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

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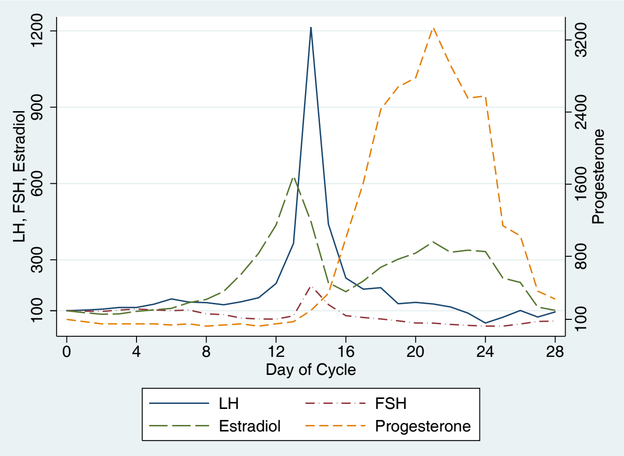
- Motivated by the variation in the hormonal levels of estradiol, progesterone, FSH and LH across different phases of the cycle
- Ultimate question: can a part of the gender difference in bidding be explained by the hormonal variation, assuming that men are similar to women at the beginning of their menstrual cycle?

Hormonal Variation in the Course of the Menstrual Cycle



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  - women's performance on certain "female-oriented" tasks (articulatory speech and accuracy) is better during periods of high estradiol levels

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- 8 bidders in each session, 30 rounds
- Random re-matching into groups of two bidders each round (reduction in repeated game effects)
- Bidder valuations were generated as independent draws from either a low value distribution $F^1(\cdot)$ or a high value distribution $F^2(\cdot)$ with densities

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

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  - fair breaking of ties

Experimental Design: Auction (3)

- Description of a typical round:
  1. For treatments with an unknown distribution only, each bidder estimated the chance that the valuation of the *other* bidder in the group was drawn from the high value distribution, i.e., an estimate of $1 - \delta$.
  2. Each bidder was informed of his own valuation and simultaneously and independently submitted a bid.
  3. Bids were then collected and the outcome of the auction was determined.
  4. Feedback: own valuation, own bid, the winning bid, win/lose, payoff.

Features of Experimental Sessions

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

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- Double-censoring of the measure at 4 and 8

Observed Degrees of Risk Aversion

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

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- Self-described personality and emotions

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- Number of courses taken at the UM in each of the five categories from the Registrar's Office (Dataset 1)

Summary Statistics

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

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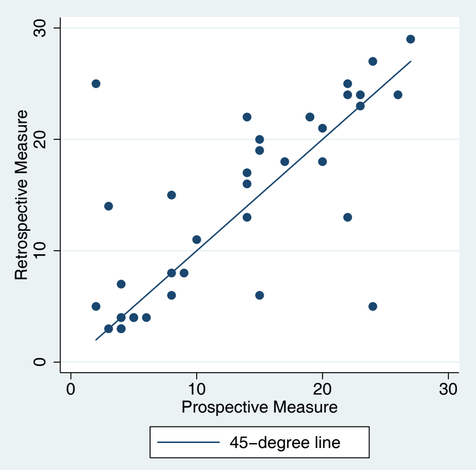
- Prospective vs. retrospective measure is a more important decision to make since the correlation between the two is 0.765

Cross-plot of the Prospective and the Retrospective Measure



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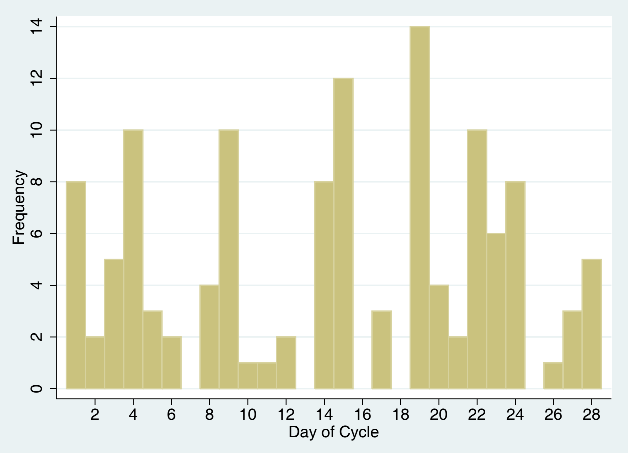
- We use the prospective measure because it is less noisy

Histogram of the Day of Cycle



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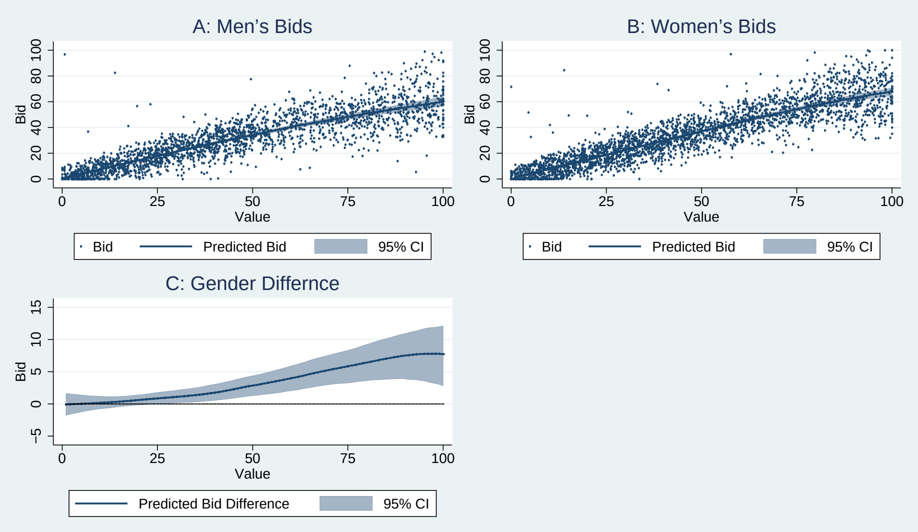
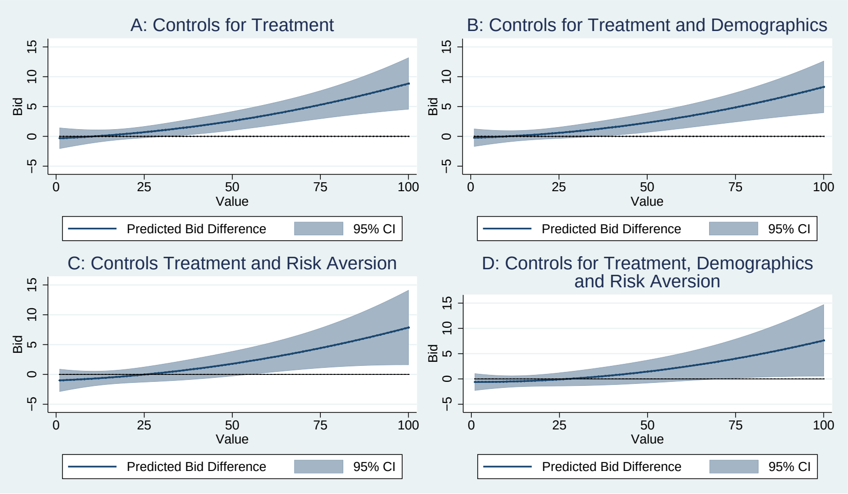
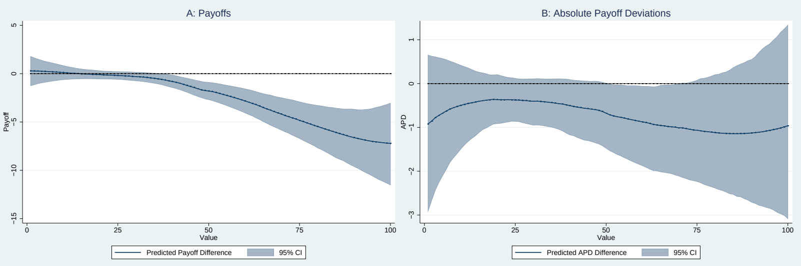
Gender Difference (Women - Men) in Bidding in FPA



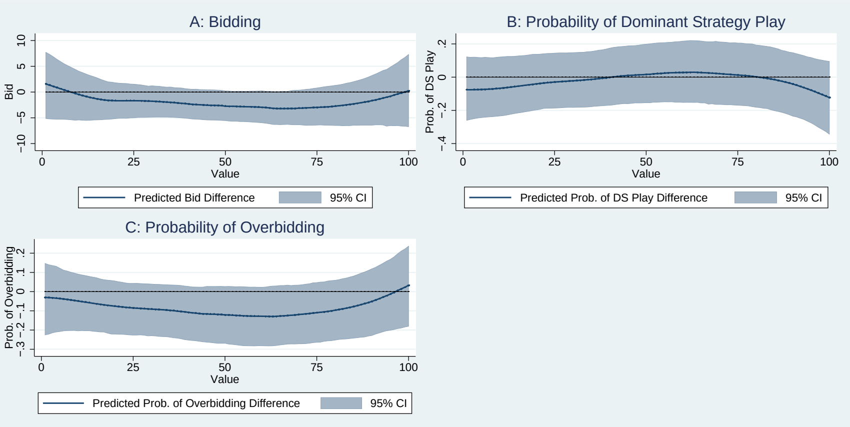
Gender Difference (Women - Men) in Bidding in FPA with Controls for Treatment, Demographics and Risk Aversion



Gender Difference (Women - Men) in Payoffs and Absolute Payoff Deviations in FPA



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



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- SPA: no significant gender differences

Methodology of Non-Parametric Estimation of menstrual Cycle Effects on Bidding

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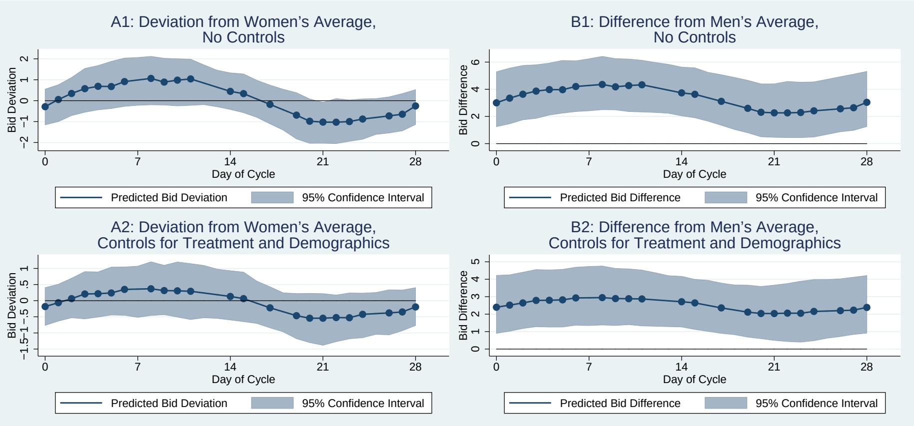
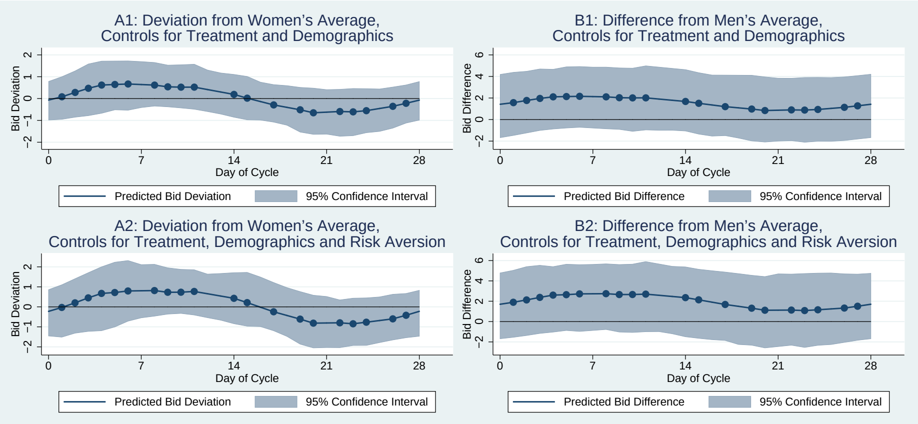
- Note: no additional clustering issues

Effect of the Menstrual Cycle on Bidding in FPA (Dataset 1 and Dataset 2 Combined



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

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



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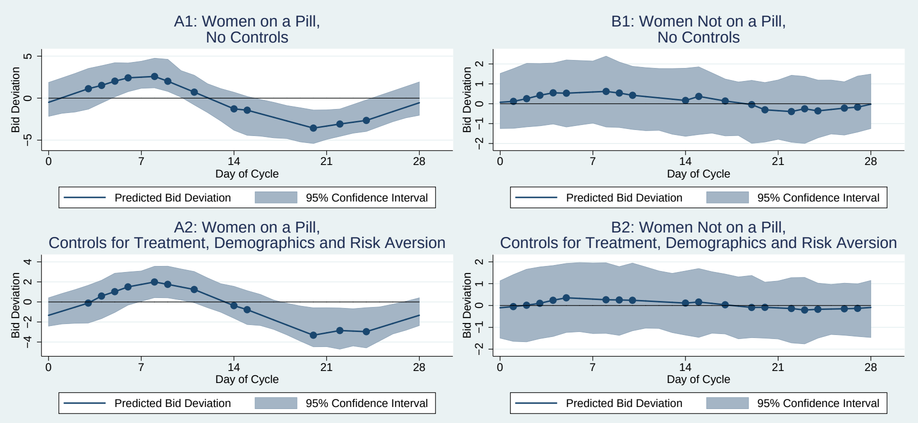
Effects of Menstrual Cycle on Bidding in FPA By Pill Usage, Deviation from Own Group Mean (Dataset 2)



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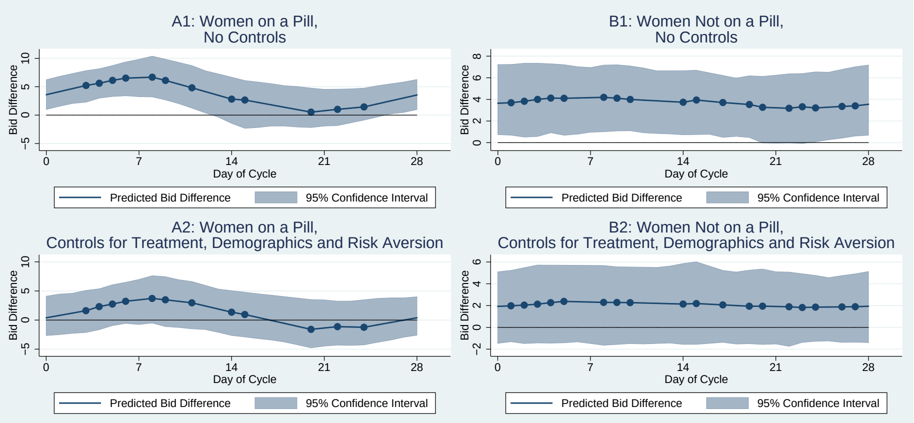

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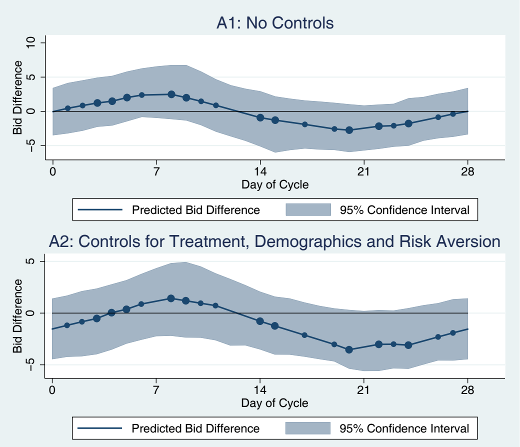
Effect of Pill Usage (Women on a Pill - Women Not on a Pill) on Bidding in FPA (Dataset 2)



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- Pill non-users have a flat bidding profile in FPA over the cycle, bidding more than men, but the difference can statistically be accounted for by differences in treatment, demographics and risk aversion

Conclusion (2)

- Pill users have a strong sinus-like pattern of bidding over the cycle, bidding significantly more than on average in the follicular phase and significantly less than on average in the luteal phase, even in the presence of controls; difference vis-a-vis men goes away when controls are included

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- More research is necessary on the impact of the menstrual cycle as well as on the impact of hormonal variation