Games and Economic Behavior 77 (2013) 181–213

Contents lists available at SciVerse ScienceDirect

Games and Economic Behavior

www.elsevier.com/locate/geb

Why can't a woman bid more like a man?

Yan Chen [a,*], Peter Katuščák [b,1], Emre Ozdenoren [c,2]

[a] School of Information, University of Michigan, 105 S. State Street, Ann Arbor, MI 48109, United States
[b] CERGE-EI, Politických vězňů 7, 110 00 Praha 1, Czech Republic
[c] London Business School, Regent's Park, London, NW1 4SA, United Kingdom

ARTICLE INFO

Article history:
Received 21 May 2009
Available online 11 October 2012

JEL classification:
C91
D44
D83

Keywords:
Gender
Menstrual cycle
Contraceptive pills
Auction
Experiment

ABSTRACT

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 or earnings in the second-price auction. Focusing on the first-price auction, we find that, while the gender gap in bidding and earnings persists over the entire course of the menstrual cycle, bidding of contraceptive pill users follows a sine-like pattern throughout the menstrual cycle, with higher than average bidding in the follicular phase and lower than average bidding in the luteal phase. In comparison, pill non-users have a flat bidding profile throughout the cycle.

1. Introduction

Gender differences in decision-making have long fascinated economists, psychologists and other social scientists. In a recent survey, Croson and Gneezy (2009) 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 (Gneezy et al., 2003; Gneezy and Rustichini, 2004; Niederle and Vesterlund, 2007). 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).[3]

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

* Corresponding author. Fax: +1 734 764 1555.
E-mail addresses: yanchen@umich.edu (Y. Chen), Peter.Katuscak@cerge-ei.cz (P. Katuščák), eozdenoren@london.edu (E. Ozdenoren).
[1] 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.
[2] London Business School and CEPR.
[3] 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.

0899-8256/$ – see front matter
http://dx.doi.org/10.1016/j.geb.2012.10.002

and professional background. In contrast to this approach, we examine the effects of biological processes on behavior. In particular, the menstrual cycle has been documented to influence women's cognition (visual information processing, and memory) and mood (Richardson, 1992), suggesting that strategic decision-making may also be influenced by the menstrual cycle. This motivates us to investigate whether the menstrual cycle has an effect 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 women's 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.[4] In a pioneering study, Chawla et al. (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 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.[5]

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 bidder risk preferences, while in the SPA, bidding one's true value is a weakly dominant strategy regardless of bidder 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 or earnings in the SPA. Our second finding relates to menstrual cycle effects in the FPA. Specifically, we find that, pooling across all women, women in all phases of their cycle bid significantly higher and earn significantly less than men do. Our third finding further distinguishes the impact of the menstrual cycle between contraceptive pill users and non-users. Pill users display a sine-like bidding pattern throughout the cycle, with higher than average bids in the follicular phase and lower than average bids in the luteal phase. They bid significantly higher than men do only in the follicular phase. We obtain analogous results with a reversed sign for earnings. Pill non-users, on the other hand, have a flat bidding profile throughout the cycle. When pooling across all phases of the cycle, they bid more and earn less than men do. In addition, the results are robust to controlling for treatment differences, a set of demographic variables, a set of academic major indicators and, in relevant specifications, also a set of risk aversion indicators.

Our paper thus presents the first experimental study in economics on how the menstrual cycle affects economic decision-making and market outcomes. We provide evidence of a systematic variation in bidding behavior in the FPA among contraceptive pill users depending on the phase of the cycle. 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.[6]

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–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,

[4] 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.

[5] Herrmann and Rockoff (2012) argue, though, that this evidence is not robust to a correction of coding errors or small changes in specification, and they find no evidence of increased female absenteeism on 28-day cycles in data on school teachers.

[6] Since our 2005 working paper was posted, others have looked at correlations between menstrual cycle and women's behavior in economic environments, such as selection into tournaments (Wozniak et al., 2010; Buser, 2012a) and social preferences (Buser, 2012b).

Table 1
Features of experimental sessions.

Wave	Auction mechanism	Subjects per session	Value distribution	Exchange rate	No. of sessions	No. 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

Casari et al. (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 (in press) 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. We discuss our experimental design in Section 2. We then present our results on gender differences in bidding in Section 3, and the effects of menstrual cycle and contraceptive pill use on behavior in the FPA in Section 4. Section 5 discusses differences between our 2005 working paper and the current version. Finally, Section 6 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. Wave 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 et al. (2007).[7] Wave 2 was designed to address concerns about the lack of control for risk aversion and the usage of contraceptive pills in Wave 1, and was conducted in October 2006. In Wave 2, 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 Wave 1. Lastly, we over-recruited women in Wave 2 by admitting more women into each session than men, resulting in 64% women in Wave 2, compared to 49% in Wave 1.[8]

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 Wave 1, sessions lasted from 40 to 60 minutes, with an average per subject earning being \$13.00 in the FPA and \$19.40 in the SPA. In Wave 2, sessions usually took from 60 to 80 minutes due to the presence of the lottery, with an average per subject earning being \$12.64 from the FPA and \$10.52 from the lottery (with an average total earning of \$23.16).

2.1. Auctions

Wave 1 employs a 2×2 factorial design. In the mechanism dimension, we use the FPA and SPA, while in the information dimension we use treatments with known and unknown value distribution. Using both the FPA and SPA enables us to study gender differences in situations with varying degrees of 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 focus of Chen et al. (2007). Wave 2 focuses on the FPA with known value distribution only.

Table 1 summarizes the features of the auction experiments, including mechanisms, number of subjects per session, information conditions, exchange rates, number of sessions 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 Wave 1 and 10 in Wave 2, and a total of 240 subjects.

[7] Note that Chen et al. (2007) do not contain any description or analysis of demographic or menstrual cycle effects. They focus solely on estimations of the structural models of risk and ambiguity.

[8] Of all students who signed up for a session, we emailed twice as many women as men telling them they were admitted into the session. Before each session, we admitted the first eight students who showed up irrespective of gender.

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

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 from 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 $\{1, 2, \ldots, 100\}$, and the respective densities, f^1 and f^2, are given by:

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

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

In all sessions, we set the probability that bidder value is drawn from $F^1(\cdot)$ at 0.70. In treatments with known value 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 value distribution.

Each round of bidding consists of the following stages:

1. For treatments with unknown value distribution only, each bidder is asked to submit his or her estimate of the probability that the value of the *other* bidder in the group is drawn from the high value distribution.
2. Next, each bidder is informed of his own value. 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 the two bids coincide.
4. After each auction, each bidder receives the following feedback on his screen: his value, 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 Wave 2, 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.[9] 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 points and a 0.6 probability of getting 10 points. 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.

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

[9] We did not present the lotteries in random order. Therefore, it is possible that our presentation format suggests a cutoff strategy, which consequently generates more accessible risk preferences than there would be otherwise.

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

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.

Of the 80 subjects in Wave 2, 72 display accessible 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.[10] 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 the subsequent analysis we use a doubly-censored measure with categories 4 (including the subject with the measure equal to 1), 5, 6, 7 and 8 (including the subjects with the measure equal to 9).

2.3. Survey

At the end of the experiment, all participants complete a survey (Appendix B) to elicit demographic information, academic major information (in Wave 2), 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).[11]

For the demographic information, we elicit gender, ethnic origin, age, and number of siblings.[12] In Wave 1, 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 of courses our subjects took at the University of Michigan prior to participating in the experiment. In Wave 2, we elicit academic major information in the survey.

We group academic majors into six different categories: Mathematics and statistics, Science and engineering, Economics and business, Other social sciences, Humanities and other, and Undetermined. These categories cluster academic major types with a similar exposure to analytic and strategic reasoning.

Summary statistics on demographic variables and academic major indicators are reported separately for the FPA and SPA in Wave 1 and the FPA in Wave 2 in the upper part of Table 4. Of the 240 subjects, 129, or 54%, are women (78 in Wave 1 and 51 in Wave 2). Overall, the average age is 21.9, and subjects have 1.67 siblings on average. Regarding the ethnic background composition, 48% of subjects are white, 35% are Asian or Asian American, 8% are African American, 5% are Hispanic, and the rest identify themselves as belonging to other ethnic groups. Because of the relatively low number of non-white or non-Asian/Asian American subjects, we group all other ethnic groups into "Other ethnicity" category in the analysis. Regarding the academic majors, 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 Wave 1).

2.4. Menstrual cycle measurement

Our aim in this subsection is to construct a measure of where a female subject is in her menstrual cycle. 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. As noted by Sommer (1992), however, day count could be used as a legitimate indicator of hormone levels if the sample size is large.

Before going to the individual measures, it is useful to review some stylized knowledge about a "typical" menstrual cycle that lasts 28 days. Fig. 1 presents the variation in hormonal levels over the course of the cycle of naturally cycling

[10] Of these eight subjects, five are female.

[11] The primary objective of eliciting this information was to study ambiguity attitude in our companion paper (Chen et al., 2007). The emotion variables are not correlated with the menstrual phases (see analysis reported on the first author's website, http://yanchen.people.si.umich.edu/).

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

Table 4
Summary statistics for demographics, academic majors and menstrual phases.

Variable	First-price auction (Wave 1)					Second-price auction (Wave 1)					First-price auction (Wave 2)				
	Obs.	Mean	S.d.	Min	Max	Obs.	Mean	S.d.	Min	Max	Obs.	Mean	S.d.	Min	Max
Demographics:															
Female	80	0.48	0.50	0	1	80	0.50	0.50	0	1	80	0.64	0.48	0	1
Age	80	21.21	2.89	18	36	80	22.00	4.19	18	41	80	22.51	3.49	18	31
Number of siblings	80	1.46	1.01	0	6	80	1.91	1.45	0	9	80	1.64	1.20	0	5
White	80	0.50	0.50	0	1	80	0.46	0.50	0	1	80	0.47	0.50	0	1
Asian	80	0.39	0.49	0	1	80	0.40	0.49	0	1	80	0.27	0.44	0	1
African	80	0.05	0.22	0	1	80	0.08	0.27	0	1	80	0.11	0.31	0	1
Hispanic	80	0.03	0.16	0	1	80	0.04	0.19	0	1	80	0.08	0.25	0	1
Other ethnicity	80	0.04	0.19	0	1	80	0.03	0.16	0	1	80	0.08	0.27	0	1
Academic major:															
Mathematics or statistics	80	0.04	0.19	0	1	80	0.00	0.00	0	0	80	0.05	0.22	0	1
Science or engineering	80	0.35	0.48	0	1	80	0.19	0.39	0	1	80	0.39	0.49	0	1
Economics or business	80	0.08	0.27	0	1	80	0.18	0.38	0	1	80	0.10	0.30	0	1
Other social sciences	80	0.05	0.22	0	1	80	0.04	0.19	0	1	80	0.18	0.38	0	1
Humanities or other	80	0.14	0.35	0	1	80	0.15	0.36	0	1	80	0.29	0.46	0	1
Undetermined major	80	0.35	0.48	0	1	80	0.45	0.50	0	1	80	0.00	0.00	0	0
Menstrual cycle:															
m_1	37	16.57	8.44	1	28	36	13.47	8.03	1	28	51	13.27	8.01	1	27
Menstrual phase	37	0.16	0.37	0	1	36	0.25	0.44	0	1	51	0.27	0.45	0	1
Follicular phase	37	0.14	0.35	0	1	36	0.17	0.38	0	1	51	0.18	0.39	0	1
Peri-ovulatory phase	37	0.14	0.35	0	1	36	0.17	0.38	0	1	51	0.16	0.37	0	1
Luteal phase	37	0.35	0.48	0	1	36	0.33	0.48	0	1	51	0.29	0.46	0	1
Pre-menstrual phase	37	0.22	0.42	0	1	36	0.08	0.28	0	1	51	0.10	0.30	0	1

Notes:

1. Summary statistics for menstrual phase variables are reported for women only.
2. Of the 38/40/51 women in FPA in Wave 1/SPA in Wave 1/FPA in Wave 2, menstrual cycle information is available for 37/36/51, respectively.

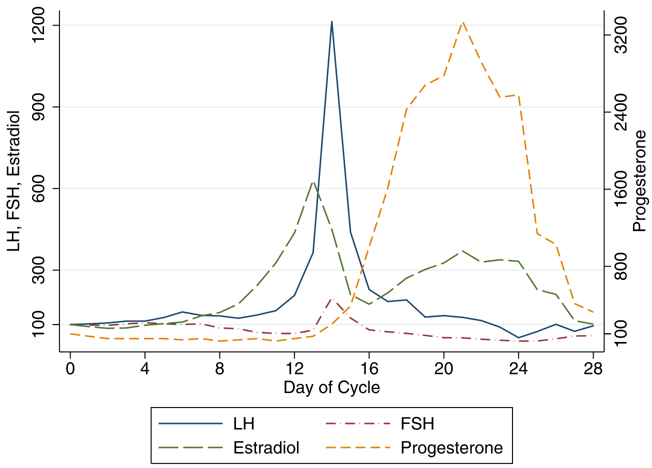

Fig. 1. Hormonal variation during the menstrual cycle.
Note: LH stands for luteinizing hormone and FSH for follicle-stimulating hormone. The plot is based on median values reported in Stricker et al. (2006), with day 0 values normalized to 100.

women, i.e., women who do not use hormonal contraceptives, which we refer to as the "pill" regardless of its application method. 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), 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 luteinizing hormone. Women during this phase have large amounts of circulating estradiol and very little progesterone. During the *peri-ovulatory phase* (days 14–15), luteinizing hormone reaches its peak at mid-cycle, which causes the mature follicle to release the ovum through the wall of the ovary. 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.

Hormonal variation over the menstrual cycle of pill users is different. The application of the pill modifies the natural hormonal profile over the cycle in order to prevent conception. The resulting hormonal profile depends on the particular chemical structure of the given pill. While combination pills contain both estrogen and progestin, some are progestin-only pills. As most pills contain active ingredients for 21 days, and inactive ingredients for 7 days, one can view the pill cycle as having two phases, a high and a low progestin phase. Because of the different hormonal profiles of pill users and non-users, we will estimate the profile of bidding and payoffs over the course of the menstrual cycle separately for the two groups of female subjects in later portion of Section 4.

Our menstrual cycle information comes from answers to Question 8 in the survey. In Wave 1, 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 label this variable x. We ask the same question in the Wave 2, 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 (z). 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 Wave 2. We ask female subjects about contraceptive pill usage, the average duration of their cycle (d), the average number of cycles per year (c), the average duration of menstruation (l) 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 (y). We also elicit the presence of the pre-menstrual syndrome (PMS) in both waves of the data. Since the PMS variable is not statistically significant in any of our results, we exclude it from the analysis presented here.

In Wave 1, the measure of the day of the menstrual cycle we use in our analysis, denoted by m_1, is computed as $m_{1i} = 29 - x_i$, whenever x_i is available, where i indexes female subject i.[13] Because this measure is based on estimating the beginning of the next cycle, m_1 is a *prospective* measure, which assumes a 28-day duration of the cycle. To constrain m_{1i} between 1 and 28 in Wave 1, we reset it to missing for one subject who reports $x_i = 60$, to 28 for four subjects who report $x_i = 0$, and to 1 for five subjects who report $x_i = 30$. These adjustments provide menstrual cycle data for 73 out of 78 female subjects in Wave 1.

In Wave 2, we first pay attention to whether a subject is currently menstruating. If yes (12 subjects), we set $m_{1i} = z_i$ (available for all 12 subjects and satisfying $z_i \leqslant l_i$ for all 12 of them). If not (39 subjects), we set, as in Wave 1, $m_{1i} = 29 - x_i$.[14] In the latter group, x_i is available for 36 subjects, and hence we obtain m_{1i} for 48 out of 51 subjects in Wave 2. For the remaining three subjects we impute m_{1i} to be equal to y_i. We use these three observations in our subsequent analysis, but do not use them later in this section when comparing various measures and discussing the measurement error. Hence, in Wave 2, m_{1i} is available for all 51 female subjects. In all 51 cases, m_{1i} is between 1 and 28. Altogether, m_{1i} is available for 124 out of 129 female subjects across both waves. It is the most widely available measure of the menstrual cycle in our data since it is the only one available in Wave 1. For this reason, we use m_1 to categorize female subjects into the five phases of the menstrual cycle as outlined above. Summary statistics for m_1 and for the indicator variables for the individual phases are presented in the bottom part of Table 4. Also, Panels A–C of Fig. 2 plot histograms of m_1 for our female subjects separately for the FPA in Wave 1 (Panel A), SPA in Wave 1 (Panel B) and FPA in Wave 2 (Panel C), respectively.[15]

As for the other menstrual cycle variables elicited in Wave 2, the pill usage data is available for all 51 female subjects. The cycle duration d_i is available for 50 subjects and it 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 cycle duration 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 $d_i = 28$, 2 report $d_i = 29$, 1 reports

[13] That is, if a female subject reports being one day away from the first day of the next menstrual period, 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.

[14] Of the 12 subjects who report to be currently menstruating, there is one who also reports $z_i = 4$, $x_i = 14$ and $d_i = 32$, which are mutually incompatible. We assume that being currently menstruating and the associated measure of $z_i = 4$ provides a more reliable information, and we hence set $m_{1i} = 4$.

[15] Looking at Fig. 2, one may wonder whether the distribution of m_1 differs systematically across Panels A through C. For example, there is a relatively large fraction of women with $m_{1i} = 1$ in Wave 1 (Panels A and B), whereas this fraction is much lower in Wave 2 (Panel C). This could be related to the fact that the construction of m_1 in Wave 2 is based on an additional question about women currently menstruating, whereas we do not use this question in Wave 1. As a result, it may be easy for currently menstruating women in Wave 1 to answer that they are 28 days away from the beginning of the next menstrual cycle, whereas such an option is not available in Wave 2. We thank an anonymous referee for pointing out this possibility. While we cannot rule out this possibility, we conduct pairwise Kolmogorov–Smirnov tests to check for differences between empirical distributions of m_1 in FPA in Wave 1, SPA in Wave 1, and FPA in Wave 2. In none of the three tests can we reject the null hypothesis of no difference. Since part of the analysis is based on phases of the cycle defined by m_1, we also run pairwise joint F-tests of fractions of women in the five phases of the cycle (see Table 4) being the same in the three conditions. Again, in none of the three tests can we reject the null hypothesis of no difference. Based on these tests we conclude that even though a modified way of eliciting the prospective measure of the menstrual cycle in Wave 2 as compared to Wave 1 may affect some realizations of m_1, the incidence of this problem is relatively minor.

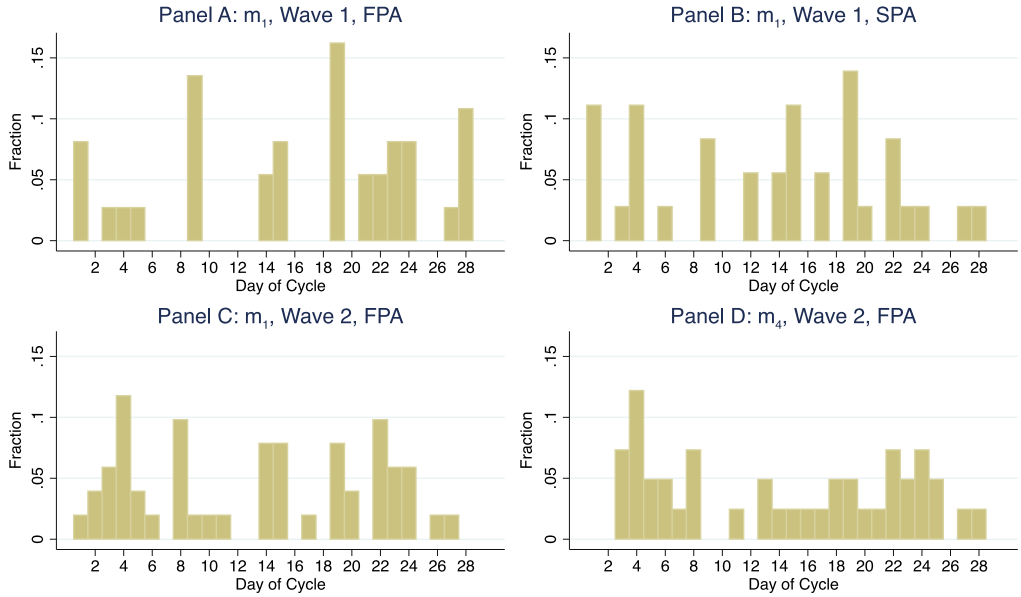

Fig. 2. Histograms of the prospective measure m_1 (by wave and auction type) and retrospective measure m_4.

$d_i = 32$, 2 report a duration of "less than 25," and one does not report anything.[16] The number of cycles per year c_i is available for all 51 female subjects, of whom 8 report having 11 cycles per year, 39 report having 12 cycles per year and 4 report having 13 cycles per year. The reported values of d_i and c_i are consistent to the extent that the empirical distribution of d_i for $c_i = 11$ first-order stochastically dominates the distribution of d_i for $c_i = 12$, which in turn first-order stochastically dominates the distribution of d_i for $c_i = 13$. The duration of menstruation l_i is available for 50 out of 51 subjects and it ranges from 3 to 8 days, with a mean of 5.16, median of 5 and standard deviation of 1.25. Days from the start of the cycle y_i is available for 47 out of 51 female subjects and it varies from -11 (a subject reporting the start of the last cycle after the day of the experiment) to 38.

The prospective measure (m_1) may suffer from at least two sources of measurement error. First, especially for women who do not use the pill, the average cycle duration may differ from 28 days and the duration of the individual cycle phases may vary accordingly as well.[17] Second, 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. To evaluate the extent to which m_1 is affected by such measurement errors and the extent to which our results based on m_1 are robust, we develop a series of alternative measures of the menstrual cycle, all of which are available only in Wave 2, however.

The severity of the first problem can be evaluated by following a slightly adjusted procedure for the computation of the prospective measure. We denote such adjusted normalized prospective measure m_2. As an intermediate step, we compute a natural (non-normalized) measure M. As before, if a female subject reports to be currently menstruating, we set $M_i = z_i$. Unlike before, for women who are not currently menstruating, we set $M_i = d_i + 1 - x_i$ (instead of $28 + 1 - x_i$). As before, we impute M_i by y_i for the three subjects who are not currently menstruating and for whom x_i is missing. M is available for 47 out of 51 subjects. For the remaining 4 subjects (none of them in the menstrual phase), d_i is unavailable or it is reported as "less than 25 days." Having constructed M, we then consider the length of the individual phases of the cycle. We set the length of the menstrual phase to be equal to the self-reported value of l_i (instead of 5), implying that the other four phases last altogether $d_i - l_i$ days (instead of 23 days). For one subject for whom l_i is missing, we assume that $l_i = 5$ (the median and close to the mean in our sample). We then normalize M to the standard 28-day cycle by mapping the days 1 to l_i of the natural cycle linearly to days 1 though 5 of the normalized cycle and days $l_i + 1$ to d_i of the natural cycle linearly to days 6 through 28 of the normalized cycle. Hence

$$m_{2i} = \begin{cases} round[5 \times (M_i/l_i)] & \text{if } M_i \leqslant l_i, \\ round[5 + 23 \times (M_i - l_i)/(d_i - l_i)] & \text{if } M_i > l_i. \end{cases} \tag{1}$$

The measure m_2 is, like M, available for 47 out of 51 subjects.

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

[17] In addition, the realized length of cycle may vary from cycle to cycle. We do not have sufficient information in our data to address issues stemming from this variation.

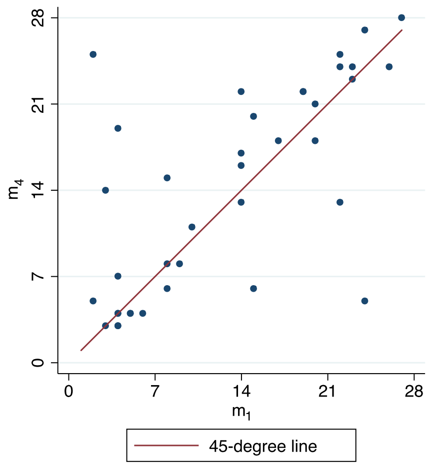

Fig. 3. Cross-plot of the prospective measure m_1 and the retrospective measure m_4. *Note:* Points $(4, 3)$, $(4, 4)$, $(5, 4)$ and $(19, 22)$ represent two observations. The remaining 30 points represent one observation each.

The normalization implicit in (1) assumes that the duration of follicular, peri-ovulatory, luteal and pre-menstrual phase of the cycle is each scaled proportionately to $d_i - l_i$. In a related study, Pearson and Schipper (in press) refer to an adjustment procedure parallel to this one as "uniform adjustment" (except that they do not additionally adjust for a variable length of the menstrual phase). However, based on the observation of Hampson and Young (2008) that "most of the variation in cycle length from woman to woman is attributable to differences in the length of the follicular phase," Pearson and Schipper (in press) also use what they label as "follicular adjustment" of the menstrual cycle measure. In this method, any difference of the length of the cycle from 28 days is attributed to the difference of the length of the follicular phase from its usual length in the 28-day cycle, whereas the other four phases of the cycle are assumed to have the same length as in the standard 28-day cycle. Adopting this idea to our setting, we modify this procedure to also allow for variable length of the menstrual phase. As we standardize the peri-ovulatory phase to 2 days, the luteal phase 8 days and the pre-menstrual phase 5 days, this procedure assumes that the menstrual phase lasts from day 1 to day l_i, the follicular phase from day $l_i + 1$ to day $d_i - 15$, the peri-ovulatory phase from day $d_i - 14$ to day $d_i - 13$, the luteal phase from day $d_i - 12$ to day $d_i - 5$ and the pre-menstrual phase from day $d_i - 4$ to day d_i. Based on this cycle breakdown, we construct a follicular-adjusted prospective measure m_3. In particular, starting from M as constructed above, we normalize it to the standard 28-day cycle by mapping the days 1 to l_i of the natural cycle linearly to days 1 though 5 of the normalized cycle, days $l_i + 1$ to $d_i - 15$ of the natural cycle linearly to days 6 through 13 of the normalized cycle and days $d_i - 14$ to d_i of the natural cycle linearly to days 14 through 28 of the normalized cycle. Hence

$$m_{3i} = \begin{cases} round[5 \times (M_i/l_i)] & \text{if } M_i \leqslant l_i, \\ round[5 + 8 \times (M_i - l_i)/(d_i - 15 - l_i)] & \text{if } M_i > l_i \text{ and } M_i \leqslant d_i - 15, \\ M_i + (28 - d_i) & \text{if } M_i > d_i - 15. \end{cases} \tag{2}$$

Like m_2, m_3 is available for 47 out of 51 subjects.

The severity of the second problem can be evaluated by constructing a *retrospective* measure m_4 defined by $m_{4i} = y_i$. This measure is available for 41 out of 51 female subjects, as y_i is missing for 4 subjects and negative for 1 subject while $y_i > d_i$ for 5 subjects. To constrain m_4 to the range 1 to 28, for one subject for whom $y_i = 29$ (and $d_i = 31$), we set $m_{4i} = 28$. Panel D of Fig. 2 plots the histogram of this measure.

Similar to m_2 and m_3, we construct retrospective measures that adjust for cross-sectional variation in the length of the menstrual phase and the entire cycle. The starting point is a variable M defined by $M_i = y_i$ for all female subjects for whom y_i is not missing, negative, or larger than d_i. This measure is identical to m_4, except for one subject whose $y_i = 29$, for whom we set $m_{4i} = 28$ and $M_i = 29$. In parallel to m_2, we then define the "uniformly adjusted" measure m_5 by the right-hand side of (1). Likewise, in parallel to m_3, we define the "follicular-adjusted" measure m_6 by the right-hand side of (2). Both of these measures are available for 40 out of 51 female subjects. Compared to the availability of M, one subject is lost due to not currently menstruating and having a cycle duration of "less than 25 days."

Table 5 presents the correlation matrix of the six measures. These correlations are computed using subjects for which the individual measures are available, excluding from the prospective measures m_1, m_2 and m_3 the three subjects for whom these measures are imputed based on y_i. The results indicate that the three prospective measures, m_1, m_2 and m_3, are highly correlated among themselves, with correlation coefficients above 0.99, whereas the three retrospective measures, m_4, m_5 and m_6, exhibit similarly high pairwise correlations, with correlation coefficients above 0.975. On the other hand, the correlations across these two blocks of measures are much lower, approximately 0.7. Hence adjustment of the measures for different length of the menstrual phase and the overall cycle, whether uniform or follicular, matters relatively little in

Table 5
Correlations among the six measures of the day of menstrual cycle.

	m_1	m_2	m_3	m_4	m_5	m_6
m_1	1 (48)					
m_2	0.992 (44)	1 (44)				
m_3	0.996 (44)	0.996 (44)	1 (44)			
m_4	0.690 (38)	0.687 (36)	0.683 (36)	1 (41)		
m_5	0.706 (37)	0.699 (35)	0.701 (35)	0.991 (40)	1 (40)	
m_6	0.702 (37)	0.682 (35)	0.693 (35)	0.979 (40)	0.994 (40)	1 (40)

Note: Number of subjects from whom pairwise correlations are computed is reported in parentheses.

comparison to whether one uses a prospective or a retrospective measure. To illustrate differences between the two sets of measures, Fig. 3 presents a cross-plot of m_1 and m_4.

Which of these six measures is the best one? In order to shed light on this question, within each pair of measures we obtain an indicator of which one is less noisy. In particular, 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 $Var(\varepsilon_1) \gtreqless Var(\varepsilon_2)$. Based on such comparisons, we find that m_1 is the least noisy measure, followed by m_6, m_5, m_4, m_3 and m_2, respectively.

Based on these comparisons, and also because m_1 is the only measure that is available in Wave 1, we will use m_1 as the baseline measure of the day of menstrual cycle in our analysis in Section 4. However, Section 4.2 will examine the robustness of the results based on this baseline measure to use of the other measures.

3. Gender differences in bidding and payoffs

In this section, we present the results on gender differences (females minus males) in competitive bidding and payoffs. We begin with the FPA. Table 6 presents results from a set of OLS regressions with bid (Panel A) and payoff (Panel B) being the two outcome variables. Apart from the displayed variables, in all specifications we additionally control for a cubic polynomial in value and also a set of indicators for periods 2 to 30 (period 1 being the omitted category) to account for potential effects of learning. In all cases, standard errors are adjusted for clustering at the session level. In specifications (1a) and (1b), which use both waves of the data, we only include the female indicator on the right-hand side. The estimated gender difference in bidding is 2.811, significant at the 1% level. While higher bids do not necessarily reduce the average payoff as they increase the probability of winning, they do reduce the average payoff if the proportional loss in payoff conditional on winning is larger than the proportional gain in the probability of winning. Indeed, the estimated gender difference in payoffs is −1.998, also significant at the 1% level.

Specifications (1a) and (1b) ignore that bidding may differ across subjects for reasons other than gender (and value and period). To the extent that these omitted variables may be correlated with gender, the estimated gender differences may potentially be biased. To address such a possibility, in specifications (2a)–(5a) and (2b)–(5b), we control for a set of other variables. In specifications (2a) and (2b), which use data from both waves, we additionally control for treatment details by including indicators for the treatment with an unknown value distribution, for Wave 2 data, and for the lottery stage before the auction in Wave 2. The treatment with the known value distribution in Wave 1 is the omitted category. The estimated gender difference in bidding or payoffs is hardly affected compared to the first pair of specifications. In specifications (3a) and (3b), we additionally control for a set of demographic variables including age, the number of siblings, Asian/Asian American indicator, Other ethnicity indicator (with white being the excluded category), Mathematics or statistics major, Science or engineering major, Others social science major, Humanities or other major and Undetermined major (only present in Wave 1; Economics or business major is the excluded category). The estimated gender differences in bidding and payoffs are still statistically highly significant, although the gender difference in bidding is about 8% smaller in comparison to specification (1a).

One potential explanation for the gender gap in bidding is a gender difference in risk aversion (Croson and Gneezy, 2009). In a symmetric Bayesian Nash equilibrium with known (Riley and Samuelson, 1981) or unknown distribution of values (Chen et al., 2007), higher risk aversion increases bids in the FPA. We can assess this explanation by using the Holt and Laury measure of risk aversion reported in Table 3, available only in Wave 2 of our data. We first check whether, as shown in previous research (Croson and Gneezy, 2009), women are more risk averse than men. A simple comparison of means shows that even though women are somewhat more risk averse than men (6.27 vs. 6 on average), the difference is not statistically significant. However, when we control for the same variables as in specifications (3a) and (3b) (lottery

Table 6
Gender difference in bidding and payoffs in FPA.

Dependent variable	Panel A: Bid					Panel B: Payoff				
Subsample	(1a) Waves 1&2	(2a) Waves 1&2	(3a) Waves 1&2	(4a) Wave 2	(5a) Wave 2	(1b) Waves 1&2	(2b) Waves 1&2	(3b) Waves 1&2	(4b) Wave 2	(5b) Wave 2
Female	2.811***	2.712***	2.610***	1.627*	1.743	−1.998***	−1.932***	−1.941***	−1.050**	−1.115*
	(0.637)	(0.604)	(0.580)	(0.860)	(1.060)	(0.387)	(0.364)	(0.352)	(0.402)	(0.600)
Unknown value distr.		−1.555	−1.284				0.910	0.559		
		(1.123)	(0.993)				(0.863)	(0.798)		
Wave 2		1.644	2.172**				−1.149	−1.569**		
		(1.002)	(0.971)				(0.729)	(0.609)		
Lottery before auction		−4.309***	−4.076***	−4.213***	−4.618***		2.847***	2.762***	2.796***	2.934***
		(1.159)	(1.254)	(1.140)	(1.162)		(0.729)	(0.766)	(0.674)	(0.752)
Age			−0.012	−0.105	−0.072			0.002	0.101	0.082
			(0.123)	(0.169)	(0.148)			(0.070)	(0.090)	(0.080)
Number of siblings			−0.485*	−0.139	−0.186			0.141	0.027	0.035
			(0.238)	(0.334)	(0.310)			(0.115)	(0.169)	(0.190)
Asian/Asian American			−0.993	−0.421	−0.472			0.030	−0.205	−0.177
			(0.802)	(1.207)	(1.221)			(0.420)	(0.742)	(0.749)
Other ethnicity			0.119	−0.434	−0.705			−0.625	−0.370	−0.214
			(0.782)	(0.914)	(1.043)			(0.500)	(0.617)	(0.585)
Mathematics or statistics			1.854*	2.799**	1.978			−0.428	−1.596	−1.182
			(0.993)	(1.222)	(1.831)			(0.941)	(0.971)	(1.407)
Science or engineering			0.026	1.125	0.767			0.250	−1.023	−0.802
			(0.907)	(1.097)	(1.060)			(0.682)	(0.666)	(0.773)
Other social sciences			−0.577	0.204	−0.441			−0.086	−0.889	−0.512
			(1.589)	(1.623)	(1.364)			(0.830)	(0.876)	(0.895)
Humanities or other			1.495	1.611	0.773			−0.377	−1.170	−0.705
			(1.071)	(1.131)	(1.021)			(0.820)	(0.933)	(0.775)
Undetermined major			2.010					−1.204		
			(1.652)					(1.169)		
Risk aversion controls	N/A	N/A	N/A	No	Yes	N/A	N/A	N/A	No	Yes
Observations	4800	4800	4800	2400	2400	4800	4800	4800	2400	2400
R^2	0.83	0.84	0.84	0.86	0.86	0.50	0.51	0.51	0.50	0.50

Notes:

1. Estimated by OLS. Clustered standard errors (at session level) in parentheses. Significant at: * 10% level; ** 5% level; *** 1% level.
2. A cubic polynomial in value and period indicator variables are controlled for in each specification.

before the auction indicator, age, number of siblings and the set of ethnic and academic major indicators), the difference between women and men grows from 0.27 to 0.49, with a p-value of 0.062. As a result, after accounting for observable heterogeneity, the gender difference in risk aversion becomes marginally statistically significant.

As risk aversion data is only available in Wave 2, controlling for risk aversion indicators involves two changes compared to specifications (3a) and (3b): an expanded set of control variables and a reduction in the sample. To separately examine the impact of these two changes on the estimates, in specifications (4a) and (4b), we first repeat the same analysis as in specifications (3a) and (3b), respectively, but only on Wave 2 data. The estimated gender differences in both bidding and payoffs are smaller than those in specifications (3a) and (3b). The estimated bidding difference is 1.627, statistically significant only at the 10% level. The estimated payoff difference is -1.050, statistically significant at the 5% level. In specifications (5a) and (5b), we add risk aversion indicators into the set of controls. The estimated gender difference in bidding is 1.743, which is no longer statistically significant. The estimated gender difference in payoffs is -1.115, significant at the 10% level. However, both estimates are larger in absolute value than the corresponding estimates in specifications (4a) and (4b). Gender differences in risk aversion, as measured by the Holt–Laury measure, thus do not seem to be able to account for any of the identified gender differences in bidding or payoffs. The decrease in statistical significance, in comparison to specifications (4a) and (4b), is driven by larger standard errors rather than by smaller coefficient estimates. We therefore speculate that the lack of (stronger) statistical significance in specifications (5a) and (5b) is due to small sample size rather than a lack of an economic impact.

One common feature of the specifications in which we control for treatment details is that in Wave 2 sessions in which the lottery is presented before the auction, bidders bid significantly less than in sessions in which the auction is presented first. We conjecture that this could be due to either a wealth effect from lottery earnings or a lottery priming effect where subjects take more risk in the auction after playing the lottery. To separate these two effects, we estimate an additional set of regressions in which we add the lottery profit as an explanatory variable into specifications (2a)–(5a), imputed by zero for those subjects (from Wave 1 or Wave 2) for whom the auction was presented first. The estimates on the lottery-before-auction indicator remain negative and statistically significant while the profit variable is insignificant. This suggests that priming rather than the wealth effect is the driving force behind the negative coefficient on the lottery-before-auction indicator in specifications (2a)–(5a).

It is interesting to put the size of the estimated gender differences into perspective. We focus on the lower end of the estimates from specifications (4a) and (4b) first. The estimated gender difference in bidding of 1.63 points constitutes approximately 3.6% of the theoretical and empirical mean value of 45.5. The estimated gender difference in payoffs of 1.05 points in favor of men constitutes approximately 2.3% of the mean value of 45.5. Converted into cash, this is 5.25 cents per round and $1.58 for the whole experiment. Next, focusing on the higher estimates from specifications (3a) and (3b), the estimated gender difference in bidding of 2.61 points constitutes approximately 5.7% of the mean value of 45.5. The estimated gender difference in payoffs of 1.94 points in favor of men constitutes approximately 4.3% of the mean value of 45.5. Converted into cash, this is 9.7 cents per round and $2.92 for the whole experiment. Given the average auction cash payoffs of $13.00 in Wave 1 and $12.64 in Wave 2, this gender difference in payoffs constitutes about 12% to 22% of the average cash payoff. We summarize these findings in the following result.

Result 1 *(Gender). In the first-price auction, women bid significantly higher than men do, and earn significantly less. Gender difference in risk aversion* (*as measured by the Holt–Laury instrument*) *does not explain this difference.*

A significant gender difference in bidding is also observed in Pearson and Schipper (in press) in the FPA with known distribution in the same economic environment as ours, but without controlling for risk attitudes. In a follow-up study in the same economic environment, Schipper (2012) finds that this gender effect persists even after risk attitude is controlled for. In comparison, Casari et al. (2007) find that, in common value auctions, inexperienced women bid substantially higher than men do 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, the extent to which their gender difference result is due to differences in risk attitudes is not clear.

Since all three studies find that women bid higher than men do, one might wonder whether this is a tendency across auctions due to differences in strategic reasoning or attitudes toward competition (Gneezy et al., 2003; Gneezy and Rustichini, 2004; Niederle and Vesterlund, 2007). Although our data do not enable us to directly identify any gender differences in attitudes toward competition, we examine this hypothesis indirectly by investigating whether there is any gender difference in bidding behavior in the SPA (Wave 1).[18] Table 7 presents results from a set of OLS regressions with bid (Panel A), indicator for dominant strategy play (Panel B), indicator for overbidding own value (Panel C) and payoff (Panel D) being the outcome variables.[19] Apart from the displayed variables, in all specifications we additionally control for a cubic polynomial in value and also a set of indicators for periods 2 to 30 (period 1 being

[18] We thank an anonymous referee for pointing out that the SPA has many equilibria and that the overbidding in SPA observed in our study and other previous studies might suggest non-dominant-strategy equilibrium or out-of-equilibrium play.

[19] Specifications in Panels B and C are linear probability models. We have also estimated analogous probit and logit specifications with no qualitative difference in results.

Table 7
Gender difference in bidding, dominant strategy play, overbidding and payoffs in SPA.

Dependent variable	Panel A: Bid			Panel B: Dominant strategy play			Panel C: Overbidding			Panel D: Payoff		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)	(1d)	(2d)	(3d)
Female	−2.109	−2.077	−2.495	−0.012	−0.006	0.006	−0.094	−0.095	−0.109	−0.268	−0.294	−0.276
	(1.791)	(1.819)	(1.608)	(0.093)	(0.097)	(0.106)	(0.087)	(0.093)	(0.091)	(0.577)	(0.598)	(0.618)
Unknown value distr.		−0.331	−0.837		−0.060	−0.029		0.008	−0.038		0.266	0.501
		(1.744)	(1.616)		(0.087)	(0.088)		(0.100)	(0.082)		(1.213)	(1.301)
Age			0.052			0.002			−0.008			0.051
			(0.315)			(0.011)			(0.011)			(0.172)
Number of siblings			−0.103			−0.012			−0.003			−0.211
			(0.799)			(0.031)			(0.027)			(0.531)
Asian/Asian American			1.499			−0.098			0.104			−0.635
			(1.568)			(0.076)			(0.067)			(0.949)
Other ethnicity			2.768			−0.118			0.106			1.367*
			(2.573)			(0.078)			(0.086)			(0.726)
Science or engineering			1.021			0.067			0.027			0.547
			(2.286)			(0.130)			(0.102)			(0.850)
Other social sciences			5.945			−0.295**			0.256			−2.737*
			(6.617)			(0.124)			(0.149)			(1.291)
Humanities or other			6.264**			−0.145			0.270**			−0.640
			(2.445)			(0.157)			(0.084)			(1.630)
Undetermined major			4.379*			−0.148			0.244**			−0.375
			(1.960)			(0.106)			(0.086)			(1.111)
Observations	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400
R^2	0.77	0.77	0.78	0.01	0.02	0.07	0.03	0.03	0.10	0.40	0.40	0.40

Notes:

1. Estimated by OLS. Clustered standard errors (at session level) in parentheses. Significant at: * 10% level; ** 5% level; *** 1% level.
2. A cubic polynomial in value and period indicator variables are controlled for in each specification.

the omitted category) to account for potential effects of learning. In all cases, standard errors are adjusted for clustering at the session level. In specifications (1a)–(1d), we include only the female indicator on the right-hand side. In specifications (2a)–(2d), we also control for the unknown value distribution indicator. In specifications (3a)–(3d), we additionally control for a set of demographic variables including age, the number of siblings, Asian/Asian American indicator, Other ethnicity indicator (with white being the excluded category), Science or engineering major, Other social science major, Humanities or other major, and Undetermined major (no subject has Mathematics or statistics major in this subsample; Economics or business major is the excluded category). None of the coefficients on the female indicator is statistically significant at the conventional level in any of the estimated specifications. The findings from Panel A indicate that women do not have a generic tendency to overbid in auctions. If anything, they appear to bid less than men in the SPA. Nor do the women differ from men in dominant strategy play or overbidding, suggesting the lack of any gender differences in strategic reasoning or attitudes toward competition in our experimental environment.

4. Effects of the menstrual cycle and oral contraceptives

Having identified the gender gap in bidding and payoffs 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 data from Wave 1, we also analyze the effect of the menstrual cycle on bidding, probability of dominant strategy play, probability of overbidding and payoffs in the SPA. Unlike in the case of the FPA, however, we do not find any systematic effects (see additional analysis on the first author's website). We therefore focus on the FPA in this section. We first assume that the bidding function is given by:

$$b_{it} = \beta_0 + \beta_1 v_{it} + \beta_2 v_{it}^2 + \beta_3 v_{it}^3 + \gamma' X_i + f(m_i, P_i) + \delta_t + u_{it}, \tag{3}$$

where b_{it} and v_{it} are the bid and value, respectively, of subject i in period $t \in \{1, \dots, 30\}$, X_i is the set of treatment, demographic and academic major (and risk aversion) controls, δ_t is the period effect and u_{it} is a zero mean unobserved disturbance. In addition, $f(m_i, P_i)$ captures the impact of the day of menstrual cycle m_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 $v_{it}, v_{it}^2, v_{it}^3$ and X_i, and is independent of (m_i, P_i).

There are several possible approaches to estimate the cycle and pill effect $f(m_i, P_i)$. One approach would be to model $f(m_i, P_i)$ non-parametrically by a set of 28 or 56 indicator variables, depending on whether the pill effect is taken into account or not. However, given that we have menstrual cycle information for only 73 female subjects in Wave 1 and 51 in Wave 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 estimate the term $f(m_i, P_i) + u_{it}$ up to a constant as a residual from OLS applied to (3) with only the constant, $v_{it}, v_{it}^2, v_{it}^3$ and X_i and time period indicators 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 (see the discussion that follows Result 3), this method would lead to biased estimates of $f(m_i, P_i)$.

Consequently, to best capture the cycle and pill effects, we use the following two-stage method. In the first stage, we use OLS to estimate the following model:

$$b_{it} = \beta_0 + \beta_1 v_{it} + \beta_2 v_{it}^2 + \beta_3 v_{it}^3 + \gamma' X_i + \sum_{m=1}^{28} \left[\alpha_m^{NP}(1 - P_i) 1_{\{m_i = m\}} + \alpha_m^P P_i 1_{\{m_i = m\}}\right] + \delta_t + w_{it}. \tag{4}$$

Depending on the specification, the set of additional control variables X_i may vary from being empty to including controls for treatment, demographics and academic major (and risk aversion). We then record the estimated residuals when we set $\hat{\alpha}_d^{NP} = \hat{\alpha}_m^P = 0$ for all days $m \in \{1, \dots, 28\}$. 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 the indicator for pill users and then focus on the relevant residuals. If we are interested in the deviation from the men's average bid, we leave the residuals unchanged. The resulting second-stage adjusted residual is then the dependent variable in the non-parametric estimation, as described in detail in Appendix C, with the day of cycle being the explanatory variable.[20] We construct 95% confidence intervals for these estimates 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

[20] 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.

the restriction $\alpha_m^{NP} = \alpha_m^P$, $m \in \{1, 2, \ldots, 28\}$. We use the same analysis to investigate the impact of the menstrual cycle and pill usage on subject payoffs by replacing b_{it} with π_{it}, the payoff of subject i in round t.

In what follows, we first present our baseline results for bidding and payoffs based on the day-of-cycle measure m_1 in Section 4.1. In Section 4.2 we then discuss the robustness of the baseline results to using the alternative measures m_2 through m_6.

4.1. Baseline results based on measure m_1

Fig. 4 presents non-parametric estimates of the bidding profile of women throughout the cycle using data from both Wave 1 and Wave 2, in which the day of cycle is based on measure m_1. This analysis ignores pill usage difference as information on pill usage is not available in Wave 1. As a consequence, we impose the constraint $\alpha_m^{NP} = \alpha_m^P$ in Eq. (4). Panel A1 shows that, including basic controls only, i.e., leaving X_i empty in Eq. (4), 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. The estimated difference between the highest and the lowest bidding cycle points is approximately 2.5 points. When comparing to the average female bid throughout the cycle, at the beginning of the follicular phase (days 6–10) women bid significantly more than on average. During the rest of the cycle, the difference from the average is not statistically significant. In Panel A2 we repeat this analysis, but this time controlling for the same set of variables as in specifications (3a)–(4a) of Table 6 (indicator variables for unknown value distribution, Wave 2, running lottery before auction in Wave 2, and also age, number of siblings, Asian/Asian American and Other ethnicity indicators and a set of indicators for academic majors). The overall pattern of bidding throughout the cycle is similar to Panel A1, but deviations from the average are smaller and they are not statistically significant in any part of the cycle.

Panels B1 and B2 of Fig. 4 are analogous to Panels A1 and A2, respectively, but this time plotting the estimates of the gender difference throughout the cycle. In terms of the estimated curve, these two plots are vertical shifts of the plots in Panels A1 and A2, respectively. The results show that the gender difference is statistically significant in all phases of the cycle irrespective of whether we control for treatment, demographic and academic major variables or not.

We also conduct analysis analogous to Fig. 4 for payoffs. The results are mirror images of the results for bids.[21] These observations lead to our next result:

Result 2 *(Menstrual cycle). In the first-price auction, women on average bid more and earn less than men do throughout all phases of the menstrual cycle.*

As discussed above, there is some degree of bidding variation throughout the cycle (the sine-like pattern), even though it is not statistically significantly different from the average bid of women once the expanded set of controls is accounted for. The observed behavioral variation could come from natural hormonal variations or psychological effects related to the cycle. As contraceptive pill usage elevates estradiol and progesterone levels in all but the menstrual phase, we investigate the extent to which pill usage might affect the observed variation in bidding behavior. Using data from Wave 2 only, we split the female sample into contraceptive pill users (17 subjects) and non-users (34 subjects). For each subsample, we compare the women's bids with the average women's bid in that subsample and with the average men's bid, respectively (controlling for variables included on the right-hand side of (4)). Our results are summarized in the next two figures.

Fig. 5 compares the bids of pill users (Panels A1 and A2) and non-users (Panels B1 and B2) with the average bids of their own group. In Panels A1 and B1, we include basic controls only, i.e., leaving X_i empty in Eq. (4), whereas in Panels A2 and B2, we control for the same set of variables as in specifications (3a)–(4a) of Table 6. Regardless of whether a smaller or a larger set of control variables is used, we observe that the bidding behavior of pill users follows the sine-like pattern first presented in Fig. 4. Moreover, compared to that figure, the bidding deviation from the own group mean is now statistically significant around the follicular phase maximum and the luteal phase minimum. Also, the estimated magnitude of the deviation around the group mean is now larger than the deviation observed in Panels A1 and A2 of Fig. 4. For example, focusing on Panel A2, the deviation reaches 2.78 points above the mean at the maximum and 5.32 points below the mean at the minimum. At the maximum (minimum) bidding point, this deviation constitutes 6.1% (11.7%) of the theoretical and empirical mean value of 45.5. The estimated payoff deviations for the same two days of the cycle are 2.24 points below the mean and 2.26 points above the mean, or 4.9% and 5.0% of the mean value of 45.5, respectively. In terms of payoffs, this is 11.2 cents per round below the mean and 11.3 cents per round above the mean, which is equivalent to \$3.36 below the mean and \$3.39 above the mean earning from the auction. Given the average auction cash payoff \$12.64 in Wave 2, these deviations are in excess of one quarter of average earnings. When we add the two deviations together, the difference of 8.1 points between the two extremes constitutes 17.8% of the mean value of 45.5. The difference between estimated payoffs for the same two days of the cycle is 4.5 points, or 9.9% of the mean value of 45.5. Converted into cash, this is 22.5 cents per round and \$6.75 for the whole experiment, which is in excess of 50% of the average

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

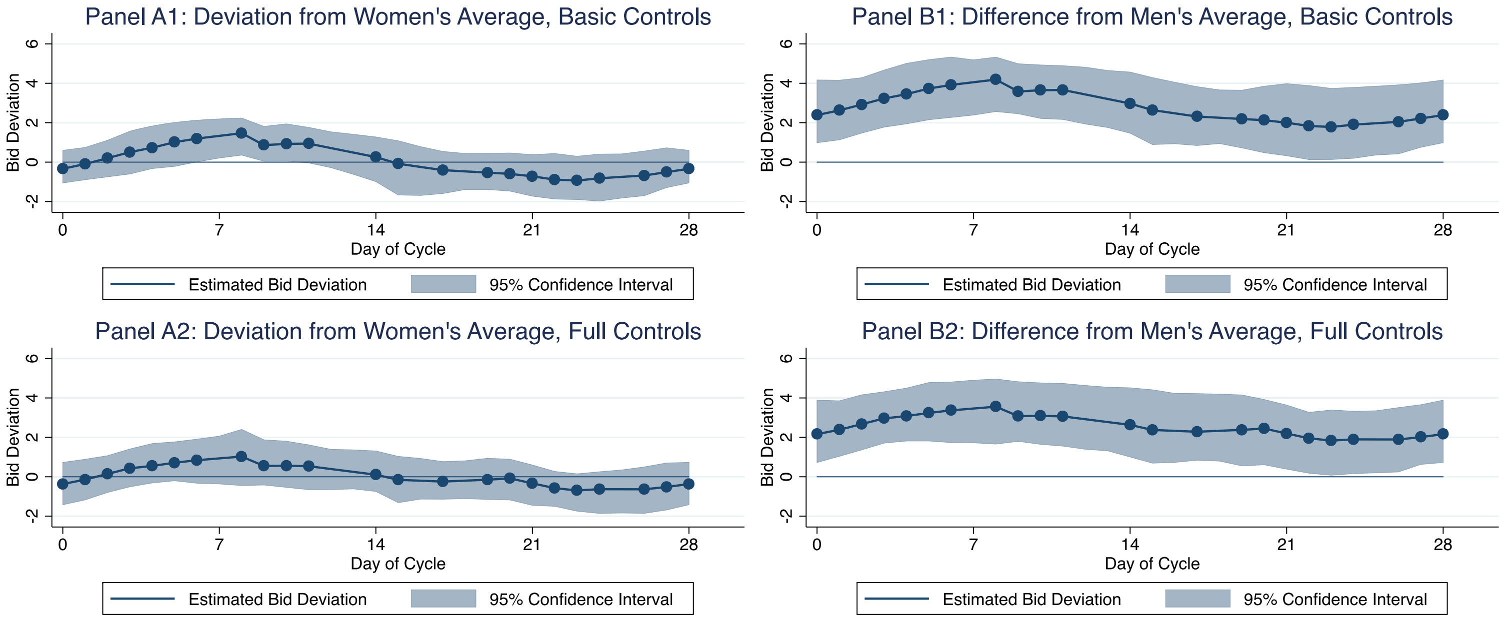

Fig. 4. Effects of menstrual cycle on FPA bidding behavior (Waves 1 and 2 combined), day of cycle based on measure m_1.
Note: The marked points on the estimated curve signify that at least one subject is available with a given day of the cycle.

auction payoff of \$12.64. Hence the implied differences in payoffs of pill users across phases of the menstrual cycle are sizeable.

In comparison, Panels B1 and B2 indicate that the bidding profile for pill non-users is flat and statistically insignificantly different from the own group mean throughout the cycle.[22]

Fig. 5 therefore presents one of the key findings of the paper. The sine-like bidding curve presented in Fig. 4 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.

Fig. 6 separately compares the bidding behavior of pill users (Panels A1 and A2) and non-users (Panels B1 and B2) to that of men. Again, in Panels A1 and B1, we include basic controls only (i.e., leaving X_i empty in Eq. (4)), whereas in Panels A2 and B2, we control for the same set of variables as in specifications (3a)–(4a) of Table 6. In terms of the estimated curves, these four plots are vertical shifts of the four respective plots in Fig. 5. Panels A1 and A2 show that pill users bid more than men during the menstrual, follicular and peri-ovulatory phases, and less than men during the luteal and pre-menstrual phases. However, the difference is statistically significant only during the follicular phase. On the other hand, Panels B1 and B2 show that pill non-users bid more than men throughout the cycle, but the difference is statistically insignificant.[23] We have also conducted an analogous analysis of payoffs when splitting the sample of women into pill users and non-users, and the results are mirror images of the results for bidding.[24]

These findings may seem to be in a partial contradiction of Results 1 and 2. However, this is due to the confidence intervals being much larger in Fig. 6 compared to regression estimates in Table 6 or plots in Panels B1 and B2 of Fig. 4 due to a smaller number of observations in any given subperiod of the cycle. Indeed, when we replicate estimations of specifications (4a)–(4b) and (5a)–(5b) of Table 6, distinguishing females into pill users and pill non-users, the estimated coefficients [session-clustered standard errors (p-values)] for pill non-users are 1.675 [0.972(0.119)], 1.783 [1.151(0.156)], −1.213 [0.486(0.034)] and −1.249 [0.675(0.097)] in specifications (4a), (5a), (4b) and (5b), respectively. That is, pill non-users on average earn less (marginally significant in specification (5b)) than men do. In relative terms, the gender difference in payoffs is about 2.7% of the mean value of 45.5 in favor of men. Expressed in dollar terms, the gender difference in payoffs is about 6.1 cents per round or \$1.83 for the whole experiment (about 14.5% of the average payoff of \$12.64) in favor of men. On the other hand, the corresponding estimates for the pill users are 1.527 [1.003(0.162)], 1.650 [1.364(0.257)], −0.718 [0.400(0.107)] and −0.802 [0.720(0.294)], respectively. In relative terms, the gender difference in payoffs is (based of the estimate from specification (4b)) about 1.6% of the mean value of 45.5 in favor of men. Expressed in dollar terms, the gender difference in payoffs is about 3.6 cents per round or \$1.08 for the whole experiment (about 8.5% of the average payoff of \$12.64) in favor of men. Even though this differences is neither as large as the one for pill non-users, nor statistically significant, things look differently at the peak of the bidding in the follicular phase. Focusing on Panel A2 of Fig. 6, the gender difference in bidding at this point in the cycle is 4.24 points, or 9.3% of the mean value of 45.5. The gender payoff difference at the same point in the cycle is −2.84 points or 6.2% of the mean value of 45.5. Expressed in dollar terms, this is 14.2 cents per round, or \$4.26 for the whole experiment (about 33.7% of the average payoff of \$12.64). Hence the payoff differential between pill users and men at this point in the cycle is sizeable. We summarize these observations in the following result:

Result 3 *(The pill). In the first-price auction, pill users follow a sine-like pattern of bidding throughout the cycle, with the maximum in the follicular phase and the minimum in the luteal phase. In both of these extremes, the average bidding behavior is statistically significantly different from the cycle average. Pill users also bid more than men do during the follicular phase, whereas pill non-users have a flat bidding profile throughout the cycle. Pooling across all phases of the cycle, they on average bid marginally more than men do and earn significantly less than men do.*

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.

One study of particular note for us is that of Pearson and Schipper (in press), who use measures analogous to m_4, m_5 and m_6 and find that naturally cycling women bid significantly higher than men do except during the mid-cycle, i.e., follicular, peri-ovulatory and luteal phases (lack of statistical significance differing slightly across different measures of the day of menstrual cycle). We speculate that the partial difference between our results and theirs could be due to a number of factors, including estimation techniques, retrospective versus prospective measures of the cycle, and subject

[22] We have also re-plotted Panels A2 and B2 of Fig. 5 when the set of control variables X_i is further expanded to include risk aversion indicators, as in specification (5a) of Table 6. The only qualitative difference compared to Fig. 5 is that, in Panel A2, the difference from the own group mean is no longer statistically significant (by a small margin). The plots are available from the authors upon request.

[23] Again, we have also re-plotted Panels A2 and B2 of Fig. 6 when the set of control variables X_i is further expanded to include risk aversion indicators. The results are qualitatively unchanged compared to Fig. 6 and are available from the authors upon request.

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

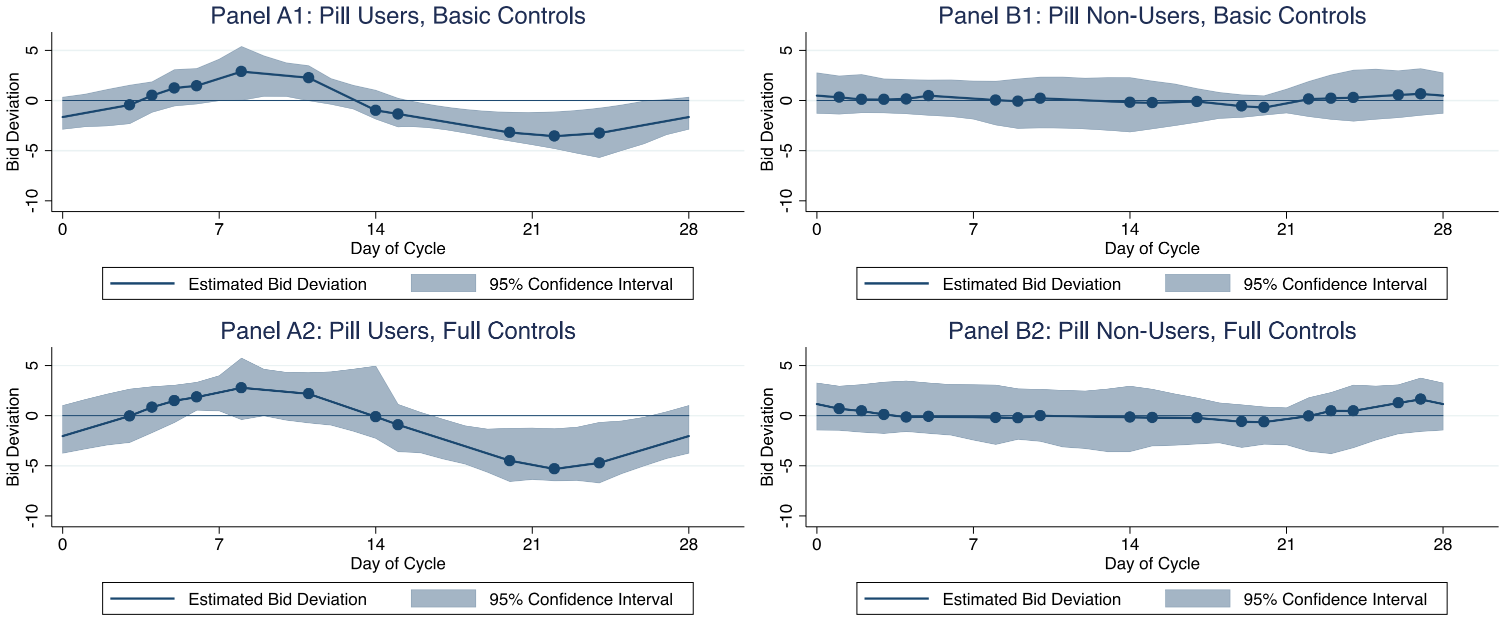

Fig. 5. Effects of menstrual cycle on FPA bidding behavior by pill usage (Wave 2, deviation from own group mean), day of cycle based on measure m_1.
Note: The marked points on the estimated curve signify that at least one subject is available with a given day of cycle.

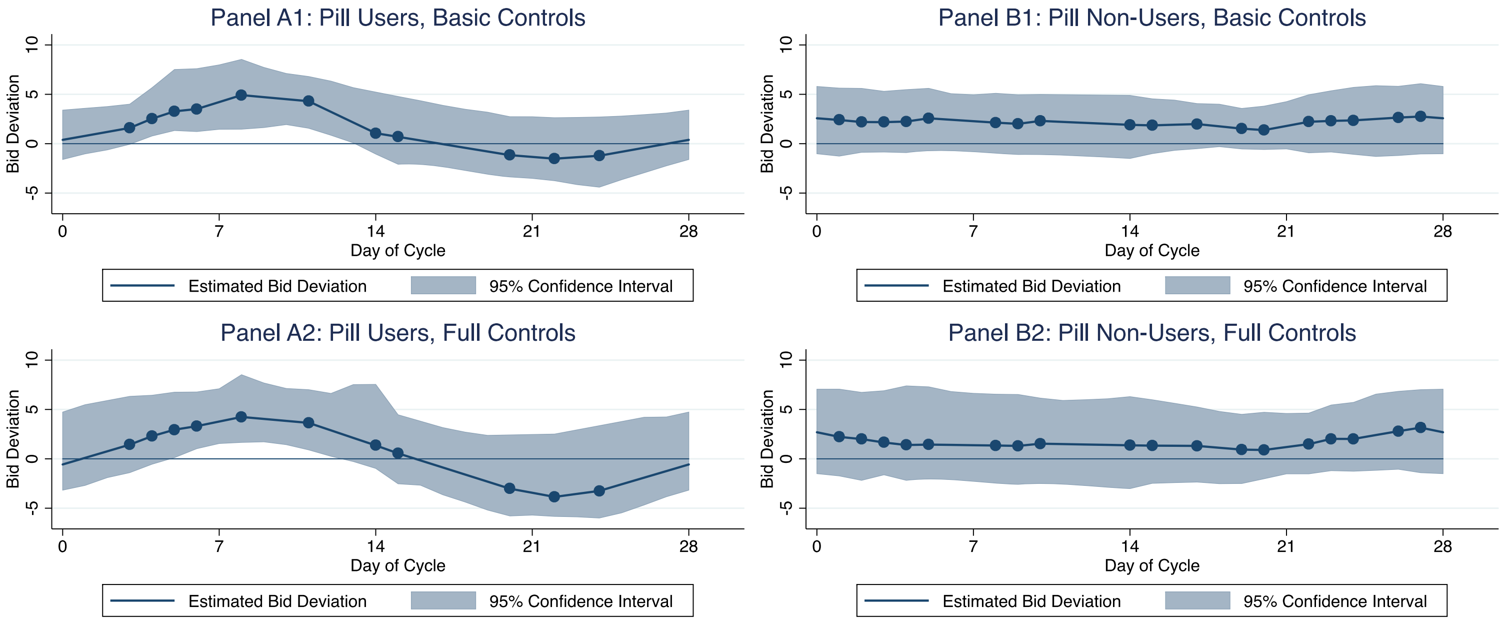

Fig. 6. Effects of menstrual cycle on FPA bidding behavior by pill usage (Wave 2, difference from men's mean), day of cycle based on measure m_1.
Note: The marked points on the estimated curve signify that at least one subject is available with a given day of the cycle.

pool composition (a higher proportion of Asians/Asian Americans and a lower proportion of whites in Pearson and Schipper).

Three remarks are in order. First, even though we control for a set of subject-level control variables 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 possibility, there are two sources of indirect evidence against such explanation. First, apart from some differences becoming statistically marginally insignificant, there is no qualitative change in the results regardless of whether we control for treatment, demographics and academic major (and even 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 and academic major variables (and, in another specification, also risk aversion indicators), using robust standard errors, the only significant explanatory 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).

Second, 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 reporting their state of the menstrual cycle, as most pill packages number the pill by the day of the cycle. This may explain why we are able to identify significant cycle effects for pill users, while we are not able to find any significant cycle effects for pill non-users due to the attenuation bias.[25] If pill users are indeed more precisely reporting their day of the menstrual cycle, it should be the case that their prospective and retrospective measures are more tightly correlated than for non-users. However, if we recompute the correlation matrix of m_1 through m_6 as reported in Table 5 separately for pill users and non-users and focus on the correlation of the two classes of measures, correlations for the pill users are in fact smaller than for non-users.

Lastly, the day counting method that we use is likely to contain measurement errors (see Section 2.4). 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 a more precise assessment of the cycle. However, as this type of assessment requires a medical procedure, we leave it to future research.

Results in this section relate to findings in the extensive behavioral endocrinology literature on the menstrual cycle, hormones and cognition, although 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 responsiveness, creativity, dressing behavior, asymmetric hemispheric activity, facial preference, body image and interest in erotica” (Epting and Overman, 1998). Hampson and Kimura (1992) find that women perform better on certain male-oriented tasks (e.g., spatial ability) when estradiol levels are low. Conversely, women perform better on certain female-oriented tasks (e.g., articulatory speed and accuracy) during periods of high estradiol levels. This result is confirmed by Hausmann et al. (2000), who find a significant cycle difference in spatial ability, with high scores during the menstrual phase and low scores during the luteal phase. Summarizing research on estradiol and cognitive functioning in women, Sherwin (2003) points out that, estradiol, and not progesterone, is responsible for cycle-related changes in cognition in young women. One explanation is that elevated levels of estradiol among combination pill users might be responsible for the increase in bids in the follicular phase.

An alternative explanation of the sine-like bidding pattern of women on hormonal contraceptives relates to the progestin cycle among pill users.[26] The “pill cycle” consists of two phases: a high progestin phase of 21 days when pill users take pills containing the active ingredient, progestin, a synthetic version of progesterone, and a low progestin phase of 7 days when pill users either take reminder pills (placebos) or no pill at all. In this second phase of the pill cycle, progestin drops and the withdrawal bleeding occurs, which resembles menstrual bleeding in appearance. If bidding is positively correlated with progesterone, as suggested in an experiment by Schipper (2012) in which salivary progesterone is correlated with bidding in our auction environment, then for women on hormonal contraceptives, we should observe a pattern of bidding that resembles more or less a sine curve.

4.2. *Robustness checks using measures m_2 through m_6*

In this subsection, we investigate the extent to which Results 2 and 3 presented in the previous subsection are sensitive to the choice of measure m_1 of the day of cycle. Since the alternative measures m_2 through m_6 are only available in Wave 2, as is the pill usage information, we first consider the robustness of Result 2 to reducing the sample only to Wave 2 while still using the measure m_1. As in Fig. 4, bidding follows a sine-like pattern and it is statistically significantly different from the average only for a part of the follicular phase and if only the basic set of controls is included. The estimated gender difference in bidding (earnings) is still positive (negative) throughout the cycle, but smaller than when both waves of the data are used and no longer statistically significant. This finding is analogous to the comparison of estimates in specifications (3a) and (4a) for bidding and (3b) and (4b) for payoffs in Table 6.

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

[26] We thank Burkhard Schipper for suggesting this explanation.

Table 8
Features of experimental sessions in the 2005 working paper.

Auction mechanism	Subjects per session	Value distribution	Exchange rate		No. of sessions	No. of subjects
			Bidders	Auctioneers		
FPA	8	Known	20	–	5	40
	8	Unknown	20	–	5	40
	12	Known	12	60	5	60
	12	Unknown	12	60	5	60
SPA	8	Known	20	–	5	40
	8	Unknown	20	–	5	40
	12	Known	12	60	5	60
	12	Unknown	12	60	5	60

When we re-plot Fig. 4 for any of the other measures m_2 through m_6, we find that bidding (earnings) of women in any phase of the cycle is statistically insignificantly different from the average bid of women whether we use only the basic or the expanded set of control variables. On the other hand, there is a statistically significant gender difference in bidding (earnings) during most of the cycle when we use only the basic set of control variables. This difference remains positive but ceases to be statistically significant when we expand the set of control variables.

These observations suggest that statistical significance of Result 2 is sensitive to reducing the sample to Wave 2 only and to using an extended set of control variables. On the other hand, the pattern of gender differences over the course of the cycle is not sensitive to the choice of the menstrual cycle measure.

Re-plotting Fig. 5 for any of the other measures m_2 through m_6, the sine-like profile of bidding throughout the cycle for pill users is still present for any of these measures. The statistical significance of the deviation from the average at the follicular phase peak is preserved using m_2 (for the basic set of controls) and m_3, and the statistical significance of the deviation from the average at the luteal phase bottom is preserved using m_3, m_4, m_5 and m_6. We obtain mirror image results for payoffs. Pill non-users still have a flat profile of bidding (earnings) throughout the cycle.

Re-plotting Fig. 6 for any of the other measures m_2 through m_6, the gender difference for pill users is statistically significant at the follicular phase peak when using m_2, m_3 and m_4 (only for the basic set of controls), but not m_5 and m_6. We obtain mirror image results for payoffs. There is no statistically significant gender difference during other parts of the cycle. For pill non-users, the gender difference in bidding (earnings) is again positive (negative) but statistically insignificant throughout the cycle.

These observations suggest that the first part of Result 3, namely the sine-like pattern of bidding of pill users with statistically significant deviations at the extremes, is reasonably robust to using alternative measures of the day of menstrual cycle, although the luteal phase bottom is more robust than the follicular phase peak. On the other hand, the second part of the result, namely a flat bidding and payoff profile for pill non-users, is very robust to using various day-of-cycle measures.

5. Comparisons with our 2005 working paper

As the first experimental study which investigates the effects of menstrual cycle on competitive bidding, our 2005 working paper has been widely cited in the literature. Thanks to many useful comments from colleagues and anonymous reviewers, the paper has evolved from its 2005 version in the data composition, analysis methods and some of the results. All of the new data we have collected since then pertains to the first-price auction, hence there are no changes in data or results pertaining to the second-price auction. The rest of the discussion in this section therefore refers to the first-price auction.

Our 2005 paper highlights three main findings: (1) women bid on average more than men do; (2) the difference is highest in the follicular phase; (3) the difference is statistically insignificant in the menstrual phase. Given the results reported in the previous two sections, the first two results still hold. However, the third one no longer holds since there is a statistically significant gender difference in bidding in FPA in all phases of the cycle (Result 2). Note, however, that the estimated gender difference in the 2005 paper is positive even in the menstrual phase, although not statistically significant. In what follows, we explain differences in data composition and estimation methods that underlie this difference.

First, the two versions of the paper differ in data composition. Our 2005 working paper used data collected between October 2001 and January 2002. In addition to the 8-subject treatments used in the current version, it also used data from 12-subject treatments, where 4 of the subjects in each session were auctioneers (Table 8). Several reviewers pointed out that the presence of auctioneers might have imposed different psychological effects on the bidders and their bidding behavior. Therefore, we drop the treatments with auctioneers from both our 2007 *JET* paper (Chen et al., 2007) as well as from the present paper. In addition, some reviewers and commentators were concerned about the lack of control for risk preferences and the usage of contraceptive pills in the 2001–2002 data. To address these concerns, we conducted the second wave of FPA experiments in October 2006, with the same auction environment, but with additional measures of risk attitudes and a modified version of the questionnaire, which elicited usage of a contraceptive pill and multiple measures of the day of the menstrual cycle.

Second, the two versions differ in the analysis methods. The 2005 version studies the impact of the menstrual cycle by categorizing female subjects for whom the relevant information is available into the five phases of the cycle (see Section 2.3) and then relying on OLS analysis with indicator variables for the five phases as explanatory variables. The reason for this step-function approach is that it is *a priori* unclear what the shape of impact of the menstrual cycle on bidding is. As pointed out by some readers, such step-function analysis is sensitive to measurement error in the day-of-cycle measure. With the Wave 2 data, we find evidence that there indeed is a non-negligible measurement error in both the prospective measure m_1 and various other prospective and retrospective measures of the menstrual cycle we use in this paper. Such evidence calls for a new approach which is less sensitive to the day-of-cycle measurement error around the boundaries of the phases and yet preserves the identification freedom for the shape of the menstrual cycle impact. We therefore opt to use a non-parametric approach based on the lowess smoother that uses directly the day of cycle rather than the cycle phase as the explanatory variable. In this procedure, the effect of the day of cycle is estimated from a weighted linear regression using "nearby" observations, with weights declining with distance. As a result, measurement error around the boundaries of the phases no longer has a disproportionate effect on the quality of the estimates. Another advantage of this procedure is that it allows utilization of the cyclical nature of the cycle. That is, observations near the beginning of the cycle improve estimation of the impact on bidding at the end of the (previous) cycle and vice versa (see Appendix C for details). The cost of using this procedure is that one needs to follow more elaborate steps in order to control for other variables that are likely to impact bidding (see Section 4 for details).

In Table 9, we conduct a series of OLS regressions to demonstrate the difference between our present menstrual cycle results and those from our 2005 paper, and to investigate the extent to which any difference can be accounted for by the change in sample composition as opposed to the change in the estimation method. We first point out some common features that apply to all the estimated specifications. First, the day of menstrual cycle is measured by m_1, since this is the only measure available in our 2001–2002 data. Based on this measure, we categorize each female for which the measure is available into one of the five phases of the cycle as described in Section 2.4 and then use the five phase indicator variables in the analysis. Second, in all specifications we control for details of the treatment (indicators for unknown value distribution, presence of auctioneers, Wave 2 data and lottery preceding the auction), demographics (age, number of siblings, Asian/Asian American and Other ethnicity), and a set of academic major indicators. The omitted category is white males in Economics or business major in Wave 1 sessions without auctioneers. Third, all specifications are estimated by OLS and the standard errors are adjusted for clustering at the session level. Fourth, we use a 5% statistical significance level (unless stated otherwise) to claim existence of an effect. Fifth, we use a cubic polynomial in value (and reserve price, with all the interactions, when observations from sessions with auctioneers are included) to approximate the dependence of bids on values (and reserve prices). Sixth, all specifications also control for period indicator variables in order to capture any effects of learning.[27]

In specification (1a), we use the 2001–2002 bidder data, i.e., Wave 1 data plus data from sessions with auctioneers. This specification essentially replicates our 2005 paper results. Compared to Wave 1 data, this brings into the sample additional 80 bidders, of which 42 are male and 38 are female. We have menstrual cycle measure for 37 out of 38 of these females.[28,29] Because of the reserve prices, it may happen that a bidder's value does not exceed the reserve price in some rounds. Bids in such rounds are likely to be uninformative since any bid below the reserve price is payoff-equivalent. We therefore use only bidder-round observations in which value exceeds the reserve price, which yields a sample size of 3786 bidder-rounds.[30] In specification (2a), we drop the auctioneer treatments, using only Wave 1 data. In specification (3a), we add data from Wave 2. In specification (4a), we use data from Wave 2 only. Apart from analyzing bids (Panel A), we also analyze bidder payoffs using the same set of regressions (Panel B).

Focusing on the impact of the menstrual cycle, we find throughout all the specifications that bidding (payoff) is highest (lowest) in the follicular phase of the cycle, a result that is consistent between the current paper and our 2005 working paper. Furthermore, a comparison with Fig. 4 indicates that this result is insensitive to the estimation method. Focusing on gender difference in the menstrual phase, we find a positive but statistically insignificant estimate in specification (1a), which corresponds to our finding in the 2005 paper. On the other hand, in specification (1b), there is a significant negative gender difference in payoffs in the menstrual phase, which was also present in our 2005 analysis.

[27] Coefficient estimates for the value and reserve price polynomial and period indicator variables are not displayed but are available from the authors upon request.

[28] These are the same exact numbers as for the FPA auctions without auctioneers in Wave 1 (see Note 2 below Table 4). This is not an error, just a coincidence.

[29] Among 38 female bidders in sessions with auctioneers, all 38 report the number of days from the beginning of the next cycle. For six subjects who report 0, we set $m_1 = 28$. For 5 subjects who report 30, we set $m_1 = 1$. For one subject who reports 33, we set m_1 to missing. These are the adjustments we used also in our 2005 paper.

[30] In our 2005 paper, we use 3463 observations. We have updated the categorization of majors since then to deal with the missing information problem, which accounts for the increase in the number of observations from 3463 to 3786. This distinction is immaterial for the purpose at hand since the results are qualitatively equivalent between the two samples.

Table 9
Comparison of results on the impact of menstrual cycle with the 2005 working paper.

Dependent variable	Panel A: Bid				Panel B: Payoff			
Subsample	(1a) Wave 1 + AT	(2a) Wave 1	(3a) Waves 1&2	(4a) Wave 2	(1b) Wave 1 + AT	(2b) Wave 1	(3b) Waves 1&2	(4b) Wave 2
Unknown value distribution	−0.933	−1.488*	−0.896		0.230	0.520	0.250	
	(0.671)	(0.807)	(0.985)		(0.596)	(0.820)	(0.873)	
Session with auctioneers	−4.317**				2.838**			
	(1.848)				(1.068)			
New data indicator			2.430**				−1.856**	
			(1.081)				(0.709)	
Lottery before auction			−4.011***	−4.207***			2.714***	2.818***
			(1.249)	(1.124)			(0.703)	(0.580)
Age	−0.026	0.122	−0.018	−0.126	−0.114	−0.146	0.010	0.106
	(0.192)	(0.205)	(0.119)	(0.171)	(0.081)	(0.089)	(0.065)	(0.084)
Number of siblings	−0.713**	−1.104***	−0.515**	−0.168	0.198	0.474*	0.173	0.024
	(0.289)	(0.317)	(0.237)	(0.303)	(0.180)	(0.233)	(0.127)	(0.163)
Asian/Asian American	−1.453	−1.572	−1.265	−0.552	−0.119	0.352	0.281	−0.034
	(1.082)	(1.194)	(0.886)	(1.085)	(0.572)	(0.644)	(0.496)	(0.731)
Other ethnicity	0.987	1.833	0.245	−0.641	−1.031*	−1.066	−0.675	−0.355
	(1.067)	(1.489)	(0.757)	(0.785)	(0.594)	(0.722)	(0.429)	(0.546)
Mathematics or statistics	−0.346	0.130	1.721	2.870**	0.998	1.555*	−0.449	−1.781*
	(1.363)	(1.948)	(1.008)	(1.212)	(1.239)	(0.792)	(0.911)	(0.895)
Science or engineering	−1.839	−0.837	−0.334	1.477	1.459*	1.621	0.490	−0.984
	(1.237)	(1.375)	(1.053)	(1.296)	(0.715)	(0.901)	(0.755)	(0.688)
Other social sciences	−1.384	−1.357	−0.936	0.356	−0.877	−0.681	0.176	−0.541
	(2.002)	(2.477)	(1.688)	(1.855)	(0.739)	(1.100)	(0.883)	(0.882)
Humanities or other	0.238	2.639	1.099	1.603	−0.096	0.002	−0.060	−0.864
	(1.503)	(1.900)	(1.205)	(1.313)	(0.842)	(1.251)	(0.879)	(0.948)
Undetermined major	−0.434	2.171	1.974		−0.296	−0.939	−1.225	
	(1.695)	(2.063)	(1.574)		(0.897)	(1.103)	(1.061)	
Menstrual phase	2.101	3.843***	2.654***	1.963*	−2.622***	−3.698***	−1.693***	−0.602
	(1.434)	(1.103)	(0.732)	(1.050)	(0.767)	(0.595)	(0.538)	(0.569)
Follicular phase	5.647***	4.443**	3.975***	3.287*	−3.214***	−3.052***	−3.050***	−2.568**
	(1.282)	(1.528)	(1.271)	(1.589)	(0.814)	(0.885)	(0.726)	(0.885)
Peri-ovulatory phase	3.323**	3.302	1.914	1.232	−1.683	−0.971	−0.829	−0.323
	(1.203)	(2.086)	(1.111)	(1.260)	(1.201)	(2.340)	(0.912)	(0.721)
Luteal phase	3.126***	4.397***	2.502***	0.457	−1.948**	−3.159***	−1.930***	−0.571
	(0.979)	(0.983)	(0.871)	(1.103)	(0.812)	(0.750)	(0.518)	(0.562)
Pre-menstrual phase	1.567*	0.705	1.139	2.280	−1.445*	−1.621	−1.698*	−2.290
	(0.800)	(1.141)	(1.193)	(2.330)	(0.703)	(0.963)	(0.898)	(1.731)
Observations	3786	2370	4770	2400	3786	2370	4770	2400
R^2	0.83	0.83	0.84	0.86	0.53	0.54	0.51	0.50

Notes:
1. Estimated by OLS. Clustered standard errors (at session level) in parentheses. Significant at: * 10% level; ** 5% level; *** 1% level.
2. A cubic polynomial in value and reserve price (including the interactions) and period indicator variables are controlled for in each specification.
3. AT stands for treatments with auctioneers. In these treatments, only observations in which the value exceeds the reserve price are included.

Once we remove treatments with auctioneers from the data (specification (2a)), however, the gender difference in bidding in the menstrual phase becomes positive and statistically significant, and remains so even when we add Wave 2 data to the sample (specification (3a)). On the other hand, the gender difference in payoffs during the menstrual phase remains negative and statistically significant in specifications (2b) and (3b). When we use only Wave 2 data, the bidding difference in the menstrual phase in specification (4a) is statistically significant only at the 10% level, whereas the payoff difference in specification (4b) is no longer statistically significant. We therefore conclude that the change in the sample composition alone, especially dropping data from treatments with auctioneers (specifications (2a) and (2b) vs. (1a) and (1b)), can account for the difference between Result 2 and the finding of no statistically significant gender difference in bidding in the menstrual phase in our 2005 paper, whereas the change in the estimation technique does not account for this change in the results. As far as estimates in specifications (4a) and (4b) are concerned, the lack of statistical significance is likely to be due to a smaller sample size once Wave 1 data are dropped from the sample.

Finally, to obtain regressions analogous to the ones presented in our 2005 working paper, Table 11 in Appendix D reports estimates of Eq. (4) that are modifications of estimates that underlie Figs. 4–6. In Table 11, instead of using indicators for each individual day in the cycle, we use only five indicators for the five phases of the cycle based on measure m_1.

6. Conclusions

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, 2009). 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, as measured by the Holt and Laury (2002) instrument, cannot account for 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 or payoffs.

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, the non-users' bidding behavior does not exhibit such phasic changes. For pill users, given their bidding profile throughout the cycle, the gender difference in bidding is positive and significant in the follicular phase, whereas in other phases pill users do not bid significantly differently from 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. Furthermore, our study suggests that dominant strategy mechanisms, such as the second-price auction, offer theoretically and empirically gender neutral and menstrual-cycle tolerant implementation.[31] More studies are needed to fully understand why this is the case empirically.

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 a direct assay of hormones. Joint studies on economics and behavioral endocrinology would be an interesting endeavor to better understand the biological foundations of economic behavior.

Acknowledgments

We thank David Cooper, Rachel Croson, Catherine Eckel, Uri Gneezy, Jacob Goeree, Štěpán Jurajda, John Kagel, Nancy Kotzian, Laura Straková, Muriel Niederle, Andreas Ortmann, Matthew Pearson, Steve Salant, Burkhard Schipper, Dan Silverman, Robert Slonim, Lise Vesterlund and seminar participants at Case Western, CERGE-EI, Free University Berlin, Harvard, Hebrew University, Michigan, Ohio State, Simon Fraser, UBC, UC-Davis, UCSD, the 2005 Economic Science Association Meetings (Montreal, Canada), Stanford Institute for Theoretical Economics, and Maastricht Behavioral and Experimental Economics Symposium, and an anonymous referee for helpful comments. We thank Tyler Fisher, 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 through grants No. SES-0079001 and SES-0962492. Any remaining errors are our own.

Appendix A. Experimental instructions

FIRST-PRICE AUCTION

[*The complete instructions for the first-price auction with known value distribution treatment are shown here. The instructions for the first-price auction with unknown value distribution treatment are identical except where pointed out.*]

---

[31] We thank an anonymous referee for suggesting this implication.

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.

    [*In the treatment with unknown value distribution, this paragraph is replaced by*:]

  - In each of 30 rounds, each bidder's value will be randomly and independently drawn from the high value distribution with a predetermined chance of x%, and from the low value distribution with $(100 - x)$% chance. You will not be told what x is. You will not be told which distribution your value is drawn from either. 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 be asked to give an estimate of the chance that the value of the *other* bidder in the group is drawn from the high value distribution, i.e., an estimate of x. We then ask how confident you are about your estimate. You can choose one among the following five categories: not confident at all, slightly confident, moderately confident, fairly confident, and very confident.

    [*This paragraph is only given for the treatment with unknown value distribution. The remainder of this section is the same for both treatments except that the next paragraph begins with "Then each bidder…" for the treatment with unknown value distribution.*]

- 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 20 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.

   [*This question is omitted in treatments with the unknown value distribution.*]

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.

SECOND-PRICE AUCTION

[*Instructions for the second-price auction* (*for both known and unknown value distribution*) *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.*]

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 20 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.

   [*This question is omitted in auctions with the unknown value distribution.*]

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.

LOTTERY

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 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 $1, 2, 3, \ldots, 10$. 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* $(1, 2, \ldots, 31)$)
   - Do you currently experience any symptoms of PMS (Pre-menstrual Syndrome)? (please choose one)
     – none _____
     – mild _____
     – severe _____

Thank you very much for your participation!

Appendix C. Non-parametric estimation technique

This appendix describes the non-parametric estimation used in Section 4. For a given analysis, let $\hat{w}_{it}$ be the estimated residual from the first-stage regression (4), let m_i be the measure of the day of cycle for female subject i and let N be the sample size, counting multiple bids of each individual bidder separately. Now consider the following procedure. We first order the data in an increasing order of m_i, with ties being broken deterministically based on subject and round numbering. Label the resulting index of observations j. We then compute the prediction $\tilde{w}_j$ of $\hat{w}_j$ for each observation 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. We use $B = 0.5$. We tried to experiment with other bandwidths and concluded that larger bandwidths result in oversmoothing and smaller bandwidths in excessively noisy estimates. The weight for each observation $k \in \{j_-, \ldots, j_+\}$ is given by the tricube weighting function $[1-(|m_k - m_j|/\Delta)^3]^3$, where $\Delta \equiv 1.0001 \max(m_{j_+} - m_j, m_j - m_{j_-})$.[32] Finally, the estimate for any value m of the day-of-cycle variable is computed as the arithmetic average of all $\hat{w}_j$s for which $m_j = m$. Confidence intervals for these estimates are obtained by bootstrapping with clustering based on 250 replications (see the discussion in the main text). If some value for the day of cycle from the domain $\{1, \ldots, 28\}$ is missing in a particular bootstrap draw, we impute the prediction $\hat{w}$ for this value by using linear interpolation and extrapolation based on predictions for the available values of the day of cycle. Note that this approach to constructing confidence intervals typically results in larger confidence intervals than one would obtain by drawing the bootstrap samples that would assure (by construction or via a larger sample size) some degree of stratification based on phase of the cycle. As a result, we consider the resulting confidence intervals to be rather conservative.

If we were to run the estimation procedure this way, the estimates at the beginning and at the end of the cycle would be less precise due to “missing observations on the other side of the boundary.” In order to overcome this problem, we take advantage of the fact that the day of the menstrual cycle is a cyclical variable, allowing us to treat any day $t \in \{1, \ldots, 28\}$ of the current cycle as the same day of the previous or the next cycle. This means that we can use not only days $1, 2, \ldots,$ etc., but also days $28, 27, \ldots,$ etc. to identify the predicted bid for day 1. Likewise, we can use not only days $28, 27, \ldots,$ etc., but also days $1, 2, \ldots,$ 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 $B/3 = 0.5/3$ of the expanded sample. Note that, due to the size of the bandwidth, the expansion of the sample does not lead to any local estimate 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.

Appendix D. Additional tables

This appendix contains two additional tables. More tables and figures can be found from the first author’s website (http://yanchen.people.si.umich.edu/).

In Table 10, we investigate the extent to which the gender difference in bidding and payoffs in the FPA in Table 6 differs across various details of the treatment. Specifications (1a)–(1b) and (2a)–(2b) report estimates based on Wave 1 for treatments with known and unknown value distribution, respectively. There is a sizeable positive gender difference in bidding and negative gender difference in payoffs in both subsamples, with the effects being even stronger than reported in Table 6. The difference between the gender difference in the two columns is statistically significant neither for bidding, nor for payoffs. Specifications (3a)–(3b) and (4a)–(4b) report estimates based on Wave 2 for the treatment in which the auction precedes the lottery and the treatment in which the lottery precedes the auction, respectively. The estimated gender differences in bidding and payoffs are comparable to those in specifications (4a)–(4b) of Table 6. Again, the difference between the gender difference in the two columns is statistically significant neither for bidding, nor for payoffs.

Table 11 reports estimates of Eq. (4) that are modifications of estimates that underlie Figs. 4–6. The modification is that instead of using indicators for each individual day in the cycle, we use only five indicators for the five phases of the cycle based on measure m_1. We implement this modification in order to obtain regressions analogous to the ones presented in the 2005 working paper. In particular, specification (1) underlies Panels A1 and B1 of Fig. 4. Specification (2) underlies Panels A2 and B2 of Fig. 4. It coincides with specification (3a) of Table 9 (estimates of treatment effects not displayed) and is reproduced here for completeness. Specification (3) underlies Panels A1 and B1 of Figs. 5 and 6. Specification (4) underlies Panels A2 and B2 of Figs. 5 and 6. Finally, specification (5) is reported for completeness. It would underlie Panels A2 and B2 of Figs. 5 and 6 if we additionally controlled for risk aversion (see footnotes 22 and 23). We observe that in specifications (1) and (2), the overall profile of bidding throughout the cycle replicates our findings in Fig. 4. One exception is that the gender difference in bidding is not statistically significant in the pre-menstrual phase and, in specification (2), in the peri-ovulatory phase. In specifications (3)–(5), for pill users we broadly find the sine-like pattern of bidding throughout the first four phases of the cycle, which is in line with Figs. 5 and 6. However, we find low bidding, on the level of the luteal phase or lower, also in the pre-menstrual phase, which is not in line with Figs. 5 and 6. However, the estimate for this subgroup is based on one subject only, so it is not very reliable. This illustrates the advantages of the non-parametric method we use in the main text which, by construction, relies on multiple subjects for any point estimate. On the other hand, the results for pill non-users are in line with findings in Figs. 5 and 6 with a fairly flat bidding profile throughout the cycle and, with the exception of the pre-menstrual phase in specification (4), statistically insignificant gender differences in all phases of the cycle.

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

Table 10

Gender difference in bidding and payoffs in FPA: known vs. unknown distribution, auction vs. lottery first.

Dependent variable	Panel A: Bid				Panel B: Payoff			
Subsample	(1a) Known distribution	(2a) Unknown distribution	(3a) Auction before lottery	(4a) Lottery before auction	(1) Known distribution	(2) Unknown distribution	(3) Auction before lottery	(4) Lottery before auction
Female	3.710**	3.018**	1.396	2.124	−3.224**	−2.186**	−1.153	−1.302*
	(1.292)	(0.905)	(1.267)	(1.397)	(0.775)	(0.577)	(0.645)	(0.474)
Age	0.423	0.104	−0.078	−0.225	−0.250	−0.146	0.085	0.141
	(0.438)	(0.180)	(0.295)	(0.206)	(0.307)	(0.117)	(0.131)	(0.102)
Number of siblings	−1.021*	−0.754	−0.207	−0.219	0.301	0.487	0.035	0.111
	(0.381)	(0.541)	(0.294)	(1.016)	(0.167)	(0.391)	(0.137)	(0.476)
Asian/Asian American	0.013	−2.648	1.278	−1.334	0.563	−0.082	−1.120	0.394
	(0.930)	(2.044)	(2.365)	(0.910)	(0.377)	(0.864)	(1.394)	(1.010)
Other ethnicity	−2.265**	4.963**	0.638	−1.455	0.147	−1.846	−0.864	−0.240
	(0.792)	(1.235)	(1.441)	(1.287)	(0.486)	(1.268)	(0.879)	(0.858)
Mathematics or statistics	1.816	−0.901	−0.409	5.844*	1.341	2.558	0.537	−4.702**
	(2.527)	(1.437)	(2.873)	(2.628)	(1.299)	(2.015)	(1.681)	(1.240)
Science or engineering	−0.353	−2.225	−0.553	1.520	0.284	2.255	0.054	−1.298*
	(1.903)	(1.900)	(2.835)	(1.455)	(0.702)	(1.802)	(1.531)	(0.585)
Other social sciences	1.044	−3.903	−2.473	2.081	−0.365	1.071	0.799	−2.177*
	(3.171)	(2.388)	(2.844)	(2.588)	(1.600)	(1.933)	(1.706)	(0.827)
Humanities or other	3.748	1.508	−0.375	2.233	−0.916	0.349	−0.578	−0.573
	(4.375)	(1.775)	(2.928)	(1.141)	(2.318)	(2.041)	(1.691)	(1.082)
Undetermined major	3.561	−0.744			−2.443	0.922		
	(2.873)	(1.843)			(1.446)	(2.727)		
Observations	1200	1200	1200	1200	1200	1200	1200	1200
R^2	0.84	0.83	0.87	0.85	0.54	0.53	0.46	0.56

Notes:

1. Estimated by OLS. Clustered standard errors (at session level) in parentheses. Significant at: * 10% level; ** 5% level; *** 1% level.
2. A cubic polynomial in value and period indicator variables are controlled for in each specification.

Table 11
Effect of phases of menstrual cycle on bidding in FPA.

Subsample	Panel A: Waves 1&2		Panel B: Wave 2		
	(1)	(2)	(3)	(4)	(5)
Age		−0.018		−0.159	−0.112
		(0.119)		(0.149)	(0.136)
Number of siblings		−0.515**		−0.139	−0.146
		(0.237)		(0.320)	(0.249)
Asian/Asian American		−1.265		−0.965	−1.081
		(0.886)		(1.023)	(0.882)
Other ethnicity		0.245		−0.452	−1.108
		(0.757)		(0.727)	(0.788)
Mathematics or statistics		1.721		3.164*	1.692
		(1.008)		(1.529)	(2.037)
Science or engineering		−0.334		1.595	1.239
		(1.053)		(1.059)	(0.870)
Other social sciences		−0.936		0.583	−0.458
		(1.688)		(1.575)	(1.207)
Humanities or other		1.099		1.500	0.354
		(1.205)		(1.292)	(1.184)
Undetermined major		1.974			
		(1.574)			
Menstrual phase	3.295***	2.654***			
	(0.982)	(0.732)			
Follicular phase	4.639***	3.975***			
	(1.118)	(1.271)			
Peri-ovulatory phase	2.355**	1.914			
	(0.998)	(1.111)			
Luteal phase	2.197**	2.502***			
	(0.900)	(0.871)			
Pre-menstrual phase	1.272	1.139			
	(1.302)	(1.193)			
Pill users:					
Menstrual phase			2.770**	1.887*	2.325
			(1.108)	(0.977)	(1.707)
Follicular phase			4.636**	4.445***	5.366**
			(1.803)	(1.263)	(1.829)
Peri-ovulatory phase			−0.089	0.527	0.889
			(1.457)	(1.240)	(1.400)
Luteal phase			0.037	−3.304***	−4.548***
			(1.248)	(0.711)	(1.124)
Pre-menstrual phase			−4.098**	−5.493***	−4.540***
			(1.307)	(1.269)	(1.387)
Pill non-users:					
Menstrual phase			2.427	1.831	2.351
			(1.863)	(1.497)	(1.617)
Follicular phase			2.634	0.649	1.556
			(3.627)	(4.598)	(4.278)
Peri-ovulatory phase			2.372	1.976	1.817
			(1.541)	(1.242)	(1.211)
Luteal phase			1.271	0.890	0.904
			(1.177)	(1.232)	(1.164)
Pre-menstrual phase			3.186	4.344**	3.352
			(2.705)	(1.803)	(1.929)
Treatment controls	No	Yes	No	Yes	Yes
Risk aversion controls	No	No	No	No	Yes
Observations	4770	4770	2400	2400	2400
R^2	0.83	0.84	0.85	0.86	0.87

Notes:

1. Estimated by OLS. Clustered standard errors (at session level) in parentheses. Significant at: * 10% level; ** 5% level; *** 1% level.
2. A cubic polynomial in value and period indicator variables are controlled for in each specification.

References

Almagor, M., Ben-Porath, Y.S., 1991. Mood changes during the menstrual cycle and their relation to the use of oral contraceptive. J. Psychosom. Res. 35 (6), 721–728.

Becker, G.M., DeGroot, M.H., Marschak, J., 1964. Measuring utility by a single-response sequential method. Behavioral Sci. 9 (3), 226–232.

Buser, T., 2012a. The impact of the menstrual cycle and hormonal contraceptives on competitiveness. J. Econ. Behav. Organ. 83 (1), 1–10.

Buser, T., 2012b. Digit ratios, the menstrual cycle and social preferences. Games Econ. Behav. 76 (2), 457–470.

Casari, M., Ham, J.C., Kagel, J.H., 2007. Selection bias, demographic effects and ability effects in common value auction experiments. Amer. Econ. Rev. 97 (4), 1278–1304.

Chawla, A., Swindle, R., Long, S., Kennedy, S., Sternfeld, B., 2002. Pre-menstrual dysphoric disorder: Is there an economic burden of illness? Med. Care 40 (11), 1101–1112.

Chen, Y., Katuščák, P., Ozdenoren, E., 2007. Sealed bid auctions with ambiguity: Theory and experiments. J. Econ. Theory 136 (1), 513–535.

Croson, R.T.A., Gneezy, U., 2009. Gender differences in preferences. J. Econ. Lit. 47 (2), 448–474.

Epting, L.K., Overman, W.H., 1998. Sex-sensitive tasks in men and women: A search for performance fluctuations across the menstrual cycle. Behavioral Neurosci. 112, 1304–1317.

Glick, I.D., Bennett, S.E., 1981. Psychiatric complications of progesterone and oral contraceptives. J. Clin. Psychopharmacol. 1 (6), 350–367.

Gneezy, U., Rustichini, A., 2004. Gender and competition at a young age. Amer. Econ. Rev. 94 (2), 377–381.

Gneezy, U., Niederle, M., Rustichini, A., 2003. Performance in competitive environments: Gender differences. Quart. J. Econ. 118, 1049–1074.

Hampson, E., Kimura, D., 1992. Sex differences and hormonal influences on cognitive function in humans. In: Becker, J.B., Breedlove, S.M., Crews, D. (Eds.), Behavioral Endocrinology. MIT Press, Cambridge, MA.

Hampson, E., Young, E., 2008. Methodological issues in the study of hormone-behavior relations in humans: Understanding and monitoring the menstrual cycle. In: Becker, J., Berkley, K., Geary, N., Hampson, E., Herman, J., Young, E. (Eds.), Sex Differences in the Brain: From Genes to Behavior. Oxford University Press, New York, pp. 63–78.

Hausmann, M., Slabbekoorn, D., Goozen, S.H.M.V., Cohen-Kettenis, P.T., Gunturkun, O., 2000. Sex hormones affect spatial abilities during the menstrual cycle. Behavioral Neurosci. 114 (6), 7035–7044.

Herrmann, M.A., Rockoff, J.E., 2012. Does menstruation explain gender gaps in work absenteeism? J. Human Res. 47 (2), 493–508.

Hersch, J., 1996. Smoking, seat belts and other risky consumer decisions: Differences by gender and race. Managerial Dec. Econ. 17 (5), 471–481.

Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. Amer. Econ. Rev. 92 (5), 1644–1655. http://www.jstor.org/stable/3083270.

Ichino, A., Moretti, E., 2009. Biological gender differences, absenteeism, and the earnings gap. Amer. Econ. J. Appl. Econ. 1 (1), 183–218.

Jensen, A., 1998. The g Factor: The Science of Mental Ability. Praeger, Westport, CT.

Jianakoplos, N.A., Bernasek, A., 1998. Are women more risk averse? Econ. Inquiry 36, 620–630.

Niederle, M., Vesterlund, L., 2007. Do women shy away from competition? Do men compete too much? Quart. J. Econ. 122 (3), 1067–1101.

Nyborg, H., 1983. Spatial ability in men and women. Advances Behav. Res. Therapy 5, 89–140.

Pearson, M., Schipper, B.C., in press. Menstruation cycle and competitive bidding. Games Econ. Behav.

Richardson, J.T.E., 1992. The menstrual cycle, cognition, and paramenstrual symptomatology. In: Richardson, J. (Ed.), Cognition and the Menstrual Cycle. Springer-Verlag, New York.

Riley, J.G., Samuelson, W.F., 1981. Optimal auctions. Amer. Econ. Rev. 71 (3), 381–392.

Rutstrom, E.E., 1998. Home-grown values and incentive compatible auction design. Int. J. Game Theory 27 (3), 427–441.

Schipper, B.C., 2012. Sex hormones and competitive bidding. Manuscript, University of California at Davis.

Sherwin, B.B., 2003. Estrogen and cognitive functioning in women. Endocrine Rev. 24 (2), 133–151.

Sommer, B.S., 1992. Cognitive performance and the menstrual cycle. In: Richardson, J. (Ed.), Cognition and the Menstrual Cycle. Springer-Verlag, New York.

Stricker, R., Eberhart, R., Chevailler, M.C., Quinn, F., Bischof, P., Stricker, R., 2006. Establishment of detailed reference values for luteinizing hormone, follicle stimulating hormone, estradiol, and progesterone during different phases of the menstrual cycle on the abbott architect analyzer. Clin. Chem. Lab. Med. 44 (7), 883–887.

Wozniak, D., Harbaugh, W.T., Mayr, U., 2010. The menstrual cycle and performance feedback alter gender differences in competitive choices. Unpublished.