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Abstract: We revisit the claims about the biological underpinnings of economic behavior by specifically exploring if observed gender differences in risk/time preferences can be explained by natural fluctuations in progesterone/estradiol levels during the menstrual cycle and by prenatal exposure to testosterone and estrogen levels. We find no effect of the menstrual cycle (and thereby, of associated fluctuations in progesterone and estradiol levels) or of the digit ratio on either risk or time preferences.

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I. Introduction

Decision making is a process of complex cognitive operations that are performed consciously and is influenced by personal as well as environmental variables. Gender is among the variables that affect cognitive operations and allows researchers to establish differences at the individual level. In fact, many aspects of economic decision making have been found to differ by gender. A common finding is that these differences are caused by differences in preferences (e.g., in risk preferences, social preferences) and reactions to competition (Croson & Gneezy, 2009). Yet the reasons why there are preference differences between genders are not well known. There are two possible mechanisms by which preferences can be shaped between genders: a) preferences are shaped by gender roles that are set by social and behavioral norms and b) preferences are shaped by biological and physiological differences of the two genders. We examine this latter mechanism given that the question of how much of a role nature plays in determining preferences is still considered an open one.

Behavioral economics has embraced the view that we can use the lens of biology to look at economic behavior. In this sense, Burd (2010) argues that much of our economic

behavior is the legacy of our adaptation to survival and the reproduction tasks faced by our ancestors in natural environments. The biological basis of preferences posits that preferences are naturally hardwired on males and females due to hormonal effects that take place prenatally. This view that preferences are innately programmed is supported by the early appearance of gender differences in young boys and girls. Both males and females start off with a brain that "looks" female. However, as Brizendine (2006, pp. 14) notes, "a huge testosterone surge beginning in the eighth week will turn this unisex brain into male by killing off some cells in the communication centers and growing more cells in the sex and aggression centers. If the testosterone surge doesn't happen, the female brain continues to grow unperturbed".

Scientific evidence on sex differences in the brain have been regularly emerging. These variations occur throughout the brain, in regions involved in language, memory, emotion, vision, hearing and navigation (Society for Women's Health Research, 2008, March 3). Physiologically understanding the relevant sex differences from the expression of steroid hormone receptors, to neuronal spines and to the entire brain systems (Becker et al., 2008) might be essential in explaining documented gender differences in economic decision making contexts. While the question of whether preferences of males and females have biological roots is important in the quest of understanding human nature and behavior, it may also have policy relevance given that gender differences have been observed in important domains including consumption, investment and in the labor market.

In contrast to the "nature" explanation discussed above, Gender Role theory posits that males and females learn behavior and attitudes from their peer environment and from the overall culture they grow up with. This theory considers non-physical gender differences to be a product of socialization. Thus, people internalize gender roles as they grow up and perform gendered identities and behaviours as either masculine or feminine. Gneezy et al. (2009) provide some evidence that peoples' preferences are shaped by the roles imposed by society.

Our aim in this study is to explore the role of nature (instead of nurture) in economic decision making. Despite its importance, this topic has received much less attention in the literature. No other known study has examined a direct link between hormonal levels and non-hypothetically elicited time preferences while the studies that examined hormones and risk preferences have not provided consistent results.

In this study, we examine the effect of prenatal exposure to testosterone and estrogen levels and natural fluctuations of two female hormones (progesterone and estradiol) on risk and time preferences using a conventional lab experiment. We also examine the permanent as well as the temporary differences in behavior. For example,

natural fluctuations in hormones during the menstrual cycle might induce short-run behavioural deviations. It is also possible that prenatal exposure to testosterone or estrogens can induce permanent traits.

We proxy prenatal exposure to testosterone and estrogen using a biological marker, the ratio of the length of the 2nd (index) finger to the 4th (ring) finger of the subjects' hand (2D:4D).[1] The natural fluctuations of progesterone and estradiol levels are proxied by self-reported menstrual cycle information from female subjects in our experiment.[2] Simply put, with the 2D:4D, we measure a trait that is prenatally determined due to testosterone or estrogen exposure. In terms of the menstrual cycle, we measure fluctuations of hormonal levels by categorizing females into one of the menstrual phases where levels of estradiol and progesterone are expected to be high or low.[3] Progesterone

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[1] A low digit ratio is thought to indicate prenatal exposure to high testosterone while a high digit ratio indicates prenatal exposure to high estrogen. Sexual dimorphism of the digit ratio was noted since the late 1800s and has been established in the early 1900s by George (1930). The idea that the digit ratio is a marker of prenatal sex hormones has first been speculated in Manning et al. (1998) which observed the dimorphism from at least 2 year old children. This was further developed in Manning (2002). Since then, several evidences have established that fetal sex hormone levels cause the sex difference in 2D:4D. For example, sex differences in the digit ratio are already observable at the end of the first trimester of fetal development (Malas *et al.*, 2006). In addition, right hand 2D:4D at the age of two years was found to be negatively correlated with the testosterone/estradiol ratio as measured by amniocentesis in the second trimester (Lutchmaya *et al.*, 2004).

[2] Self-reported measures of menstrual cycle information are likely to suffer from measurement errors. For example, in one study women on average overestimated their cycle length by 0.7 days (Jukic et al., 2008). However, another study assessed the cycle-phase reliability between self-reports and urine hormonal levels and found that they were in fair (but not excellent) agreement (Wojtys et al., 2002). In other studies self-reported menstrual cycle phases have been confirmed by salivary assay of sex-hormone levels (Ertman *et al.*, 2011; Slauterbeck *et al.*, 2002).

Admittedly, the ease of collection of self-reported menstrual cycle information has made it a popular data collection method for determining hormonal levels. Given that the relevant literature relies on reporting statistically significant associations from self-reported measures, reporting null results from this study is valuable in its own right. As one reviewer noted, reducing measurement errors from self-reported measures would entail following up females for a period of time after the experiment, asking them to report the onset of menstruation (e.g., in a diary). This is, however, likely to create sample attrition problems which then requires bigger samples to start with.

[3] During a menstrual cycle, a Gonadotropin-releasing hormone (GnRH) is released first by the hypothalamus. This causes a chemical reaction in the pituitary gland and stimulates the production of Follicle-stimulating hormone (FSH) and Luteinizing hormone (LH). Estrogen, progesterone, and testosterone are produced by the ovaries in reaction to stimulation by FSH and LH. Particular menstrual cycle phases may not uniquely identify just estradiol or just progesterone since other things happen at the same time. For instance, the rise in progesterone is involved in the elevation of body temperature following ovulation. Thus, as one reviewer notes, the correlation with hormones may be speculative and while the literature is more focused on discussing correlation with hormones, it may be more appropriate to talk about correlation with menstrual cycle phases.

and estradiol levels fluctuate only for female subjects. Hence, we will be able to tell whether females in their low hormonal level phases behave similarly to males or whether observed gender differences emerge when estradiol and progesterone are at their highest levels.

In general, our results suggest that neither natural fluctuation in estradiol and progesterone levels nor prenatal exposure to testosterone or estrogen has an effect on either risk or time preferences. We describe the experiment in the next section and then discuss the characteristics of our sample. Estimation procedures and results are discussed in section four. We then conclude and discuss our results within the context of the relevant literature in the final section.

II. Experimental procedures

To elicit risk and time preferences, we used the multiple price list procedure proposed by Holt and Laury (2002) for risk preferences and by Coller and Williams (1999) for discount rates. In the multiple price list procedure, subjects get to choose between a left and a right option in a series of ordered list of options. For the discount rate task, individuals choose between a principal at a sooner date and a larger amount of money at a future date. The list is ordered in increasing order of the amount of money. The implied discount rate for the first few pairs of choices is negligible, thus we would expect few subjects to choose the future payment. On the other hand, the implied discount rate for the last pairs of choices in this ordered list of choices is larger and we would expect more subjects to delay payment.

The intuition is similar for the risk preference task. Choices in this task are between lotteries; a safer and a more riskier lottery. Probabilities of lotteries are varied along the list so that the list is ordered in increasing order of expected payoffs. For the first few rows one option dominates the other in terms of expected payoff while for the last few rows this pattern reverses. Thus we would expect risk averse subjects to make more safer choices (i.e., choose the left option more often) while risk loving subjects to make more riskier choices (i.e., choose the right option more often).

The risk preference task is essential for our experimental design since it allows us to control for the curvature of the utility function. Precise inferences about discount rates can only be made once we identify the utility function. Andersen et al. (2008) showed that it is essential to have one experimental task for measuring the curvature of the utility

function, another task to identify the discount rate conditional on knowing the utility function, and then jointly estimate the structural model defined over the parameters of the utility function and discount rate[4]. We varied the order of risk and time preference tasks as in Andersen et al. (2011c) to account for order effects (Harrison et al., 2005).

To reassure subjects about the credibility of the payment from the time preferences task, we used a front end delay on the sooner payments.[5] This allowed us to equalize the credibility of future payments. In addition, payments were promised by a permanent faculty member of the university's department by means of a notarized post-dated check.[6]

A. Description of the experiment

The conventional lab experiment was conducted using the z-Tree software (Fischbacher, 2007). Subjects consisted of undergraduate students at the Agricultural University of Athens and were recruited using the ORSEE recruiting system (Greiner, 2004). During the recruitment, the nature of the experiment and the expected earnings

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[4] More recently, Andreoni and Sprenger (2012) extended the methodology proposed by Andersen et al. (2008) by developing a procedure they called the Convex Time Budget (CTB) method that does not require a separate risk aversion task to identify the curvature of the utility function. The procedure involves giving the subject 100 tokens to allocate between the sooner and later time period, and then varying the exchange rate between tokens and money for sooner or later amounts. In our case the exchange rate is the same for sooner and later amounts. We opted not to use this procedure since we were also interested in knowing the specific effects of key variables on risk preferences. See also Cheung (2012) for a quibble on Andreoni and Sprenger (2012).

[5] Front-end delay refers to delaying the sooner payment for the future. A treatment without a front end delay refers to the sooner payment being paid in the present.

[6] As one reviewer pointed out, at the time the experiment was run in Athens, Greece, there was some uncertainty about whether Greece would remain in the Euro area. However, any uncertainty would not arise due to whether the check could be cashed or not, but rather due to whether the check would be cashed in Euros or another currency. We believe that the latter is not an issue. Of course one could argue that the purchasing power of another currency would be less than the purchasing power of Euro therefore creating an uncertainty in itself. However, there is comparable uncertainty with inflation in post-dated checks that we cannot really control in time discounting tasks. This uncertainty is inherent in many decisions in the future: e.g., a promised check may never arrive, hyperinflation could render the money worthless or one might die before having the chance to spend the money. People weight these probabilities in their decision and in this respect our time preference task is not different from other time discounting tasks. Moreover, when we estimate a Rank-Dependent, expo-power utility specification with no covariates, we get an estimate of the discount rate of 0.171 with a 95% CI of [0.123, 0.219] which is comparable to many other studies in the literature (see, for example, Table 6 in Andersen *et al.*, 2011c). Thus, we believe that any uncertainty on whether people would really get their money from the banks did not really affect our estimates.

were not mentioned. However, subjects were told that they will be given the chance to make more money during the experiment.[7]

Subjects participated in sessions of group sizes that varied from 8 to 11 subjects per session. In total, 157 subjects participated in 16 sessions that were conducted between May and June 2011. Each session lasted about an hour and subjects were paid a fixed €15 participation fee. Subjects made on average 1.04€ (S.D.=4.394) in the risk preference task and 20.74€ (S.D.=64.787) in the time preference task. Subjects were given a power point presentation explaining the risk and time preferences tasks as well as printed copies of instructions. Every subject had time to read the instructions at their own pace.

B. The risk preferences phase

To elicit risk preferences, we used the multiple price list (MPL) design devised by Holt and Laury (2002). In this design each subject is presented with a choice between two lotteries, A or B as illustrated in Table 1. In the first row the subject is asked to make a choice between lottery A, which offers a 10% chance of receiving €2 and a 90% chance of receiving €1.6, and lottery B, which offers a 10% chance of receiving €3.85 and a 90% chance of receiving €0.1. The expected value of lottery A is €1.64 while for lottery B it is €0.475, which results in a difference of €1.17 between the expected values of the lotteries. Proceeding down the table to the last row, the expected values of the lotteries increase but increases much faster for lottery B.

For each row, a subject chooses A or B and one row is then randomly selected as binding for the payout. The last row is a simple test of whether subjects understood the instructions correctly.[8] In our experiments subjects undertook three risk aversion tasks: they made choices from Table 1 (the 1x table), a table where payoffs were scaled up by 6 (the 6x table) and by 14 (the 14x table).

Each choice was presented separately showing probabilities and prizes (as in Andersen *et al.*, 2011c)[9]. The order of appearance of the tables for each subject was completely randomized to avoid order effects (Harrison et al., 2005). The 6x and 14x tables served as

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[7] Stochastic fees have been shown to be able to generate samples that are less risk averse than would otherwise have been observed (Harrison *et al.*, 2009).

[8] 19 out of 157 subjects failed to pass this test concerning comprehension of lotteries and were dismissed from our sample.

[9] For half of the sessions probabilities where displayed using pie charts, while for the other half probabilities where only shown as text. A dummy variable controls for this variation in the experimental design.

an elicitation vehicle of risk when larger payoffs are involved.[10] Thus, to infer risk preferences, subjects were asked to provide 30 binary choices from the risk preference task. Example screens are displayed in the appendix. Financial constraints precluded us from paying every single subject in each session; subjects were given a 10% chance of having their choices realized.

C. The time preferences phase

The experimental design for measuring discount rates is based on the experiments of Coller and Williams (1999), Harrison, Lau, and Williams (2002) and Andersen et al. (2008). Subjects are confronted with payoff tables similar to Table 2 and they made choices from three tables with different time horizons: the 4-month time horizon table, the 16-month time horizon table and the 32-month time horizon table.

In Table 2, option A offers 250€ in 6 months and option B offers 250€ +*x* € in 38 months, where *x* ranged from annual interests rates of 5% to 50% on the principal of 250€, compounded semi-annualy to be consistent with national banking practices on savings accounts. The table also includes the annual and annual effective interest rates to facilitate comparisons between lab and field investments (Andersen et al., 2008).

The tasks provided two future income options instead of one instant and one future option. This front-end delay on the early payment has two advantages: it holds the transaction costs of future options constant (see Coller & Williams, 1999 for a discussion) and it avoids the passion for the present that decision makers exhibit when offered monetary amounts today or in the future. It also allows us to equalize the credibility of future payments.

As previously noted, payments were promised by a permanent faculty member of the university's department by means of a notarized post-dated check. A national bank served as the third party guarantor as well.

We varied between subjects the front end delay (3 weeks vs. 6 weeks) and the principal of the sooner option (100€ vs. 250€). Table 2 displays a sample payoff matrix table with a 32 month time horizon, a 250€ principal and a front end delay of 6 months.

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[10] As Drichoutis and Lusk (2012b) note, since the H&L task entails choices made over only four dollar amounts, the task reveals little information about the curvature of the utility function. Thus, it is necessary to scale up the payoffs to allow for a wider range of dollar amounts, providing more information on the shape of the utility function.

At the end of the experiment only one choice was randomly drawn as binding. Financial constraints precluded us from paying every single subject in each session; subjects were given a 10% chance of having their choices realized.[11]

D. The post-experiment phase

At the end of each session subjects completed a questionnaire asking for basic demographic information. Female participants were asked about menstrual cycle information as displayed in the appendix. They were told that this is an important part of the survey and were asked to take all the time they need to answer the questions accurately. The questions were adopted from Pearson and Schipper (2013) and Chen et al. (2013).

We also measured the length of the index finger (2^{nd} digit) and ring finger (4^{th} digit) of the right hand of the respondents using a ruler. Fingers were measured from the crease where the finger joins the hand to the tip of the finger. Measures were taken separately by two persons: one of the authors and a research assistant. Both persons were trained in measuring the 2^{nd} and 4^{th} digit fingers before the conduct of the experiments. We use the ratio of 2D average and 4D average to form the digit ratio. None of the subjects refused the measurement of the fingers.[12]

III. Sample

The sample consists of 157 students of which 19 had to be dropped since they failed to pass a comprehension of lotteries test in the risk preference task, as described in a

[11] Andersen et al. (2011c) varied the probability of payment for the discounting task from 10% to 100% and found no significant differences.

[12] Although many of the studies on digit ratios in the literature scan individuals' palms and then measure distances from pictures, this was considered very invasive and would have raised privacy issues with student bodies/organizations in our university. It could also involve an accurate imprint of subjects' fingerprints. Fingerprints are considered private data in the country; even the national police do not keep a record of non-active fingerprints.

previous section.[13] Of the remaining 138 subjects, 10 indicated using oral contraceptives.[14] None of the female subjects was pregnant.

Table 3 presents the distribution across menstrual cycle phases before and after sample attrition. Although we use the sample of 138 students for estimating risk and time preferences, it is useful to look at the distribution of the menstrual phases of the sample of female students before we consider dropping some of them from the sample. The distribution shown in Table 3 assumes that all females in our sample follow a cycle of 29-days. In contrast to common beliefs, the average duration of a cycle is 29 days (Chiazze *et al.*, 1968; Fehring *et al.*, 2006) and not 28 days as previous studies have assumed. Average duration of a cycle for females younger than 35 is 29 days but this drops to an average of 28 days for females older than 35 years old (Fehring *et al.*, 2006). Thus, considering the age of our sample of students, a 29-day cycle is more appropriate to assume.

The menstrual cycle can be divided into several different phases. The follicular phase (days 1 to 16) can be further divided into the menstrual phase (days 1 to 5)[15], the

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[13] Out of the 19 persons dropped for choosing the dominated option in the risk preference task, 15 were female. Given that there were more female participants than male participants in our experiment (58.6% vs. 41.4%), the dropped observations correspond to 6.15% of males and 16.30% of females. Fisher's exact test of whether taking the dominated option differs between males and females does not reject the null at the 5% level (p-value=0.080).

[14] In our sample, 12 out of 92 females (13.04%) use some kind of hormonal contraceptive. This largely depicts the picture on preventive policies in Greece. Greece has one of the highest rates of abortions in Europe (one in ten women in the 16-24 age group) which indicates that women continue to rely on abortion to control births (Ioannidi-Kapolou, 2004). According to a 2001 national household survey only about 5% of women take hormonal pills (Tountas et al., 2004). The 13% rate in our study seems like an improvement as compared to the 2001 figure.

A second issue pointed out by a reviewer is whether the "pill takers" group can actually be grouped together in our analysis. First, given the small size of the group and given that the results hardly change when including or excluding pill takers in our estimations, we believe that for this particular dataset we can safely group together the pill takers. Second, in the Greek market, popular hormonal contraceptives form a rather homogeneous group with few exceptions. Table A1 in the Appendix shows that for 7 out of 9 pills a 21-day intake is followed by a 7-day break while another one is very close to that particular intake period (Gracial; 22-day intake, 6-day break). The only outlier is a relatively new quadriphasic pill (Qlaira) which involves a 26-day intake period. To confirm which brand our subjects use, we asked, through a web survey in December 2012, the 12 female subjects to recall which pill they were using at the time of the experiment. The distribution of responses was as follows: Yasmin (1 subject), Yasminelle (10 subjects) and Mercilon (1 subject). These pills release about the same doses of estrogen (ethinylestradiol) with a 7-day break following a 21-day intake period. Thus we can safely assume that the pill takers group forms a relatively homogeneous group in our study. In addition, none of the results changes when we exclude pill takers from the estimations.

[15] Duration for the follicular phase and the menstrual phase are average durations reported by several studies reviewed in Table 2 in Fehring et al. (2006).

proliferative phase (days 6 to 14) and the ovulatory phase (days 15 to 16)[16]. The secretory phase lasts about 13 days (days 17 to 29) on average (see Fehring *et al.*, 2006) and can be divided into the luteal phase (days 17 to 24) and the premenstrual phase (days 25 to 29)[17]. Females that use hormonal contraceptives do not have a natural menstrual cycle since their circulating levels of hormones may differ from naturally cycling women; hence they are treated as a separate group.

Table 3 also indicates the expected number of subjects if we assume that the probability of participation does not vary over the cycle (pill takers are excluded from this calculation)[18]. A χ^2 goodness of fit test allows us to test whether the observed proportions for the observed distribution differ from hypothesized proportions. We find that we cannot reject equality of distributions for the full sample (χ^2=4.7, p-value=0.320) and even for the sample after attrition (χ^2=4.06, p-value=0.398). Thus selective participation in the experiment due to menstruating female subjects staying away is not a significant problem with our data. Dropping observations does not also significantly affect the observed distribution of menstrual phases.

The assumption of a 29-day cycle is a restrictive one since subjects in our sample exhibit significant variation in cycle length. The average duration in our sample is 28.7 days with a standard deviation of 2.43. However, we can use the collected cycle length information to construct individualized menstrual cycle phases as in Pearson and Schipper (2013). Since the length of the secretory phase is relatively fixed (it usually exhibits less variation as compared to the proliferative phase as shown in Fehring et al. (2006)), we consider adjusting the length of the proliferative phase only. The procedure is similar to Pearson and Schipper (2013) and more details are provided in the Appendix.

Table 3 exhibits the distribution across adjusted menstrual cycle phases which we use for all further analysis. Note that this distribution is not in sharp contrast with unadjusted menstrual cycle phases. In fact, Pearson and Schipper (2013) found that their results remain robust when using adjusted phases as controls.

As previously discussed, the fingers for the digit ratios were measured by two researchers. We use the ratio of the average 2D and average 4D in the analysis. To examine the effect of the digit ratio on risk and time preferences, we first normalized the

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[16] Duration for the proliferative phase is derived as residual of the follicular phase after subtracting the menstrual and ovulatory phases. The ovulatory phase is usually taken to last 2-days which corresponds to the high fertility window in Figure 1 in Fehring et al. (2006).

[17] The secretory phase is often referred to as the luteal phase and includes the premenstrual phase.

[18] For example, for the menstrual phase there should be [5 days x (N female subjects – n Pill takers)]/29 days cycle length ≈ 14 subjects.

digit ratios into z-scores by subtracting off the sample mean and dividing by the standard deviation. With this transformation, the 2D:4D coefficient estimates reveal the effect of a one-standard-deviation increase in the digit ratio on risk and time preferences.

Figure 2 shows the kernel densities of the distribution of digit ratios by sex. It is obvious that the distribution for males is shifted to the left, implying lower digit ratios than females. A t-test confirms Figure 2. Females have a mean digit ratio of 1.025 while males have a mean digit ratio of 1.002. The difference is statistically significant (t=2.598, p-value=0.010).

IV. Estimation and results

Each subject in our experiment responded to 60 binary tasks (30 for the risk preference tasks and 30 for the time preference tasks). Dropping data from subjects who chose lottery A over lottery B in the last row of Table 1 resulted in a sample size of 138 subjects, with 4140 risk aversion choices and 4140 discount rate choices. Figures A1 to A18 in the Appendix show the proportion of choices for each decision in the risk or time preference tasks by menstrual phase, progesterone/estradiol level, and digit ratio group.

A. OLS regressions

A simple way to look for some patterns in our data is to regress the number of A choices (i.e., choosing the left option in each choice) on our variables of interest. This comes with some caveats. First, since we did not impose monotonicity on choices (i.e., constrain subjects to switch only once across a given table), multiple switching occurred. While our structural econometric methods (presented momentarily) can accommodate this behavior, we have to drop these observations in an OLS regression. Second, one has to essentially estimate a separate regression for each task unless one is willing to sacrifice a lot of observations in favor of a model that uses only the observations that overlap.

In Table 4 we show OLS regression results where we regress the number of A choices on the treatment variables and a male dummy.[19] The first three columns show results for each of the risk preference tasks, while the last three columns show results from the three time preference tasks. We avoid pooling the data together because this would dramatically reduce the sample size. As shown, gender differences are apparent for risk preferences while no effect appears for time preferences. In particular, males switch

[19] The dummy variables in this and subsequent tables signify the treatments consistent with their names. *Visual* is a dummy for the treatment where probabilities were visualized using pie charts, *Task Order* signifies the order of the risk and time preferences tasks (1 if risk preference task was first), FED is a dummy for the front end delay (1 if FED was 6 weeks) and *Principal* is a dummy for the amount in the sooner option in the time preference task (1 if the sooner option is 250€).

earlier to choice B in the x1 and x9 risk preference task (which effectively establishes males as less risk averse). Note that the principal is statistically significant for all time preference tasks signaling that a higher principal causes subjects to switch earlier to choice B.

In order to explore the role of menstrual cycle on risk and time preferences, we use dummies that indicate one of the five phases of the cycle of our female subjects. The omitted variable is males, so that all comparisons are with respect to male subjects. Table 5 shows results with and without pill takers for each task separately (models (1) to (6) refer to the risk preference tasks while models (7) to (12) refer to the time preference tasks). Results are fairly robust to the inclusion/exclusion of pill takers. Some statistically significant results emerge for the x1 risk preference task. However, these do not carry over to the x9 and x14 tasks. In particular, it looks as if females in the luteal and proliferative phase switch later to choice B as compared to male subjects (indicating higher risk aversion). In addition, females in the ovulatory phase switch earlier to choice B in the 16 week interval time preference task indicating increased patience. However, the effect does not carry over to the other time preference tasks. The principal is statistically significant across all week intervals.

Another way to analyze the data with menstrual cycle information (also taken by Buser, 2012) is to divide female subjects into high-estradiol and low-estradiol, as well as, high-progesterone and low-progesterone subjects. The high estradiol phase corresponds to cycle phases two and four while the high progesterone phase coincides with the fourth phase. Table 6 shows the parameter estimates when we replaced the menstrual cycle dummies of Table 5 with dummies that indicate high progesterone/estradiol levels. As shown in Table 6, none of the relevant variables is consistently statistically significant across the tasks.

As mentioned previously, we use the digit ratio to explore the role of prenatal exposure to testosterone and estrogen on risk and time preferences. Recent work on the relationship between testosterone and risk-taking suggests that the effect can be nonlinear (Garbarino et al., 2011; Sapienza et al., 2009). One way to model this non-linearity is to add a squared term of the digit ratio as a covariate; a second approach is to divide males and females into quartiles. Thus we also created gender specific dummies based on the 25th and 75th quartile. Subjects on the 25th quartile of their same gender distribution were categorized into the low digit ratio group; subjects above the 75th quartile of their same gender distribution were classified into the high digit ratio group. The remaining subjects (i.e., between the 25th and 75th quartile) formed the medium digit ratio group. As shown in Table 7, digit ratios do not seem to systematically affect risk or time preferences. The largest effect we observe is for the 4 week interval time preference task, where subjects with medium or high digit ratios switch earlier to choice B as compared to low digit ratio subjects. The effect is absent for the 16 and 32 week interval.

B. Joint estimation of risk and time preferences

As noted before, the OLS approach is rather restrictive in nature since we cannot accommodate behavioral errors that may emerge during the choice process (e.g., the multiple switching behavior observed in our data). We address this issue by adopting a joint estimation framework of risk and time preferences. Our structural approach follows closely the framework of Andersen et al. (2008), so we will only repeat the basic information here. Andersen et al. (2008) discussed in detail how to put parametric structure on the identification of risk and time preferences, the theoretical issues involved, and the statistical specification.

Let the utility function be the constant relative risk aversion (CRRA) specification:

$$U(M) = \frac{M^{1-r}}{1-r} \tag{1}$$

for $r \neq 1$, where r is the CRRA coefficient. In (1), $r=0$ denotes risk neutral behavior, $r>0$ denotes risk aversion behavior and $r<0$ denotes risk loving behavior.

In addition, if we assume that Expected Utility Theory (EUT) holds for the choices over risky alternatives and that discounting is exponential, then the subject is indifferent between two income options M_t and $M_{t+\tau}$ if and only if:

$$U(M_t) = \frac{1}{(1+\delta)^{\tau}} U(M_{t+\tau}) \tag{2}$$

where $U(M_t)$ is the utility of monetary outcome M_t for delivery at time t, δ is the discount rate, τ is the horizon for delivery of the later monetary outcome at time $t+\tau$, and the utility function is separable and stationary over time[20]. δ is the discount rate that equalizes the present value of the two monetary outcomes in the indifference condition (2).

The binary choices of the subjects in the risk preference tasks can be explained by different CRRA coefficients. For example, a subject that made four safe choices (i.e., choosing option A) and then switched to option B would have revealed a CRRA interval of -0.15 to 0.40. The intervals are reported in Table 1. Similarly, the binary choices in the time preference tasks can be explained by different discount rates. A subject that chose

[20] The assumption that the utility function is additively separable implicitly imposes intertemporal risk neutrality. For a relaxation of this assumption see Andersen et al. (2011a). Andersen et al. (2011a) find that relaxing the assumption of intertemporal risk neutrality leads to comparable results with their earlier results in Andersen et al. (2008) that assumed intertemporal risk neutrality. In addition, since our primary purpose is to check whether biological indices have an effect on risk and time preferences, imposing or relaxing the assumption of intertemporal risk neutrality would make little difference when comparing different groups of people.

300€ in 1 month would have revealed a discount rate higher than $(x/300)\cdot 100\%$; otherwise she would have revealed an annual discount rate of $(x/300)\cdot 100\%$ or less.

Andersen et al. (2008) explicitly write the likelihood function for the choices that subjects make in these tasks and jointly estimate the risk parameter *r* and the discount rate δ. The contribution to the overall likelihood from the risk aversion responses can be written for each lottery *i* as:

$$EU_i = \sum_{j=1,2} \left(p\left(M_j\right) \cdot U\left(M_j\right) \right) \qquad (3)$$

where $p\left(M_j\right)$ are the probabilities for each outcome M_j that are induced by the experimenter (i.e., columns 1, 3, 5 and 7 in Table 1). To specify the likelihoods conditional on the model, a stochastic specification from Holt and Laury (2002) is used. The expected utility (EU) for each lottery pair is calculated for the candidate estimate of *r* and the ratio:

$$\nabla EU = \frac{\exp\left(EU_B/\mu\right)}{\exp\left(EU_A/\mu\right) + \exp\left(EU_B/\mu\right)} \qquad (4)$$

is then calculated where EU_A and EU_B refer to options A and B respectively, and μ is a structural noise parameter used to allow some errors. The index in (4) is linked to observed choices by specifying that the option B is chosen when $\nabla EU > 1/2$. Wilcox (2011) proposed the "contextual error" specification whereas instead of the latent index in (4), we have:

$$\nabla EU = \frac{\exp\left(EU_B/c/\mu\right)}{\exp\left(EU_A/c/\mu\right) + \exp\left(EU_B/c/\mu\right)} \qquad (5)$$

In (5) *c* is a new normalizing term for each lottery pair A and B. The normalizing term is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair. Since the value of *c* varies between lottery choices, it is said to be "contextual." Contextual utility basically accounts for lottery specific heteroskedasticity. Drichoutis and Lusk (2012a) have shown that different error specifications, with and without accounting for contextual utility, produce strikingly different results in models of individual decision making under risk. They also show that certain model fit criteria can be used to identify the model that best fits the data. In our case, the Luce error story that accounts for contextual utility provides the best model fit with our data.

The conditional log-likelihood can then be written as:

$$\ln L^{RA}\left(r, \mu; y, \mathbf{X}\right) = \sum_i \left(\left(\ln\left(\nabla EU\right) \mid y_i = 1 \right) + \left(\ln\left(1 - \nabla EU\right) \mid y_i = -1 \right) \right) \qquad (6)$$

Where y_i=1(-1) denotes the choice of the option B (A) lottery in the risk preference task *i*. Subjects were allowed to express indifference between choices and were told that if that choice was selected to be played out, the computer would randomly choose one of the two options for them and that both choices had equal chances of being selected.[21] Thus the likelihood for these choices can be modified such that choices imply a 50/50 mixture of the likelihood of choosing either lottery:

$$\ln L^{RA}\left(r,\mu;y,\mathbf{X}\right)=\sum_i\left(\begin{array}{l}\left(\ln\left(\nabla EU\right)\mid y_i=1\right)+\left(\ln\left(1-\nabla EU\right)\mid y_i=-1\right)\\+\left(\frac{1}{2}\ln\left(\nabla EU\right)+\frac{1}{2}\ln\left(1-\nabla EU\right)\mid y_i=0\right)\end{array}\right) \tag{7}$$

The conditional log-likelihood for the time preference task can be written in a similar manner if we write the discounted utility of each option as:

$$PV_A=\frac{M_A^{1-r}}{1-r}\qquad\text{and}\qquad PV_B=\frac{1}{\left(1+\delta\right)^{\tau}}\frac{M_B^{1-r}}{1-r} \tag{8}$$

and the index of the present values as:

$$\nabla PV=\frac{\exp\left(PV_B/\nu\right)}{\exp\left(PV_A/\nu\right)+\exp\left(PV_B/\nu\right)} \tag{9}$$

where *v* is a noise parameter for the discount rate tasks[22]. The log-likelihood will then be:

$$\ln L^{DR}\left(r,\delta,\nu;y,\mathbf{X}\right)=\sum_i\left(\begin{array}{l}\left(\ln\left(\nabla PV\right)\mid y_i=1\right)+\left(\ln\left(1-\nabla PV\right)\mid y_i=-1\right)\\+\left(\frac{1}{2}\ln\left(\nabla PV\right)+\frac{1}{2}\ln\left(1-\nabla PV\right)\mid y_i=0\right)\end{array}\right) \tag{10}$$

and the joint likelihood will be:

$$\ln L\left(r,\delta,\mu,\nu;y,\mathbf{X}\right)=\ln L^{RA}\left(r,\mu;y,\mathbf{X}\right)+\ln L^{DR}\left(r,\delta,\nu;y,\mathbf{X}\right) \tag{11}$$

Each parameter in equation (11) can be allowed to be a linear function of treatment effects and/or demographic variables. Equation (11) can be maximized using

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[21] Although we allowed indifference between choices in the risk and time preferences tasks, it is still possible that subjects displayed multiple switches between options. We did not impose monotonicity on choices or provide warnings when monotonicity was violated. Although such a procedure could be implemented, it is unclear if it is superior to simply observing how people behave when unconstrained. We do not consider multiple switching as much of an issue either. Data displaying local intransitivity are modeled as they are, resulting in the standard error on the utility functions being a little bigger than if they had been transitive. In addition, when we pool these data together with data from subjects that do not display intransitivity, it should not affect estimates too much, while still recognizing that this is an imprecise estimate for that particular subject. According to Fisher's exact tests, we find no evidence that number of multiple switching differs among males and females as well.

[22] Contextual utility correction does not need to be applied for these choices since these are over deterministic outcomes.

standard numerical methods. We used the routines made available as a supplemental material in Andersen et al. (2008) with appropriate modifications. For a more thorough and pedagogical treatise on maximum likelihood estimation of utility functions, see Appendix F in Harrison and Rutstrom (2008). The statistical specification also takes into account the multiple responses given by the same subject and allows for correlation between responses of the same subject (clustered standard errors). Standard errors were computed using the delta method.

There are several extensions to the above specifications that we consider. For example the exponential discounting model is just one of the discounting functions out of a menagerie of discounting functions (Andersen *et al.*, 2011c). We can test for the robustness of the results by considering an alternative discounting function assumed by hyperbolic discounting models[23]. Others have found that results are generally robust when considering the choice between an exponential discounting model and hyperbolic discounting (e.g., Andersen *et al.*, 2008).

When considering a hyperbolic discounting function, one would need to replace (8) with:

$$PV_A = \frac{M_A^{1-r}}{1-r} \qquad \text{and} \qquad PV_B = \frac{1}{(1+k\tau)}\frac{M_B^{1-r}}{1-r} \tag{12}$$

for $k > 0$.

In addition, the specifications above have only assumed Expected Utility for risk. Since the Allais paradoxes (Allais, 1953) for EUT and the Nobel-prize winning work of Kahneman and Tversky (1979), we know that EUT often fails and that one must account for probability weighting especially when using smaller scale payoffs. Rank Dependent Utility (Quiggin, 1982) extends the EUT model by allowing for decision weights on lottery outcomes. To calculate decision weights under RDU one replaces expected utility defined by (3) with:

$$EU_i = \sum_{j=1,2}\left(w\left(p\left(M_j\right)\right)\cdot U\left(M_j\right)\right) = \sum_{j=1,2}\left(w_j \cdot U\left(M_j\right)\right) \tag{13}$$

where $w_2 = w(p_2 + p_1) - w(p_1) = 1 - w(p_1)$ and $w_1 = w(p_1)$, with outcomes ranked from worst (outcome 2) to best (outcome 1) and $w(\cdot)$ is some weighting function. We adopt the weighting function proposed by Tversky and Kahneman (1992) which has been extensively used in the literature and assumes weights of the form:

$$w(p) = p^{\gamma} \Big/ \left[p^{\gamma} + (1-p)^{\gamma}\right]^{1/\gamma} \tag{14}$$

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[23] As discussed in Andersen et al. (2008), the use of the quasi-hyperbolic specification is not possible due to the existence of a front end delay in our tasks.

In (14), when $\gamma = 1$, it implies that $w(p)=p$ and this serves as a formal test of the hypothesis of no probability weighting.

Finally, the assumption of a CRRA function, implicitly assumes that risk aversion is constant across different prize domains. We can relax this assumption by adapting a more flexible form, the hybrid expo-power function of Saha (1993). The expo-power function can be defined as $u(M) = \left(1 - \exp\left(-aM^{1-r}\right)\right)/a$, where M is income and α and r are parameters to be estimated. Relative risk aversion (RRA) is then $r + a(1-r)M^{1-r}$, so RRA varies with income if $a \neq 0$. The expo-power function nests CRRA (as $\alpha \to 0$).

C. Results of joint estimation

Table 8 shows basic estimates when assuming a CRRA utility function and EUT under both exponential and hyperbolic discounting (models (1) and (2) respectively). Gender differences emerge (statistically significant at the 10% level) for risk and time preferences. Males have higher discount rates and are less risk averse than females. In addition, the principal has a direct effect on discount rates. This is consistent with the magnitude effect (Andersen *et al.*, 2011b) wherein higher discount rates are inferred from choices made with lower principals.[24] Results are virtually identical when assuming either hyperbolic or exponential discounting. Hence, the choice of the discounting function seems not relevant, at least with our data. To simplify the estimations that follow, we only use the exponential discounting model.

The third column in Table 8 (model (3)) generalizes model (1) by allowing for RDU and an expo-power function under exponential discounting. We can directly test whether RDU and/or the expo-power function is appropriate by testing whether $\gamma=1$ and/or $\alpha=0$. Since all the covariates used are dummies we need to test for several linear combinations of the coefficients. For example, we can test for $\alpha_0 + \alpha_1 Gender + a_2 Visual = 0$ or for $\alpha_0 + a_2 Visual + a_3 TaskOrder = 0$. All of these tests reject the null, thus rendering support for an expo-power function. In addition, the corresponding tests for $\gamma=1$ reject the null in all cases as well, thus rendering support for RDU. Joint significance tests for $\gamma=1$ and $\alpha=0$ also reject the null.

Table 9 shows parameter estimates under RDU, expo-power and exponential discounting for three models that try to capture the effect of menstrual cycle. Models (1) and (2) use menstrual cycle dummies (excluding and including pill takers respectively)

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[24] Andersen et al. (2011b) note that with some exceptions, all evidence of the magnitude effect occur in samples of college-age students (see Andersen et al. (2011c) for an exception). They observe only a small statistically significant magnitude effect in the discounting behavior of their sample of adult Danes.

while model (3) uses progesterone and estradiol dummies. Wald tests indicate that we reject the null that α=0 or the null that γ=1 or the null that α=0 and γ=1 for all three models. Thus, there is support for RDU and expo-power.

As evident, the only significant variable is the luteal phase dummy for the α parameter. However, since we might be more interested on the effect of this variable on RRA, one needs to evaluate marginal changes of the respective variables on the expression $r+a(1-r)M^{1-r}$.[25] Table A2 in the appendix shows that none of these marginal changes for each of the menstrual cycle dummies is statistically different from zero.

Figure 3 illustrates RRA predictions for the range of prizes given at the experiment using model (3) of Table 9. RRA increases across the prize domain. However, predictions for males and female subjects irrespective of their estradiol/progesterone level are similar. All subjects exhibit higher risk aversion at higher incomes.

Similarly, null results emerge in Table 10 when using the same digit ratio variables we used in the OLS regressions. None of the variables is statistically significant. Wald tests support the use of an expo-power utility function and RDU. Table A2 in the appendix shows that none of the marginal changes associated with the digit ratio variables is statistically different from zero. Figure 4 illustrates RRA predictions for the range of prizes given at the experiment using model (2) of Table 10. There is no indication that RRA differs among males or females classified under different digit ratio groups. Thus we conclude that there is no effect of the digit ratio on elicited discount rates and risk preferences.

D. Multiple test procedures

Given the number of parameters estimated in each of the expo-power/RDU specifications and some scattered significant results, one may wonder about the probability of not observing at least one statistically significant difference. This probability tends to fall with number of parameters, even if all null hypotheses are true. Multiple test procedures can then be used that calculate a corrected overall critical *p*-value such that an individual null hypothesis is considered to be acceptable only if its corresponding *p*-value is greater than the corrected overall critical *p*-value. Several

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[25] For a dummy variable this would simply correspond in calculating the expression $\Delta RRA=RRA_1-RRA_0$ where RRA_1 is simply the RRA value for when the respective dummy takes the value of 1 and RRA_0 is the RRA value for when the respective dummy takes the value of zero. For a continuous covariate x the appropriate expression is given by: $\frac{\partial RRA}{\partial x}=\frac{\partial r}{\partial x}\left[1-alfaM^{1-r}\left(1+(1-r)^2M\right)\right]+\frac{\partial a}{\partial x}(1-r)M^{1-r}$.

methods can be used to calculate the corrected *p*-value (Newson and the ALSPAC study team (2003) offer an exposition and Stata implementation). We used the Bonferroni method although results remain unchanged with alternative methods.

Table A3 in the Appendix shows the results of this multiple test procedure applied to each of the models in Tables 9 and 11. As shown, most corresponding *p*-values are greater than the overall critical *p*-value which indicates that the null hypothesis of no effect for the variables of interest is credible. Thus, we safely conclude that neither the menstrual cycle variables nor the digit ratio variables have any effect on estimated discount rates or any of the risk parameters. The only null hypothesis that is not credible is the one associated with the principal variable. This supports the result that the magnitude effect we observe is credible.

V. Discussion and Conclusions

The issue of whether preferences of males and females have biological roots is relevant given that gender differences have been observed in important domains of economic decision making including consumption, investment and in the labor market. Knowledge about the possible biological underpinnings of people's preferences and how these factors influence differences in behavior between genders can be used to further illuminate the debate on gender-specific market outcomes and provide some important insights into the biology of people's risk and time preferences. This is important in our quest of understanding human nature as well. The findings however of the studies that examined the relationship between hormones and risk preferences have been mixed and no other known study has really examined the direct link between hormonal levels and non-hypothetically elicited time preferences. Hence, given the generally scant literature but increasing interest in this area of research, we attempted to examine the biological roots of people's risk and time preferences by exploring if observed gender differences can be explained by (a) natural fluctuations in progesterone and estradiol levels during the menstrual cycle and by (b) prenatal exposure to testosterone or estrogen levels.

We elicited risk and time preferences using two popular experimental tasks. After fitting simple OLS regression models, we jointly estimated the parameters of interest using a structural econometrics model. First we find that observed differences in aggregate gender effects can be sensitive to the functional forms assumed. Indeed, when we used a more flexible functional form for the utility (the expo-power) function and allowed for probability weighting for the risk choices (rank-dependent utility), the gender differences in risk and time preferences, as captured by a gender dummy, disappeared.

The second thing our results suggest is that none of the variables of interest robustly affects risk or time preferences. While we do observe some scattered statistically significant results, we find that none of the results stands this scrutiny when we employ multiple testing procedures.

Our (null) results for time discounting contrast with two studies from the literature (Millet & Dewitte, 2008; Takahashi *et al.*, 2012) that find statistically significant effects. However, both studies were hypothetical and the evidence on hypothetical biases in hypothetical surveys is overwhelming (see for example footnote 35 in Andersen et al., 2011c and citations therein).

Results from the risk preference literature are rather mixed. On the one hand, studies such as Schipper (2011) found no significant correlation between risk aversion and the menstrual cycle or the digit ratio. Similarly, Apicella *et al.* (2008) and Sapienza *et al.* (2009) did not find a statistically significant relation with the digit ratio. In contrast, other studies find significant correlations with the digit ratio. For example, results from Garbarino et al. (2011), Brañas-Garza and Rustichini (2011) and Dreber and Hoffman (2007) imply that lower digit ratios are associated with higher risk taking.[26] Therefore, our study reinforces the strand of results indicating a null finding.[27]

We posit that our null results are not due to sample size since our sample size is comparable to other studies that find statistically significant results. For example, Garbarino et al. (2011) use a sample size of 152, Brañas-Garza and Rustichini (2011) analyze data from 188 subjects and Dreber and Hoffman (2007) have 147 subjects in their sample. Although Apicella et al. (2008) reports results from a smaller sample size (98 subjects) as compared to the rest of the studies, Schipper (2011) collected data from as much as 208 subjects, the largest sample size from the above cited studies. Yet, he fails to reject the null as well.

On the methodological front, while we have been very careful in collecting hormonal measures based on menstrual cycle information and digit ratios, it is still possible that these measures could suffer measurement errors. While there are other ways to more accurately measure hormones such as with blood or saliva samples, these procedures have their own problems as well. For example, blood draws may scare away risk-averse people or could create expectations that affect hormonal levels. Moreover, while

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[26] Since the digit ratio is sexual dimorphic and could vary between ethnicities, we should note that Dreber and Hoffman (2007) used a racially homogeneous sample while Apicella *et al.* (2008) and Sapienza *et al.* (2009) did not. In addition, Apicella *et al.* (2008) report results from an all-male sample while Sapienza *et al.* (2009) do find a marginally statistically significant effect for the female sub-sample alone.

[27] Two more studies (Coates *et al.*, 2009 ; Coates & Page, 2009) report associations between digit ratios and performance of professional male traders from a trade floor in London but risk is only implicitly assumed from traders' performance and not directly measured.

hormones can be more accurately measured in blood than in saliva, steroid hormones in blood are not necessarily free to act on receptors. In addition, hormones such as LH or the FSH cannot be measured in saliva but in blood. Even methods that exogenously vary hormones (e.g., testosterone administration) may not be feasible in many situations, not to mention the sensitivity and challenge of getting institutional approvals for such procedures.

Our study adds to the scant literature of null results and contributes against the positive-results bias. As the literature piles up, meta-analysis methods can help to contrast and combine results from different studies, in the hope of identifying patterns and sources of disagreement that will advance the literature on the biology of risk and time preferences.

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Table 1. Sample payoff matrix in the risk aversion experiments

Lottery A				Lottery B				EV^A (€)	EV^B (€)	Difference (€)	Open CRRA interval if subject switches to Lottery B	
p	€	*p*	€	*p*	€	*p*	€					
0.1	2	0.9	1.6	0.1	3.85	0.9	0.1	1.640	0.475	1.17	-∞	-1.71
0.2	2	0.8	1.6	0.2	3.85	0.8	0.1	1.680	0.850	0.83	-1.71	-0.95
0.3	2	0.7	1.6	0.3	3.85	0.7	0.1	1.720	1.225	0.50	-0.95	-0.49
0.4	2	0.6	1.6	0.4	3.85	0.6	0.1	1.760	1.600	0.16	-0.49	-0.15
0.5	2	0.5	1.6	0.5	3.85	0.5	0.1	1.800	1.975	-0.18	-0.15	0.14
0.6	2	0.4	1.6	0.6	3.85	0.4	0.1	1.840	2.350	-0.51	0.14	0.41
0.7	2	0.3	1.6	0.7	3.85	0.3	0.1	1.880	2.725	-0.85	0.41	0.68
0.8	2	0.2	1.6	0.8	3.85	0.2	0.1	1.920	3.100	-1.18	0.68	0.97
0.9	2	0.1	1.6	0.9	3.85	0.1	0.1	1.960	3.475	-1.52	0.97	1.37
1	2	0	1.6	1	3.85	0	0.1	2.000	3.850	-1.85	1.37	+∞

Note: Last four columns showing expected values and implied CRRA intervals were not shown to subjects.

Table 2. Payoff table for 32 month horizon in discount rate experiments

Payoff alternative	Payment option A in € (Pays amount below in 6 month)	Payment option B in € (Pays amount below in 38 months)	Annual interest rate in %	Annual effective interest rate in %
1	250	257.78	5	4.5
2	250	265.56	10	9
3	250	273.33	15	13.5
4	250	281.11	20	18
5	250	288.89	25	22.5
6	250	296.67	30	27
7	250	304.44	35	31.5
8	250	312.22	40	36
9	250	320.00	45	40.5
10	250	327.78	50	45

Table 3. Participation by menstrual cycle phases

Menstrual cycle phases	**Days**	**Full sample**		**Sample after attrition**			**Expected percentage of subjects**
		29-days cycle	*Expected number of subjects*	*29-days cycle*	*Expected number of subjects*	*Adjusted*	
Menstrual phase	1-5	8	14	8	10	12	17%
Proliferative phase	6-14	22	25	17	18	21	31%
Ovulatory phase	15-16	7	6	7	4	5	7%
Luteal phase	17-24	25	22	20	16	18	28%
Pre-menstrual phase	25-29	18	14	15	10	12	17%
Hormonal contraceptives		12	-	10	-	10	-
Total		**92**		**77**		**77**	

Table 4. OLS regressions on number of A choices with male dummy

	(1) x1	(2) x9	(3) x14	(4) 4 weeks	(5) 16 weeks	(6) 32 weeks
Visual	-0.454	0.377	0.339			
	(0.408)	(0.384)	(0.393)			
Task Order	-0.300	-0.105	-0.145	0.966*	0.872*	0.513
	(0.404)	(0.371)	(0.390)	(0.533)	(0.480)	(0.496)
Male	-1.206**	-0.644*	-0.279	-0.291	0.369	0.681
	(0.415)	(0.378)	(0.386)	(0.569)	(0.464)	(0.492)
FED				0.354	0.158	0.138
				(0.541)	(0.475)	(0.501)
Principal				-1.671**	-1.465**	-1.283**
				(0.547)	(0.472)	(0.488)
Constant	6.307**	6.419**	6.649**	8.524**	8.162**	8.215**
	(0.396)	(0.411)	(0.391)	(0.647)	(0.489)	(0.496)
N	95	108	124	95	108	123
Adj. R-sq.	0.072	0.009	-0.014	0.073	0.088	0.048

Standard errors in parentheses. * p<0.10, ** p<0.05

Table 5. OLS regressions on number of A choices with menstrual cycle dummies

	(1) x1	(2) x1	(3) x9	(4) x9	(5) x14	(6) x14	(7) 4 weeks	(8) 4 weeks	(9) 16 weeks	(10) 16 weeks	(11) 32 weeks	(12) 32 weeks
Visual	-0.359	-0.483	0.469	0.482	0.629*	0.588*						
	(0.432)	(0.422)	(0.396)	(0.382)	(0.357)	(0.355)						
Task Order	-0.196	-0.236	-0.242	-0.183	-0.300	-0.270	0.975	0.955*	1.172**	1.118**	0.618	0.547
	(0.431)	(0.417)	(0.398)	(0.386)	(0.391)	(0.392)	(0.588)	(0.566)	(0.528)	(0.515)	(0.532)	(0.513)
Menstrual	-0.017	-0.036	1.193*	1.299**	1.063	1.427*	1.184	1.140	-1.234	-1.037	0.448	-0.711
	(1.350)	(1.336)	(0.657)	(0.616)	(0.855)	(0.784)	(0.731)	(0.755)	(1.215)	(1.106)	(0.916)	(1.257)
Proliferative	1.340**	1.324**	1.147**	0.964	1.247**	0.764	0.666	0.193	0.286	0.303	0.066	0.217
	(0.648)	(0.632)	(0.573)	(0.595)	(0.541)	(0.596)	(0.982)	(0.936)	(0.611)	(0.566)	(0.731)	(0.697)
Ovulatory	2.024*	2.026*	0.276	0.273	-0.255	-0.260	0.699	0.803	-2.528**	-2.539**	-1.646	-1.688
	(1.033)	(1.034)	(0.687)	(0.697)	(0.787)	(0.783)	(1.375)	(1.369)	(1.056)	(1.055)	(1.260)	(1.272)
Luteal	1.497**	1.648**	0.624	0.761	0.781*	0.997**	0.117	0.363	-0.143	-0.150	-1.123	-0.964
	(0.486)	(0.491)	(0.548)	(0.533)	(0.401)	(0.418)	(0.840)	(0.799)	(0.848)	(0.805)	(0.812)	(0.788)
Pre-menstrual	0.944	0.666	0.352	0.304	-1.379	-1.364*	-0.742	-0.499	-0.104	-0.227	-0.785	-0.695
	(0.698)	(0.671)	(0.750)	(0.700)	(0.840)	(0.788)	(1.224)	(1.112)	(0.983)	(0.921)	(0.822)	(0.789)
Pill		-0.466		-0.670		-0.437		0.422		0.435		-0.183
		(0.851)		(0.923)		(1.052)		(0.839)		(0.662)		(1.115)
FED							0.470	0.451	0.071	-0.020	0.205	0.121
							(0.592)	(0.571)	(0.501)	(0.478)	(0.520)	(0.515)
Principal							-1.528**	-1.733**	-1.323**	-1.361**	-1.340**	-1.224**
							(0.634)	(0.604)	(0.498)	(0.466)	(0.480)	(0.475)
Constant	5.004**	5.083**	5.805**	5.768**	6.300**	6.305**	8.099**	8.215**	8.354**	8.449**	8.834**	8.857**
	(0.423)	(0.416)	(0.381)	(0.374)	(0.399)	(0.400)	(0.635)	(0.617)	(0.539)	(0.514)	(0.592)	(0.578)
N	88	95	100	108	115	124	88	95	100	108	114	123
Adj. R-sq.	0.058	0.065	-0.004	-0.018	0.085	0.067	0.033	0.034	0.110	0.109	0.069	0.030

Standard errors in parentheses. * p<0.10, ** p<0.05

Table 6. OLS regressions on number of A choices with progesterone, estradiol dummies, including pill takers

	(1) x1	(2) x9	(3) x14	(4) 4 weeks	(5) 16 weeks	(6) 32 weeks
Visual	-0.427	0.418	0.406			
	(0.407)	(0.372)	(0.374)			
Task Order	-0.234	-0.043	-0.007	1.003*	0.973*	0.502
	(0.413)	(0.371)	(0.385)	(0.558)	(0.520)	(0.515)
Estradiol	1.063*	0.747	0.888	0.170	0.684	0.576
	(0.586)	(0.562)	(0.595)	(0.870)	(0.549)	(0.676)
Progesterone	0.333	-0.175	0.272	0.153	-0.468	-1.201
	(0.630)	(0.693)	(0.649)	(0.970)	(0.807)	(0.880)
Pill	-0.323	-0.486	-0.353	0.281	0.359	-0.385
	(0.775)	(0.881)	(1.053)	(0.732)	(0.589)	(1.222)
FED				0.326	0.154	0.201
				(0.541)	(0.479)	(0.501)
Principal				-1.691**	-1.482**	-1.269**
				(0.562)	(0.467)	(0.477)
Constant	5.289**	5.923**	6.122**	8.286**	8.111**	8.540**
	(0.423)	(0.335)	(0.365)	(0.597)	(0.531)	(0.546)
N	95	108	124	95	108	123
Adj. R-sq.	0.051	-0.012	0.017	0.053	0.077	0.032

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$

Table 7. OLS regressions on number of A choices with digit ratio squared term and digit ratio quartiles

	(1) x1	(2) x1	(3) x9	(4) x9	(5) x14	(6) x14	(7) 4 weeks	(8) 4 weeks	(9) 16 weeks	(10) 16 weeks	(11) 32 weeks	(12) 32 weeks
Visual	-0.426	-0.430	0.390	0.376	0.373	0.304						
	(0.408)	(0.403)	(0.382)	(0.385)	(0.394)	(0.395)						
Task Order	-0.390	-0.325	-0.151	-0.137	-0.140	-0.128	1.145**	1.077*	0.823*	0.825*	0.516	0.537
	(0.410)	(0.402)	(0.384)	(0.383)	(0.392)	(0.392)	(0.555)	(0.545)	(0.492)	(0.488)	(0.501)	(0.498)
Male	-1.001**	-1.143**	-0.628	-0.601	-0.353	-0.288	-0.604	-0.369	0.488	0.432	0.665	0.658
	(0.428)	(0.403)	(0.408)	(0.388)	(0.405)	(0.395)	(0.584)	(0.547)	(0.522)	(0.493)	(0.517)	(0.502)
2D:4D	0.394*		0.094		-0.148		-0.612**		0.195		-0.042	
	(0.221)		(0.205)		(0.205)		(0.303)		(0.264)		(0.263)	
$(2D:4D)^2$	-0.066		-0.139		-0.049		0.141		-0.017		0.004	
	(0.134)		(0.125)		(0.132)		(0.180)		(0.161)		(0.169)	
Medium 2D:4D		0.646		0.332		-0.382		-1.585**		0.394		-0.679
		(0.491)		(0.473)		(0.474)		(0.655)		(0.613)		(0.608)
High 2D:4D		1.384**		0.579		-0.065		-1.563*		0.939		-0.355
		(0.577)		(0.556)		(0.559)		(0.793)		(0.722)		(0.721)
FED							0.136	0.190	0.209	0.280	0.127	0.069
							(0.555)	(0.555)	(0.492)	(0.497)	(0.507)	(0.509)
Principal							-1.751**	-1.679**	-1.465**	-1.485**	-1.286**	-1.294**
							(0.564)	(0.549)	(0.489)	(0.484)	(0.504)	(0.499)
Constant	6.293**	5.624**	6.564**	6.107**	6.709**	6.871**	8.623**	9.777**	8.127**	7.678**	8.224**	8.682**
	(0.422)	(0.534)	(0.374)	(0.492)	(0.394)	(0.498)	(0.665)	(0.780)	(0.573)	(0.718)	(0.596)	(0.736)
N	95	95	108	108	124	124	95	95	108	108	123	123
Adj. R-sq.	0.085	0.109	0.003	0.000	-0.024	-0.024	0.098	0.117	0.075	0.086	0.032	0.042

Standard errors in parentheses. * p<0.10, ** p<0.05

Table 8. Estimates of risk and time preferences with gender dummy

		(1)		(2)		(3)	
		CRRA-exponential discounting		CRRA-hyperbolic discounting		expo-power/exponential discounting	
r	*Visual*	-0.022	(0.035)	-0.023	(0.035)	-0.116	(0.077)
	Task Order	-0.080	(0.068)	-0.084	(0.067)	-0.063	(0.090)
	Male	-0.120*	(0.069)	-0.121*	(0.068)	-0.051	(0.086)
	Constant	0.647**	(0.072)	0.636**	(0.071)	0.294**	(0.117)
α	*Visual*					0.435	(0.310)
	Task Order					0.363	(0.309)
	Male					0.262	(0.315)
	Constant					1.654**	(0.441)
γ	*Visual*					-0.089	(0.062)
	Task Order					-0.006	(0.070)
	Male					0.039	(0.064)
	Constant					0.682**	(0.090)
δ	*FED*	-0.003	(0.021)	-0.001	(0.021)	-0.010	(0.022)
	Principal	-0.089**	(0.031)	-0.090**	(0.031)	-0.157**	(0.034)
	Task Order	0.133**	(0.057)	0.132**	(0.057)	0.063	(0.048)
	Male	0.104*	(0.054)	0.102*	(0.053)	0.016	(0.043)
	Constant	0.209**	(0.048)	0.211**	(0.047)	0.256**	(0.052)
	μ	0.130**	(0.006)	0.130**	(0.006)	0.091**	(0.004)
	ν	0.039**	(0.005)	0.039**	(0.005)	0.005**	(0.001)
N		8280		8280		8280	
Log-pseudolikelihood		-3807.934		-3783.290		-3739.584	

Standard errors in parentheses. * p<0.10, ** p<0.05

Table 9. Estimates of risk and time preferences with menstrual cycle variables

		(1)		(2)		(3)	
		Excluding pill takers		Including pill takers		With progesterone, estradiol dummies, including pill takers	
r	*Visual*	-0.053	(0.103)	-0.036	(0.090)	-0.058	(0.079)
	Task	-0.049	(0.123)	0.009	(0.114)	-0.004	(0.091)
	Menstrual	-0.207	(0.197)	-0.139	(0.150)		
	Proliferative	0.118	(0.162)	-0.086	(0.255)		
	Ovulatory	0.035	(0.229)	-0.020	(0.243)		
	Luteal	0.185	(0.152)	0.252	(0.164)		
	Pre-menstrual	-0.107	(0.147)	-0.094	(0.169)		
	Pill			0.132	(0.282)	0.117	(0.177)
	Estradiol					-0.063	(0.199)
	Progesterone					0.329	(0.297)
	Constant	0.183	(0.125)	0.132	(0.108)	0.150*	(0.090)
α	*Visual*	0.323	(0.468)	0.269	(0.375)	0.383	(0.355)
	Task	0.218	(0.389)	0.208	(0.344)	0.314	(0.336)
	Menstrual	0.608	(0.591)	1.041*	(0.564)		
	Proliferative	-0.313	(0.491)	-0.258	(0.412)		
	Ovulatory	-0.118	(0.663)	-0.114	(0.645)		
	Luteal	-0.884*	(0.485)	-0.973**	(0.469)		
	Pre-menstrual	0.054	(0.595)	-0.008	(0.562)		
	Pill			-0.100	(0.499)	0.093	(0.482)
	Estradiol					-0.298	(0.392)
	Progesterone					-0.763	(0.501)
	Constant	2.505**	(0.512)	2.546**	(0.447)	2.398**	(0.437)

γ	*Visual*	-0.054	(0.096)	-0.027	(0.073)	-0.041	(0.065)
	Task	-0.007	(0.113)	0.040	(0.085)	0.030	(0.066)
	Menstrual	-0.154	(0.100)	-0.137	(0.100)		
	Proliferative	-0.069	(0.095)	-0.161	(0.123)		
	Ovulatory	-0.007	(0.222)	-0.054	(0.199)		
	Luteal	0.033	(0.141)	0.074	(0.156)		
	Pre-menstrual	-0.052	(0.103)	-0.030	(0.127)		
	Pill			0.113	(0.244)	0.128	(0.177)
	Estradiol					-0.150	(0.097)
	Progesterone					0.234	(0.203)
	Constant	0.696**	(0.122)	0.650**	(0.086)	0.657**	(0.072)
δ	*FED*	-0.004	(0.021)	-0.008	(0.023)	-0.007	(0.021)
	Principal	-0.148**	(0.029)	-0.169**	(0.033)	-0.161**	(0.027)
	Task	0.082	(0.055)	0.051	(0.052)	0.046	(0.045)
	Menstrual	0.029	(0.078)	-0.026	(0.075)		
	Proliferative	-0.014	(0.053)	0.058	(0.124)		
	Ovulatory	-0.061	(0.062)	-0.053	(0.075)		
	Luteal	0.000	(0.070)	-0.012	(0.070)		
	Pre-menstrual	0.016	(0.066)	0.022	(0.083)		
	Pill			-0.045	(0.113)	-0.060	(0.087)
	Estradiol					0.064	(0.099)
	Progesterone					-0.053	(0.090)
	Constant	0.227**	(0.040)	0.254**	(0.044)	0.247**	(0.039)
	μ	0.087**	(0.005)	0.088**	(0.005)	0.090**	(0.004)
	v	0.004**	(0.001)	0.004**	(0.001)	0.004**	(0.001)
N		7680		8280		8280	

Log-pseudolikelihood	-3384.015	-3688.220	-3710.481

Standard errors in parentheses. * p<0.10, ** p<0.05

Table 10. Estimates of risk and time preferences with 2D:4D variables

		(1)		(2)	
		With 2D:4D squared term		With 2D:4D quartiles	
r	*Visual*	-0.120	(0.074)	-0.126*	(0.070)
	Task	-0.078	(0.098)	-0.042	(0.091)
	Male	-0.065	(0.101)	-0.114	(0.149)
	2D:4D	-0.003	(0.041)		
	$(2D:4D)^2$	-0.008	(0.020)		
	Medium 2D:4D			0.152	(0.158)
	High 2D:4D			0.108	(0.108)
	Constant	0.325**	(0.128)	0.226*	(0.121)
α	*Visual*	0.407	(0.313)	0.447	(0.292)
	Task	0.327	(0.322)	0.308	(0.341)
	Male	0.341	(0.355)	0.169	(0.336)
	2D:4D	0.204	(0.132)		
	$(2D:4D)^2$	-0.077	(0.106)		
	Medium 2D:4D			0.085	(0.370)
	High 2D:4D			0.319	(0.413)
	Constant	1.815**	(0.490)	1.536**	(0.522)
γ	*Visual*	-0.094	(0.061)	-0.098*	(0.056)
	Task	-0.012	(0.082)	0.015	(0.068)
	Male	0.023	(0.077)	-0.015	(0.116)
	2D:4D	-0.020	(0.037)		
	$(2D:4D)^2$	-0.000	(0.020)		
	Medium 2D:4D			0.084	(0.138)
	High 2D:4D			-0.010	(0.076)

	Constant	0.704**	(0.095)	0.672**	(0.090)
δ	*FED*	-0.013	(0.019)	-0.017	(0.027)
	Principal	-0.141**	(0.036)	-0.190**	(0.045)
	Task	0.067	(0.049)	0.070	(0.057)
	Male	0.015	(0.042)	0.067	(0.087)
	2D:4D	-0.021	(0.018)		
	$(2D:4D)^2$	0.014	(0.010)		
	Medium 2D:4D			-0.099*	(0.056)
	High 2D:4D			-0.087	(0.056)
	Constant	0.228**	(0.056)	0.315**	(0.068)
	μ	0.092**	(0.004)	0.092**	(0.005)
	v	0.005**	(0.001)	0.005**	(0.001)
N		8280		8280	
Log-pseudolikelihood		-3722.974		-3717.063	

Standard errors in parentheses. * p<0.10, ** p<0.05

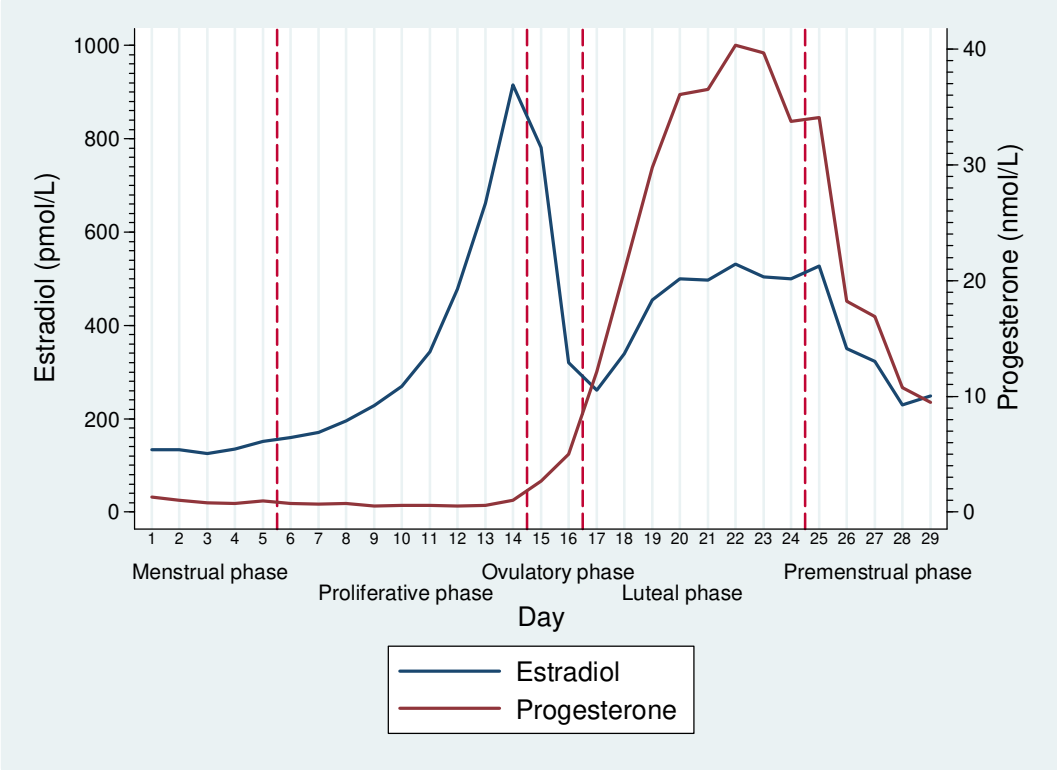

Figure 1. Hormone levels over the menstrual cycle (data obtained from Stricker *et al.*, 2006)

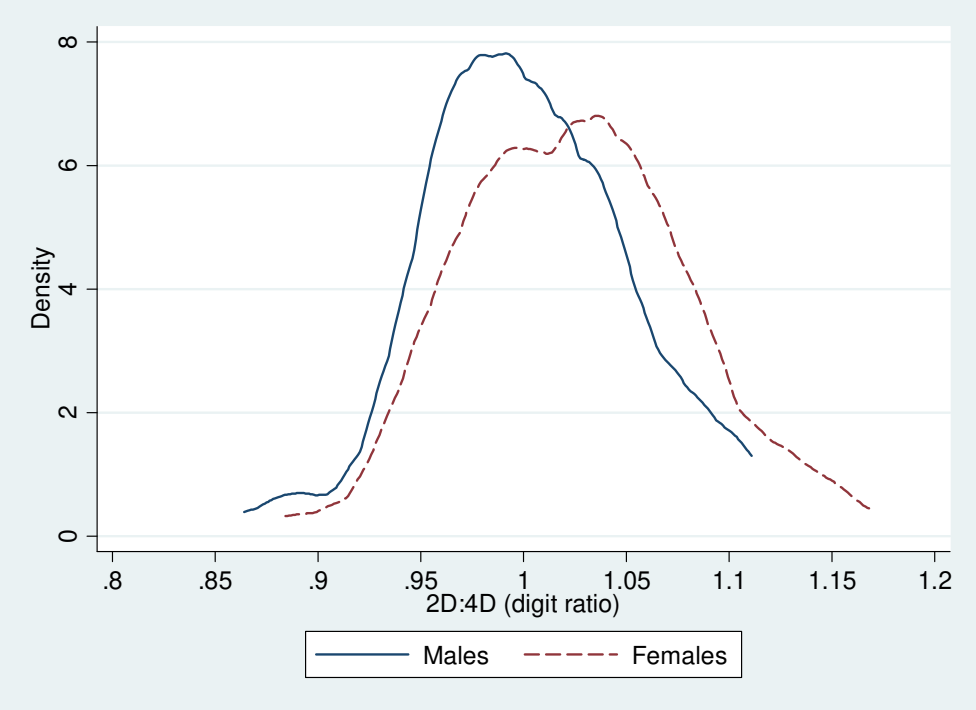

Figure 2. Kernel density of 2D:4D by sex

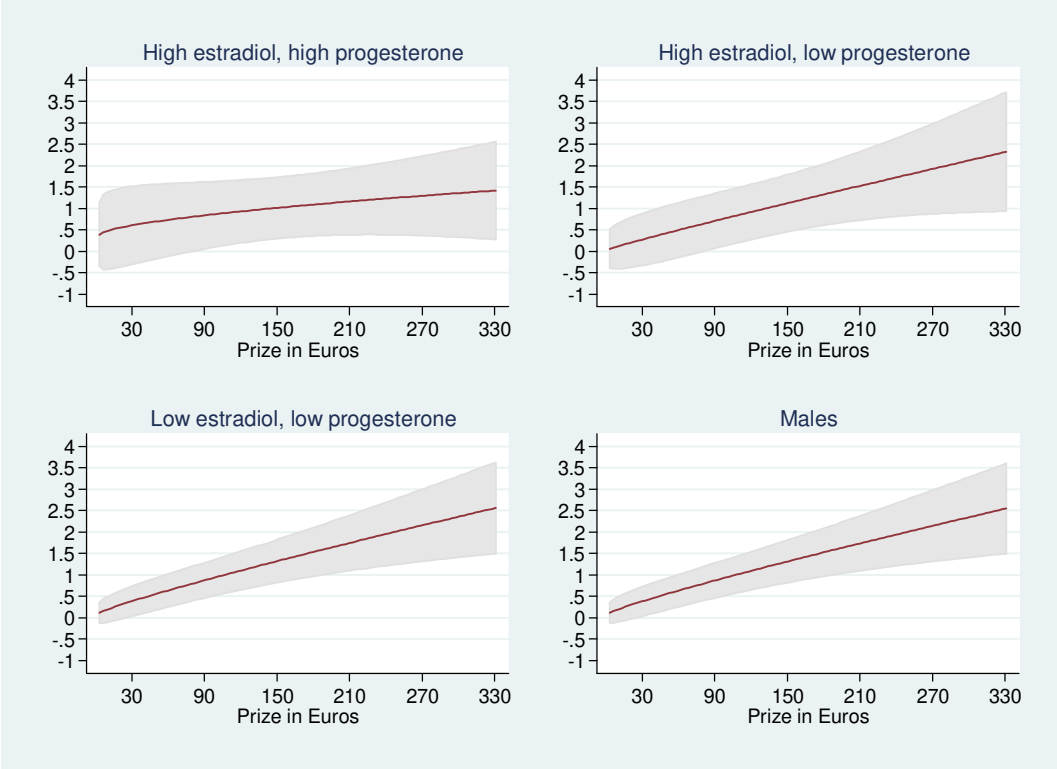

Figure 3. RRA predictions and confidence intervals

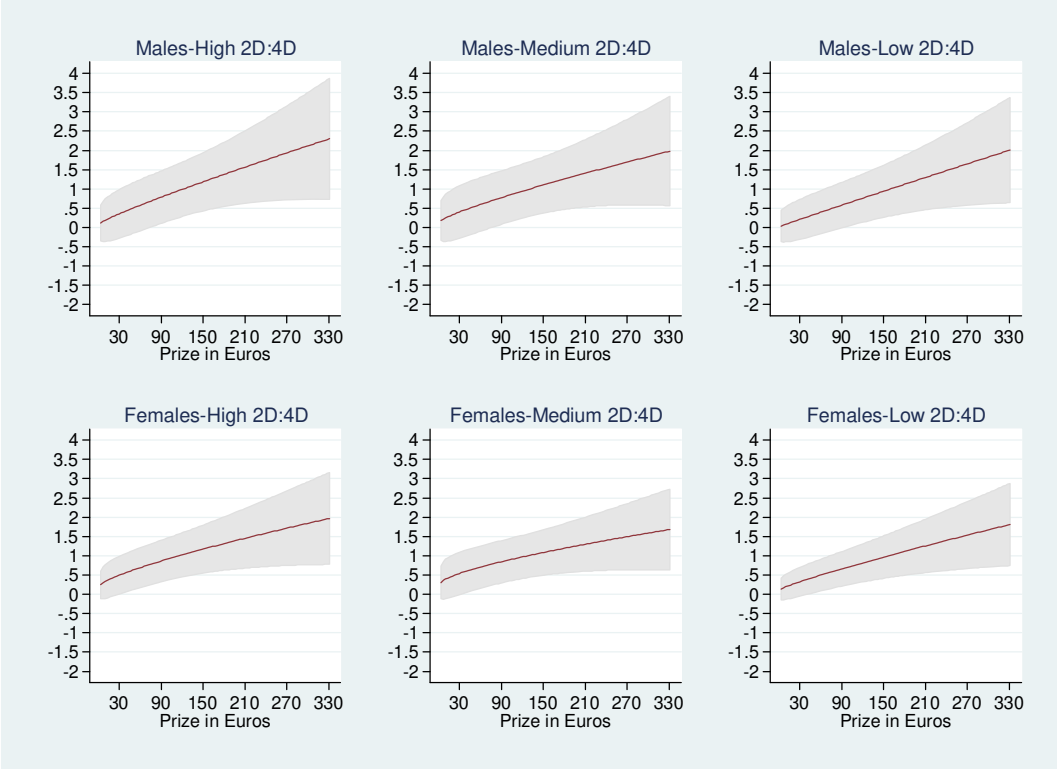

Figure 4. RRA predictions and confidence intervals