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

Yan Chen† Peter Katuščák‡ Emre Ozdenoren§

November 25, 2008

Abstract

This paper examines gender differences and menstrual cycle effects in bidding in first-price (FPA) and second-price (SPA) sealed-bid auctions with independent private values in a laboratory setting. We find that women bid significantly more and earn significantly less than men in the FPA. We also find that this difference cannot be entirely explained by gender difference in risk aversion. In the SPA, we find no evidence of a gender difference in bidding, the probability of dominant strategy play or probability of overbidding. We then move a step further and investigate biological determinants of bidding behavior among women, particularly the effect of menstrual cycle. We find a sinus-like pattern of bidding in the FPA throughout the cycle, with women bidding more than their average in the follicular phase of cycle (days 6 to 13 in a 28-day cycle) and less than their average in the luteal phase of the cycle (days 16 to 23). This variation around mean is not statistically significant, though. However, when we break up the sample into contraceptive pill users and non-users, we find that almost all of the bidding variation throughout the cycle is driven by pill users, with pill non-users having a flat bidding profile. In addition, the variation around mean is statistically significant for pill users. We do not find any significant menstrual cycle effects in the SPA.

Keywords: gender, menstrual cycle, auction
JEL Classification: C91, D44, D83

*We thank David Cooper, Rachel Croson, Catherine Eckel, Uri Gneezy, Štepán Jurajda, John Kagel, Nancy Kotzian, Laura Mentz, Muriel Niederle, Andreas Ortmann, Steve Salant, Dan Silverman, Robert Slonim, Lise Vesterlund and seminar participants at Case Western, Harvard, Michigan, Ohio State, Simon Fraser, UBC, UCSD, and the 2005 Economic Science Association Meetings (Montreal, Canada) and Stanford Institute for Theoretical Economics for helpful comments. We thank Sasha Achen, Brian Chan, David Edelman and Casey Hui for excellent research assistance, and Jim Leady for programming for the experiment. Chen gratefully acknowledges the financial support of the National Science Foundation. Any remaining errors are our own.

†School of Information, University of Michigan, 1075 Beal Avenue, Ann Arbor, MI 48109-2112, yanchen@umich.edu.

‡CERGE-EI, P.O.Box 882, Politických vězňů 7, 111 21 Praha 1, Czech Republic, Peter.Katuscak@cerge-ei.cz. CERGE-EI is a joint workplace of the Center for Economic Research and Graduate Education, Charles University, and the Economics Institute of the Academy of Sciences of the Czech Republic.

§Department of Economics, University of Michigan, 611 Tappan Street, Ann Arbor, MI 48109-1220, emreo@umich.edu.

1 Introduction

Gender differences in decision-making have long fascinated economists, psychologists and other social scientists. In a recent survey, Croson and Gneezy (2004) synthesize studies of preference differences between men and women in 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 that of men (e.g., Gneezy, Niederle and Rustichini (2003); Niederle and Vesterlund (2004); Gneezy and Rustichini (2004)).

These experimental results are consistent with findings from survey data. For example, Jianakoplos and Bernasek (1998) examine household holdings of risky assets to determine whether there are gender differences in financial risk taking. They 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. They further find that gender differences in financial risk taking are correlated with race, age and number of children. In a related study, Hersch (1996) examines data from a large national survey and finds substantial differences by 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.

While both experimental and survey results point towards robust gender differences in various decision-making tasks, we are not aware of any study in economics that would investigate potential biological sources underlying this gender difference. To address this question, we examine gender difference in bidding in first-price (FPA) and second-price (SPA) sealed-bid auctions and also 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 hormonal and physiological changes that are associated with the cyclical process of ovulation and menstruation (Richardson 1992). This is an age interval when many important life-changing decisions are made. Thus, whether these hormonal and physiological changes affect women's risk preferences, attitudes towards competition, or cognitive performance, is an important yet open question.

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). In simple cognitive tasks, Hampson and Kimura (1992) find that women perform better on certain male-oriented tasks (e.g., spatial ability) during menstruation, when estrogen is 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. Researchers have also studied the effects of the cycle on visual information processing, memory, mood, etc. None of the tasks, however, concern economic decision-making.

One study that explores potential biological effects on economic performance is a paper by Yuan, Zheng and Zhu (2006) that investigates the relationship between lunar phases and stock market returns of 48 countries. They find that stock returns are lower on the days around a full moon than on the days around a new moon. The magnitude of the return difference is three to five percentage points per year. Furthermore, the lunar effect is independent of other calendar-related anomalies. 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. Although the authors do not directly measure the effect of menstrual cycle on investment behavior, it is well known that there is a synchronous relationship between the menstrual cycle and lunar phases (Law 1986).

If the menstrual cycle and respective hormone levels can explain a significant part of the gender difference, we might be able to reduce gender gaps in various domains by adjusting policies. For example, if the menstrual cycle affects women's willingness to take risks, it might be beneficial for them to know how their risk preference systematically varies during the cycle in order to time key decisions during certain phases of the cycle. This might lead to better decisions in investments, negotiations and other competitive situations, which could improve their earnings and social position. If the menstrual cycle affects women's cognitive performance, important exams, such as the Scholastic Aptitude Test in the United States, the General Certificate of Education in the United Kingdom, and the National College Entrance Examination in many other countries should be scheduled multiple times during the exam month, so that women can choose when to take the exam based on their cycle.[1] Better exam scores can lead to better colleges, which in turn, can lead to better earning potentials.

In this paper, we examine gender differences in competitive situations by conducting laboratory experiments in first- and second-price sealed-bid auctions with independent and private valuations. Theoretically, in the FPA, the Bayesian Nash equilibrium is sensitive to bidders' risk preference, while in the SPA, bidding one's true value is a weakly dominant strategy regardless of bidder's risk preferences. Therefore the FPA involves a greater degree of strategic considerations than does the SPA. However, determining the dominant strategy in the SPA is not a trivial task in itself. Indeed, many previous experiments show that a significant proportion of bidders overbid in SPAs (e.g., Chen, Katuščák and Ozdenoren (2007)). Thus,

[1]Partly based on the widespread popular belief in the notion of paramenstrual cognitive debilitation, it is not uncommon for female high school graduates in Beijing to receive luteinizing hormone shots before the National College Entrance Exam to shift their menstrual cycle.

these two auction formats provide two different competitive situations in which to study gender differences in decision-making. Our results show different effects for the two mechanisms. In the FPA, we find that women bid significantly higher than men. On the other hand, in the SPA, bidding, the probability of dominant strategy play, or the probability of overbidding is not significantly different between men and women. These results suggest that the ability to bid in a privately optimal way, if the underlying reasoning does not involve consideration of other bidders' actions, does not differ across genders, and hence cannot account for the gender difference that we find in the FPA. As a result, gender differences in other aspects are the likely driving forces behind the gender gap in competitive bidding in the FPA.

Two such aspects that readily come to mind are risk aversion and attitudes toward competition. We measure risk attitudes in a subset of our data using the Holt and Laury (2002) measure and find that the gender difference in the FPA persists even when we control for individual differences by this measure of risk aversion. We also confirm this finding independently under the assumption of mean-variance preferences by comparing first and second moments of payoff distributions of men and women. Risk aversion therefore does not seem to be the sole driver of the gender difference in bidding in the FPA. This difference is also robust to controlling for small differences in treatment and individual differences in demographic variables such as age, race, major, and the number of siblings.

To investigate potential biological causes of the gender gap in FPA, we investigate whether women's behavior changes systematically with the phase of the menstrual cycle. Without any further control variables, we find that women in the follicular phase of the cycle (approximately days 6 to 13 of the cycle based on a 28-day cycle) bid more than women on average, whereas women in the luteal phase of the cycle (approximately days 16 to 23 of the cycle) bid significantly less, but this variation around mean is not statistically significant. However, when we split the sample by whether a woman uses a contraceptive pill or not, we discover that the variation throughout the cycle described above 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 furthermore robust to controlling for treatment, demographics and risk aversion.

We are aware of two other papers which examine the effects of demographics in auctions. Rutstrom (1998) presents an experimental study of the English, Vickrey and the Becker, DeGroot and Marschak (1964) mechanisms, using home-grown values.[2] In Rutström's study, participants bid on a box of gourmet chocolate truffles. Bidder values for the truffles are home-grown and assumed to be private. Rutström finds that whites submit lower bids on average, and females exhibit more variance in bidding behavior than males. As bidder values are not induced, the causes of these gender and race effects remain unknown.

[2]Home-grown values refer to the subjective values participants have formed for a good, in the absence of any values induced by the experimenter. It is often used in field experiments.

Casari, Ham and Kagel (2004) explore demographic and ability effects in common value auctions, using the induced-value method. The demographic and ability variables include gender, SAT and ACT scores, major, and class standing (freshman, sophomore, etc.). 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. They also find that inexperienced subjects with lower SAT/ACT scores, as well as business and economics majors, are more likely to overbid and go bankrupt. However, the authors do not investigate the biological causes for the gender difference. We will compare these results with our results in more detail in Section 4.

Our paper thus presents the first study in economics on how the menstrual cycle affects economic decision-making. We provide evidence of a systematic variation in bidding behavior in FPA among women depending on their phase of the cycle and contraceptive pill usage. The medical and psychology literature which addresses the connection between menstrual cycles and cognition has never examined the domain of auctions or other competitive tasks. Thus, this paper contributes to the general literature on that connection by opening up a new and important domain. Results in this new domain can potentially impact economic policies.

The rest of the paper is organized as follows. Section 2 discusses the experimental design and data collected via the post-experiment survey and from the Office of the Registrar. Section 3 discusses in detail our measurement of the menstrual cycle. Sections 4 and 5 present results on gender differences in bidding on FPA and SPA, respectively. Section 6 presents results on the impact of menstrual cycle and contraceptive pill use on bidding in FPA.[3] Finally, Section 7 concludes.

2 Experimental Design and Data

In this section, we summarize the main features of the experimental design, the post-experiment questionnaire, and additional sources of data that we use. 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. The data from two different sets of experiments and affiliated information are used in this study. Dataset 1, which contains data on both the FPA and the SPA, 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 of 2002. The second set of experiments, contained in Dataset 2, was designed to address concerns about

[3]We also analyzed the effect of menstrual cycle on bidding in SPA bud did not find any systematic impact.

the lack of control for risk aversion and the usage of contraceptive pills. In this set of experiments, we used the same auction environment, restricting attention to the FPA only, but also measured subject risk attitudes using the Holt and Laury (2002) incentivized lottery instrument. In addition, this set of experiments used a modified version of the questionnaire which elicited usage of a contraceptive pill and multiple measures of the phase of the menstrual cycle. In the first set of experiments, 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 auction and \$10.52 from the lottery (hence the average total earning being \$23.16). The data are available from the authors upon request.

2.1 Auction

Each experimental session consisted of 8 bidders. At the beginning of each session, subjects randomly drew a PC terminal number. Then, each subject was seated in front of the corresponding terminal and given printed instructions (see Appendix A). After the instructions were read aloud, the subjects completed a set of Review Questions to test their understanding of the instructions. The experimenter then checked their responses and answered questions. The instruction period varied between fifteen to thirty minutes, depending on the treatment.

Each session lasted for 30 rounds, without any practice rounds. In each round, bidders were randomly rematched into groups of two. Bidder valuations were 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 $F^1(\cdot)$ as $\delta = 0.70$. In 15 out of 20 FPA sessions and 5 out of 10 SPA sessions, we announced this probability (known distribution), whereas we did not do so in the other half (unknown distribution). [4]

Each round of bidding consisted of the following stages:

1. For treatments with an unknown distribution only, each bidder estimated the chance that the valuation

[4] The purpose of this additional feature of the design was to study the impact of ambiguity on bidding in auctions. The results are presented in Chen et al. (2007).

of the *other* bidder in the group was drawn from the high value distribution, i.e., an estimate of $1 - \delta$.

2. Next, each bidder was informed of his own valuation. Then each bidder simultaneously and independently submitted a bid, which could have been any integer between 1 and 100, inclusive.

3. Bids were then collected in each group and the object was allocated to the bidder with the higher bid, using a fair tie-breaking device in case the two bids coincided.

4. After each auction, each bidder received the following feedback on his screen: his valuation, his bid, the winning bid, whether he received the object, and his payoff. The payoff was equal to the difference between the induced object valuation and the paid price in case of winning the auction, and zero otherwise. The paid price was equal to the amount of the own bid in the FPA, and to the amount of the other bid in the SPA.

Table 1 summarizes the relevant features of the all auction experiments, including mechanism, the number of subjects per session, information conditions, exchange rates, and the total number of subjects in each treatment. This design gives us a total of 30 independent sessions, 20 in Dataset 1 and 10 in Dataset 2. In the former, 10 sessions contain data from FPA and the other 10 from the SPA, equally split between known and unknown distribution. In the latter, all 10 sessions contain data from FPA with the known distribution. There are altogether 240 subjects used in this study.

2.2 Lottery

In the second set of experiments, we complement the auction experiments with incentivized elicitation of risk attitudes through lottery choices using the Holt and Laury (2002) measure on the scale of zero to 10, a higher number representing a higher aversion to risk (see Appendix C). In order to avoid the results potentially being contaminated by order effects, in 5 out of 10 sessions in the second set of experiments, we had the lottery precede the auction, whereas we reversed the order in the other 5 sessions.

Of the 80 subjects in the second set of experiments, 72 displayed consistent risk preferences in that once they switched to a more risky choice, they continued choosing it, whereas the remaining 8 subjects showed at least one reversal. We therefore measure the extent of risk aversion by the number of safe choices, even if there are some preference reversals. Table 2 lists the distribution of the risk aversion measure separately for men and women. Despite women being somewhat more risk averse (6.22 vs. 6 on average), the ranksum test reveals that the two distributions are not statistically different at conventional levels of significance. Because there is only one subject with a risk aversion measure below 4 and only one with this measure above 8, in our 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 and Registrar Information

At the end of the auction and, in the second set of experiments, the lottery experiment (in whichever order they were administered), all participants completed a survey (see Appendix B) to elicit self-described personality and emotions experienced during the experiment and, importantly, demographic and menstrual cycle information. We do not include the former set of variables in the analysis, because they are likely to be endogenous to the outcome of the auction (and lottery).[5]. The menstrual cycle measurement will be discussed in more detail in the next section. Regarding the demographic information, we elicited gender, race, age, and number of siblings.[6] In the second set of experiments, we elicited academic major as well. We did not do so in the first set of experiments, but rather obtained this information from the University of Michigan Office of the Registrar, together with the list of courses our subjects took at the University of Michigan prior to participating in the experiment.

We collect information on race because there is evidence that different ethnic groups may have different attitudes toward risk aversion, for example. Age correlates with maturity and experience, and may therefore affect bidding as well. Finally, we are interested in the number of siblings because there are numerous studies in the psychology literature on how sibling relationships affect the long term cognitive, emotional and social development of both older and younger siblings.[7]

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

From the 240 subjects in both datasets, we have gender, race, age, and number of siblings information for all of them. In Dataset 2, we have academic major information for all subjects. Unfortunately, in Dataset 1 we have major information only for 96 out of 160 subjects because we were either unable to match the remaining subjects with the records at the Registrar's Office based on their identifying information (name and social security number), or, if we were able to do so, the available information was insufficient to determine the major category. We classify the remaining 64 subjects as having an "unknown" major.

[5]The primary objective of eliciting this information was to study ambiguity attitude in our companion paper (Chen et al. 2007). For example, personality information could be used to estimate the boundary for the set of priors in the α-MEU framework.

[6]If a subject reported a double ethnic origin, we make each of the relevant ethnic indicator variables we use in the analysis equal to 0.5.

[7]For example, using direct observations and interviews, Bryant (1989) finds that, among the six components of social-emotional functioning (empathy, social perspective taking, acceptance of individual differences, locus of control, attitudes toward competition and attitudes towards individualism), sibling caretaking adds significantly to the prediction of all six measures. The author also documents that having more siblings is correlated with a child's increased preference for competitive situations. The relationship between family size and intelligence has been the subject of much earlier research (Anastasi 1956). More recently, Rodgers, Harrington, van den Oord and Rowe (2000) find no direct causal link between family size and children's intelligence using survey data. In an economic study of the effect of the number of siblings on behavior in the laboratory, Glaeser, Laibson, Scheinkman and Soutter (2000) find that, in trust games, only children are much less likely to return money when they are recipients, which can be interpreted as being less trustworthy.

Summary statistics on survey responses on non-menstrual-cycle variables are contained in Table 3. Of the 240 subjects, 129, or 54%, are women (78 in Dataset 1 and 51 in Dataset 2). The average age of a subject 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 are of some other racial group. Because of the relatively low number of subjects that are not White or Asian/Asian American, we group all other racial groups into the “Other" group when conducting the analysis. Regarding the academic major, most of our subjects are Science and Engineering majors (31%), followed by Humanities and Other majors (19%), Economics and Business majors (12%), Other Social Sciences majors (9%) and Mathematics and Statistics majors (3%). We do not have academic major information for 27% of our subjects (all of them in Dataset 1).

3 Measuring the Phase of the Menstrual Cycle

Menstrual cycles occur naturally in reproductive-age women and are known to generate wide variation in hormonal levels over the course of the cycle as depicted in Figure 1. The cycle lasts 28 days on average and it can be divided into five phases. During the menstrual phase (approximately days 1-5), secretion of estradiol 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), 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 the 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.

To the extent that hormones are documented to impact human behavior, it is not surprising that bidding behavior may vary with phases of the menstrual cycle. One of the aims of this study is to relate bidding behavior directly to the phase of the cycle, and indirectly to the levels of various hormones. We do not directly measure hormonal levels, but rather measure the phase of the menstrual cycle through elicited self-reports of day counts from the beginning of the current 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 medical and psychology studies use around 20 subjects, while we have 124 female subjects. We thus believe that even though our measures the sample size allows to draw useful inferences about the effect of the cycle and, indirectly, hormones on bidding behavior.

This poses two challenges for interpretation of the results. First, self-reports of the phase of the cycle are likely to suffer from a measurement error, and we indeed provide a suggestive evidence on this below. The likely exception is women who currently menstruate, for whom we would expect more accurate information. However, as long as the measurement error is not systematically related to the true phase of the cycle, it only results in the attenuation bias by scaling toward zero any possible estimated effects of the menstrual cycle on behavior.

Second, even knowing the exact phase of the cycle, there is a variation across women in their hormonal levels. This could be either due to natural heterogeneity, as documented by Stricker, Eberhart, Chevailler, Quinn, Bischof and Stricker (2006), for example, or due to usage of a contraceptive pill. This is a more fundamental problem when trying to interpret the link between the menstrual cycle and behavior through hormonal level variation. However, even though we do not directly measure hormones, we do have information on contraceptive pill usage in Dataset 2, and hence we will be able to compare the behavioral effect of the menstrual cycle between users and non-users of the pill.

In the first set of experiments, we elicited 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 set of experiments as well, with one modification. 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 both sets of experiments we also asked female participants about experiencing the premenstrual syndrome (PMS), with possible answers being "none", "mild", or "severe". We did include this variable as one of the explanatory variables in our analysis, but discovered that it did not have any significant explanatory power, and so we will ignore it in subsequent analysis.

A drawback of the questionnaire used in the first set of experiments is that we do not elicit contraceptive pill usage, an alternative measure of the phase of the cycle or the average duration of the cycle. To remedy these drawbacks, we expand the menstrual cycle part of the questionnaire in the second set of experiments.

Most importantly, 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. The pill usage is available for all 51 female subjects, the duration information for 50 subjects, and the beginning of the last cycle is available for 47 subjects. The reported duration varies from "less than 25" to "more than 35." Among two thirds of women (34 subjects) who do not use a 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 women (17 subjects) who use a pill, 11 report a duration of 28, 2 report a duration of 29, 1 reports a duration of 32, two report a duration of "less than 25", and one does not report anything.[8] 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 the mean of 5.16, the median of 5 and the standard deviation of 1.25.

The measure of the phase of the menstrual cycle we will 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.[9] By construction, this is a "prospective" measure and it assumes a 28-day duration of the cycle. In order to constrain the measure to be between 1 and 28, in Dataset 1 we reset it to missing for one subject who reported being 60 days away from the next cycle, we reset it to 28 for four subjects who reported being 0 days away, and we reset it to 1 for five subjects who reported being 30 days away. With these adjustments, the measure is available for 73 out of 78 female subjects in the first set of experiments. In Dataset 2, if the number of days away from the next menstrual cycle in 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). This way we obtain the measure for 48 out of 51 subjects. In order to maximize the available sample size, we also impute the measure to be equal to the computed number of days from the beginning of the last menstrual period plus one.[10] We use these three observations in the subsequent analysis, but we do not use them in this section when comparing the prospective and retrospective measures and discussing the measurement error. Figure 2 plots a histogram of the prospective measure.

[8]Of these 17 women, 14 also listed name of the pill they use. Searching through usage information of these pills, we found that all of them are supposed to induce a regular 28-day cycle with minimal cycle-length variation, suggesting a measurement error in the duration variable.

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

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

As we already briefly discussed above, this prospective measure may suffer from two sources of measurement error. First, female subjects may simply underestimate or overestimate the true number of days away from the beginning of the next cycle, either because the cycle length may be random or because they simply 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.

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 available in Dataset 2. The latter is available for 47 out of 51 female subjects. However, the provided information is in some instances inconsistent with answers to other questions. In particular, one subject reports the beginning of the last menstrual period to be a date after the date of the experiment. Another 5 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 6 observations and excluding observations where the prospective measure is imputed by the retrospective one, the two measures are 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). Under the assumption that 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 measure is larger than the variance of the measurement error in the prospective measure.[11] If we additionally assume that the measurement noise in the two measures is uncorrelated, then we can also quantify the difference. In particular, the standard deviation of measurement error in the prospective and the retrospective measures is 55.4 and 67.7 percent, respectively, of the standard deviation in the true phase of the cycle.[12] These observations suggest, under the assumption that the measurement errors are uncorrelated with the true day of the cycle, that the prospective measure is superior to the retrospective measure, justifying the former's use in the analysis.

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 initial

[11]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 $Var(\varepsilon_1) \gtreqless Var(\varepsilon_2)$.

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

subtraction, and then normalizing this measure by dividing by the reported average duration of the cycle and multiplying by 28. This measure is available for 42 observations. We cannot compute this measure for six 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." The correlation between this measure and our original prospective measure is 0.995.[13] The two measures are therefore equivalent. However, because this alternative prospective measure cannot be computed in Dataset 1, we prefer to use the original prospective measure. We have also constructed a normalized retrospective measure by dividing the original retrospective measure by the reported duration and multiplying it by 28. Again, we excluded observations where the reported duration is less than the number of days from the first day of the last menstrual period, or duration is missing or it 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.

4 Gender Differences in Bidding in FPA

In this section, we present results on gender differences in competitive bidding in FPA. Before proceeding, we first point out some common features that apply throughout our analysis in this and subsequent sections. First, given that each subject gets to bid 30 times, in all the empirical models that we estimate, standard errors and confidence intervals are adjusted for clustering at the subject level.[14] Second, we use a 95% statistical confidence level to claim existence of any causal effects.

Figure 4 displays non-parametric estimates of the bidding functions in the FPA for men and women (Panels A and B, respectively) and their difference (Panel C). The bidding function is first separately estimated for each gender by a locally weighted linear regression based on 80 percent of the sample bandwidth, the tricube weighting function, and local averaging of predictions.[15] Confidence intervals for these predictions are obtained by bootstrapping (with clustering at the subject level) with 250 replications. The gender difference is then estimated as the difference of the two predicted bidding functions and its confidence interval is

[13]In a cross-plot, the observations are clustered in a narrow band around the diagonal. This cross-plot is available from the authors upon request.

[14]Given that different bidders can affect one another's bidding within the course of 30 rounds, one could argue that clustering at session level would be more appropriate. However, given that we have 20 FPA sessions and 10 SPA sessions, such pattern of clustering would not leave enough degrees of freedom for a multivariate analysis of bidding.

[15]Let b_i be the bids and v_i the values, where i indexes individual bids in individual rounds in individual sessions, and let N be the sample size. Suppose that the data are ordered such that $v_i \leq v_{i+1}$ for $i = 1, .., N-1$. Then for each v_i we first calculate the predicted bid at value v_i by running a weighted linear OLS regression using the observations $i_- \equiv max(1, i-k)$ through $i_+ \equiv min(i+k, N)$, where $k \equiv [(N * B - 0.5)/2]$, and B is the sample-proportional bandwidth. The weight for each observation $j \in \{i_-, i_+\}$ is given by $[1-(|v_j - v_i|/\Delta)^3]^3$, where $\Delta \equiv 1.0001 max(v_{i_+} - v_i, v_i - v_{i_-})$. This part of estimation is conducted using the *lowess* command in Stata. Finally, the predicted bid for any value $v \in \{1, .., 100\}$ is calculated as an arithmetic average of predicted bids for each $v_i = v$.

again estimated by bootstrapping with 250 replications.

Figure 4 shows that women bid more than men in FPA, and the 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. What can explain this difference? One obvious explanation is gender difference in risk aversion (Croson and Gneezy 2004). Because bidding more, *ceteris paribus*, decreases the payoff conditional on winning but increases the probability of winning, risk aversion increases bids in FPA.[16] However, it is not clear that it is risk aversion that drives the difference. For example, in a closely related study, Casari et al. (2004) find that, in common value auctions, women inexperienced at such auctions bid substantially higher than men and thus suffer more from the winner's curse, while women experienced at such auctions do at least as well as men. However, the theoretical prediction of the impact of risk aversion on bidding is ambiguous in their common value environment. Therefore it is not clear whether their gender difference is due to risk aversion differences or other factors. Even in our private value environment, one can find other explanations for the gender difference. First, because bidding more increases the chance of winning the auction, if this effect more than outweighs the loss in expected payoff conditional on winning, then bidding more is optimal even for a risk neutral bidder. One would therefore expect women to have a lower expected payoff if it is risk aversion that drives the result. Second, other explanations, such as differences in strategic reasoning or attitudes toward competition, could drive the result (e.g., Gneezy et al. (2003); Niederle and Vesterlund (2004); Gneezy and Rustichini (2004)).

In order to evaluate to what extent the gender difference in bidding identified in Figure 4 is due to gender differences in risk aversion and other observable personal characteristics, Figure 5 presents second-order parametric polynomial estimates of the bidding function when 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, White, Asian, Other, indicators for academic major and number of siblings) and risk aversion (indicators for five risk aversion groups), as well their interactions with second-order polynomial in value are controlled for. Panels A and B show that accounting for treatment and jointly for treatment and demographics changes the baseline result very little. Although the gender difference now becomes significant only for values larger than 31 or 35, women still overbid men by a median of 5.21 or 4.63 percentage points of their valuation, respectively. On the other hand, panels C and D show that controlling for treatment and risk aversion, without or with controlling for demographics, makes the gender difference to be statistically significant only for values above 54 or 70, and women now overbid men only by a median of 3.63 or 2.96 percentage points of valuation, respectively. As a result, it appears that gender

[16]The same also applies in a symmetric Bayesian Nash equilibrium with known (Riley and Samuelson 1981) or unknown (Chen et al. 2007) distribution of valuations.

differences 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 difference.

The finding that risk aversion differences can explain some but not all of the gender difference in bidding may be an artefact of the Holt-Laury measure. Studies show that risk aversion may be context dependent and its measurement may suffer from error. After all, as discussed in Section 2, our measurement of risk aversion displays only a small and statistically insignificant gender difference. We therefore pursue another way of looking at the extent to which a presumed gender difference in risk aversion drives the gender difference in bidding. We do so by focusing on expected value and variance of payoffs. The risk aversion-based explanation would predict that women are willing to accept smaller expected payoffs in exchange for the payoff realizations being less variable. Figure 6 presents results of a non-parametric analysis of gender differences in payoffs and absolute payoff deviations (APDs). The latter are computed as absolute deviations from a payoff predicted by a subject-specific OLS regression of payoffs on a second-order polynomial in value. Panel A shows that women's higher bids indeed result in statistically significantly lower payoffs for values above 36, with the median extent of the gap being 3.61 percentage points of valuation. Given that the payoff medians for men and women are 18.60 and 14.98 percentage points of valuations, respectively, this constitutes approximately a one-fifth reduction in the scaled size of payoffs. Panel B shows that women indeed have consistently lower variability of payoffs than men by about 1.42 percentage points of valuation, but the difference is statistically significant only for values between 51 and 70. Given that the APD medians for men and women are 12.63 and 11.26 percentage points of valuations, respectively, this constitutes approximately a one-ninth reduction in the scaled size of APDs. This implies that both the mean and the variance of the relative payoffs get scaled down by a factor of about 0.8.

Are there results consistent with a reasonable gender difference in the degree of risk aversion? Although the answer is ambiguous in general since preferences may depend on higher moments of the payoff distribution, a simple reasoning reveals that the answer is no if the decision-maker cares only about the mean and the variance of the payoff distribution. Given that payoffs are, conditional on rational bidding behavior, non-negative, every rational mean-variance decision-maker, irrespective of his or her risk preferences, would prefer the distribution of male payoffs to the same distribution scaled down by a factor of 0.8. But given that the variance of the latter is only 0.64 times the variance of the original distribution, the latter is in turn strictly preferred to the distribution of female payoffs.[17] As a result, we conclude that although a part of the gender difference in bidding may be due to a higher risk aversion of women, the latter cannot explain

[17] We obtain the same qualitative conclusion by using a parametric second-order polynomial estimates of payoff and APD functions controlling for treatment and demographics.

the entire gender gap in bidding.

5 Gender Differences in Bidding in SPA

Unlike in the FPA, where bidding behavior may reflect individual heterogeneity in risk attitudes, for example, bidding one's own valuation is a weakly dominant bidding strategy in the SPA. This strong prediction implies that we should not be able to find gender differences in bidding in the SPA. We perform a non-parametric analysis analogous to the one discussed in the previous section for the SPA, focusing on bidding, the probability of dominant strategy play and probability of overbidding.[18] The results are presented in Figure 7. Panel A shows that women bid somewhat less than men and Panel C shown that they are somewhat less likely to overbid compared to men, but the difference is not statistically significant for any values in either case. Panel B shows that the two genders are no different in the probability of dominant strategy play either. These conclusions are furthermore robust to controlling for treatment or demographics.[19]

To the first order, these results confirm the hypothesis that there should be no gender difference in bidding in SPA. However, it is by far not the case that this is due to majority of subjects playing the dominant strategy. In particular, out of the 2,400 SPA bids recorded in Dataset 1, only 861 (35.88 percent) are equal to the value, while 1,194 (35.88 percent) are above the value and only 345 (14.38 percent) are below the value. Ours is by far not the first study which finds a significant extent of overbidding in SPA.

6 Effect of the Menstrual Cycle on Bidding in FPA

In this section, we move one step further and ask whether menstrual cycle and contraceptive pill usage have an impact on women bidding behavior and the gender gap in bidding in the FPA we identified in Section 4. Using Dataset 1, we also analyzed the effect of menstrual cycle on bidding in the SPA but, unlike in the case of FPA, did not find any systematic impact.[20] We therefore collected additional data only for the FPA in the second set of experiments, and the rest of this section will therefore focus on this auction format.

Figure 8 presents the baseline estimates. As in the previous two sections, the estimation methodology is based on locally weighted linear regression that uses 80 percent of the sample bandwidth with the tricube weighting function and local averaging of predictions.[21] However, unlike in the previous section, in this estimation we take advantage of the fact that day of menstrual cycle is a cyclical variable. That is, we can treat any day $t \in 1, .., 28$ of the current cycle as the same day of the previous or the next cycle. This means

[18]We thank John Kagel for suggesting the analysis of overbidding to us.

[19]These results are available from the authors upon request.

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

[21]We have also rerun all the estimations using a narrower bandwidth of 50 percent of the sample, with the same conclusions.

that we can use not only days 1, 2, and so on, but also days 28, 27, and so on to identify the predicted bid for day 1. Likewise, we can use not only days 28, 27, and so on, but also days 1, 2, and so on to identify the predicted bid for day 28.

In order 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. That way, we run the estimation on the overall sample three times the size of the original sample in which the day of sample ranges from -27 to 56. Accordingly, the bandwidth is adjusted to be the fraction 0.8/3 of the expanded sample. The main benefit of this procedure is that predicted bids are estimated more precisely near the edges of the 1-28 day window. As before, confidence intervals for these predictions are obtained by bootstrapping (with clustering at the subject level) with 250 replications. 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, which rules out any higher-order clustering problems.

Furthermore, unlike in the previous two sections that used polynomial approximations, the estimations that control for other variables are conducted semi-parametrically. In particular, in the first stage we run a linear regression of bids on a set of control variables, including an indicator variable for men and 27 indicators for various days of the cycle (one day being the omitted category). In the second stage, we take prediction errors from the first stage computed when all the day of cycle indicator variables are set to zero and demean them according to the relevant comparison category.[22] The resulting demeaned prediction error is then the dependent variable in the non-parametric estimation. Note that this procedure uses male observations to identify the coefficients on the control variables in the first stage and hence in general results in smaller standard errors compared to the case when, beginning from the first stage, we use only data for female subjects. In the latter case, the estimates are broadly similar to results when male data is included, except that the estimates are less precise.[23] However, in case there are no control variables, the two sets of results are identical.

The estimates of Figure 8 are based on data from both datasets. Panel A1 of shows that, in the absence of any control variables, female bidding throughout the cycle has a shape of a sinus curve that reaches its maximum in the follicular phase (days 5 to 13) of the cycle when women bid more than one point above the average, and reaches its minimum in the luteal phase (days 16-23) of the cycle when women bid more than

[22]For example, if we are interested in deviation from women's average, we regress the first-stage prediction errors for women on a constant and then focus on prediction errors from this regression. On the other hand, if we are interested in a deviation from men's average, we compute the mean of the first-stage predictions errors for men and subtract this mean from women's first-stage prediction errors.

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

one point below the average. However, the deviation from the mean is not statistically significant throughout the cycle. Similar results obtain in Panel A2 when treatment and demographic controls are included, except that the amplitude of the deviation from the mean is approximately halved. We find a similar sinus-like curve in Panels B1 and B2 when comparing to bids of men, but this time female bids are statistically significantly higher than male bids throughout the cycle.

Panels A1 and B1 in Figure 9 are analogous to panels A2 and B2 in Figure 8 except that only data from Dataset 2 are used in the estimation. The purpose of these two plots is to give a basis of comparison of results in Figure 8, where data from both datasets are used and subsequent estimation, which uses data from Dataset 2 only since risk aversion and pill usage are measured only in this dataset. The results in Panel A1 of Figure 9 are similar to results in Panel A2 of Figure 8, except that the confidence interval is somewhat wider. This is not the case for Panel B1 of Figure 9 and Panel B2 of Figure 8 as the gender difference fails to be statistically significant in the former due to the difference estimates being smaller and the confidence interval being wider. Panels A2 and B2 of Figure 9 additionally control for risk aversion, and the results are analogous to Panels A1 and B1.

In Figure 10, we split the female sample into contraceptive pill users and non-users. Panels A1 and A2 show that, irrespective of whether treatment, demographics and risk aversion are controlled for or not, the bidding pattern of pill users follows a strong sinus-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). Although the sinus pattern is similar to findings in Figures 8 and 9, the bidding deviation from the mean now becomes statistically significant around the maximum and the minimum. In addition, the amplitude is larger, reaching over 3 points above the mean in the maximum and over 3 points below the mean in the minimum. On the other hand, Panels B1 and B2 show that bidding of pill non-users barely differs from the mean throughout the cycle.

Figure 10 therefore presents one of the key findings of the paper. The sinus-like bidding curve presented in Figures 8 and 9 is a weighted average of the bidding behavior of pill users and pill non-users and it masks the fact that the pattern of deviation from the mean is almost entirely driven by pill users. This result may seem surprising at first since one could expect that a contraceptive pill, by regulating hormonal variation throughout the cycle, should make the pattern of bidding flatter compared to pill non-users. However, many hormonal pills may contribute rather than subtract from hormonal variation throughout the cycle, hence generating a more variable bidding behavior for pill users.

Figure 11 separately compares bidding behavior of pill users (Panels A1 and A2) and pill non-users (Panels B1 and B2) to bidding behavior of men. Panels A1 and B1 show that when no controls are included, pill non-users bid significantly more than men throughout most of the cycle, whereas pill users do so only in the menstrual and follicular phases (days 1 to 13) and just before menstruation. However, the gender difference becomes statistically insignificant throughout the cycle when treatment, demographics and risk aversion are controlled for.

Finally, Figure 12 compares the bidding behavior of pill users to that of pill non-users without controls (Panel A1) and with controls for treatment, demographics and risk aversion (Panel A2). As expected from previous results, the shape of the difference is sinus-like, but the difference is not statistically significant throughout the cycle.

To our knowledge, this is the first set of results in the economics literature which examines the effect of the menstrual cycle on decision-making. One clear finding of our analysis is that pill users behave somewhat differently than pill non-users. In particular, even though the difference between bidding of these two groups is not statistically significantly different from zero, pill users appear to have much more variable sinus-like biding behavior throughout the menstrual cycle, bidding significantly above their average in the follicular phase and significantly below the average in the luteal phase. On the other hand, pill non-users appear to have a fairly flat bidding behavior throughout the cycle. When information from both Dataset 1 and Dataset 2 is combined, women bid more than men throughout the cycle regardless of whether treatment and demographics are controlled for. Relying only on Dataset 2, however, this is no longer the case when the two groups are pooled. Within Dataset 2, we find a significant gender difference for pill non-users throughout the cycle and pill users in the menstrual and follicular phases only when no controls are included.

Our results relate to findings in the medical and psychology literature on menstrual cycle and cognition. The list of cognitive tasks in such studies includes "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)). Based on these summaries as well as our own reading of more recent studies, the findings seem to be task-specific. 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. Hausmann, Slabbekoorn, Goozen, Cohen-Kettenis and Gunturkun (2000) find a significant cycle difference in spatial ability as tested by the Mental Rotation Test, with high scores during the menstrual phase and low scores during the luteal phase. As estrogen levels are lowest during the menstrual phase and highest during the follicular, peri-ovulatory and luteal phases, such results lead to the hypothesis (Hampson and Kimura 1992) that women perform better on certain male-oriented tasks (e.g., spatial ability) during menstruation than during other phases in the menstrual cycle. Conversely, women perform better on certain female-oriented tasks (e.g., articulatory speed and accuracy) during periods of high estrogen levels (follicular, peri-ovulatory and luteal phases).

7 Conclusion

Women's and men's average levels of general intelligence are the same, based on the best psychometric estimates (Jensen (1998), chapter 13). However, the minds of men and women are not identical. Sex hormones, most notably estradiol and androgen, cause the brains of boys and girls to diverge during development (Pinker (2002), chapter 18). Researchers in psychology and medicine have found that, when estradiol levels are high, women perform better at tasks at which they typically do better than men, such as verbal fluency tasks. However, when estradiol levels are low, women perform better at tasks at which men typically do better, such as spatial ability tasks. In this study, we investigate gender differences in competitive bidding situations and explore the extent to which menstrual cycle variation can account for these differences.

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

Furthermore, we use, for the first time in economics, menstrual cycle information to explore a biological basis for the gender difference in behavior. We find that women who use a contraceptive pill behave somewhat differently than the ones who do not. Pill users appear to have much more variable sinus-like biding behavior throughout the menstrual cycle, bidding significantly above their average in the follicular phase and significantly below the average in the luteal phase. On the other hand, pill non-users appear to have a fairly flat bidding behavior throughout the cycle. The gender difference in bidding is present throughout the cycle if pill-users and non-users are lumped together and all available data is used. This is true regardless of whether treatment and demographics are controlled for. However, if we use data only from the second set of experiments, gender difference disappears for both pill users and non-users if we control for treatment, demographics and risk aversion. We hope that this study will spur more interest in the biological foundations of gender differences in behavior in economics.

References

Anastasi, Alessandro, "Intelligence and Family Size," *Psychological Bulletin*, 1956, *53*, 187–209.

Becker, Gary M., Morris H. DeGroot, and Jacob Marschak, "Measuring Utility by a Single-response Sequential Method," *Behavioral Science*, 1964, *9* (3), 226–232.

Bryant, B.K., "The Child's Perspective on Sibling Caretaking and its Relevance to Understanding Social-emotional Functioning and Development," in P.G. Zukow, ed., *Sibling Interaction Across Culture: Theoretical and Methodological Issues*, New York: Springer-Verlag, 1989.

Casari, Marco, John C. Ham, and John H. Kagel, "Selection Bias, Demographic Effects and Ability Effects in Common Value Auction Experiments," 2004. Manuscript, Ohio State University.

Chen, Yan, Peter Katuščák, and Emre Ozdenoren, "Sealed Bid Auctions with Ambiguity: Theory and Experiments," *Journal of Economic Theory*, September 2007, *136*, 513–535.

Croson, Rachel T. A. and Uri Gneezy, "Gender Differences in Preferences," 2004. Manuscript.

Dye, Louise, "Visual Information Processing and the Menstrual Cycle," in J.T.E. Richardson, ed., *Cognition and the Menstrual Cycle*, New York: Springer-Verlag, 1992.

Epting, L. K. and William H. Overman, "Sex-sensitive Tasks in Men and Women: A Search for Performance Fluctuations across the Menstrual Cycle," *Behavioral Neuroscience*, 1998, *112*, 1304–1317.

Glaeser, Edward L., David I. Laibson, Jose A. Scheinkman, and Christine L. Soutter, "Measuring Trust," *Quarterly Journal of Economics*, 2000, *115* (3), 811–846.

Gneezy, Uri and Aldo Rustichini, "Gender and Competition at a Young Age," *American Economic Review*, May 2004, *94* (2), 377–381.

__ **, Muriel Niederle, and Aldo Rustichini**, "Performance in competitive environments: Gender differences," *Quarterly Journal of Economics*, August 2003, *118*, 1049–1074.

Hampson, Elizabeth and Doreen Kimura, "Sex Differences and Hormonal Influences on Cognitive Function in Humans," in J. B. Becker, S. M. Breedlove, and D. Crews, eds., *Behavioral Endocrinology*, Cambridge, MA: MIT Press, 1992.

Hausmann, Markus, Ditte Slabbekoorn, Stephanie H. M. Van Goozen, Peggy T. Cohen-Kettenis, and Onur Gunturkun, "Sex Hormones Affect Spatial Abilities During the Menstrual Cycle," *Behavioral Neuroscience*, December 2000, *114* (6), 7035–7044.

Hersch, Joni, "Smoking, Seat Belts and Other Risky Consumer Decisions: Differences by Gender and Race," *Managerial and Decision Economics*, 1996, *17* (5), 471–481.

Holt, Charles A. and Susan Laury, "Risk Aversion and Incentive Effects," *American Economic Review*, 2002, *92*, 1644–1655.

Jensen, Arthur, *The g Factor: The Science of Mental Ability*, Westport, Conn: Praeger, 1998.

Jianakoplos, Nancy A. and Alexandra Bernasek, "Are Women More Risk Averse?," *Economic Inquiry*, 1998, *36*, 620–630.

Komnenich, Pauline, "Hormonal Influences on Verbal Behavior in Women," *Dissertation Abstracts International*, 1974, *35* (6), 3065B.

Law, S.P., "The Regulation of Menstrual Cycle and its Relationship to the Moon," *Acta Obstetricia et Gynecologica of Scandinavica*, 1986, *65*, 45–48.

Niederle, Muriel and Lise Vesterlund, "Do Women Shy Away from Competition?," 2004. Manuscript.

Nyborg, H., "Spatial Ability in Men and Women," *Advances in Behavior Research and Therapy*, 1983, *5*, 89–140.

Pinker, Steven, *The Blank Slate: The Modern Denial of Human Nature*, New York: Penguin, 2002.

Richardson, John T. E., "The Menstrual Cycle, Cognition, and Paramenstrual Symptomatology," in J.T.E. Richardson, ed., *Cognition and the Menstrual Cycle*, New York: Springer-Verlag, 1992.

Riley, John G. and William F. Samuelson, "Optimal Auctions," *American Economic Review*, June 1981, *71* (3), 381–392.

Rodgers, Joseph Lee, Honalee Harrington, Edwin J. C. G. van den Oord, and David C. Rowe, "Resolving the Debate Over Birth Order, Family Size and Intelligence," *American Psychologist*, June 2000, *55* (6).

Rutstrom, E. Elizabeth, "Home-grown Values and Incentive Compatible Auction Design," *International Journal of Game Theory*, November 1998, *27* (3), 427–441.

Sommer, Barbara S., "Cognitive Performance and the Menstrual Cycle," in J.T.E. Richardson, ed., *Cognition and the Menstrual Cycle*, New York: Springer-Verlag, 1992.

Stricker, Reto, Raphael Eberhart, Marie-Christine Chevailler, Frank Quinn, Paul Bischof, and Rene Stricker, "Establishment of Detailed Reference Values for Lutenizing Hormone, Follicle Stimulating Hormone, Estradiol, and Progesterone During Different Phases of the Menstrual Cycle on the Abbott ARCHITECT®Analyzer," *Clinical Chemistry and Laboratory Medicine*, 2006, *44* (7), 883–887.

Wuttke, Wolfgang, Peter Arnold, Detlef Becker, Otto D. Creutzfeldt, S. Langenstein, and W. Tirsch, "Hormonal Profiles and Variations of the EEG and of Performance in Psychological Tests in Women with Spontaneous Menstrual Cycles and under Oral Contraceptives," in G. Laudahn Itil, T.M. and W.M. Herrman, eds., *Psychotropic Action of Hormones*, New York: Spectrum, 1976.

Yuan, Kathy, Lu Zheng, and Qiaoqiao Zhu, "Are Investors Moonstruck? Lunar Phases and Stock Returns," *Journal of Empirical Finance*, 2006, *13* (1), 1–23.

APPENDIX A. INSTRUCTIONS

The complete instructions for the twelve-subject, first-price auction with known distribution treatment are shown here. Instructions for the twelve-subject, first-price auction with unknown distribution treatment are identical except that 30% is replaced by x% and bidders are asked to give an estimate of x. Instructions for the corresponding eight-subject treatments are identical to their twelve-subject counterparts except that the parts concerning auctioneers are deleted in the eight-subject treatments.

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.

Experiment Instructions – K1$_{12}$

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. If the number on your slip is from PCLAB 2 to PCLAB 9, you will stay in this room and you will be a bidder for the entire experiment. If the number on your slip is from PCLAB 10 to PCLAB 13, you will go to Room 212 after the instruction, and you will be an auctioneer for the entire experiment.
- In each of 30 rounds, you will be *randomly* matched with two other participants into a group. Each group has an auctioneer and two bidders. You will not know the identities of the other participants in your group. Your payoff each round depends ONLY on the decisions made by you and the other two participants 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 auctioneer will set a minimum selling price, which can be any integer between 1 and 100, inclusive.
  - Bidders are informed of the minimum selling prices of their auctioneers, and then each bidder will simultaneously and independently submit a bid, which can be any integer between 1 and 100, inclusive. If you do not want to buy, you can submit any positive integer below the minimum selling price.
  - The bids are collected in each group and the object is allocated according to the rules of the auction explained in the next section.
  - Bidders will get the following feedback on their screen: your value, your bid, the minimum selling price, the winning bid, whether you got the object, and your payoff.

    Auctioneers will get the following feedback: whether you sold the object, your minimum selling price, the bids, and your payoff.

- The process continues.

Rules of the Auction and Payoffs

- **Bidders**: In each round,

- if your bid is less than the minimum selling price, you don't get the object:
  Your Payoff = 0
- if your bid is greater than or equal to the minimum selling price, and:
  * 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.

- **Auctioneers**: In each round, you will receive two bids from your group.
  - If both bids are less than your minimum selling price, the object is not sold, and :
    Your Payoff = 0;
  - if at least one bid is greater than or equal to your minimum selling price, you sell the object to the higher bidder and
    Your Payoff = the Higher Bid.
- For example, if the minimum selling price is 1, bidder A bids 25, and bidder B bids 55, since $55 > 1$ and $55 > 25$, bidder B gets the object. Bidder A's payoff = 0; bidder B's payoff = her value - 55; the auctioneer's payoff = 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.
- Bidders: the exchange rate is $1 for ____________ points.
- Auctioneers: 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. The minimum selling price is 30 and your bid is 25, your payoff = __.
6. 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 two participants for the entire experiment.
   (d) __A bidder's payoff depends only on his/her own bid.
   (e) __If you are an auctioneer and your minimum selling price is higher than both bids, your payoff will be zero.

Experiment Instructions – K2$_{12}$

. . . . . .

Rules of the Auction and Payoffs

- **Bidders**: In each round,
  - if your bid is less than the minimum selling price, you don't get the object:
    Your Payoff = 0
  - if your bid is greater than or equal to the minimum selling price, and:
    - if your bid is greater than the other bid, you get the object. The price you pay depends on the minimum selling price and the other bid:
      - if the other bid is greater than or equal to the minimum selling price, you pay the other bid:
        Your Payoff = Your Value - the Other Bid;
      - if the other bid is less than the minimum selling price, you pay the minimum selling price:
        Your Payoff = Your Value - the Minimum Selling Price;
    - 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.

- **Auctioneers**: In each round, you will receive two bids from your group.
  - If both bids are less than your minimum selling price, the object is not sold, and :
    Your Payoff = 0;
  - if both bids are greater than or equal to your minimum selling price, you sell the object to the higher bidder and
    Your Payoff = the Lower Bid.
  - if one bid is greater than or equal to your minimum selling price and the other bid is less than your minimum selling price, you sell the object to the higher bidder and
    Your Payoff = the Minimum Selling Price.
- For example, if the minimum selling price is 1, bidder A bids 25, and bidder B bids 55, since $55 > 1$ and $55 > 25$, 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;
  the auctioneer's payoff = 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.
- Bidders: the exchange rate is $1 for ____________ points.
- Auctioneers: 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 the minimum selling price is 1, 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 the minimum selling price is 1, 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 the minimum selling price is 1, 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. The minimum selling price is 30 and your bid is 25, your payoff = __.

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 two participants for the entire experiment.

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

   (e) __If you are an auctioneer and your minimum selling price is higher than both bids, your payoff will be zero.

APPENDIX B. POST-EXPERIMENT SURVEY

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. What is your gender?
   - Male ____
   - Female ____
2. What is your ethnic origin?
   - White ____
   - Asian/Asian American ____
   - African American ____
   - Hispanic ____
   - Native American ____
   - Other ____
3. What is your 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. For female participants only:

- How many days away is your next menstrual cycle? ____
- Do you currently experience any symptoms of PMS? (please choose one)
  - none ____
  - mild ____
  - severe ____

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

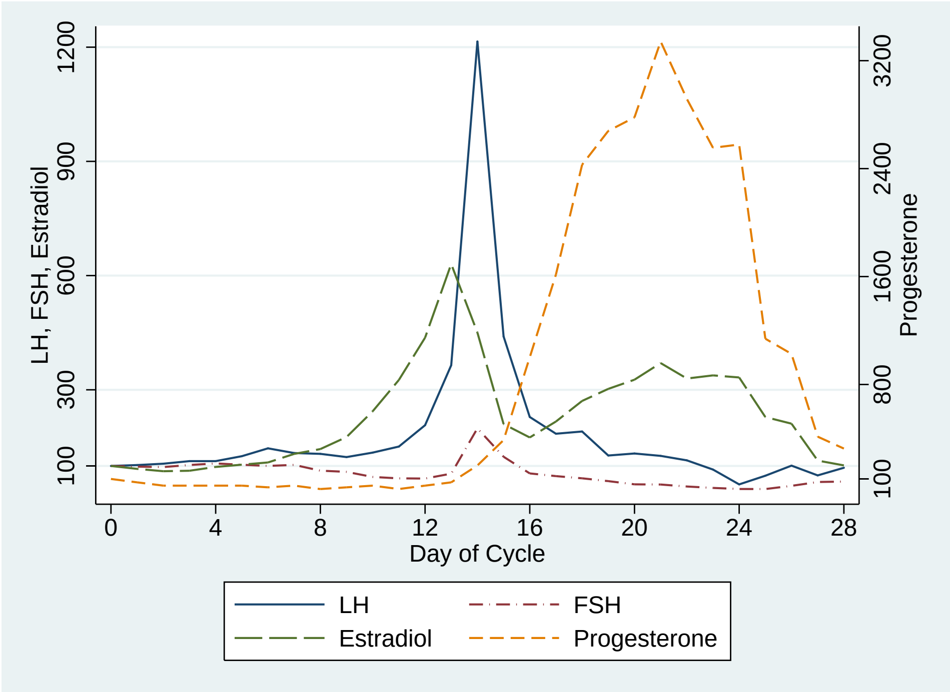
Table 2: Distribution of Holt-Laury Risk Aversion Measure by Gender (frequency of answers)

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 3: 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 Variation during the Menstrual Cycle



Note: Based on Stricker et al. (2006), median values, day 0 values normalized to 100.

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

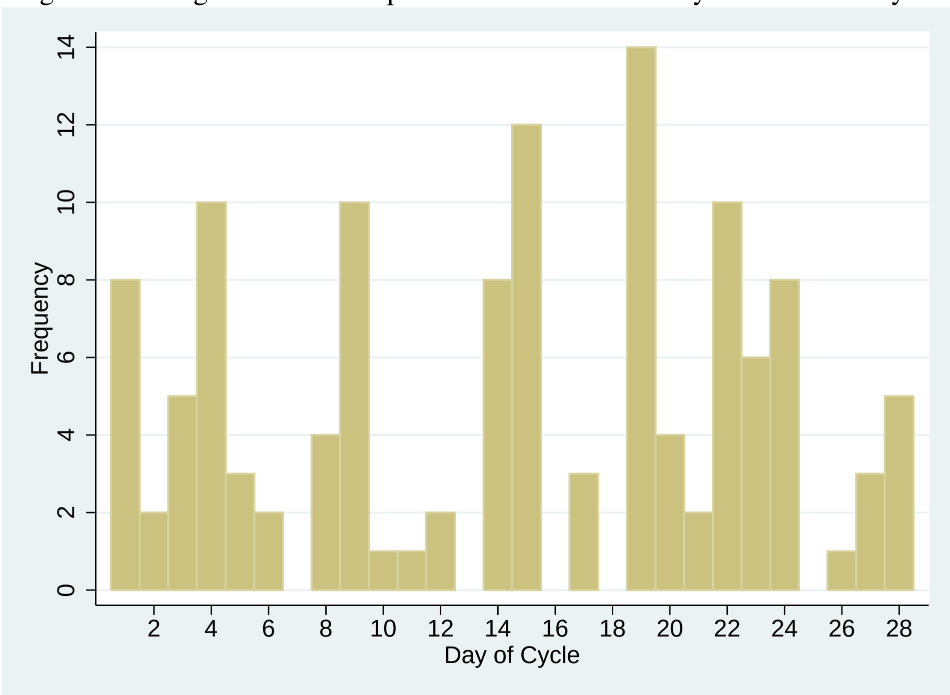
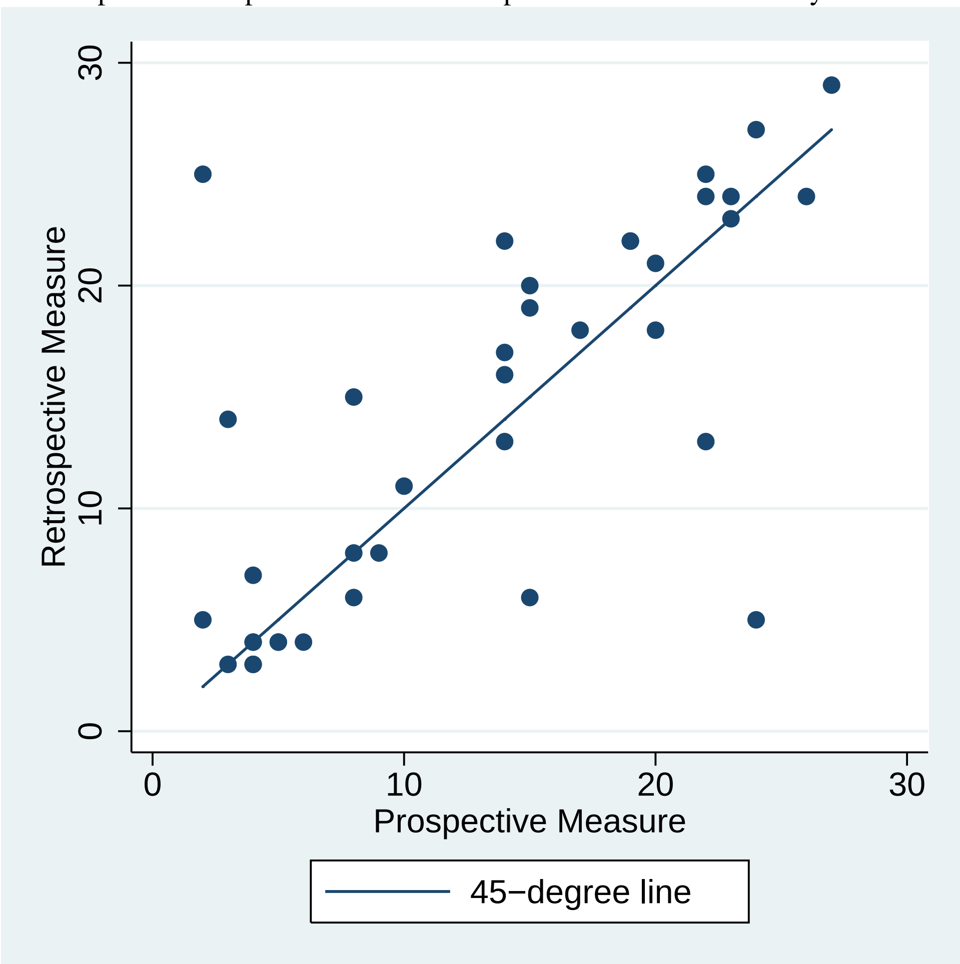


Figure 3: Cross-plot the Prospective and the Retrospective Measure of the Day of Menstrual Cycle



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 Difference in Bidding in FPA

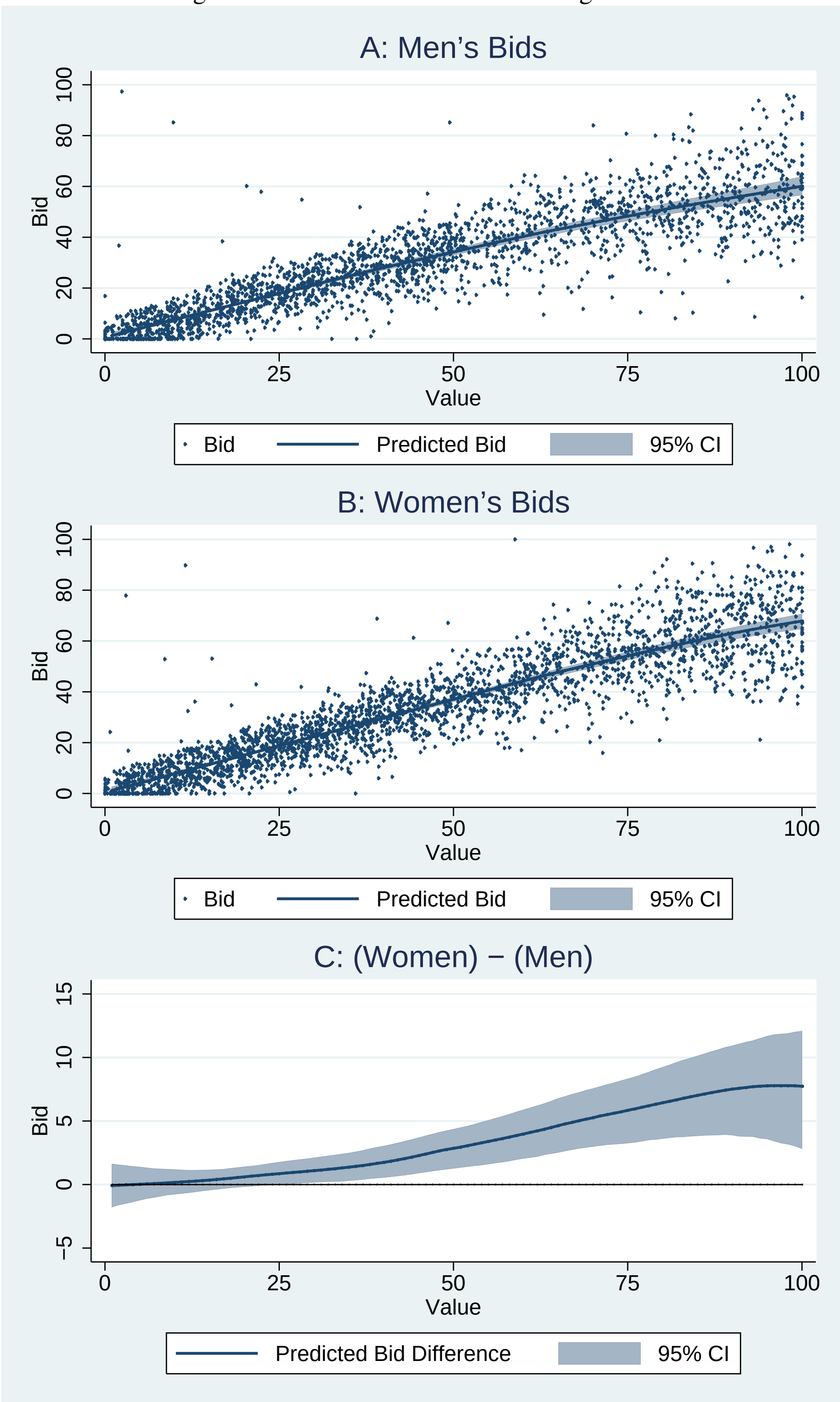


Figure 5: Gender Difference (Women - Men) in Bidding in FPA with Controls for Treatment, Demographics and Risk Aversion

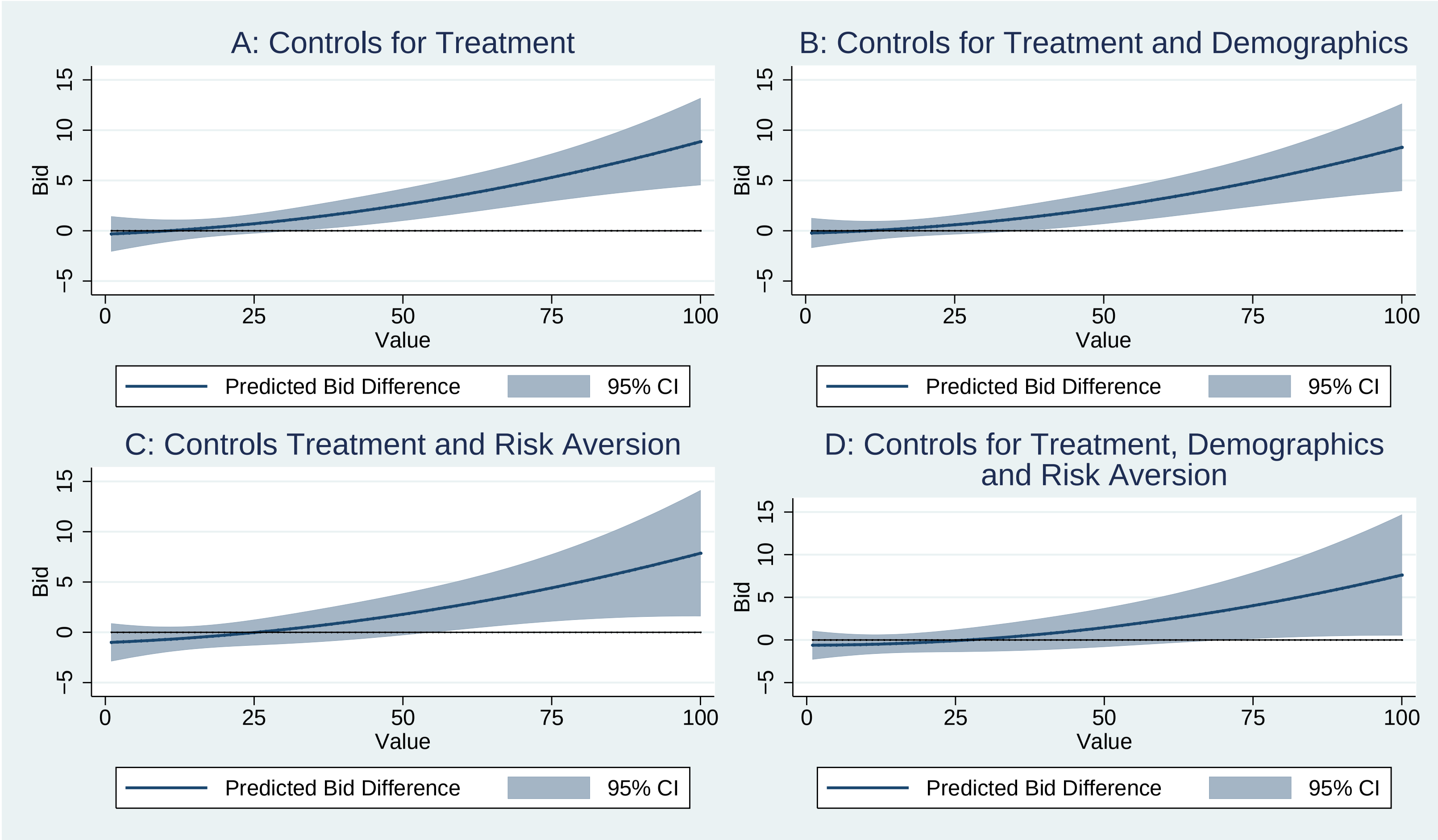


Figure 6: Gender Difference in Payoffs and Absolute Payoff Deviations in FPA

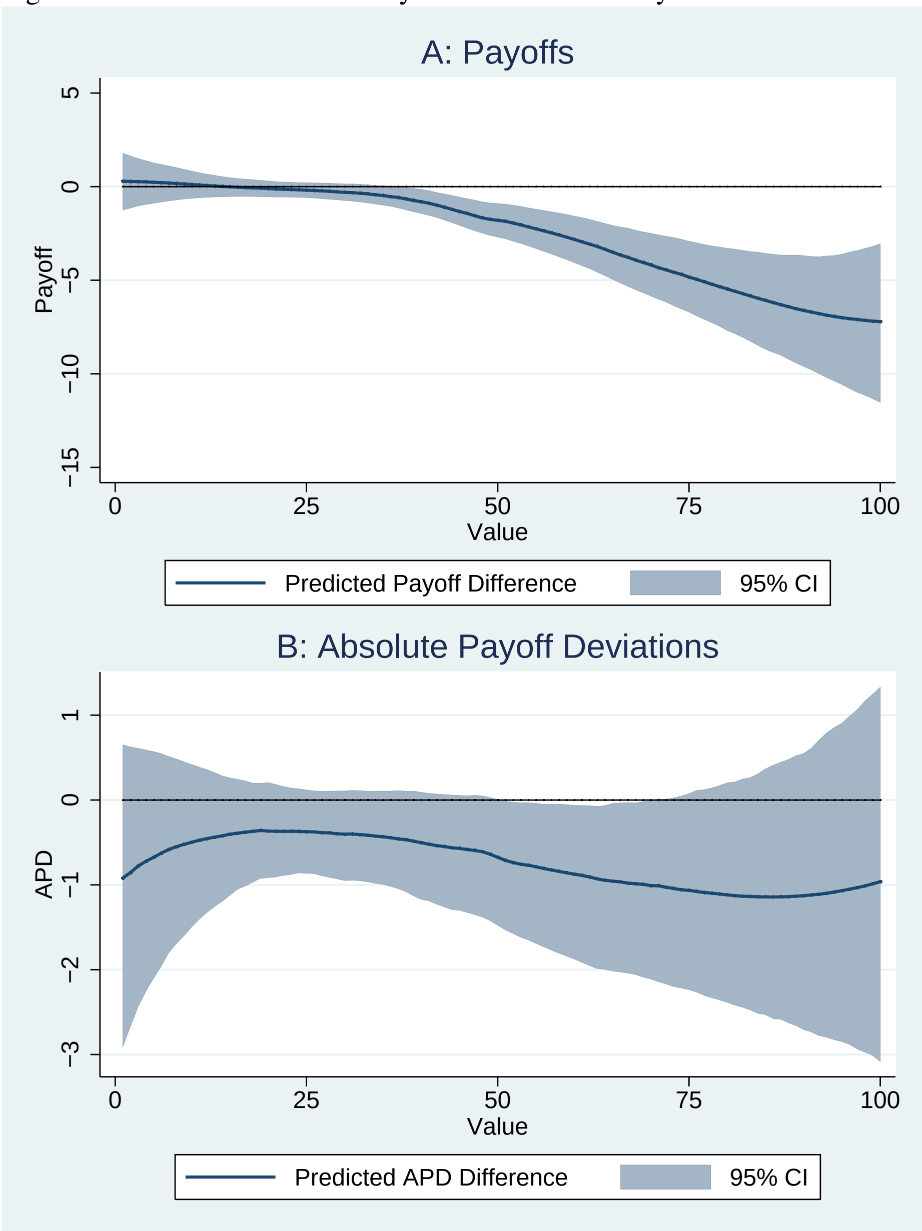


Figure 7: Gender Difference (Women - Men) in Bidding, Dominant Strategy Play and Overbidding in SPA

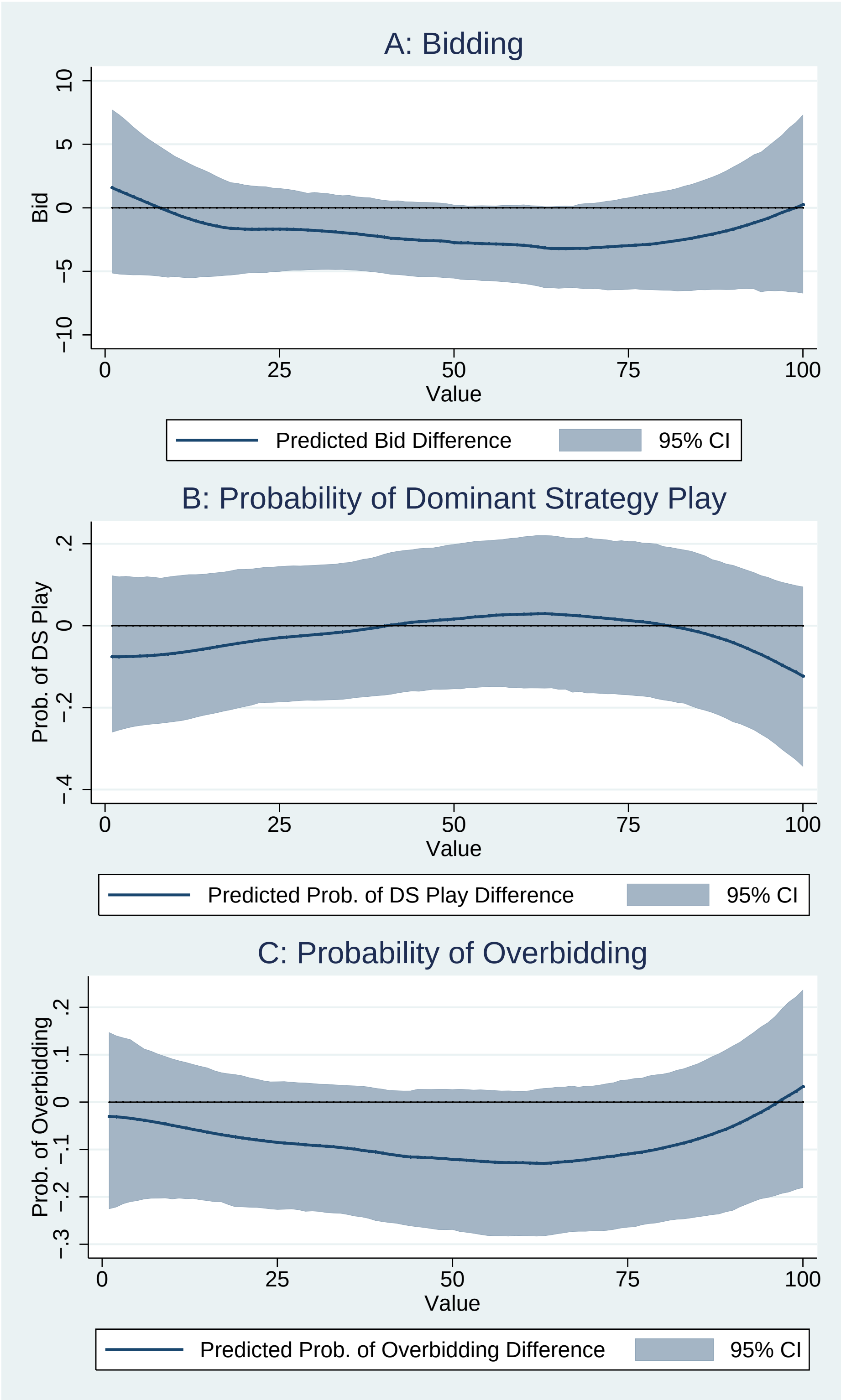
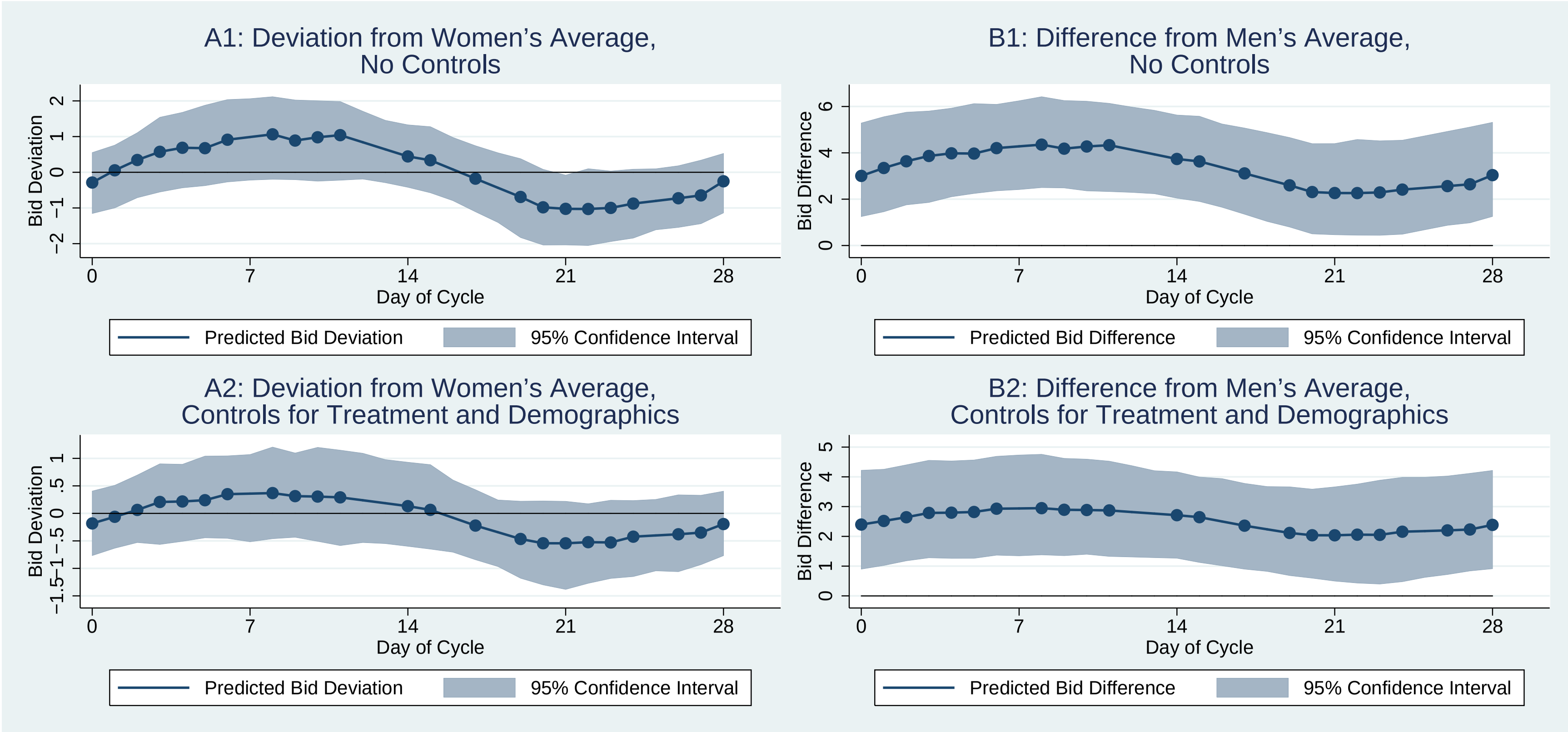
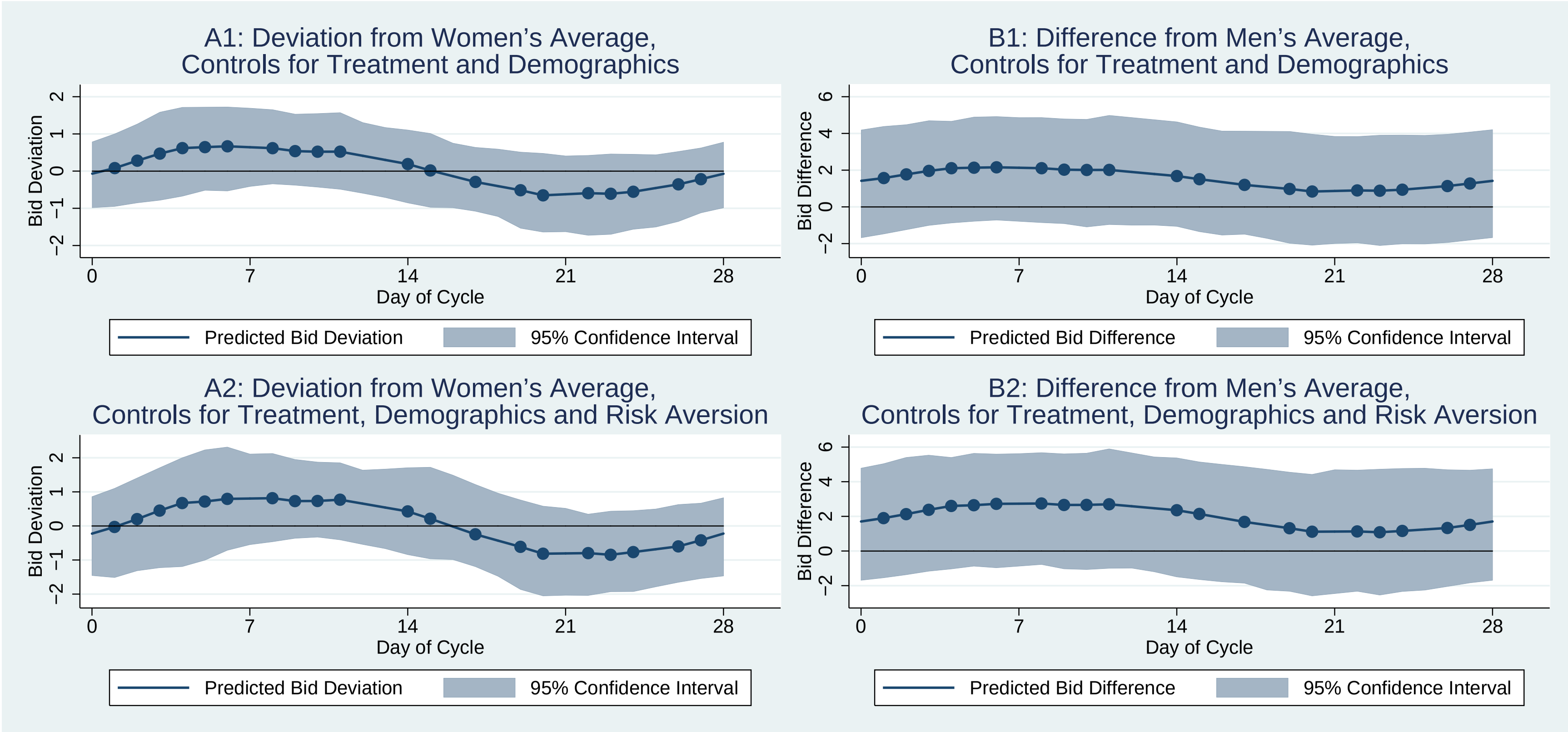


Figure 8: Effects of Menstrual Cycle on Bidding in FPA (Dataset 1 and Dataset 2 Combined)



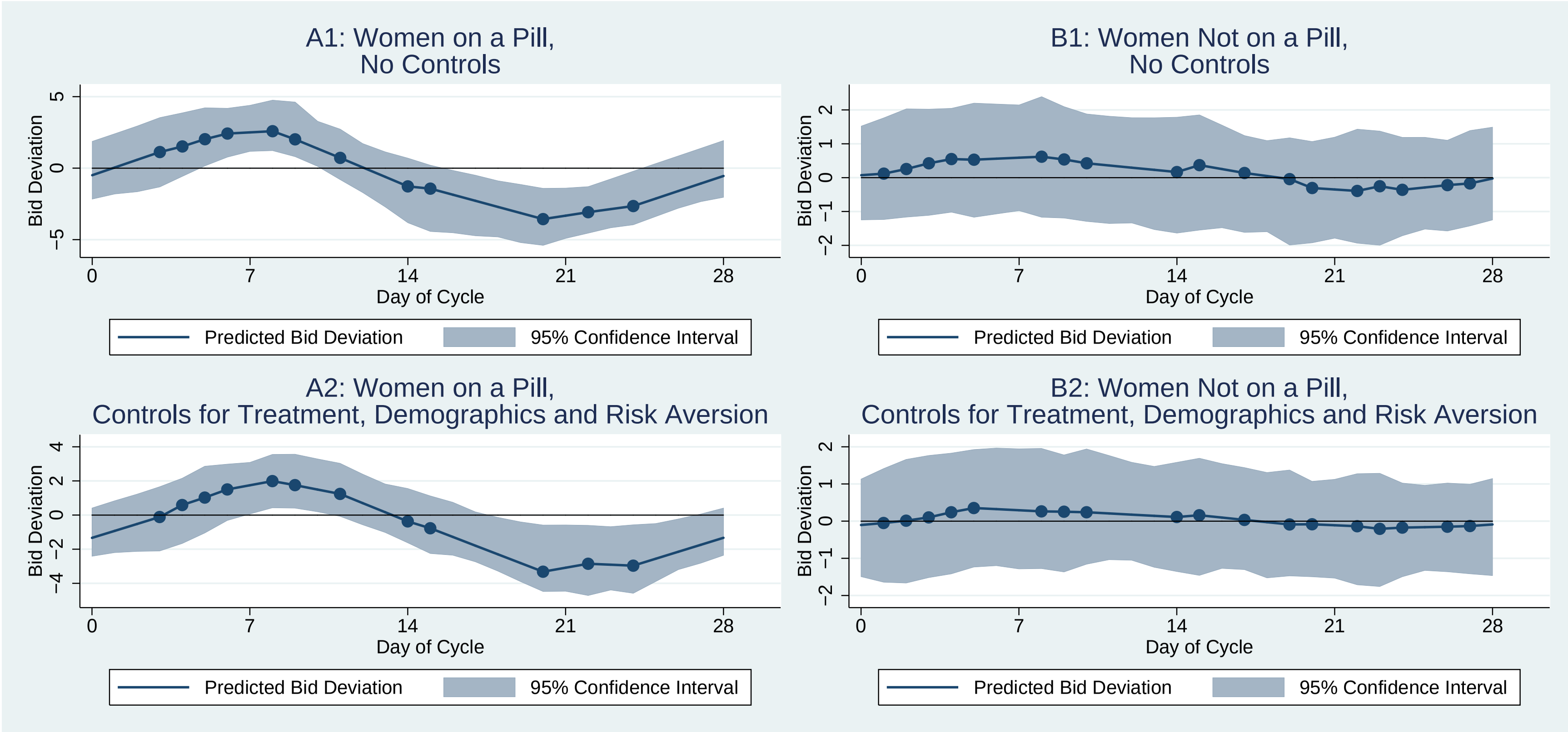
Note: The marked points on the prediction curve signify that at least one subject is available with a given day of cycle.

Figure 9: Effects of Menstrual Cycle on Bidding in FPA (Dataset 2)



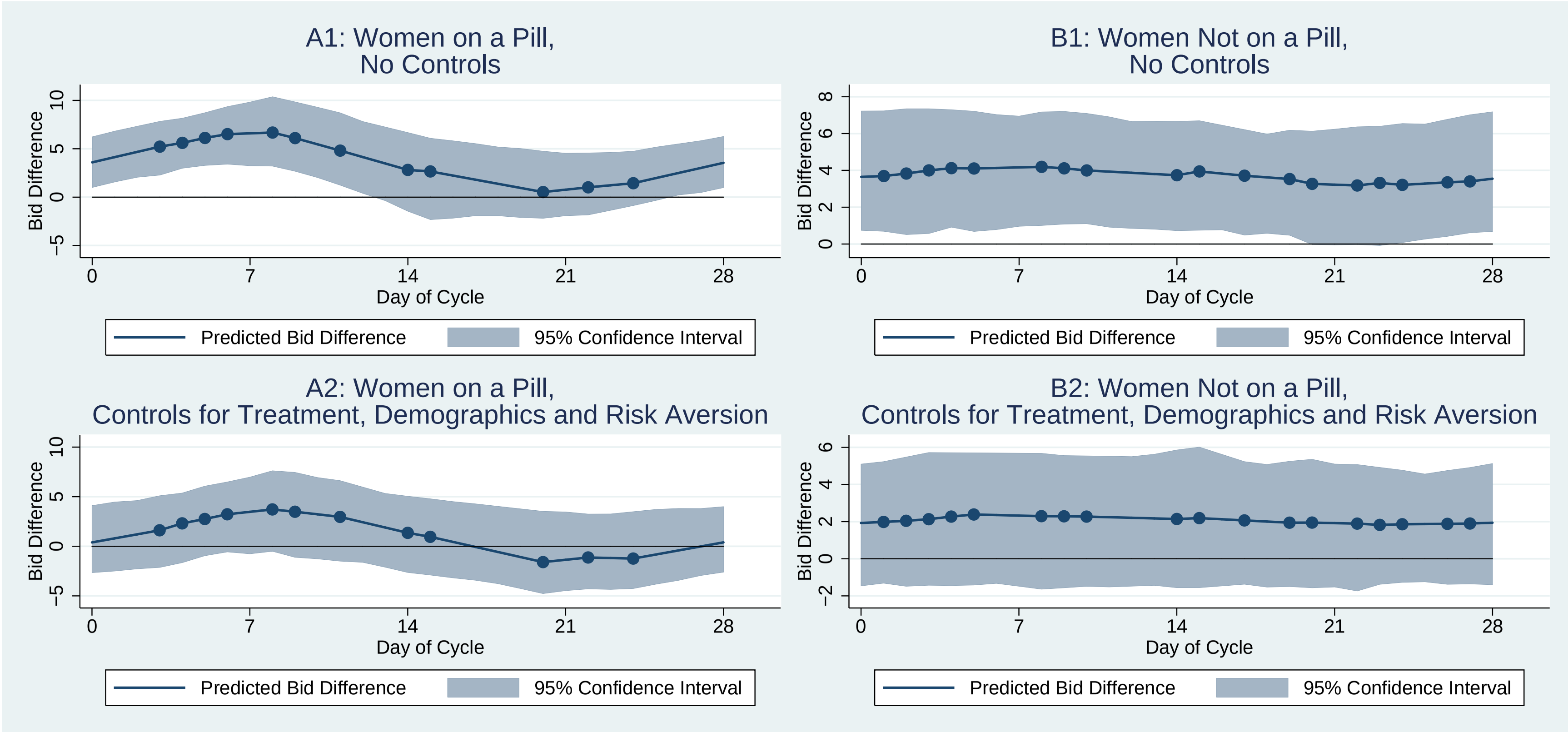
Note: The marked points on the prediction curve signify that at least one subject is available with a given day of cycle.

Figure 10: Effects of Menstrual Cycle on Bidding in FPA By Pill Usage, Deviation from Own Group Mean (Dataset 2)



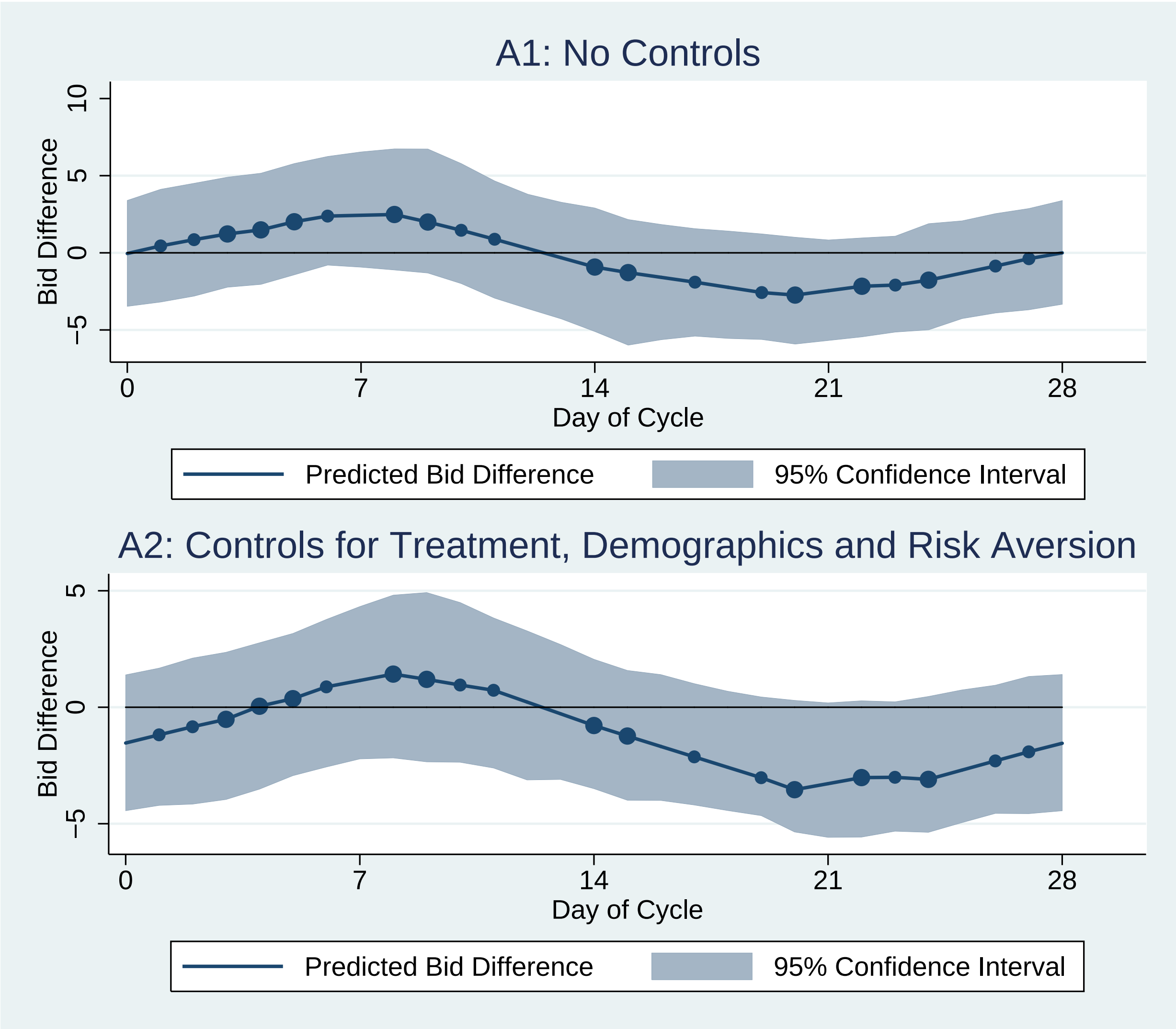
Note: The marked points on the prediction curve signify that at least one subject is available with a given day of cycle.

Figure 11: Effects of Menstrual Cycle on Bidding in FPA By Pill Usage, Difference from Mean for Men (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 12: Effect of Pill Usage (Women on a Pill - Women Not on a Pill) on Bidding in FPA (Dataset 2)



Note: The thick-marked points on the prediction curve signify that at least one subject is available with a given day of cycle in both groups. The thin-marked points on the prediction curve signify that at least one subject is available with a given day of cycle in exactly one of the two groups.