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12 March 2012

Online at https://mpra.ub.uni-muenchen.de/37320/
MPRA Paper No. 37320, posted 13 Mar 2012 15:07 UTC

Do risk and time preferences have biological roots?

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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 levels. Results suggest that natural fluctuations in progesterone levels have a direct effect on discount rates and that estradiol/progesterone levels can indirectly affect time preferences by changing the curvature of the utility function. Using measured D2:D4 digit ratio, results imply that subjects with low digit ratio exhibit higher discount rates and risk loving preferences.

JEL codes: *C91, D81*

Keywords: *discount rates, risk aversion, lab experiment, menstrual cycle, D2:D4 ratio, hormones, estradiol, progesterone, testosterone*

Acknowledgements: *Authors thank Glenn Harrison for invaluable help with the estimations, Justin Sydnor for helpful comments and suggestions on earlier draft of this paper, and Spiros Stachtiaris and Achilleas Vassilopoulos for their assistance in data collection. All errors are ours alone.*

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. One of the variables that could affect cognitive operations is gender. 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.

The question of whether preferences of males and females have biological roots is relevant especially from a policy perspective given that gender differences have been observed in important domains including consumption, investment and in the labor market. Therefore, understanding gender differences can be used to illuminate the debate on gender-specific outcomes in the labor and goods markets. Also, given the important welfare consequences associated with economic decision making in many domains, understanding the biological mechanisms that mediate such people's economic preferences is of utmost importance. As

discussed in the next section, 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 entirely provided consistent results.

In our study, we examine the effect of prenatal exposure to testosterone levels and natural fluctuations of two female hormones (progesterone and estradiol) on risk and time preferences using a conventional lab experiment. We proxy prenatal exposure to testosterone using a biological marker, the ratio of the length of the 2nd (index) finger to the 4th (ring) finger of the subjects' hand (D2:D4 ratio). Natural fluctuations of progesterone and estradiol levels are proxied by self-reported menstrual cycle information from female subjects in our experiment. Our results suggest that natural fluctuations in progesterone levels have a direct effect on discount rates and that estradiol and progesterone levels can indirectly affect time preferences by changing the curvature of the utility function (i.e., risk preferences). Our findings also imply that prenatal exposure to testosterone is a significant predictor of risk and time preferences, particularly among males.

This paper is structured as follows. To properly set the context and importance of the topic of our study, the next section reviews the scant but accumulating evidence on the role of hormones on economic decision making and the approaches taken in the literature. Section 3 describes our experimental procedures in detail. Section 4 describes our sample and particularly how we measured and handled menstrual cycle information and the D2:D4 ratio. Section 5 reviews our structural approach in jointly estimating risk and time preferences. We then present the main results in section 6 and conclude in the last section.

II. Literature review

The literature that examines the association between hormones and economic decision making, while small, is growing at a fast pace. Our literature review search identified 36 papers that examine the role of at least one hormone in an economic game, experiment or decision making in general. This literature uses either (1) indirect measures of hormones (e.g., the menstrual cycle as a proxy for estrogens and progesterone), (2) indirect measures of prenatal exposure to hormones (i.e., use of the D2:D4 ratio as a proxy of testosterone exposure), (3) direct

measurements of hormones (i.e., saliva samples or blood plasma are usually taken from experimental subjects) or (4) experiments with exogenous administration of hormones. The last approach uses placebo groups as control groups when making comparisons.

Table 1 lists the papers that fall under one or more of the categories we listed above. Obviously several studies can be classified under more than one category. The studies shown in the table have been published in various journals most of which are non-economics journals. It is encouraging to see, however, that a few papers have made it to major experimental economics journals like *Journal of Economic Behavior & Organization* and *Experimental Economics* (Buser, 2010; Pearson & Schipper, 2012) or even more general audience journals such as the *American Economic Review* and *Journal of Risk & Uncertainty* (Garbarino *et al.*, 2011; Zak *et al.*, 2005a). Table 1 shows that the majority of the studies employ proxies of hormones such as the menstrual cycle or the digit ratio. The reason for this is intuitive; data collection of these proxies is less invasive and of minimal cost. Studies that analyze saliva or blood samples are expected to be more costly (although more accurate measurements can be achieved) and thus adoption of these methods is subject to budget constraints. Experiments that exogenously administer hormones to subjects solve an inherent problem of the above mentioned methods (with the exception of the digit ratio), which is the endogeneity of hormonal measures with decision making. The caveat is that the invasive nature of these experiments precludes their wider adoption. For example, oxytocin administration to females may cause miscarriage (Zak *et al.*, 2007) and testosterone administration has only been approved in males by the US Food and Drug Administration (Zak *et al.*, 2009).

We will only review the studies that implicitly or explicitly deal with the association of risk and time preferences with one or more hormones. Obviously the literature involves a wider variety of tasks and games including self-selection into competitive environments (Apicella *et al.*, 2011; Buser, 2010; Wozniak *et al.*, 2011), explorations of the Allais paradox (Da Silva *et al.*, 2011), bidding behavior in auctions (Pearson & Schipper, 2012), decision making in trust, ultimatum, dictator, public good and prisoners' dilemma games (Burnham, 2007; Buser, 2011; Eisenegger *et al.*, 2010; Kosfeld *et al.*, 2005; Millet & Dewitte, 2006; Millet & Dewitte, 2009; Sanchez-Pages & Turiegano, 2010; van den Bergh & Dewitte, 2006; Zak *et al.*, 2005a; Zak *et al.*, 2005b; Zak *et al.*, 2007; Zethraeus *et al.*, 2009) as well as entrepreneurship decisions (White

et al., 2006). A critical synthesis of the above mentioned studies that would explain differences in methods, findings etc. is indeed warranted and is the subject of a companion working paper.

Just two of the studies reviewed deal with explicitly identifying a link between hormones and time preferences, albeit in hypothetical tasks. In Millet and Dewitte (2008) subjects were asked to indicate how much money would they require in 1 week, 1 month, 3 months, 6 months and 1 year to make them indifferent to receiving 15€ now. The authors found a significant association of digit ratios and impulsiveness when subjects were in a "subordinate" position, as induced by a loss in a contest, but they did not find a significant relationship after winning a contest. This study, however, comes with several shortcomings. For one, subjects were recruited for course credit and no salient incentives were given. The discounting task was purely hypothetical as well. Another issue is that the study used deception at some point of the procedures. To the extent that subjects suspected that deception was involved in the experiment, this may have affected the results. In addition, they implicitly assumed a utility function that was linear in wealth.

Takahashi et al. (2008) assessed testosterone levels in male students using saliva samples and then had subjects complete Kirby's (hypothetical) monetary choice questionnaire (Kirby & MarakoviĆ, 1996; Kirby *et al.*, 1999) in which subjects state their choice between smaller immediate rewards and larger but delayed rewards. They found a positive linear relationship between testosterone levels and the hyperbolic discount factor in gains, but found no relationship between testosterone levels and discount factor in losses.

Further evidence of a link between time preferences and hormones are only implicit in the associated literature. For example, Daly et al. (2009) explore the biological roots of time preferences only by relating discounting with heart rate variability and blood pressure but not with hormones. The widely used D2:D4 ratio, which has been used as a proxy of prenatal exposure to testosterone, has been shown to affect some cognitive skills (see Austin *et al.*, 2002; Manning, 2002 for a survey). In turn, several other studies have shown that time preferences are correlated with cognitive abilities such as mathematical ability (Benjamin *et al.*, 2006), IQ tests of innate cognitive ability (Dohmen *et al.*, 2010), a nonverbal IQ test (Raven's matrices) (Burks *et al.*, 2009) or a cognitive reflection test (Frederick, 2005). Thus, an implicit link between hormones and time preferences is implied in these studies. However, to our knowledge, no other known published study has explored a direct link between hormones and time preferences.

The picture is a little different when it comes to risk taking behavior. The approaches taken in the risk preferences literature vary significantly. In the next subsections, we organize the discussion of the literature on the link between hormones and risk preferences around the four ways that are used to measure or proxy hormonal levels, as mentioned in the beginning of this section.

A. Indirect measures of hormones

This strand of the literature tries to explain differences in risk preferences in terms of the five phases of female subjects' menstrual cycle. In these studies, self-reported measures of the expected beginning of the next menstruation as well as the cycle length are normally elicited from female subjects. Estrogen (estradiol is the predominant form in non-pregnant females) and progesterone secretion levels normally have diverging patterns across a regular 29-day menstrual cycle (see Figure 1)[1], thus observed differences in risk preferences between phases of the cycle and/or differences with male subjects can be attributed to the effect of the different levels of the hormones. A high estrogen (estradiol) phase corresponds to cycle phases two and four while a high progesterone phase coincides with the fourth phase. Females using hormonal contraceptives are subject to a different cycle, with a 21-day intake period followed by a 7-day break. The 21-day period is characterized by constant daily doses of an artificial estrogen and an artificial progestin. Thus, studies usually take extra care of showing the robustness of their results with and without pill takers or by comparing a separate group of oral contraceptive users with a group of normal cycling females.

Bröder and Hohmann (2003) recruited 85 female students at the University of Bonn. Participants in this study had to repeatedly answer the same questionnaire at 1-week intervals. After attrition, 51 students were analyzed in the study half of which were pill takers. Subjects were asked to check which of the 40 activities they had participated in during the preceding 24 hours. The list of activities was compiled after a pilot study with females and males, such that 20 of the activities were considered risky (e.g., get dressed sexily when going out) and the rest were considered non-risky (e.g., watch TV at home). Thus risk taking behavior was defined as risk over sexual assault in this study and not over monetary prizes. Depending on when menstruation

[1] The normal cycle is often quoted to last 28-days but as we explain later in the paper this is not true.

occurred during this 4-week interval, the fertile window of subjects (i.e., the ovulatory phase) was assessed. Results showed that women change their behavior over the ovarian cycle, by selectively reducing activities that expose them to risky activities during ovulation. The effect disappears for females who use hormonal contraception.

Burns (2006) analyzed data from 176 female students at Michigan State University. Risk preferences were elicited over hypothetical monetary choices and students were asked to choose between a sure prize of $85 and a lottery with 85% chances of receiving $100. They classified the subjects into one of the menstruation phases based on self-reports of subjects' first day of last menstruation and duration of menstrual cycle. Oral contraceptive use was also assessed. The authors found that females were less likely to choose the risky choice (i.e., the lottery) and more likely to choose the sure prize when at the ovulatory phase, but that this effect disappeared for females on the pill.

Schipper (2011a) administered an extended Holt and Laury (2002) task that involves lotteries with monetary losses as well (Laury & Holt, 2008) to 208 students from UC Davis. Menstrual cycle information (that were used to classify women in one of the cycle phases) and administration of hormonal contraceptives information were also obtained. The authors found no significant correlation between risk aversion and the menstrual cycle for gains or losses.

While limited, the literature overall finds that females tend to be more risk averse in the non-monetary domain as well as in the monetary domain with hypothetical payoffs when in ovulation. However, when real monetary incentives are introduced, no differences exist between phases of the menstruation cycle.

B. Indirect measures of prenatal exposure to hormones

The literature on prenatal exposure to sex hormones largely employs the D2:D4 digit ratio of the subjects' right hand. The digit ratio has been found to be positively correlated with prenatal exposure to estrogen and negatively correlated to prenatal exposure to testosterone (see Manning, 2002). Typically, males have lower digit ratios than females. In contrast to other direct or indirect measures of hormones, the digit ratio measure is exogenous to economic decision making since it is determined before birth and hence, before external socio-economic factors can affect behavior. In these types of studies, ethnic diversity is usually taken into account since the

digit ratio can vary significantly between ethnicities. Many studies employ Caucasian subjects to avoid making comparisons between ethnically diverse samples.

Dreber and Hoffman (2007) study risk taking behavior of 147 students in the Stockholm School of Economics but report results only for the Caucasian subsample (125 subjects). They elicit risk preferences by asking subjects to choose how much money out of SEK 1700 (aprox. $250) to invest in a risky investment that pays nothing with probability of ½ or 2.5 times the investment with probability of ½. The amount invested is taken as a measure of risk preferences. Subjects with higher digit ratios were less willing to take the investment risk although the effect was marginally significant when using right hand measurements (most, if not all, studies use right hand measurements). Apicella et al. (2008) using an ethnically diverse sample of 98 males (mostly Harvard University students), employed a similar investment game with Dreber and Hoffman (2007). They found that risk-taking (using an investment game) did not correlate significantly with digit ratio.

Coates and Page (2009) analyzed data from 53 male traders from a trading floor in London over a period of 20 months (no information are given on ethnicity) and found that traders with lower digit ratios (higher exposure to prenatal testosterone) take higher risk, as measured by the standard deviation of their profits and losses.

Using 550 ethnically mixed MBA students at the University of Chicago, Sapienza et al. (2009) found that risk aversion, as defined by choice of a risky career in finance after graduation, was positively correlated with the digit ratio. This suggests that higher risk aversion was associated with low prenatal testosterone exposure. The effect, however, was rather small and not statistically significant.

Trahms et al. (2010) report results from 90 Caucasian entrepreneurs sampled from a conference in Midwest USA. They measured risk propensity using a 6-item survey measure and found no significant relationship of digit ratios with risk propensity.

Schipper (2011a) used and ethnically mixed sample of 208 students from UC Davis (see previous subsection for more details on this study) and found no significant correlation between risk aversion, for losses or gains, and the digit ratio. No differences were observed within ethnic subsamples as well.

Garbarino et al. (2011) study risk taking behavior of 152 Caucasian students by asking them to perform a series of lottery choices in an Eckel and Grossman (2008) 50-50 task. They also vary between subjects the framing of lotteries as gains, losses or mixed. They find that subjects with smaller digit ratios (implying higher prenatal exposure to testosterone) chose significantly riskier financial options. Results were robust as per framing of lotteries as gains, losses or mixed.

Brañas-Garza and Rustichini (2011) examine whether digit ratios from 188 Caucasian students can predict risk aversion as elicited from two different lottery choice tasks. They find that low digit ratio in males is associated with higher risk taking. They also find that a substantial part of the effect of testosterone on attitude to risk is mediated by abstract reasoning ability. However, they find no significant correlation among females.

Overall, while some studies find that low digit ratio is correlated with higher risk taking (or lower risk aversion), there is an equal number of studies that fail to find a correlation between digit ratio and risk preferences even though sample sizes seem adequate for achieving lower noise in their estimates.

C. Direct measures of hormones

Studies that directly measure hormonal levels are more demanding and invasive in nature in the sense that blood or saliva samples are required from subjects. Samples have then to be frozen and sent for analysis in a technically specialized lab. These experiments are demanding in terms of cost, time and effort; thus their number tends to be limited in the associated literature, especially if compared with the number of studies using digit ratios. A caveat with these types of studies is that the evidence could be purely correlational given that samples that are taken before the experimental tasks could create expectations that affect hormonal levels. On the other hand, if samples are collected after the experimental task ends, one could not be sure about the direction of causality; i.e., was it hormonal levels that affected decision making or the other way around? In addition, time of the day when the experiment is conducted might create variations in hormonal levels. For example, testosterone levels exhibit circadian variation during a 24-hour cycle (Cooke *et al.*, 1993).

Schipper (2011a) measured testosterone, estradiol, progesterone, and cortisol levels from saliva samples (see previous subsection for more details on the recruited sample) and then

administered an extended Holt and Laury (2002) task that involves lotteries with monetary losses as well (Laury & Holt, 2008). He found that risk aversion was negatively correlated with testosterone and positively correlated with cortisol (a stress hormone) for gains only. In males, testosterone was negatively correlated with risk aversion for gains only, while in females cortisol was marginally significantly positively correlated with risk aversion only over gains.

Apicella et al. (2008) (see previous subsection for more details on the recruited sample) found that risk-taking (elicited as amount willing to invest in arisky investment) correlates positively with salivary testosterone levels while Sapienza et al. (2009) (see previous subsection) found that higher levels of circulating testosterone were associated with lower risk aversion among women, but not among men.

Coates and Herbert (2008) recorded testosterone and cortisol levels from 17 male traders from a trading floor in London for 8 consecutive business days, taking saliva samples twice per day, at 11:00 a.m. and 4:00 p.m. Profit and losses were recorded as well. The authors found a positive association between a trader's morning testosterone level and his day's profitability. They also found that a trader's cortisol level rises with both the variance of his trading results and the volatility of the market, which implies that cortisol levels are increased by risk.

Overall, most studies discussed above find a positive correlation between circulating testosterone levels and risk taking behavior. One study finds that risk aversion positively correlates with cortisol levels while another study finds that risk increases cortisol levels. These last two results seem like a contradiction. Only one study tries to correlate estradiol and progesterone with risk preferences, but fails to find any link.

D. Exogenous hormonal administration

Not surprisingly, there are only a few studies that exogenously administered hormones since these types of studies tend to be the most obtrusive and invasive in nature. In these studies, one group of people is typically administered the hormone under investigation while another group is administered a placebo.

Among the few that administer hormones, there is only one study that elicits risk preferences. Zethraeus et al. (2009) administered testosterone, estrogen, and placebo to 200 healthy post-menopausal females in the 50-65 years age group over a 4 week period. At the end of the treatment period, subjects' financial risk aversion was measured by choice between certain

payoffs and 50/50 gambles. However, no significant effect of hormones was observed on economic behavior regarding risk preferences.

III. 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. 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[2]. We opted not to use this procedure since we were also interested in knowing the specific effects of key variables on risk preferences.

While Andersen et al. (2008) placed the time preference task at the very end of each session, we vary the order of the risk and time preferences tasks to check for order effects (Harrison et al., 2005). Andersen et al. (2011c) found in one of their treatments that there are no statistically or economically significant order effects in the risk and time preference tasks. We confirm this finding.

To reassure subjects about the credibility of the payment from the time preferences task we use a front end delay on the sooner and later payments. This allows 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.

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 AAA University (removed for peer review; to be adjusted upon publication) and were recruited using the ORSEE recruiting system (Greiner, 2004). During the recruitment, the nature of the experiment and the expected earnings were not mentioned. However, subjects were told that they will be given the chance to make more money during the experiment. 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).

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 €15 participation fee. 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.

[2] In our case the exchange rate is the same for sooner and later amounts.

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 2. 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.[3] A risk neutral subject should switch from lottery A to lottery B at the 5th row. In our experiments subjects undertook three risk aversion tasks: they made choices from Table 2 (the 1x table), a table where payoffs were scaled up by 6 (the 6x table) and by 14 (the 14x table).

Instead of providing a table of choices arrayed in an ordered manner in the same screen (e.g., as in Holt & Laury, 2002), each choice was presented separately showing probabilities and prizes (as in Andersen *et al.*, 2011c)[4]. 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 an elicitation vehicle of risk when larger payoffs are involved. 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).

[3] 19 out of 157 subjects failed to pass this test concerning comprehension of lotteries and were dismissed from our sample.

[4] 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.

Subjects are confronted with payoff tables similar to Table 3 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 3, 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 argument for including such seemingly unimportant rates is that in many countries, including the country in which the experiment was conducted, such rates are required to be provided as part of a regulatory requirement for most consumer loans. Another reason is that the experimenter might want to avoid having subjects spending extra effort for calculating these rates along with their effort on decision making. Andersen et al. (2011a) experimentally varied the provision of such rates and found no effect on elicited discount rates. On the other hand, Andersen et al. (2011c) found that providing information on implied interest rates led to an increase in the elicited discount rate of 2.3%.

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.

Similar to the risk preference task, each choice was presented separately (as in Andersen *et al.*, 2011c). We varied between subjects the front end delay (3 months vs. 6 months) and the principal of the sooner option (100€ vs. 250€). Andersen et al. (2011c) found that varying the principal had no effect on elicited discount rates. We find that it does make a difference though. Increasing the principal results in lower discount rates. However, varying the front end delay did not have an effet on elicited discount rates. Table 3 displays a sample payoff matrix table with a 32 month time horizon, a 250€ principal and a front end delay of 6 months.

At the end of the experiment only one row 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. Andersen et al. (2011c) vary the probability of payment for the discounting task from 10% to 100% and find no significant difference.

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 (2011) and Chen et al. (2009).

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. The measures used here are based on the averages of the two digit ratios derived separately by each of the researchers. None of the subjects refused the measurement of the fingers. 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. As we show later, we think that our measures of digit ratios are accurate given the high correlation of digit ratios derived from the measurements taken by the two researchers. Both persons were also trained in measuring the 2^{nd} and 4^{th} digit fingers before the conduct of the experiments.

IV. 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 previous section. Of

the remaining 138 subjects, 10 indicated using oral contraceptives. None of the female subjects was pregnant.

Table 4 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 4 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)[5], the proliferative phase (days 6 to 14) and the ovulatory phase (days 15 to 16)[6]. 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)[7]. 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 4 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)[8]. 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 ($\chi^2 = 4.7$, p-value=0.320) and even for the sample after attrition ($\chi^2 = 4.06$, p-value=0.398). Thus selective participation in the experiment due to menstruating

[5] 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).

[6] 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).

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

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

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 (2011). 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 (2011). If we define subject *i*'s number of days since first day of the last menstrual cycle as y_i and the average duration of *i*'s menstrual cycle as d_i, then female subject *i* is in the:

1. Proliferative Adjusted Premenstrual Phase if and only if $y_i > d_i - 5$,

2. Proliferative Adjusted Luteal Phase if and only if $y_i > d_i - 13$ and *i* is not in the Proliferative Adjusted Premenstrual Phase,

3. Proliferative Adjusted Ovulatory Phase if and only if $y_i > d_i - 15$ and *i* is not in the Proliferative Adjusted Premenstrual Phase or the Proliferative Adjusted Luteal Phase,

4. Proliferative Adjusted Menstrual Phase if and only if *i* is in the Menstrual Phase.

5. Proliferative Adjusted Proliferative Phase if and only if *i* is not in any of the above Proliferative Adjusted phases.

Table 4 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 (2011) 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. The correlation coefficient of the two measures of digit ratios is 0.989. We use the average of these two measures of the digit ratio in the analysis. To examine the effect of the D2:D4 ratio on risk and time preferences, we first normalized the digit ratios into z-scores by subtracting off the sample mean and dividing by the standard deviation. With this transformation, the D2:D4 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=2.596, p-value=0.01).

V. Identification of risk and time preferences

The identification of risk and time preferences closely follows 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:

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

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:

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

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[9]. 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

[9] 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.

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 2. Similarly, the binary choices in the time preference tasks can be explained by different discount rates. A subject that chose 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:

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

where $p(M_j)$ are the probabilities for each outcome M_j that are induced by the experimenter (i.e., columns 1, 3, 5 and 7 in Table 2). 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:

$$\nabla EU = \frac{EU_B^{1/\mu}}{EU_A^{1/\mu} + EU_B^{1/\mu}} \tag{4}$$

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:

$$\nabla EU = \frac{\left(EU_B/c\right)^{1/\mu}}{\left(EU_A/c\right)^{1/\mu} + \left(EU_B/c\right)^{1/\mu}} \tag{5}$$

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." The conditional log-likelihood can then be written as:

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

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. Thus the likelihood for these choices can be modified such that choices imply a 50/50 mixture of the likelihood of choosing either lottery:

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

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:

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

and the index of the present values as:

$$\nabla PV = \frac{PV_B^{1/\nu}}{PV_A^{1/\nu} + PV_B^{1/\nu}} \tag{9}$$

where ν is a noise parameter for the discount rate tasks[10]. The log-likelihood will then be:

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

and the joint likelihood will be:

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

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 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

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

same subject and allows for correlation between responses (clustered standard errors). Standard errors were computed using the delta method.

A. *Extensions: Hyperbolic discounting*

The exponential discounting model is 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[11]. 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 $k > 0$.

B. *Extensions: Rank Dependent utility*

Up to now we 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:

[11] 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.

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

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[12].

C. Extensions: Expo-power function

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 a 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 $a \to 0$).

VI. 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 2 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. Gender differences in decision making

Panel A in Table 5 shows basic estimates when assuming exponential discounting and EUT. The first few rows show the effect of treatment variables. We find that the order of tasks has an effect on elicited discount rates but it does not affect our risk estimates. The principal has a direct effect on discount rates as well. This is consistent with the magnitude effect (Andersen *et al.*, 2011b) wherein higher discount rates are inferred from choices made with lower principals.

[12] It should be easy to show that $w(p_1 + p_2) = w(1) = 1$.

Gender differences are also evident in our estimates. Males are significantly less risk averse than females and have higher discount rates. Panel B of Table 5 shows that 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.

Table 6 shows estimates when we allow for RDU and the expo-power function under exponential discounting. We can directly test whether RDU and/or 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 $\alpha_0 + a_2 Visual + a_3 TaskOrder = 0$. Most of these tests reject the null, thus rendering support for an expo-power function. In addition, the corresponding tests for γ reject the null in all cases as well, thus rendering support for RDU. Joint significance tests for $a = 0$ and $\gamma = 1$ also reject the null.

Looking at Table 6, it is obvious that the *Gender* variable is no longer significant for any of the parameters. Thus gender differences may be sensitive to the underlying assumptions.

B. The role of menstrual cycle in decision making

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. We exclude pill takers for now. The omitted category is males, so that all comparisons are with respect to male subjects. Panel A in Table 7 shows parameter estimates under RDU, expo-power and exponential discounting. Wald tests indicate that we reject the null that $\alpha = 0$ or the null that $\gamma = 1$ or the null that $\alpha = 0$ and $\gamma = 1$. Thus, there is support for RDU and expo-power.

As evident, the only significant menstrual cycle dummies are the menstrual and the luteal phases for the a parameter. Note that the luteal phase is one of the phases where both estradiol and progesterone exhibit high levels. Wald tests for whether all the coefficients associated with each of the menstrual cycle dummies are zero across all parameters (e.g., $r_{menstrual} = a_{menstrual} = \gamma_{menstrual} = \delta_{mesntrual} = 0$), do not reject the null. However, a joint significance test for whether all menstrual cycle dummies across all estimated parameters are simultaneously equal to zero, highly rejects the null (p-value=0.0).

Panel B in Table 7 shows the estimates once we include the pill takers in our estimations. Similar to the case when we excluded the pill takers from the analysis, Wald tests indicate that RDU and expo-power are appropriate choices for our data. The change in the magnitude of the estimated menstrual cycle dummies is not large (as compared to panel A); however we can see that the effect of the luteal phase dummy becomes significant for the discount rate as well. In addition, the proliferative phase dummy (estradiol exhibits high levels during this phase) shows a statistically significant effect on r . Note that the effect of the menstrual cycle phase is marginally not significant.

Wald tests for whether the coefficients associated with each of the menstrual cycle dummies and the pill taker dummy, are zero across all parameters, do not reject the null with the exception of the dummies for the luteal phase (p-value=0.025) and the pill taking dummy (p-value=0.0). The Wald test for the proliferative dummies is marginally not significant (p-value=0.116). A joint significance for whether all menstrual cycle dummies and pill takers dummy across all estimated parameters are simultaneously equal to zero, highly rejects the null (p-value=0.0).

Another way to analyze the data with menstrual cycle information (also taken by Buser, 2010) 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 8 shows the parameter estimates when we replaced the menstrual cycle dummies of Table 7 with dummies that indicate high progesterone/estradiol levels. Wald tests show as before, that RDU and expo-power are supported by our data.

It is obvious that progesterone has a negative effect on parameters r and γ (thus indirectly affecting discount rates) and a positive direct effect on discount rates. On the other hand, estradiol has a positive effect on parameter r and a marginally not significant positive effect on γ, but no effect on discount rates. Taking pills as hormonal contraception also has a negative effect on parameters r and γ. Wald tests for whether the coefficients associated with estradiol, progesterone and the pill taker dummies, are zero across all parameters, highly reject the null with the exception of the dummies for estradiol (p-value=0.148). A joint significance for whether all progesterone/estradiol and pill takers dummies across all estimated parameters are simultaneously equal to zero, highly rejects the null (p-value=0.0).

Figure 3 illustrates the RRA predictions for the range of prizes given at the experiment. RRA increases across the prize domain. Predictions for males and female subjects in the low estradiol-low progesterone phase (phase 1 and 3) are similar and exhibit high risk aversion at higher incomes. However, subjects in the high estradiol-high progesterone group (phase 4) exhibit significant risk loving preferences for lower incomes.

C. Prenatal exposure to testosterone and decision making

As mentioned previously, we use the digit ratio to explore the role of prenatal exposure to testosterone 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.

Panel A in Table 9 shows the estimates when we add digit ratio squared as a covariate to capture possible non-linearities. Similar tests, as before, support RDU and expo-power. Neither the digit ratio nor its squared term is statistically significant for any of the parameters.

Panel B in Table 9 shows the estimates when we use dummies based on digit ratio quartile groups. Similarly, Wald tests support RDU and expo-power. The medium digit ratio group has a negative direct effect on discount rates and a positive effect on the *r* parameter as compared to the low digit ratio group. Note that low digit ratios suggest prenatal exposure to higher testosterone levels. In addition, the negative effect of the high digit ratio group on discount rates is marginally not significant.

Figure 4 illustrates the RRA predictions for the range of prizes given at the experiment. RRA increases across the range of prizes but increases less for subjects with medium digit ratios. Males with low digit ratio exhibit high risk loving preferences, at least for the lower prize domain. The pattern is less clear for females since the confidence intervals span around zero, although females with low digit ratio seem to be slightly more risk loving than other digit ratio same-sex groups.

VII. 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. The findings however of the studies that examined the relationship between hormones and risk preferences have been inconsistent 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 levels.

We elicited risk and time preferences and then 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 natural fluctuations in progesterone levels have a direct effect on discount rates. We also found that both estradiol and progesterone levels can indirectly affect time preferences by changing the curvature of the utility function (i.e., affecting risk preferences). Our results indicate that prenatal exposure to testosterone, as proxied by the digit ratio, is a significant predictor of risk and time preferences. Subjects with low digit ratio (i.e., high exposure to testosterone) exhibit higher discount rates. In addition, these subjects also exhibit risk loving preferences. This is particularly true for males, while for females the picture is not as clear.

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. Future studies should attempt to find other ways to objectively assess hormonal levels. Other types of hormonal measurement (i.e., blood or saliva samples) are quite invasive and expensive. On the other hand, exogenous variation of 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. Development or examination of accurate but more applicable methods of measuring hormonal levels can help researchers assess the robustness of our findings related to the biology of risk and time preferences.

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Table 1. Hormones and economic decision making literature

Type of study	Citations
Indirect measures of hormones (menstrual cycle) (N=9)	(Bröder & Hohmann, 2003; Burns, 2006; Buser, 2010; Buser, 2011; Chen *et al.*, 2009; Da Silva *et al.*, 2011; Pearson & Schipper, 2011; Schipper, 2011a; Wozniak *et al.*, 2011)
Indirect measures of prenatal exposure to hormones (D2:D4 ratio) (N=19)	(Apicella *et al.*, 2008; Apicella *et al.*, 2011; Brañas-Garza & Rustichini, 2011; Buser, 2011; Coates *et al.*, 2009 ; Coates & Page, 2009; Da Silva *et al.*, 2011; Dreber & Hoffman, 2007; Garbarino *et al.*, 2011; Guiso & Rustichini, 2011; Millet & Dewitte, 2006; Millet & Dewitte, 2008; Millet & Dewitte, 2009; Pearson & Schipper, 2012; Sanchez-Pages & Turiegano, 2010; Sapienza *et al.*, 2009; Schipper, 2011a; Trahms *et al.*, 2010; van den Bergh & Dewitte, 2006)
Direct measures of hormones (saliva or blood samples) (N=11)	(Apicella *et al.*, 2008; Apicella *et al.*, 2011; Burnham, 2007; Coates & Herbert, 2008; Sanchez-Pages & Turiegano, 2010; Sapienza *et al.*, 2009; Schipper, 2011a; Schipper, 2011b; White *et al.*, 2006; Zak *et al.*, 2005a; Zak *et al.*, 2005b)
Administration of hormones (N=5)	(Eisenegger *et al.*, 2010; Kosfeld *et al.*, 2005; Zak *et al.*, 2009; Zak *et al.*, 2007; Zethraeus *et al.*, 2009)

Table 2. 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 3. 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 4. 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 5. Estimates of risk and time preferences assuming CRRA and EUT

	CRRA coefficient (r)		Individual discount rate (δ for exponential, k for hyperbolic)	
	Estimate	Std. Error	Estimate	Std. Error
A. Exponential discounting (N=8280, Log pseudolikelihood= -3851.052)				
Visual	-0.001	0.044	-	-
Task Order	-0.031	0.055	0.084**	0.035
Front End Delay	-	-	-0.010	0.021
Principal	-	-	-0.070**	0.024
Gender	-0.116**	0.059	0.071*	0.037
Constant	0.551**	0.056	0.236**	0.036
μ	0.183**	0.015		
ν			0.025**	0.004
B. Hyperbolic discounting (N=8280, Log pseudolikelihood= -3823.421)				
Visual	-0.002	0.045	-	-
Task Order	-0.033	0.057	0.081**	0.034
Front End Delay	-	-	-0.007	0.021
Principal	-	-	-0.069**	0.023
Gender	-0.120**	0.060	0.069**	0.035
Constant	0.534**	0.057	0.236**	0.035
μ	0.187**	0.015		
ν			0.025**	0.004

Note: **, * = Significance at 5%, 10% level.

Table 6. Estimates of risk and time preferences assuming expo-power function and RDU (under exponential discounting)

	r		a		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.195	0.208	0.512	0.569	-0.067	0.069	-	-
Task Order	-0.147	0.218	0.655	0.472	-0.036	0.075	0.126	0.160
Front End Delay	-	-	-	-	-	-	-0.031	0.050
Principal	-	-	-	-	-	-	-0.292**	0.078
Gender	-0.004	0.166	0.322	0.501	0.026	0.060	-0.011	0.138
Constant	-0.011	0.258	0.578	0.657	0.513**	0.093	0.564**	0.123
μ	0.151**	0.007						
ν							0.036**	0.007
N=8280, Log-pseudolikelihood= -3745.362								

Note: **, * = Significance at 5%, 10% level.

Table 7. Estimates of risk and time preferences assuming expo-power function and RDU (under exponential discounting) – with menstrual cycle dummies

	A. Excluding pill takers (N=7680, Log-pseudolikelihood= -3381.641)							
	r		a		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.191	0.281	0.619	0.719	-0.068	0.082	-	-
Task Order	-0.105	0.189	0.380	0.524	-0.022	0.059	0.184	0.169
Front End Delay	-	-	-	-	-	-	-0.010	0.052
Principal	-	-	-	-	-	-	-0.279**	0.077
Menstrual	-0.094	0.415	1.727*	1.037	-0.036	0.142	-0.128	0.175
Proliferative	0.254	0.389	-0.637	1.088	0.020	0.131	-0.016	0.124
Ovulatory	-0.041	0.377	-0.026	0.954	-0.027	0.122	-0.124	0.220
Luteal	-0.168	0.235	-1.116*	0.630	-0.081	0.058	0.311	0.231
Pre-menstrual	-0.154	0.255	0.106	0.850	-0.038	0.081	0.018	0.160
Constant	-0.055	0.150	1.239	1.259	0.530**	0.050	0.500**	0.170
μ	0.142**	0.010						
ν							0.035**	0.015
	B. Including pill takers (N=8280, Log-pseudolikelihood= -3669.918)							
	r		a		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.197*	0.118	0.654	0.430	-0.063**	0.029	-	-
Task Order	-0.060	0.113	0.453	0.461	-0.008	0.029	0.132	0.132
Front End Delay	-	-	-	-	-	-	-0.030	0.059
Principal	-	-	-	-	-	-	-0.330**	0.080
Menstrual	-0.098	0.195	3.200	1.957	-0.033	0.058	-0.236	0.146
Proliferative	0.409*	0.219	-0.823	0.837	0.080	0.071	-0.104	0.145

Ovulatory	-0.071	0.291	-0.090	0.933	-0.035	0.076	-0.128	0.212
Luteal	-0.260	0.194	-1.123**	0.558	-0.094**	0.048	0.447*	0.234
Pre-menstrual	0.039	0.199	-0.133	0.848	0.030	0.066	-0.040	0.160
Pill	-0.665**	0.320	-0.011	0.644	-0.145**	0.036	0.571	0.435
Constant	-0.128	0.118	1.086	0.719	0.500**	0.039	0.599**	0.127
μ	0.142**	0.008						
ν							0.039**	0.009

Note: **, * = Significance at 5%, 10% level.

Table 8. Estimates of risk and time preferences assuming expo-power function and RDU (under exponential discounting) – with progesterone, estradiol dummies, including pill takers

	r		a		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.188*	0.105	0.648	0.418	-0.057**	0.025	-	-
Task Order	-0.111	0.096	0.725	0.493	-0.025	0.024	0.107	0.112
Front End Delay	-	-	-	-	-	-	-0.023	0.058
Principal	-	-	-	-	-	-	-0.310**	0.068
Estradiol	0.416**	0.182	-1.025	0.866	0.080	0.049	-0.045	0.134
Progesterone	-0.718**	0.231	-0.195	0.827	-0.183**	0.057	0.630*	0.358
Pill	-0.672*	0.356	0.365	0.742	-0.143**	0.040	0.383	0.365
Constant	-0.094	0.105	0.858	0.692	0.508**	0.034	0.587**	0.118
μ	0.143**	0.007						
ν							0.043**	0.010
N=8280, Log pseudolikelihood= -3702.036								

Table 9. Estimates of risk and time preferences for digit ratio assuming expo-power function and RDU (under exponential discounting)

A. With D2:D4 ratio squared term (N=8280, Log pseudolikelihood= -3728.774)

	r		*a*		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.218	0.165	0.555	0.483	-0.073	0.052	-	-
Task Order	-0.194	0.186	0.632	0.482	-0.050	0.062	0.159	0.144
Front End Delay	-	-	-	-	-	-	-0.039	0.046
Principal	-	-	-	-	-	-	-0.278**	0.073
Gender	0.010	0.168	0.349	0.541	0.028	0.058	-0.019	0.123
D2:D4 ratio	-0.017	0.087	0.254	0.231	-0.015	0.033	-0.050	0.047
(D2:D4 ratio)^2	0.006	0.024	-0.098	0.158	0.007	0.013	0.030	0.024
Constant	0.010	0.207	0.680	0.663	0.517**	0.072	0.529**	0.126
μ	0.151**	0.007						
ν							0.036**	0.007

B. With dummies based on D2:D4 ratio quartiles (N=8280, Log pseudolikelihood= -3720.218)

	r		*a*		γ		δ	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Visual	-0.170	0.113	0.470	0.391	-0.058*	0.034	-	-
Task Order	-0.071	0.110	0.462	0.507	-0.008	0.033	0.132	0.139
Front End Delay	-	-	-	-	-	-	-0.043	0.060
Principal	-	-	-	-	-	-	-0.318**	0.121
Gender	-0.328	0.228	0.400	0.607	-0.083	0.072	0.222	0.164
Medium D2:D4 ratio	0.511*	0.290	-0.405	0.665	0.167	0.128	-0.256**	0.120
High D2:D4 ratio	0.182	0.156	0.424	0.592	0.028	0.041	-0.198	0.130
Constant	-0.133	0.217	0.444	0.922	0.493**	0.071	0.663**	0.151
μ	0.151**	0.009						

ν	0.035**	0.006

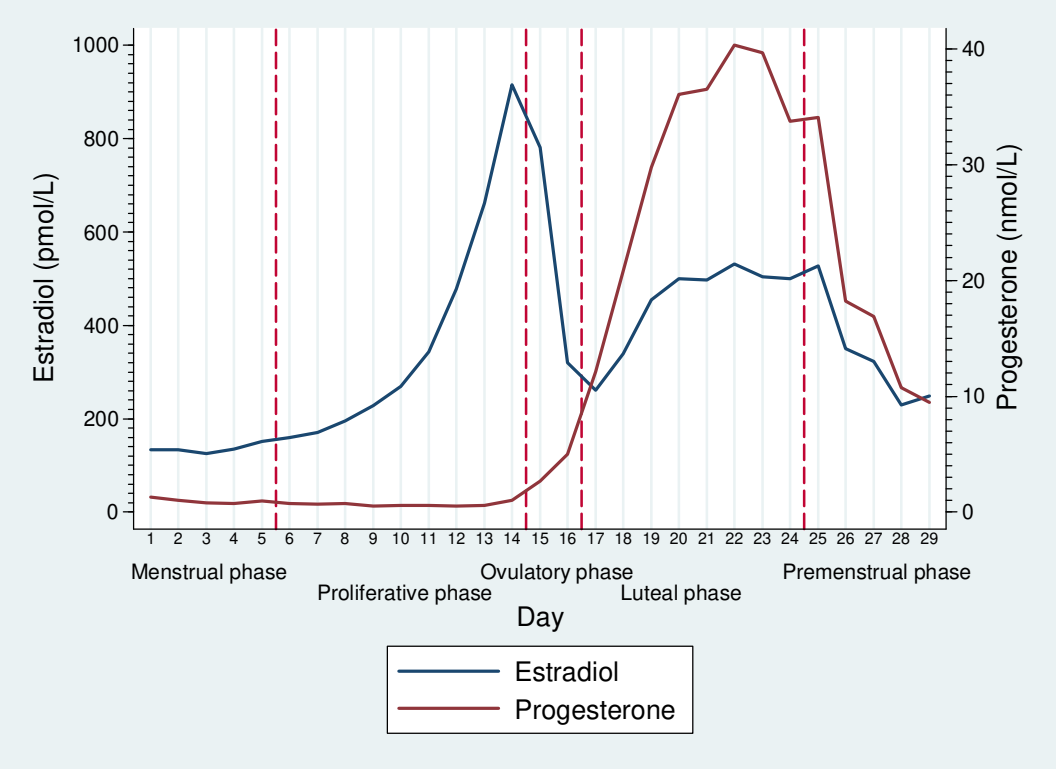


Figure 1. Hormone levels over the menstrual cycle (data obtained from Stricker *et al.*, 2006)

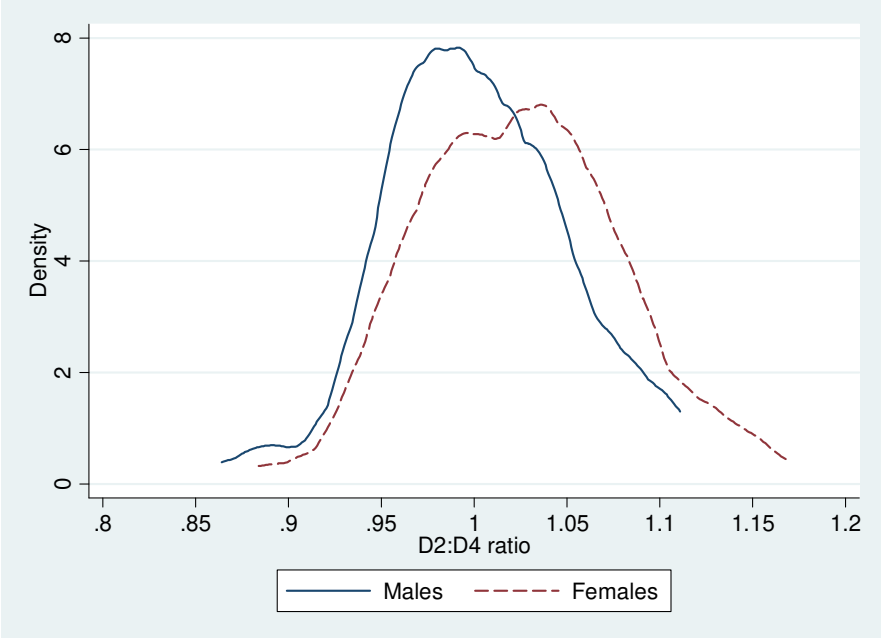


Figure 2. Kernel density of D2:D4 ratios by sex

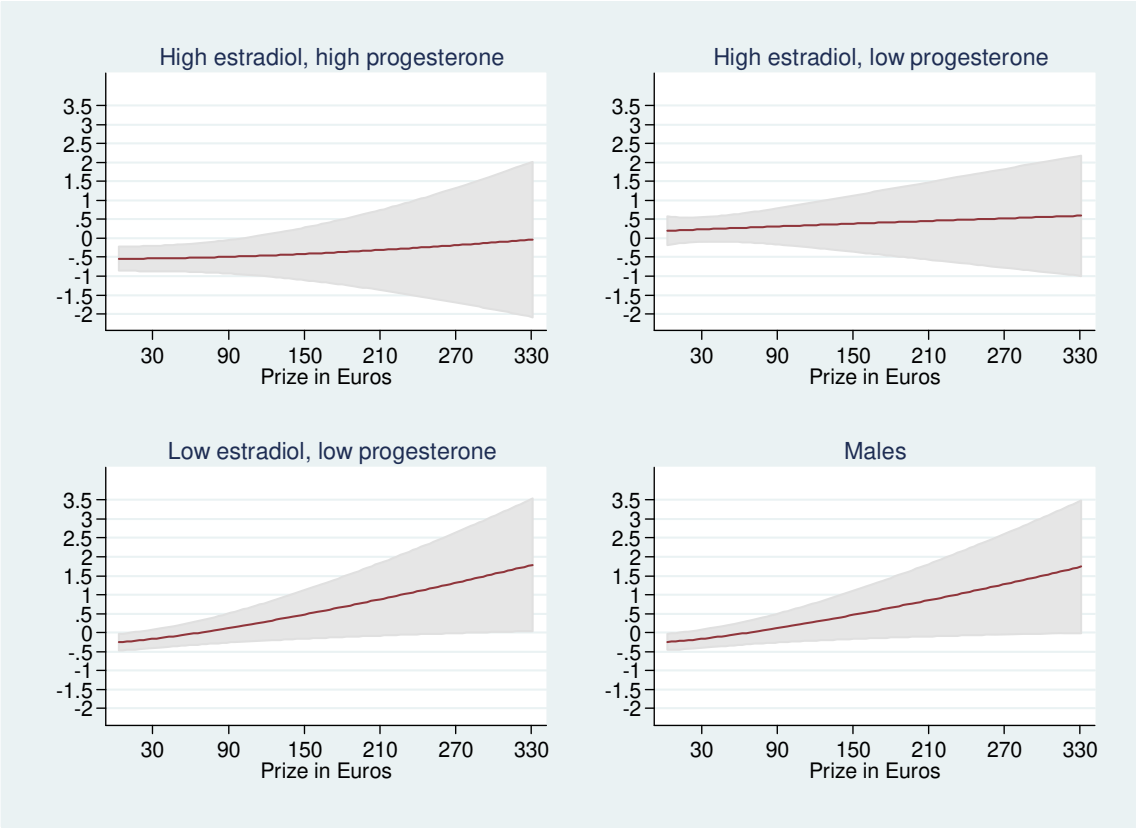


Figure 3. RRA predictions and confidence intervals

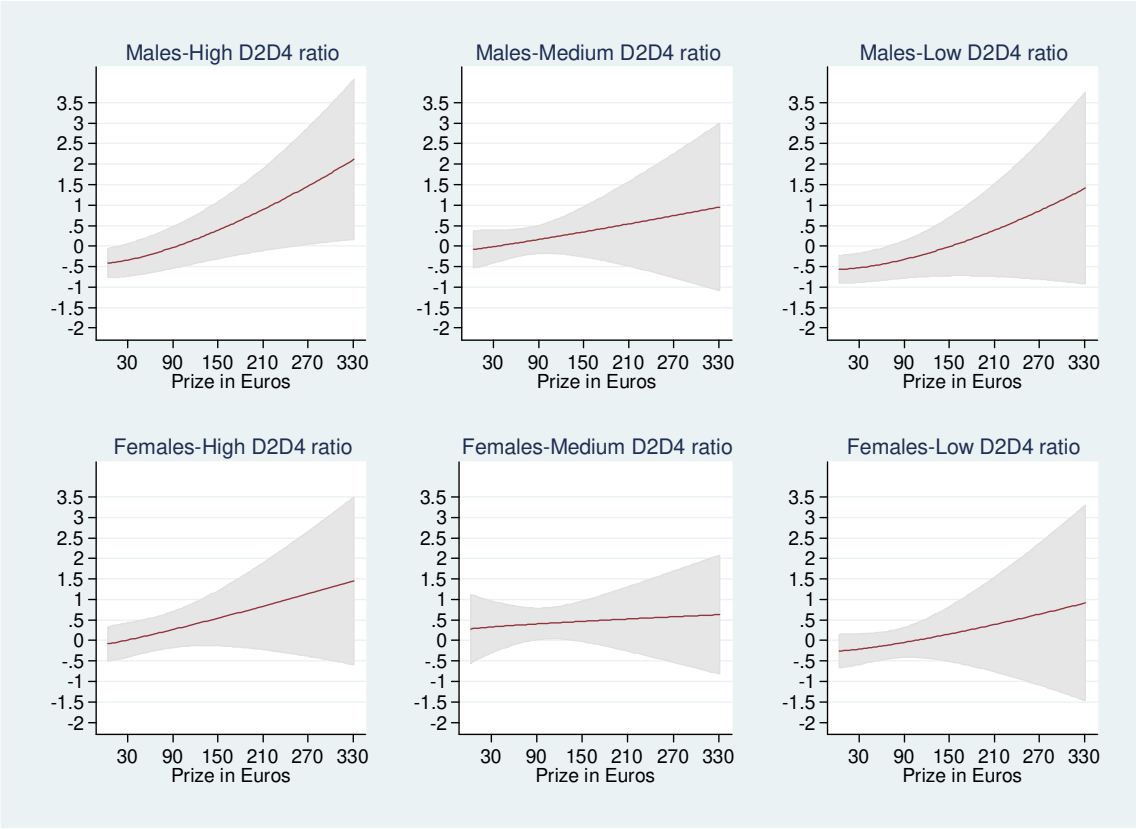


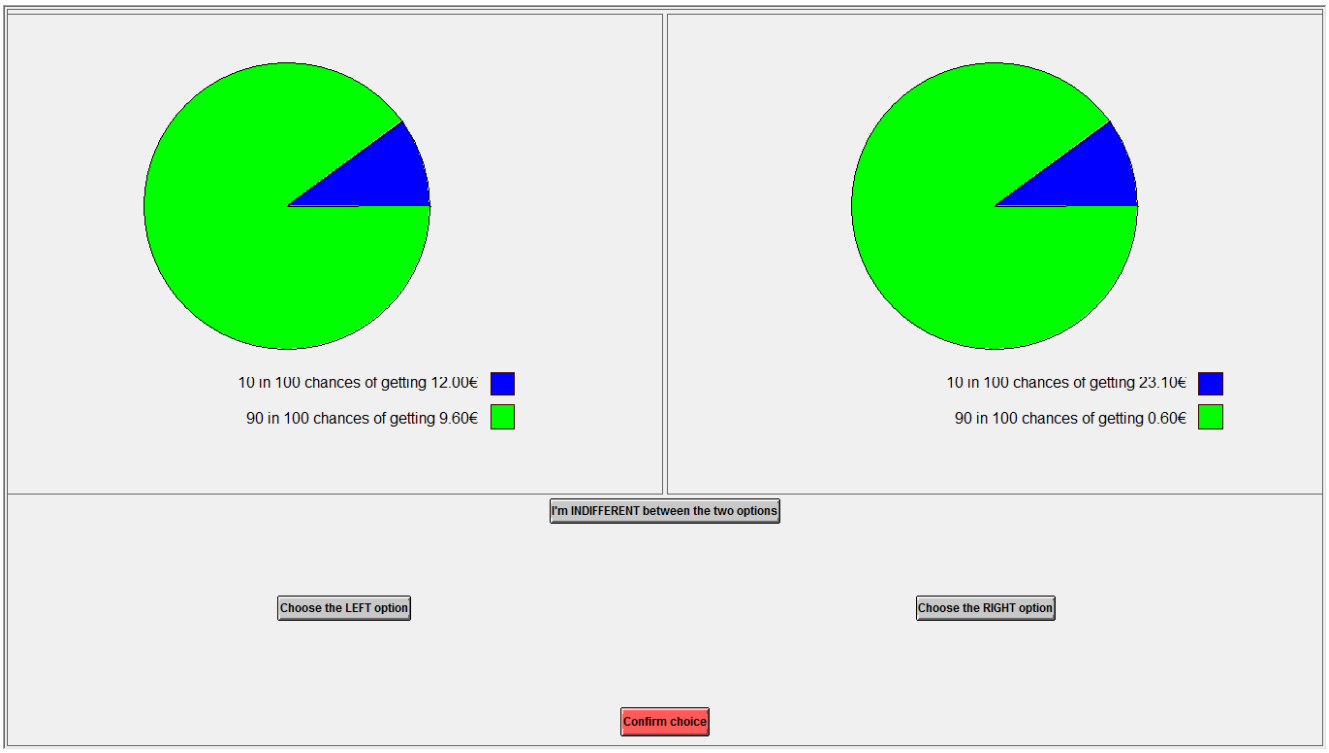
Figure 4. RRA predictions and confidence intervals

Appendix

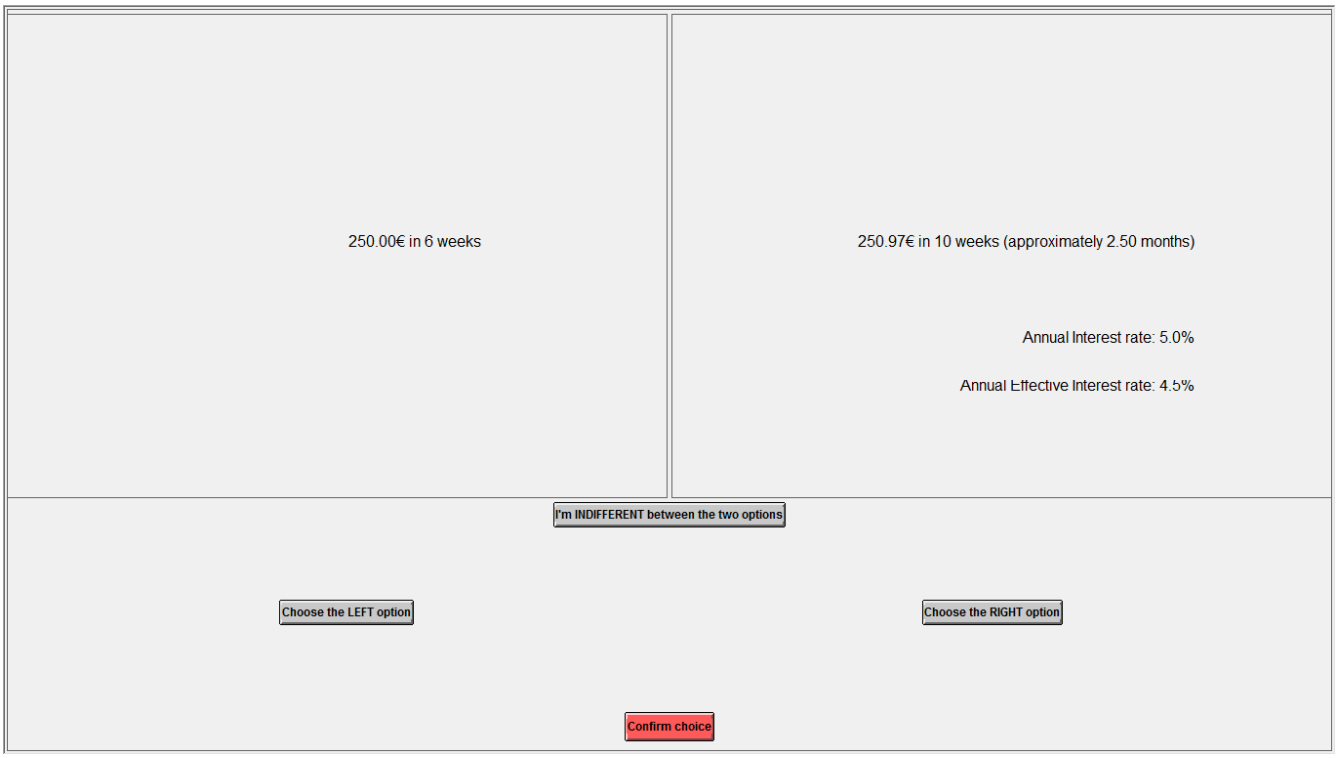
Menstrual cycle questions:

1. How many days ago was the first day of your last menstrual period (first day of your cycle)?
2. On average, how many days are there between your menstrual cycles?
   □ < 25 □ 25 □ 26 □ 27 □ 28 □ 29 □ 30 □ 31 □ 32 □ 33 □ 34 □ 35 □ 36 □ >36
3. How many days does your menstruation last on average?
   □ 2 □ 3 □ 4 □ 5 □ 6 □ 7 □ 8 □ 9
4. Do you currently use a hormone-based contraceptive like birth control pills?
   □ Yes □ No
5. Do you currently experience any symptoms of Premenstrual Syndrome?
   □ None □ Mild □ Severe
6. Are you currently pregnant?
   □ Yes □ No

Sample screen for risk preference task



Sample screen for time preference task



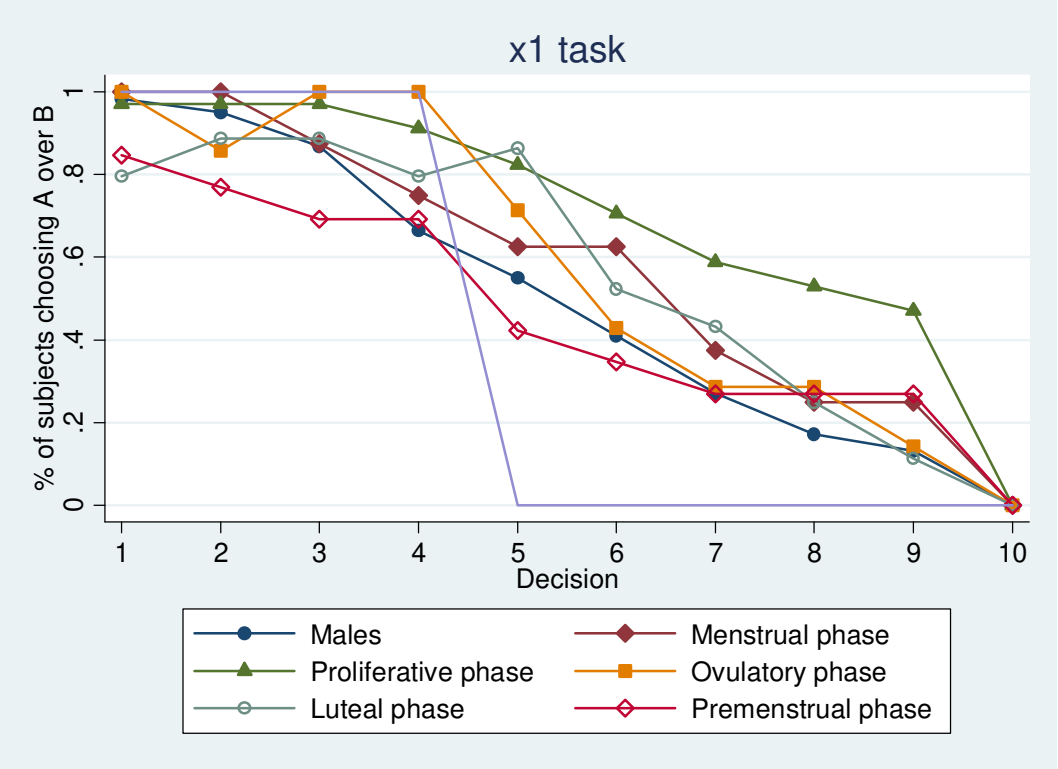


Figure A1. Proportion of choices in each decision for the x1 risk preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

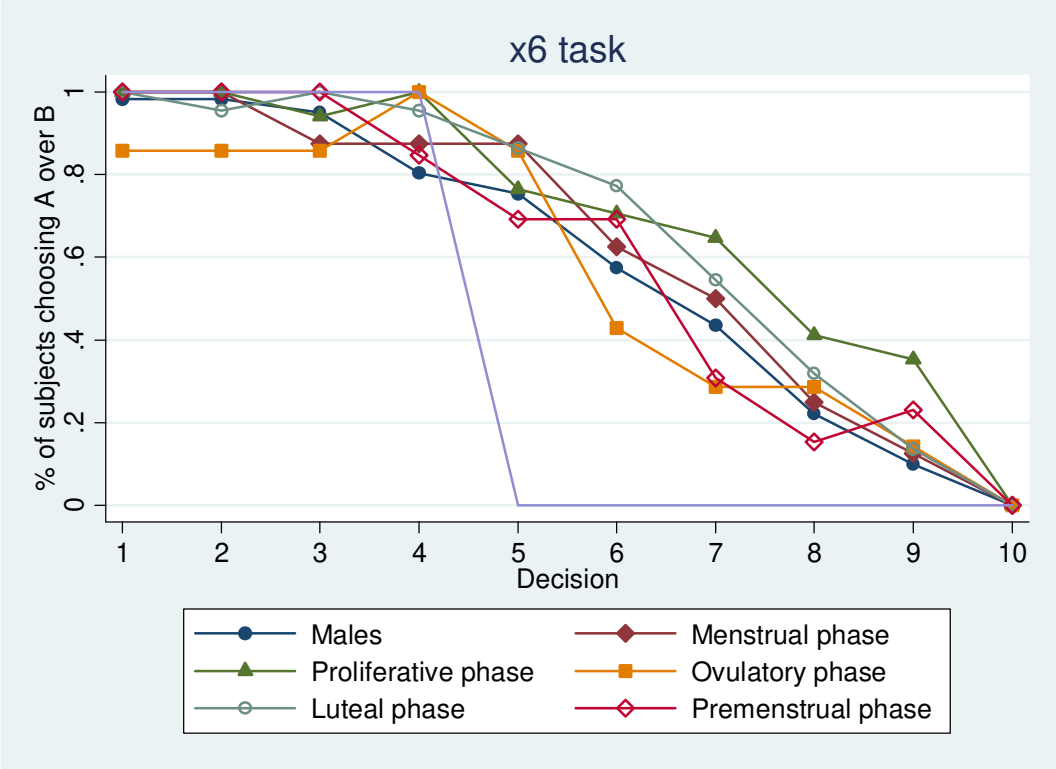


Figure A2. Proportion of choices in each decision for the x6 risk preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

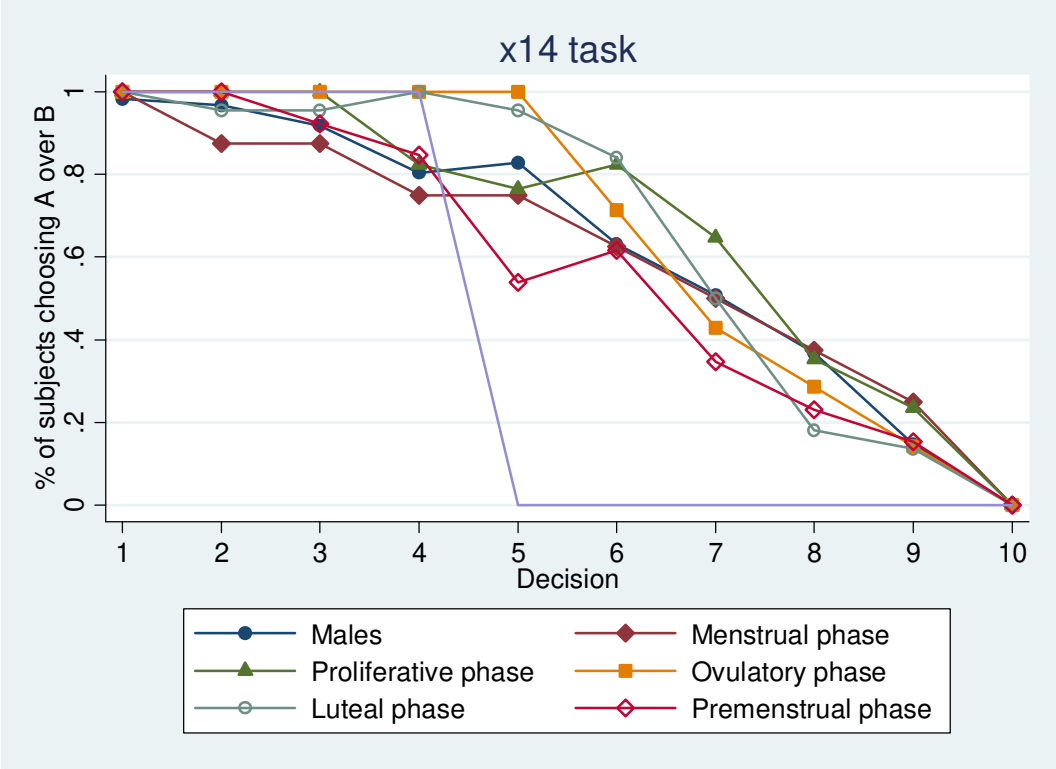


Figure A3. Proportion of choices in each decision for the x14 risk preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

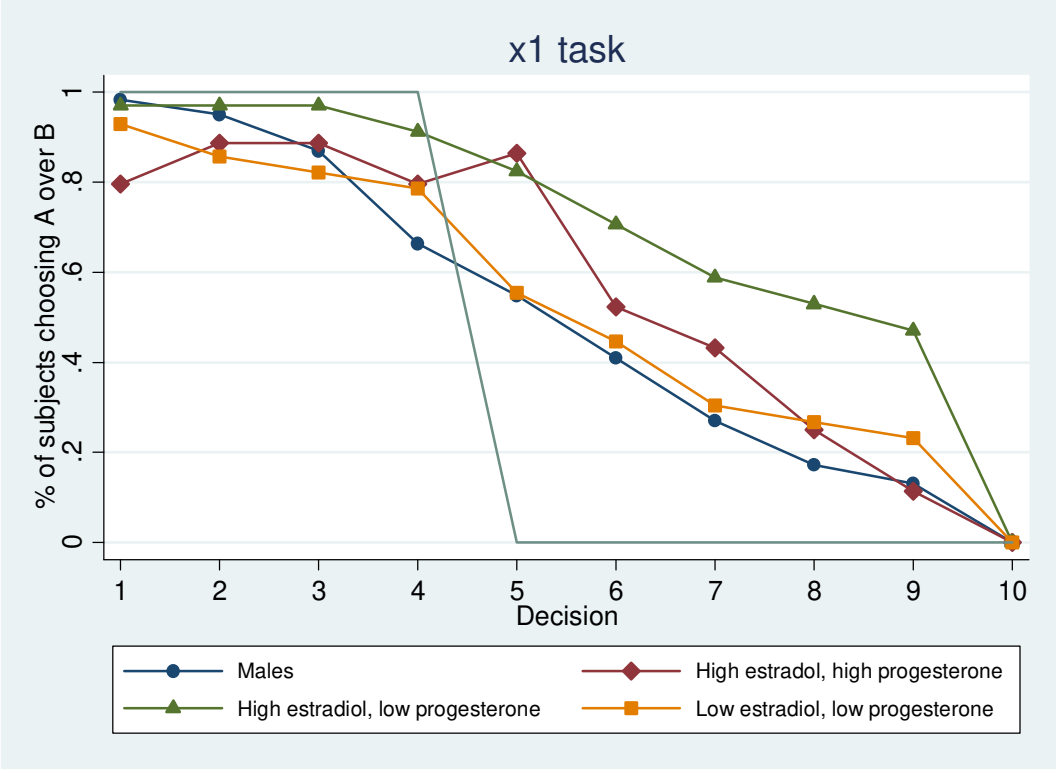


Figure A4. Proportion of choices in each decision for the x1 risk preference task by estradiol, progesterone level (solid line without markers represents risk neutrality under EUT)

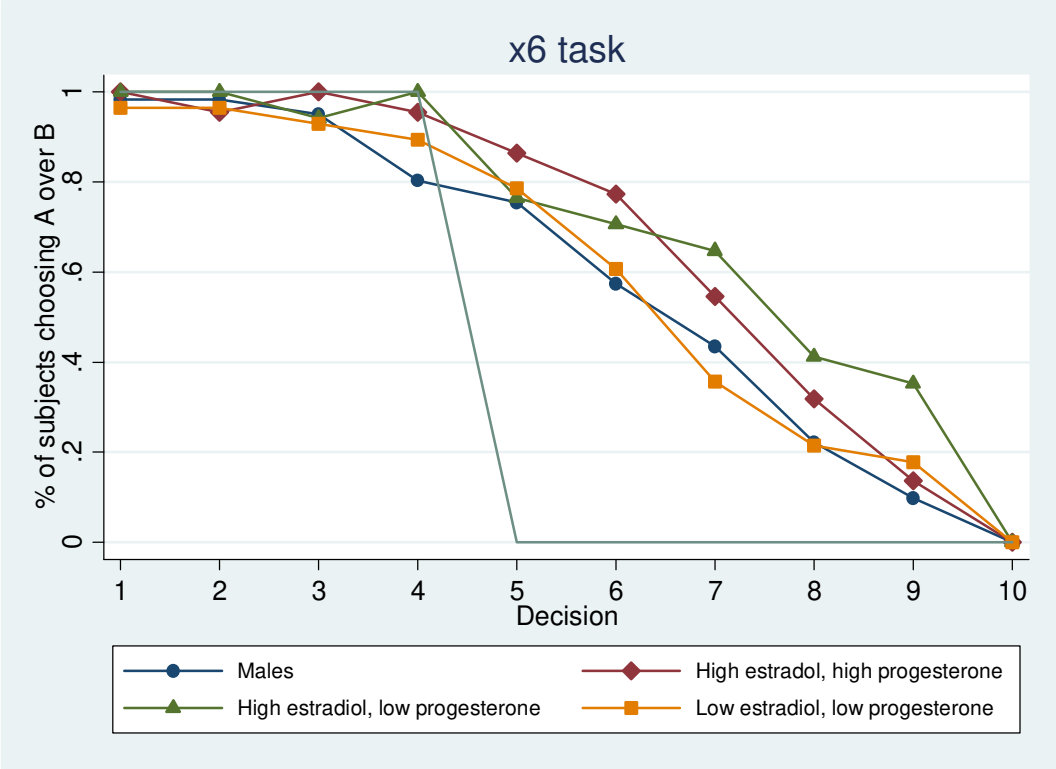


Figure A5. Proportion of choices in each decision for the x6 risk preference task by estradiol, progesterone levels (solid line without markers represents risk neutrality under EUT)

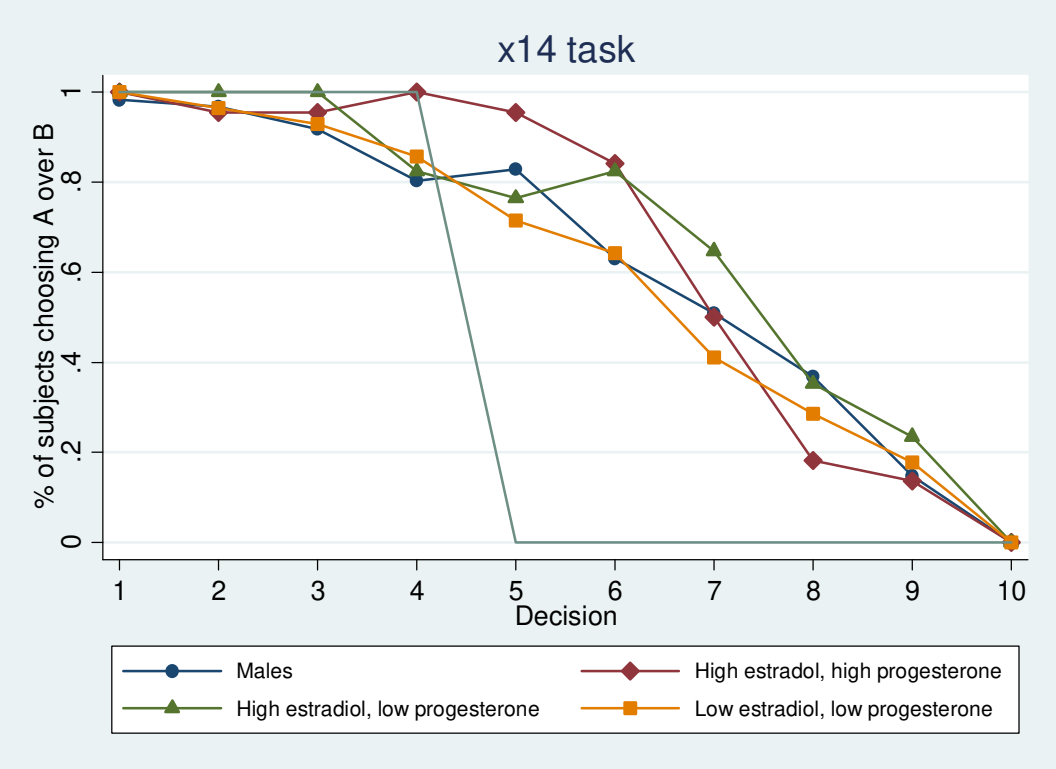


Figure A6. Proportion of choices in each decision for the x14 risk preference task by estradiol, progesterone level (solid line without markers represents risk neutrality under EUT)

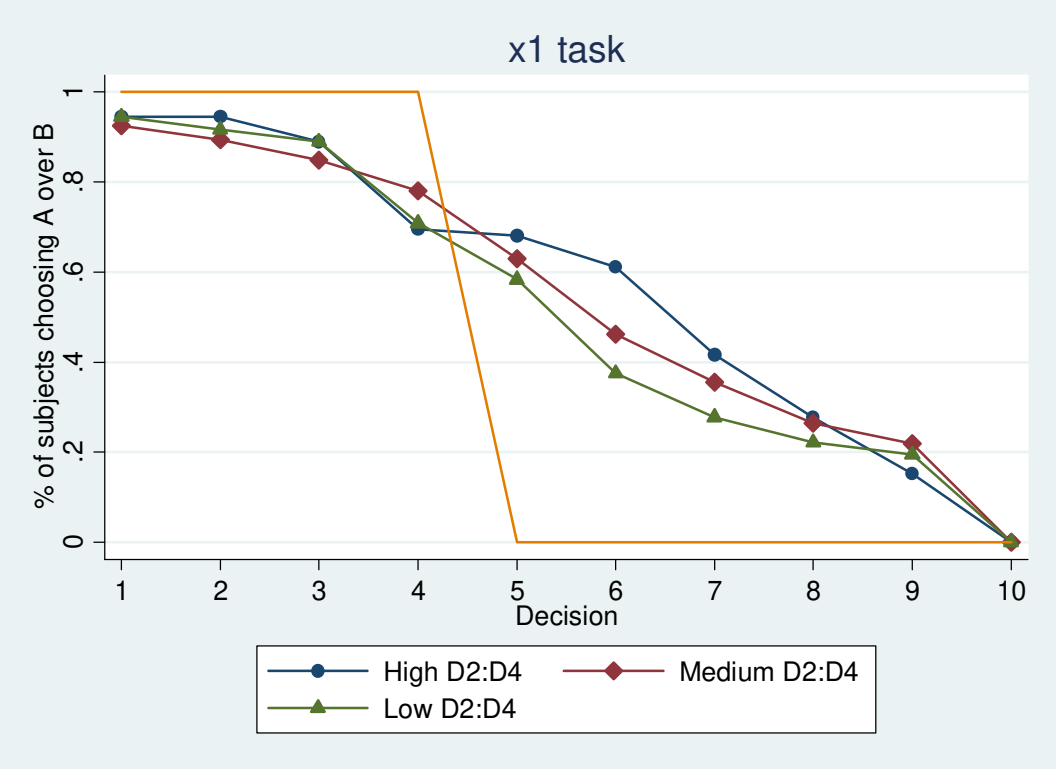


Figure A7. Proportion of choices in each decision for the x1 risk preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)

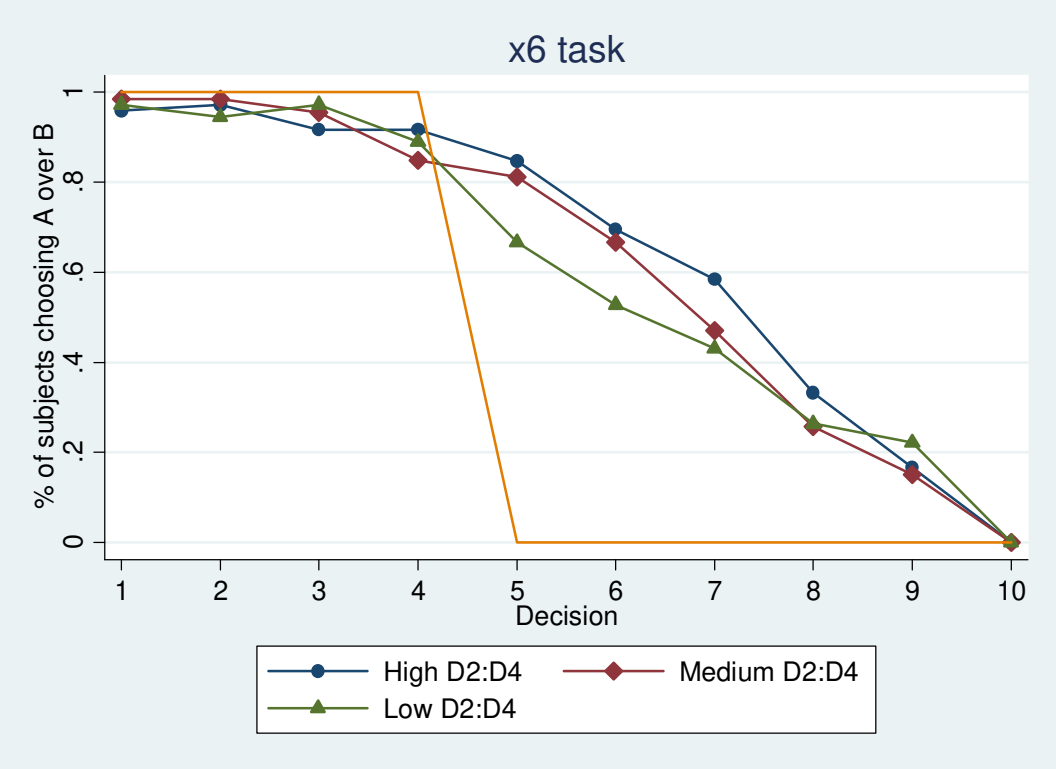


Figure A8. Proportion of choices in each decision for the x6 risk preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)

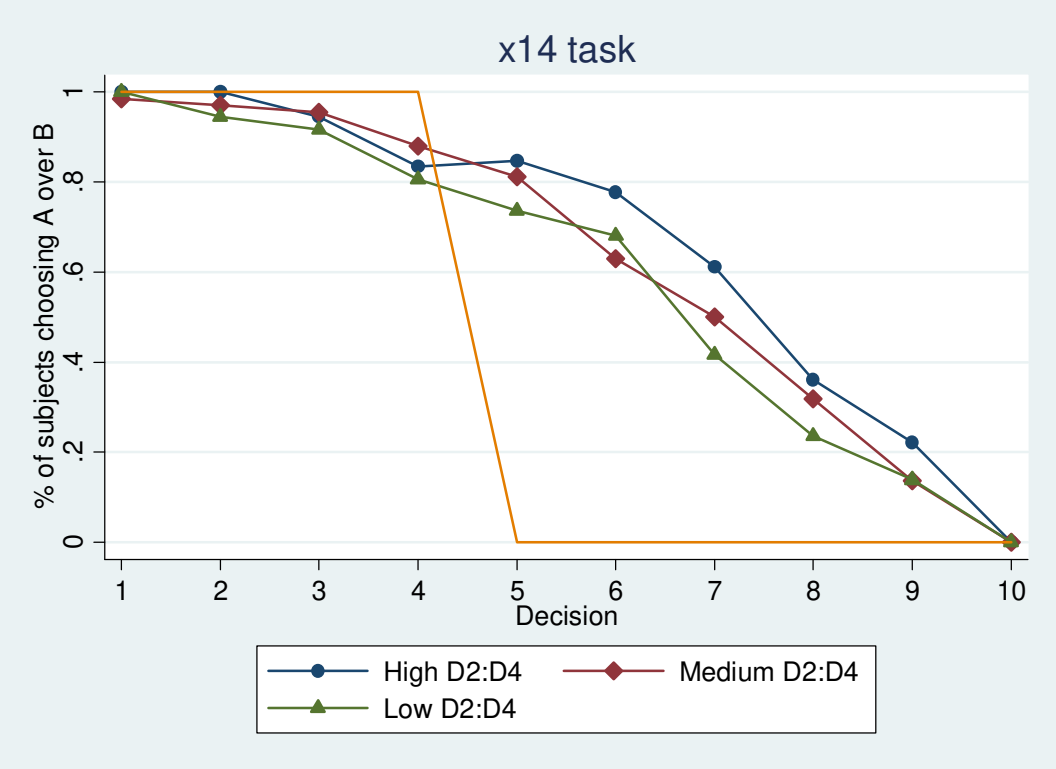


Figure A9. Proportion of choices in each decision for the x6 risk preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)

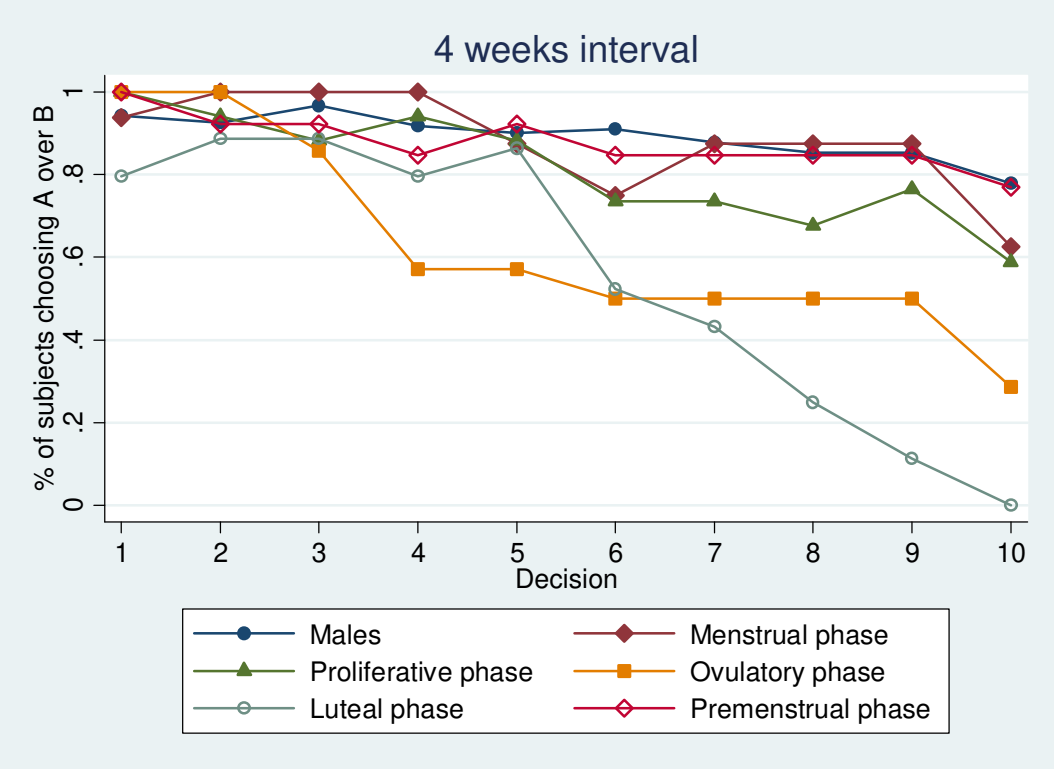


Figure A10. Proportion of choices in each decision for the 16 weeks interval in the time preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

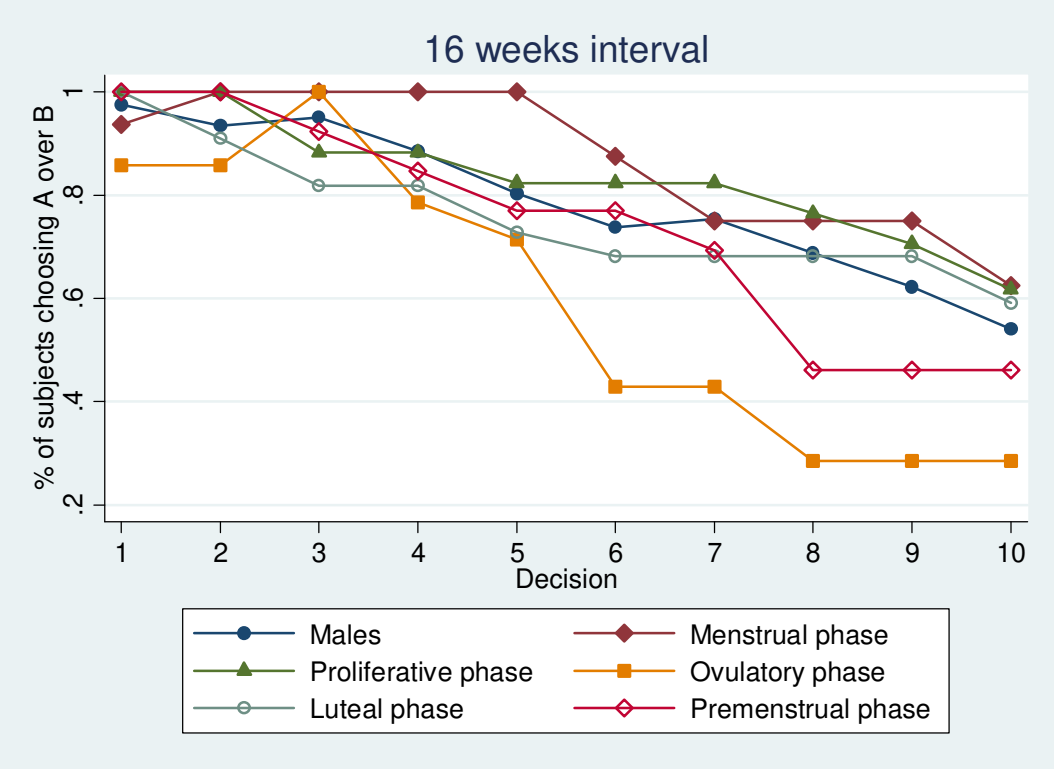


Figure A11. Proportion of choices in each decision for the 16 weeks interval in the time preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

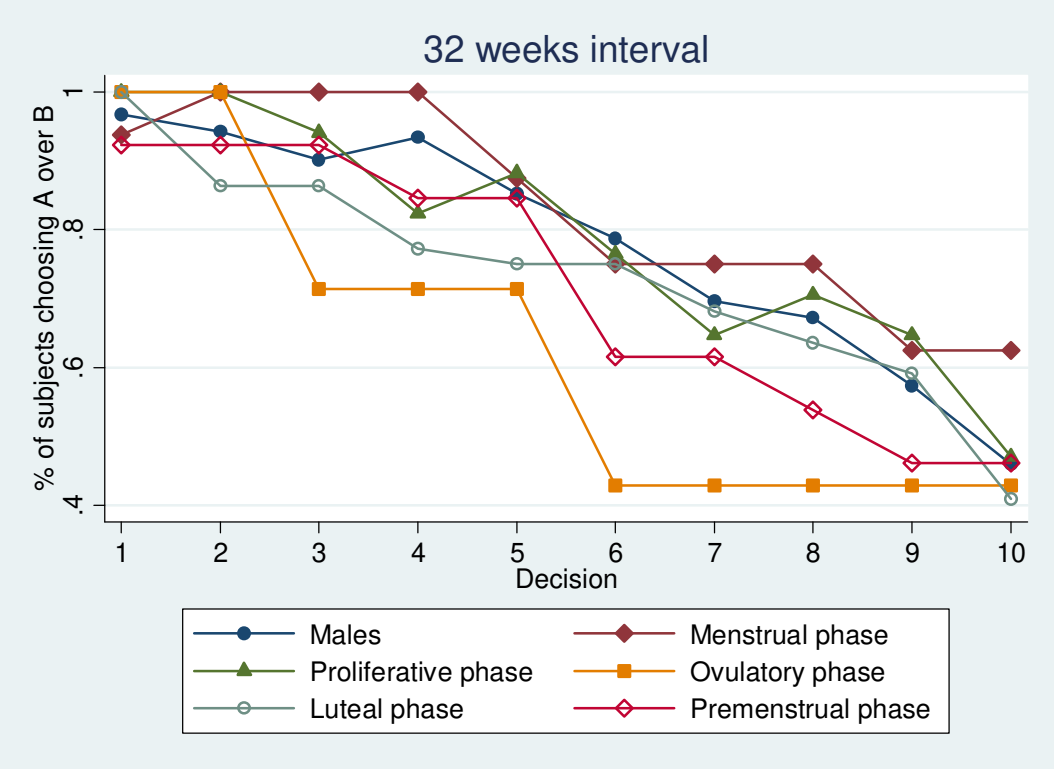


Figure A12. Proportion of choices in each decision for the 32 weeks interval in the time preference task by menstrual phase (solid line without markers represents risk neutrality under EUT)

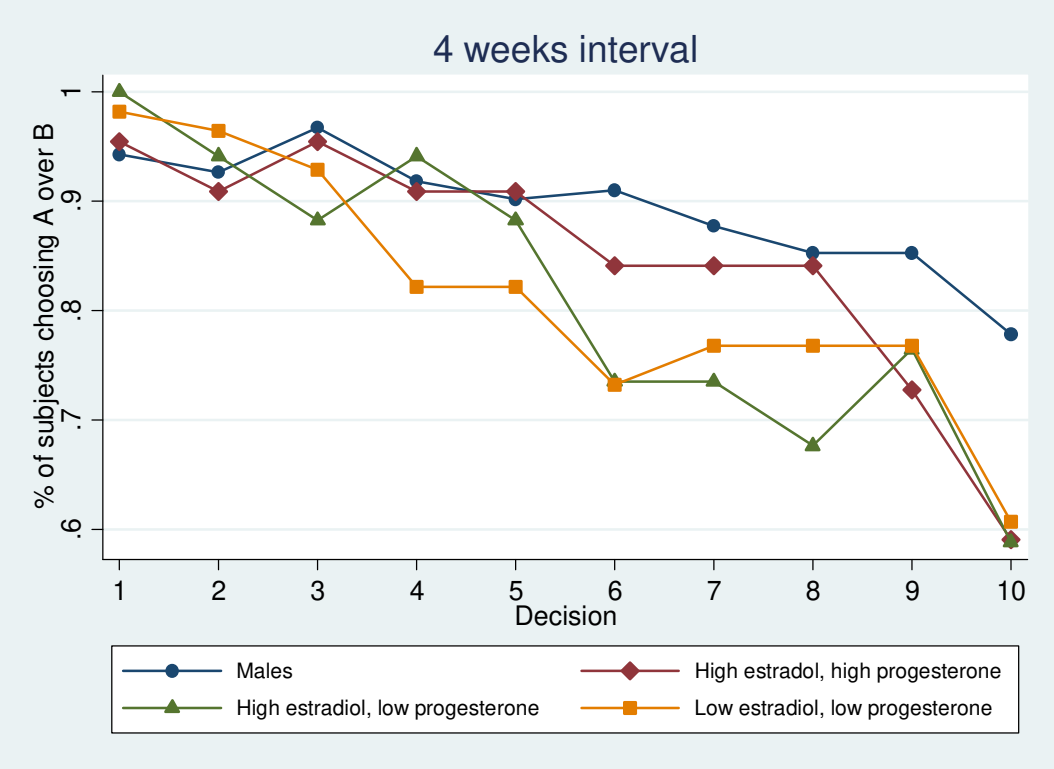


Figure A13. Proportion of choices in each decision for the 4 weeks interval in the time preference task by estradiol, progesterone level (solid line without markers represents risk neutrality under EUT)

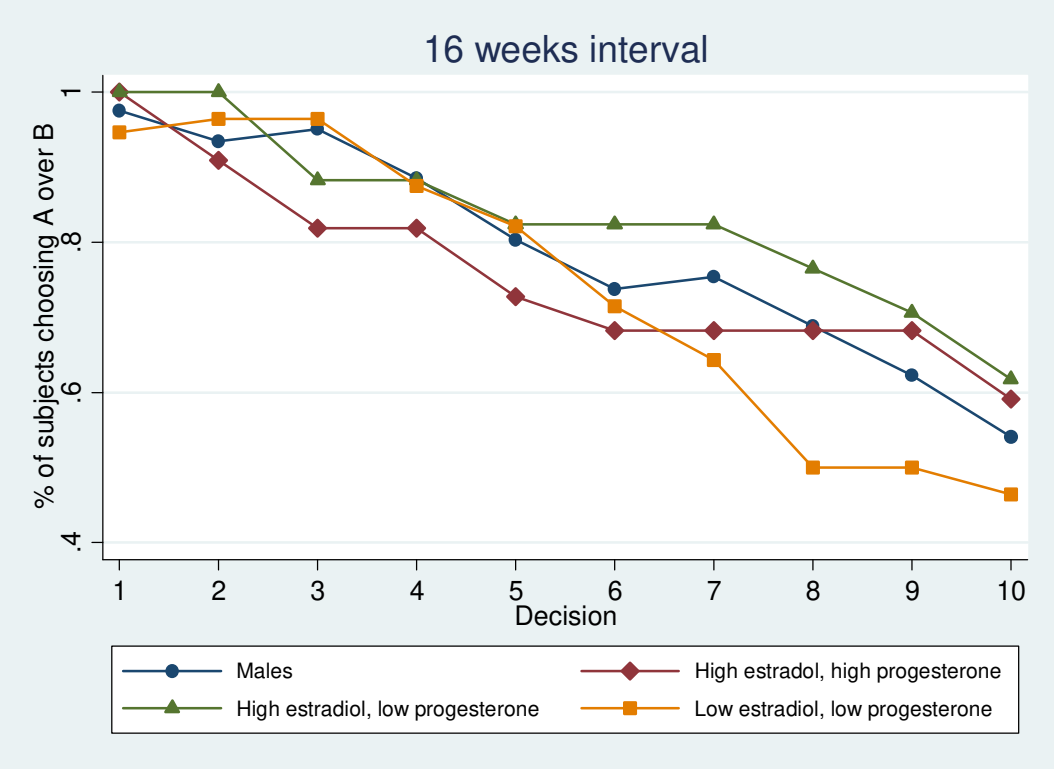


Figure A14. Proportion of choices in each decision for the 16 weeks interval in the time preference task by estradiol, progesterone level (solid line without markers represents risk neutrality under EUT)

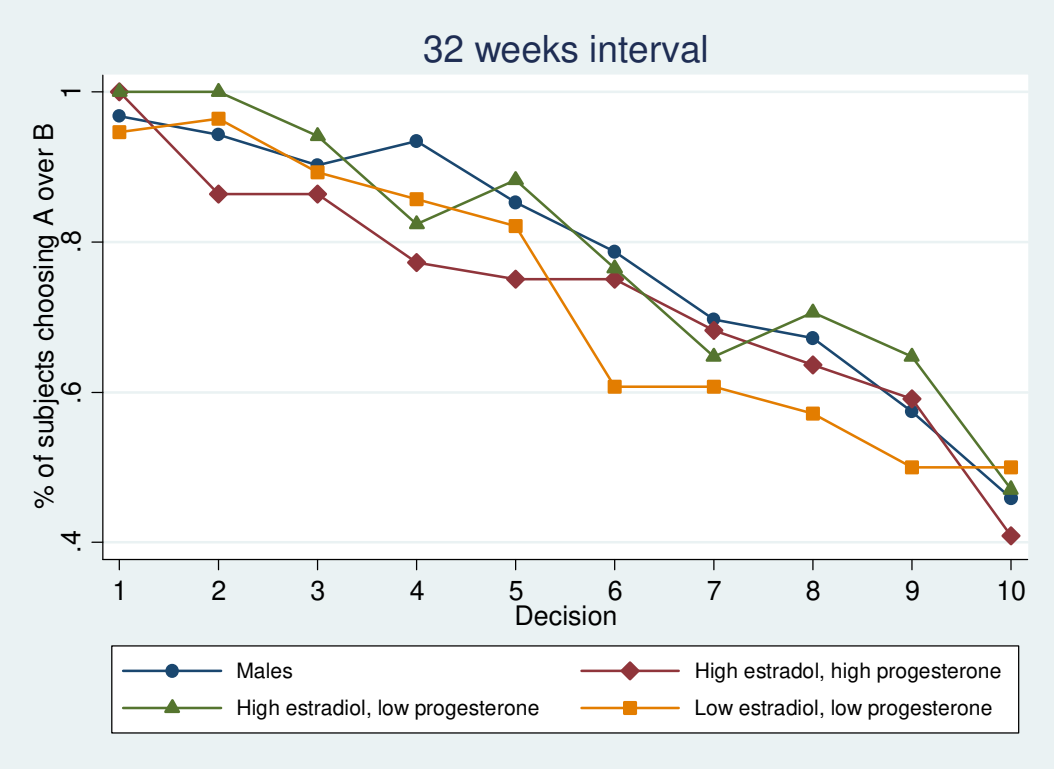


Figure A15. Proportion of choices in each decision for the 32 weeks interval in the time preference task by estradiol, progesterone level (solid line without markers represents risk neutrality under EUT)

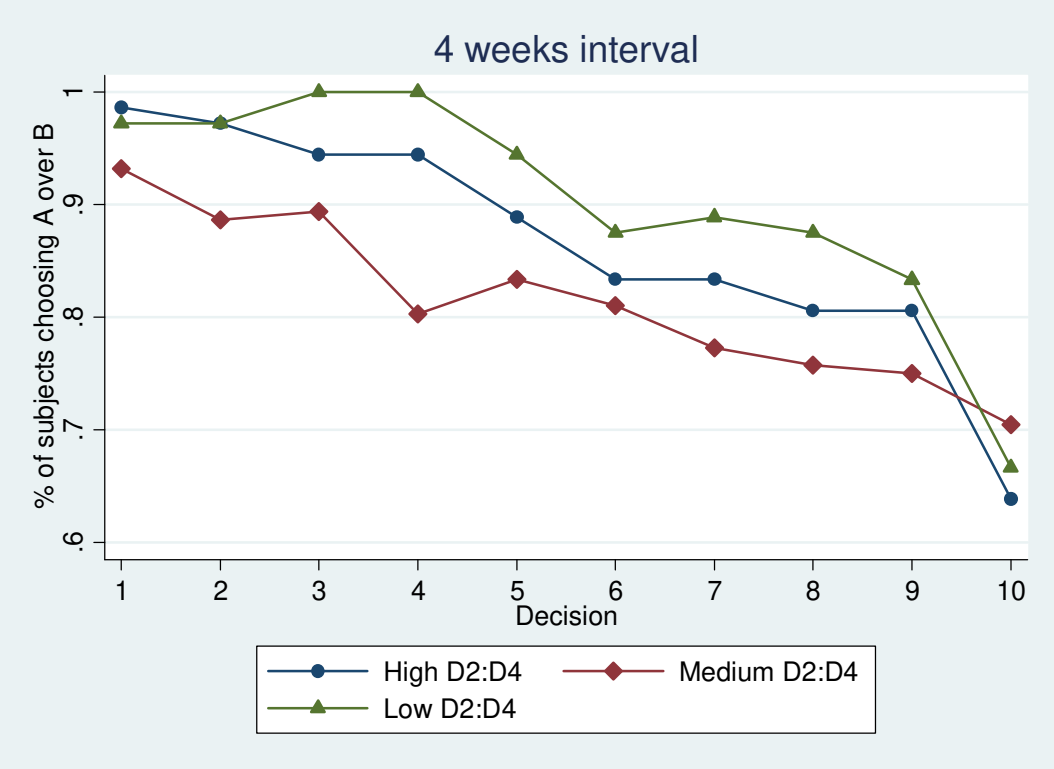


Figure A16. Proportion of choices in each decision for the 4 weeks interval in the time preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)

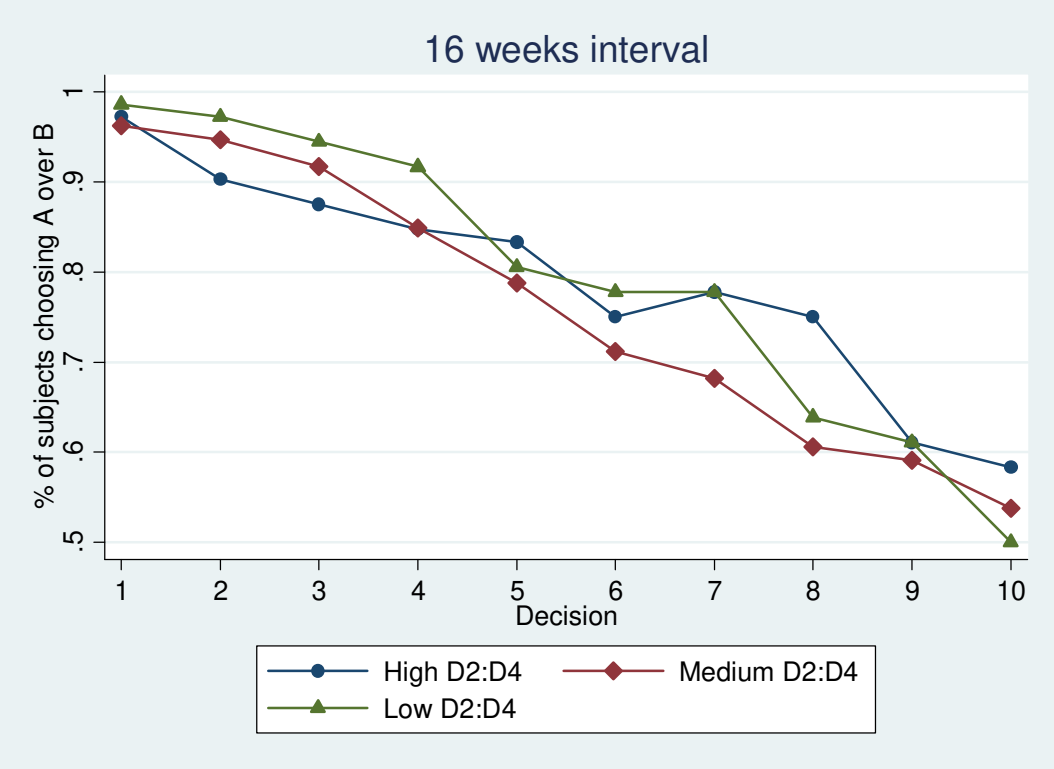


Figure A17. Proportion of choices in each decision for the 16 weeks interval in the time preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)

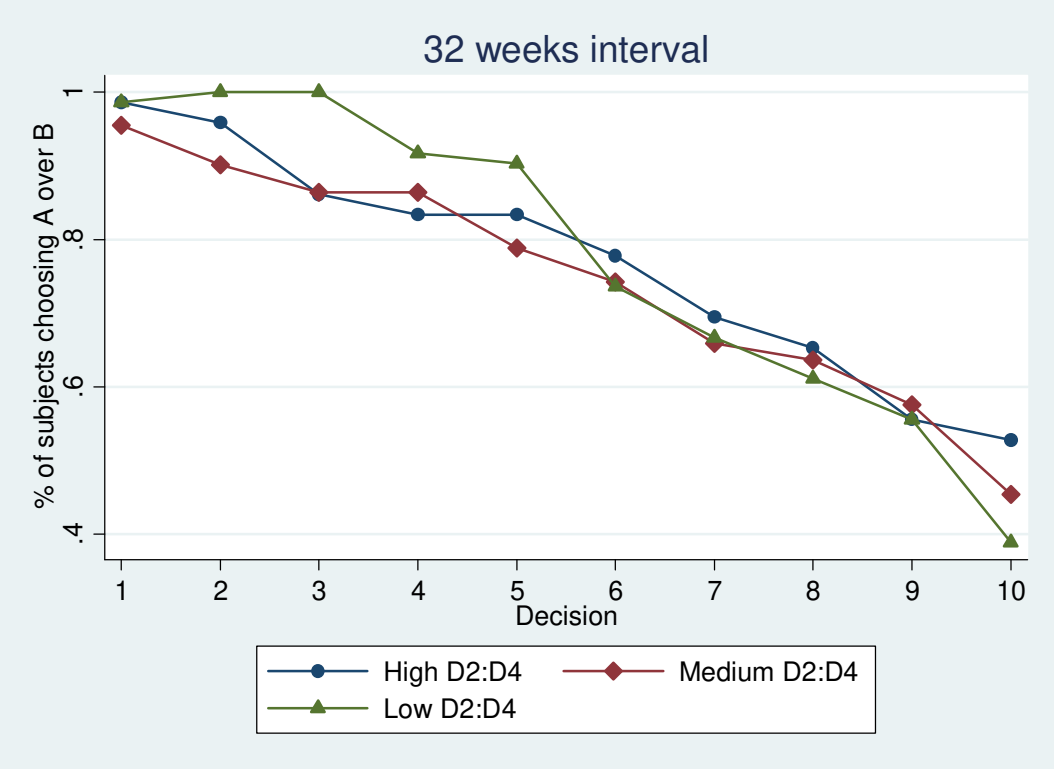


Figure A18. Proportion of choices in each decision for the 32 weeks interval in the time preference task by digit ratio group (solid line without markers represents risk neutrality under EUT)