rounds and sessions, and let N be the sample size. Suppose that the data are ordered such that $x_j \leq x_{j+1}$ for $j = 1, .., N-1$, where ties are broken deterministically based on subject and round numbering. Then we first compute the prediction $\widehat{x}_j$ for each x_j by running a weighted linear OLS regression using the observations $j_- \equiv max(1, j-k)$ through $j_+ \equiv min(j+k, N)$, where $k \equiv [(N * B - 0.5)/2]$ and B is the sample-proportional bandwidth. The weight for each observation $k \in \{j_-, .., j_+\}$ is given by the tricube weighting function $[1 - (|x_k - x_j|/\Delta)^3]^3$, where $\Delta \equiv 1.0001 max(x_{j_+} - x_j, x_j - x_{j_-})$.[18] Finally, the predicted outcome for any value x of the explanatory variable is computed as the arithmetic average of all $\widehat{x}_j$s for which $x_j = x$. Confidence intervals for these predictions are obtained by bootstrapping with clustering (see the discussion in the main text) based on 250 replications.

In Section 3, the outcome variable is the bid or payoff, while the explanatory variable is the value, and $B = 0.8$. In Section 4, the outcome variable is the estimated residual from the first-stage regression (3), the explanatory variable is the day of the cycle and $B = 0.8$.

In Section 4, we modify the procedure to gain greater precision in predicting outcomes around the edges of the cycle (days 1 and 28). In particular, we take advantage of the fact that the day of the menstrual cycle is a cyclical variable, allowing us to treat any day $t \in \{1, .., 28\}$ of the current cycle as the same day of the previous or the next cycle. This means that we can use not only days 1, 2, etc., but also days 28, 27, etc. to identify the predicted bid for day 1. Likewise, we can use not only days 28, 27, etc., but also days 1, 2, etc. to identify the predicted bid for day 28. To implement this idea, in each estimation we extend the original sample in which the day of cycle ranges from 1 to 28 backward by a pre-sample and forward by a post-sample. Both the pre-sample and the post-sample coincide with the original sample except that the day of cycle is reduced by 28 in the pre-sample and increased by 28 in the post-sample. Thus, we run the estimation on the overall sample three times the size of the original sample with the day of cycle ranging from -27 to 56. Accordingly, the bandwidth is adjusted to be $B/3$ of the expanded sample. Note that, due to the size of the bandwidth, the expansion of the sample does not lead to any local prediction being based on more than one repetition of a particular data point within the sample of the approximating linear regression, thus precluding any higher-order clustering problems.

[18] This part of the estimation is conducted using the *lowess* command in Stata.

Table 1: Features of Experimental Sessions

Dataset	Auction Mechanism	No. Subjects Per Session	Distribution	Exchange Rate	Number of Sessions	Total Number of Subjects
1	FPA	8	Known	20	5	40
		8	Unknown	20	5	40
	SPA	8	Known	20	5	40
		8	Unknown	20	5	40
2	FPA	8	Known	20	10	80

Table 2: Holt-Laury Risk Preference Elicitation Instrument

Choice	Lottery A	Lottery B
1	0.1 of 200, 0.9 of 160	0.1 of 385, 0.9 of 10
2	0.2 of 200, 0.8 of 160	0.2 of 385, 0.8 of 10
3	0.3 of 200, 0.7 of 160	0.3 of 385, 0.7 of 10
4	0.4 of 200, 0.6 of 160	0.4 of 385, 0.6 of 10
5	0.5 of 200, 0.5 of 160	0.5 of 385, 0.5 of 10
6	0.6 of 200, 0.4 of 160	0.6 of 385, 0.4 of 10
7	0.7 of 200, 0.3 of 160	0.7 of 385, 0.3 of 10
8	0.8 of 200, 0.2 of 160	0.8 of 385, 0.2 of 10
9	0.9 of 200, 0.1 of 160	0.9 of 385, 0.1 of 10
10	1.0 of 200, 0.0 of 160	1.0 of 385, 0.0 of 10

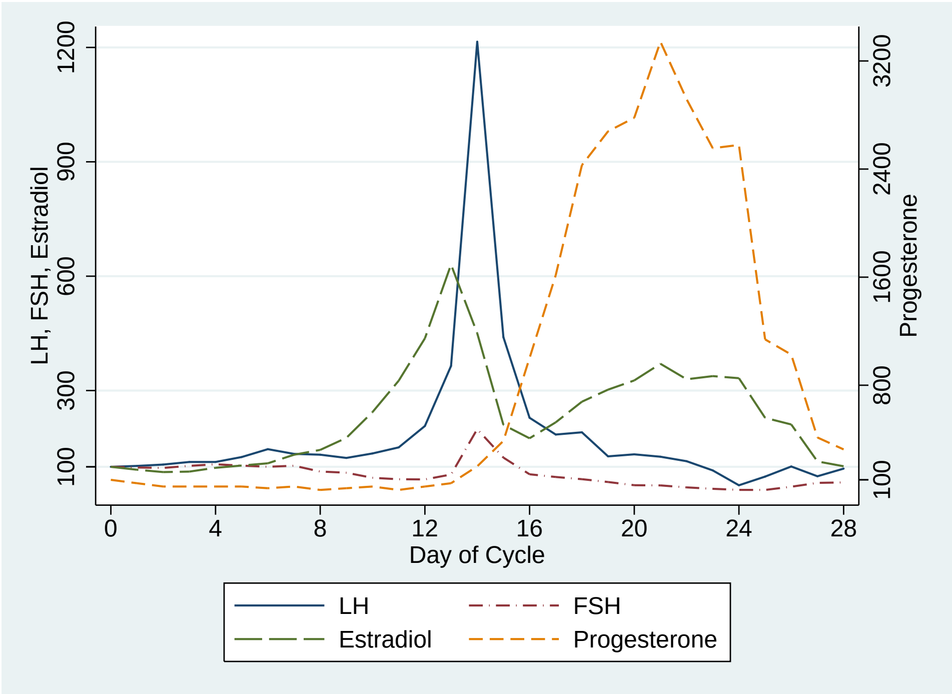
Table 3: Distribution of Holt-Laury Risk Aversion Measure by Gender (frequency of answers)

Risk Aversion	Men	Women	Total
0	0	1	1
4	3	3	6
5	5	9	14
6	13	14	27
7	5	17	22
8	3	6	9
9	0	1	1
	29	51	80

Table 4: Summary Statistics for Demographics and Academic Major

Variable	Mean	Std. Dev.	Min	Max
Female	0.54	0.50	0	1
Age	21.9	3.59	18	41
Number of Siblings	1.67	1.24	0	9
White	0.48	0.50	0	1
Asian/Asian American	0.35	0.48	0	1
African American	0.08	0.27	0	1
Hispanic	0.05	0.20	0	1
Other Ethnicity	0.05	0.21	0	1
Major:				
Mathematics and Statistics	0.03	0.17	0	1
Science and Engineering	0.31	0.46	0	1
Economics and Business	0.12	0.32	0	1
Other Social Sciences	0.09	0.28	0	1
Humanities and Others	0.19	0.39	0	1
Unknown	0.27	0.44	0	1

Figure 1: Hormonal Variations during the Menstrual Cycle



Note: LH stands for lutenizing hormone and FSH for follicle-stimulating hormone. The plot is based on median values reported in Stricker, Eberhart, Chevailler, Quinn, Bischof and Stricker (2006), with day 0 values normalized to 100.

Figure 2: Histogram of the Prospective Measure of the Day of Menstrual Cycle

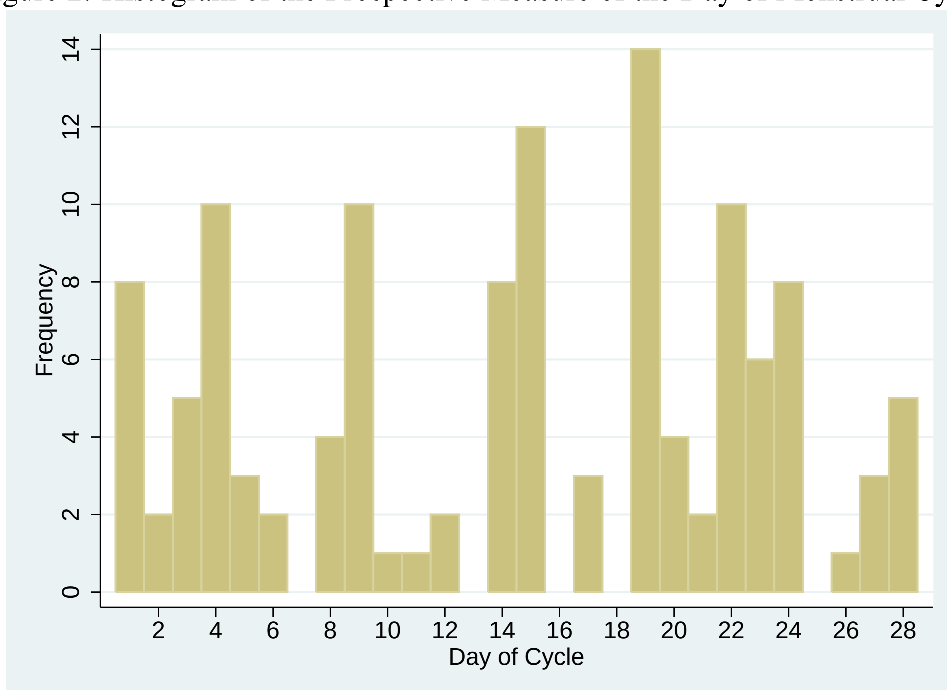
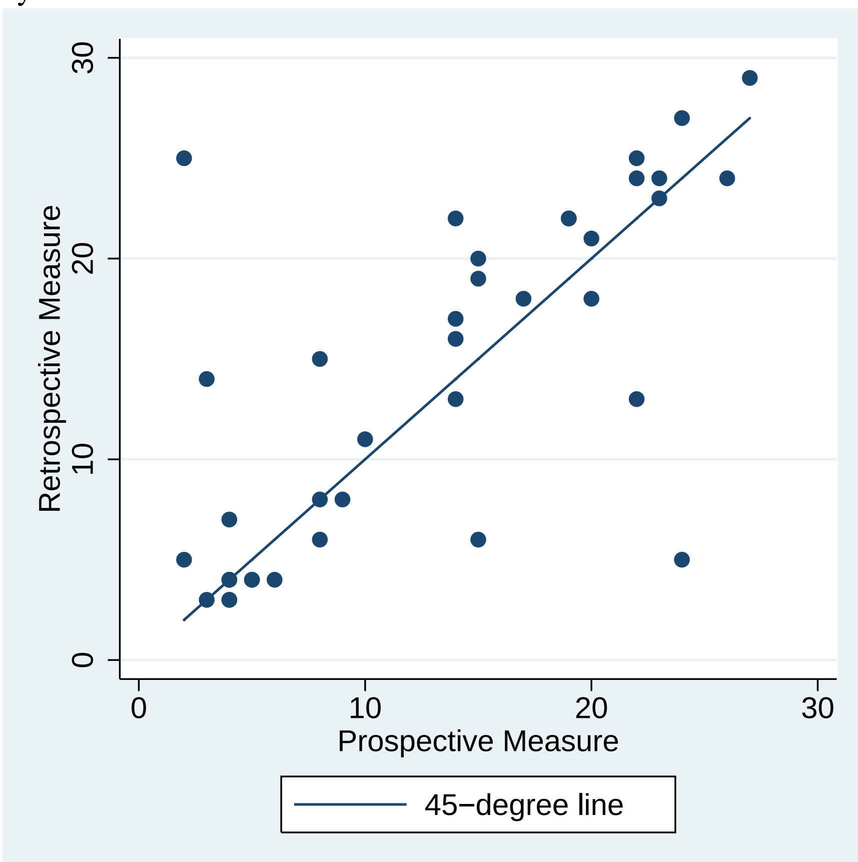


Figure 3: Cross-plot of the Prospective and the Retrospective Measures of the Day of the Menstrual Cycle



Note: Points (4,4), (4,3), (19,22) and (5,4) represent two observations. The remaining 30 points represent one observation each.

Figure 4: Gender Differences in Bidding Behavior and Payoffs in the FPA

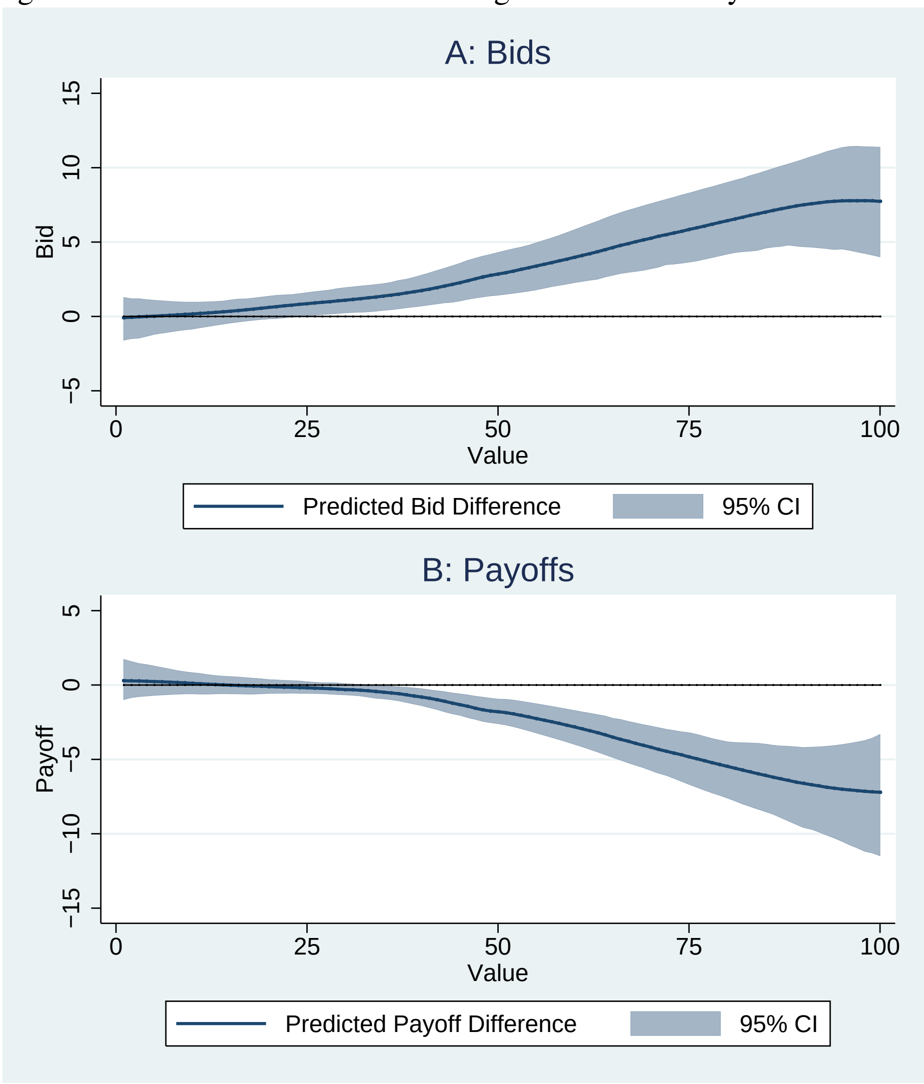


Figure 5: Gender Differences (Women - Men) in FPA Bidding Behavior with Controls for Treatment, Demographics and Risk Aversion

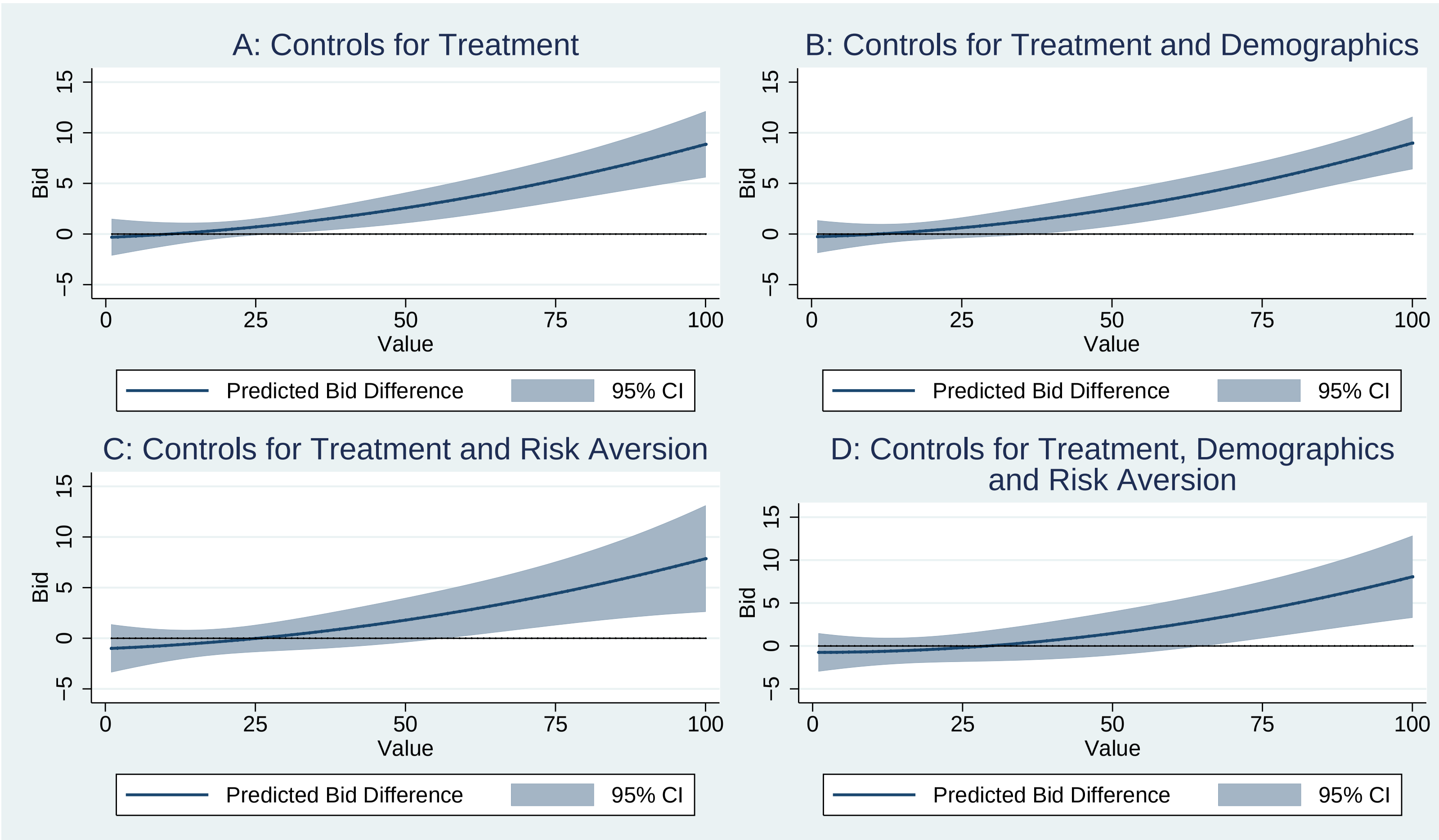


Figure 6: Gender Differences (Women - Men) in SPA Bidding Behavior, Dominant Strategy Play and Overbidding

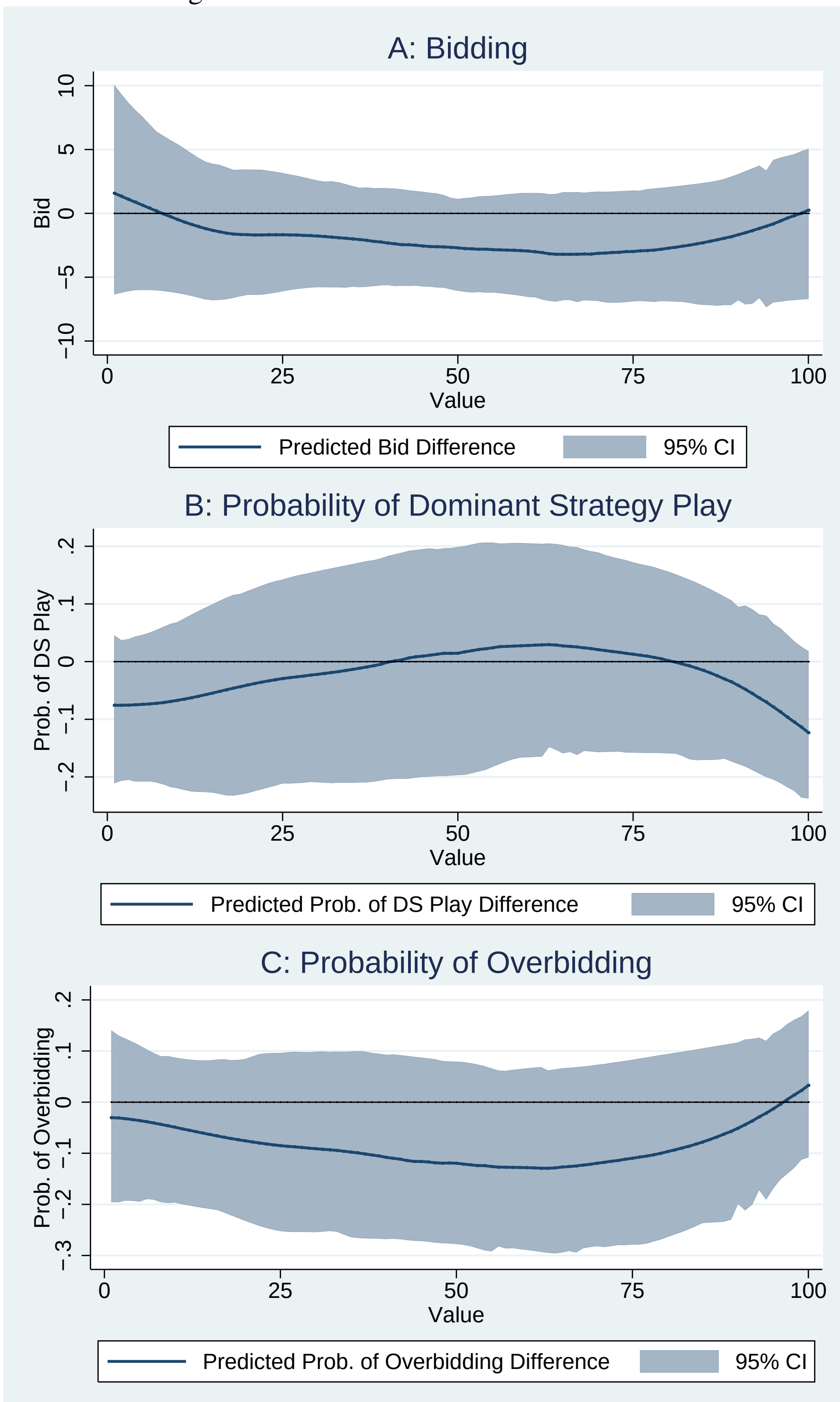
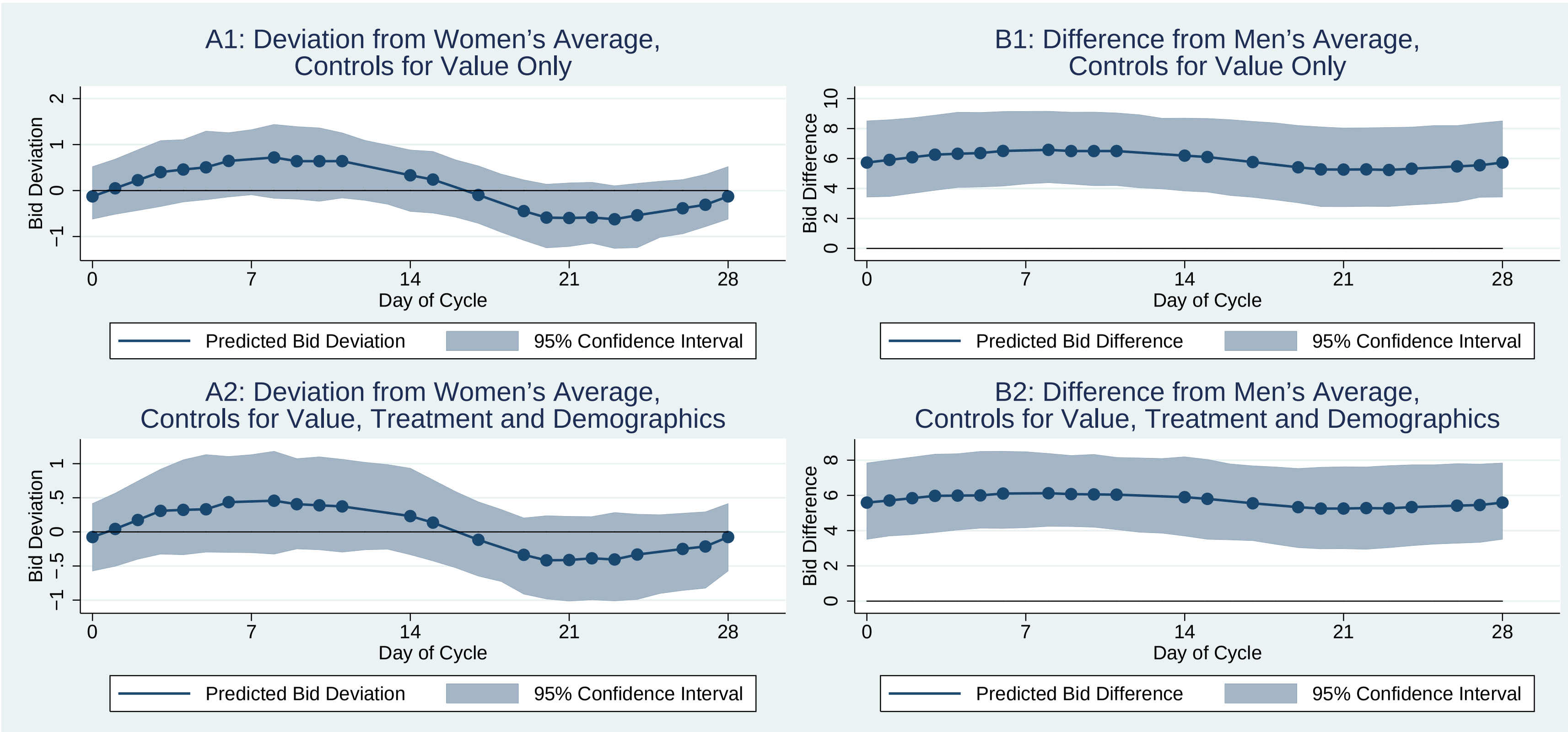
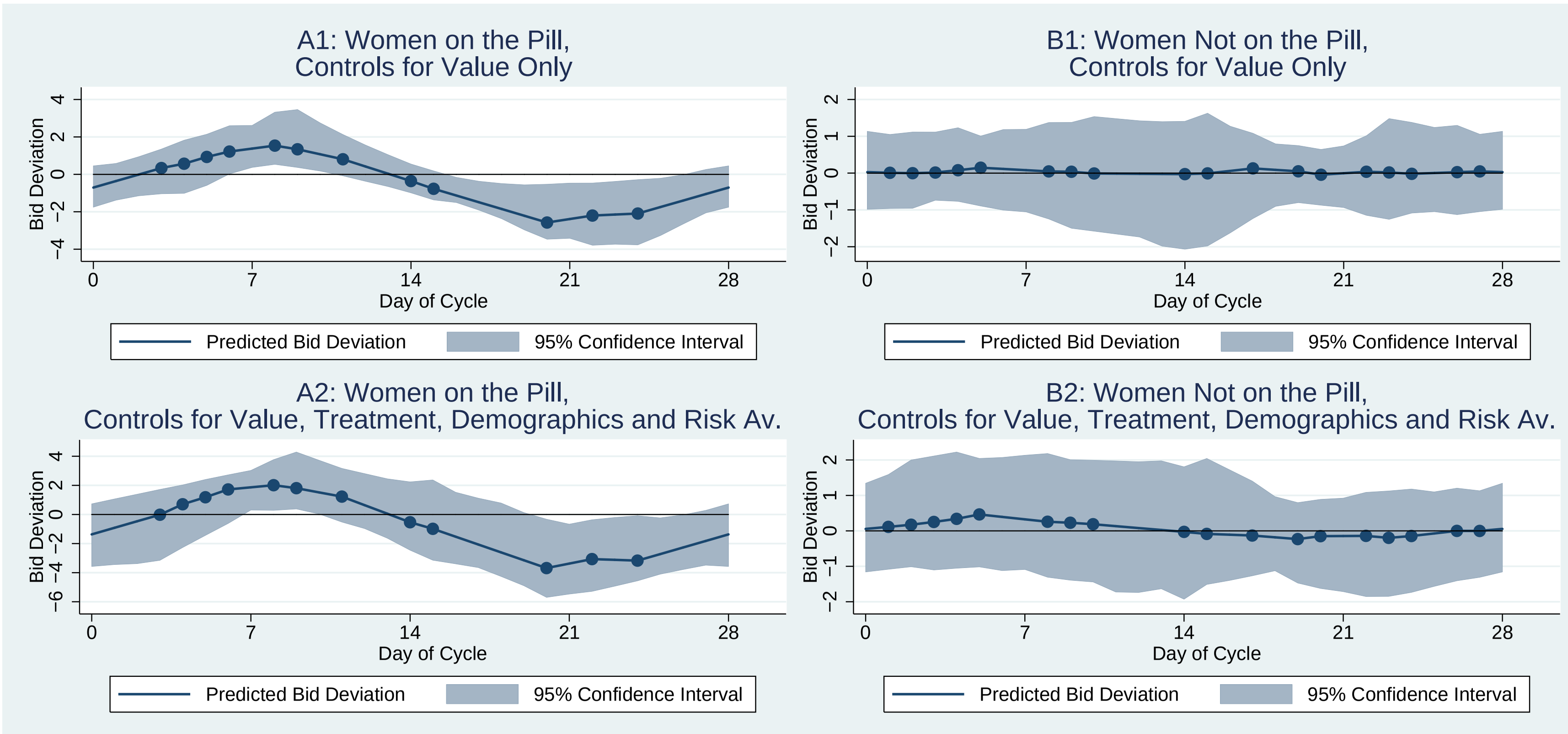


Figure 7: Effects of Menstrual Cycle on FPA Bidding Behavior (Datasets 1 and 2 Combined)



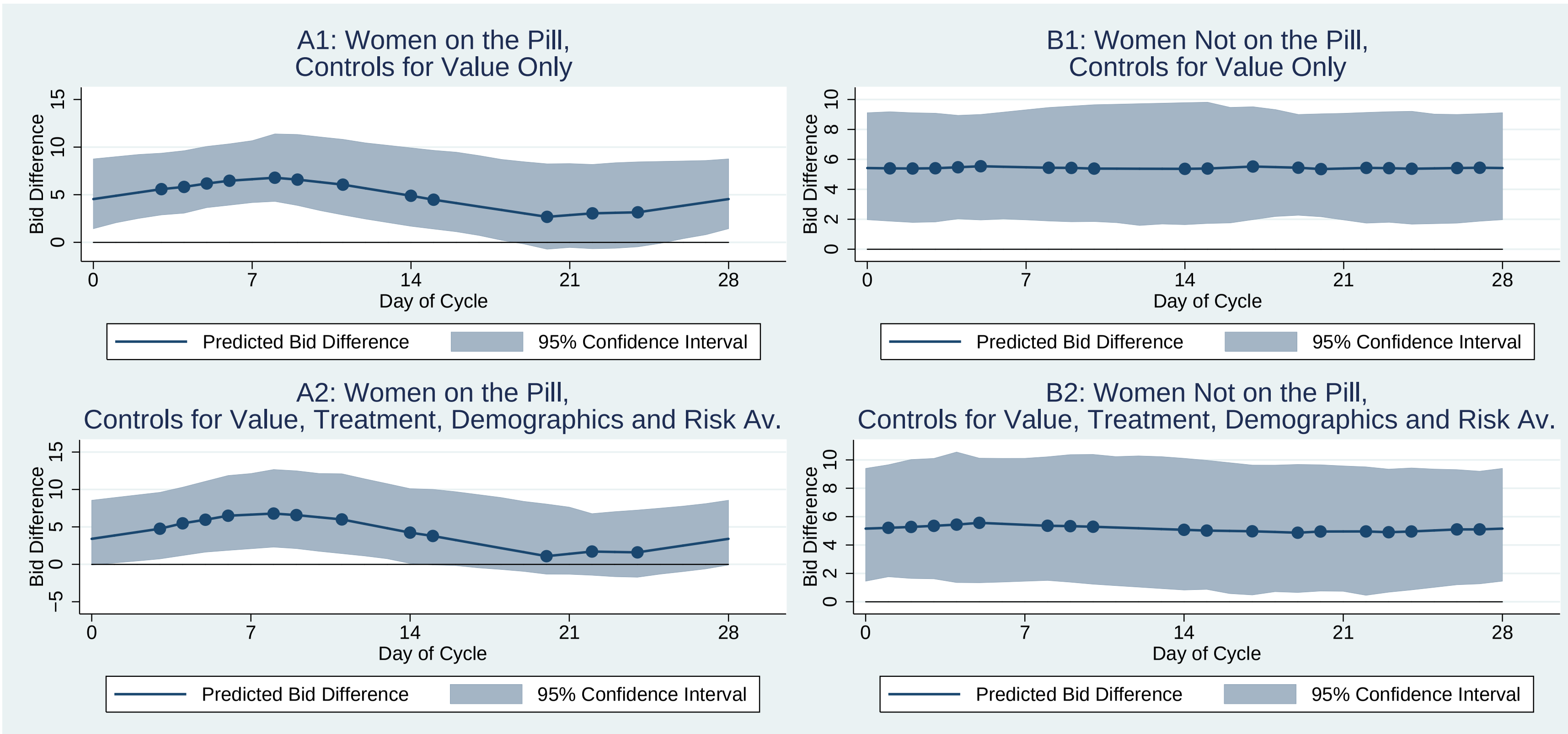
Note: The marked points on the prediction curve signify that at least one subject is available with a given day of the cycle. The difference from the men's average is estimated at the value of 80.

Figure 8: Effects of Menstrual Cycle on FPA Bidding Behavior By Pill Usage: Deviation from Own Group Mean (Dataset 2)



Note: The marked points on the prediction curve signify that at least one subject is available with a given day of cycle.

Figure 9: Effects of Menstrual Cycle on FPA Bidding Behavior By Pill Usage: Difference from Men's Mean Bids (Dataset 2)



Note: The marked points on the prediction curve signify that at least one subject is available with a given day of the cycle. The difference from the men's average is estimated at the value of 80.

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