# Can cognitive skills and risk aversion explain inconsistent choices? An experiment

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# Can cognitive skills and risk aversion explain inconsistent choices? An experiment*

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## Abstract

We study the consistency of risk preferences among undergraduate students in a developing country. Our design allow us to elicit consistency at the individual level in which each subject selects his or her most preferred lotteries under two different (but related) risk elicitation tasks. In the first task, subjects choose one lottery out of six alternatives, thus ruling out inconsistency. Our second task is a transformation of the first task into a multiple price-list lottery, intended to examine whether the choice in the first task is also revealed as preferred. Using these choices, we construct our measures of preferences inconsistency, and analyze their correlation with cognitive skills (as measured by Frederick (2005)'s Cognitive Reflection Test—CRT scores and students' GPAs) and risk preferences. We find that a low CRT score and a poor academic performance are, in general, good predictors of inconsistent choices. Results are mixed in terms of the role of risk aversion.

**Keywords:** Inconsistent choices, risk aversion, cognitive skills, experimental economics.

**JEL Classification**: C91, D81.

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## 1. Introduction

Preferences consistency is a typical assumption in the decision-making frameworks (García-Lapresta & Montero, 2004) and has important consequences for making predictions about the human behavior. However, with the surge of Behavioral Economics, recent studies have found evidence that does not conform to the standard axioms of neoclassical theory (e.g., the existence of other-regarding preferences, intransitive preferences, framing effects, and so on).

Studies about preferences inconsistency are well known in developed countries but relatively new in developing countries (e.g., Benjamin et al., 2013; Jacobson & Petrie, 2009). Previous evidence reports that almost every experiment conducted in a developed country has a non-trivial proportion of subjects who make choices inconsistent with those predicted not only by expected utility models, but also by rank-dependent utility models (e.g., Holt & Laury, 2002). However, the proportion of subjects whose choices cannot be explained by the canonical models of risk preferences in developing countries seems to be significantly larger than those observed in developed countries. This result represents a challenge for researchers, as it calls for taking a closer look at the reasons behind these inconsistencies.

When examining risk preferences, we should be aware that subjects might have preferences regarding not only the outcome of a risky event, but also its variance. Therefore, independently of the reasons that might drive subjects to choose erratically among lotteries (e.g., poor understanding, tiredness, and noise), if a set of outcomes and probabilities over the states of the world, is revealed preferred over the others, consistent subjects should prefer this lottery to other lotteries. In contrast to this assumption, subjects have often presented a more erratic pattern of choices (Jacobson & Petrie, 2009; Benjamin et al., 2013). Despite this result, even though inconsistencies are normal and typically not entirely explained by just noise, we still know little about the reasons behind them.

Another branch of the literature relevant to our paper is the one relating cognitive and risk preferences. Among the few related studies, Frederick (2005) find that subjects with higher IQs—a proxy for cognitive ability—tend to be more risk loving, a result in line with that of Dohmen et al. (2010). Similarly, Benjamin et al. (2013) report that, in small-stake lotteries, individuals with high standardized test scores are less likely to exhibit risk aversion.

On the other hand, several experimental studies, including those which examine decisions over risk (e.g., Holt and Laury 2002; Jacobson and Petrie, 2009), health (Stockman 2006) and time preferences (Castillo et al. 2008; and Meier and Sprenger

2007), report inconsistencies in decision-making. Prasad and Salmon (2013), find that subjects who earn less money in a principal-agent experiment are the ones making more decisions over risk that are inconsistent. These inconsistencies have been frequently ignored by previous research, under the premise that they are uninformative. However, we adopt the view that it is possible to learn something from inconsistencies.

There are two main approaches in the risk aversion literature, in regards to these inconsistencies: ruling them out by design or using them to enhance our understanding of peoples' choices. In the former case, by restricting the subjects' choices, inconsistent behavior cannot be observed, and clear estimates of risk aversion are then computed. The design of risk experiments thus gives subjects a single decision to make from a menu of lotteries, as in Binswanger (1980). Another way is to restrict subjects' choice to pick a switching point from risky to safe lotteries (similar to Tanaka et al. 2013; and Harrison and Rutström 2008). Using an iterative procedure to hone in on the subject's switching point; Andersen et al. (2006) find that subjects make significantly fewer unexpected choices with this procedure.[2] In the latter group, those who analyze whether mistakes can be informative, conduct experiments where subjects can actually make mistakes (e.g., Dave et al., 2010; Jacobson & Petrie, 2009; Eckel et al., 2007), and then examine whether those mistakes can explain economic decisions. For instance, Jacobson & Petrie (2009) find that mistakes *and* risk preferences explain real financial decisions, while risk aversion alone does not. While this branch of the literature is still scant, it is suggestive that, by looking at those inconsistencies, we can advance our understanding of peoples' behavior.

In this paper, we study a developing country context where, we aim to explain how subjects' risk preferences and cognitive abilities correlate with their choices over lotteries, and in particular, with their propensity to make inconsistent choices. Our measures of cognitive skills are the Frederick (2005)'s Cognitive Reflection Test (CRT), which evaluates the ability of individuals to reflect before giving an intuitive but incorrect answer to relatively simple inquiries,[3] as well as undergraduate students' GPAs. The remainder of the paper is organized as follows. Section 2 presents our

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[2] If we compare inconsistent choices in Holt and Laury (2002) and in Prasad and Salmon (2007), we can argue that, when lotteries are presented all at once rather than sequentially, people make fewer inconsistent choices. Langer and Weber (2001) and Chakravarti et al. (2002) find the same results in the areas of psychology and marketing. Probably, the explanation for these results rely on the fact that when decisions need to be made all at once, then this decisions is thought of as a "bundle," so each choice is reconciled with the others. However, when decisions are made in a sequence, choices are viewed separately, each one now having its own independent chance of error.

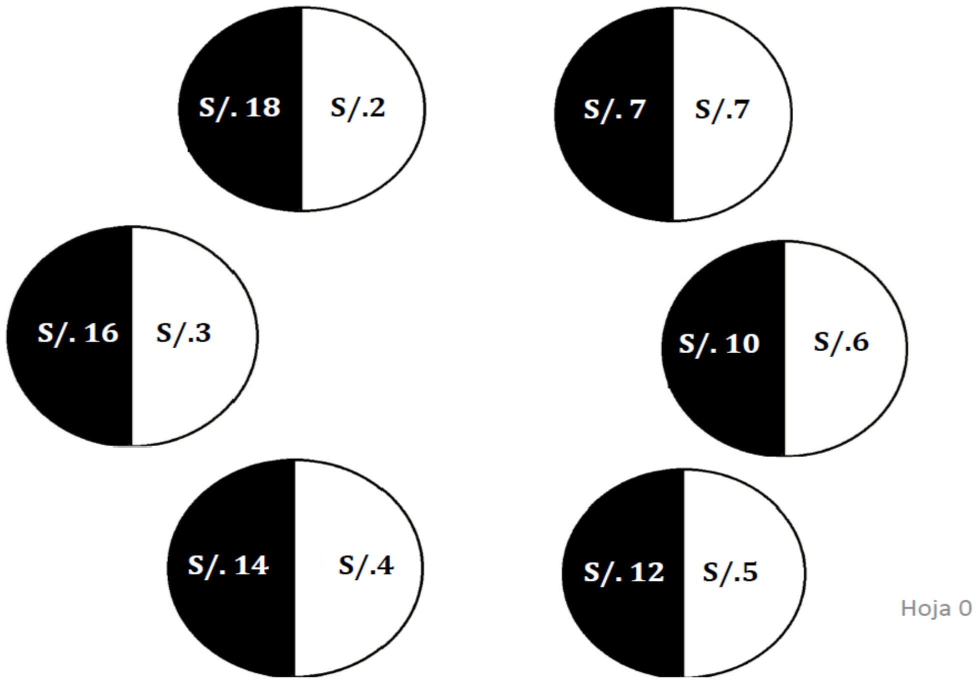
[3] The CRT has shown a strong correlation with cognitive ability (Frederick, 2005), while this result may not hold when one uses an incentivized risk elicitation method, as shown by Sousa (2010).

experimental design and explains our measures of preferences inconsistency. Section 3 introduces the data. Section 4 discusses our results and section 5 concludes.

## 2. Experimental Design

Our experimental sessions consisted of three tasks—two risk elicitation tasks (Task 1 and Task 2, conducted in that order) and the CRT–and a questionnaire. Task 1 is displayed in Figure 1, which is similar to Binswanger (1980) and Eckel and Grossman—EG (2002). According to Dave et al. (2000), the procedure used by EG (2002) produce less noise than the lotteries in Holt and Laury (2002). In Task 1, subjects have to choose their more preferred lottery among six alternative lotteries. As suggested by the pictures, each lottery has only two equally likely outcomes, and its expected value and variance increase clockwise. A similar instrument has been used in several studies conducted with students in developed countries (e.g., Dave et al., 2010) and with a non-student pool in less developed economies (Cardenas and Carpenter, 2013). Unlike the former, the latter study, does not examine the role of mistakes in decision-making.

**Figure 1. Risk Elicitation, Task 1**




Task 1 only allows for an estimation of risk aversion parameters under the assumption of a particular type of utility function, such as the commonly used Constant Relative Risk Averse (CRRA) function. As seen in Table 1, choices, shown clock-wisely, have increasing expected values (EV) and standard deviation (risk), as mentioned earlier.

**Table 1: Lotteries Features in Risk Elicitation, Task 1**

| | p | Payment | 1-p | Payment | Expected Value (EV) | Risk (Std. Dev.) |
|---|---|---|---|---|---|---|
| Lottery 1 | 0.5 | 7 | 0.5 | 7 | 7 | 0 |
| Lottery 2 | 0.5 | 10 | 0.5 | 6 | 8 | 2.83 |
| Lottery 3 | 0.5 | 12 | 0.5 | 5 | 8.5 | 4.95 |
| Lottery 4 | 0.5 | 14 | 0.5 | 4 | 9 | 7.07 |
| Lottery 5 | 0.5 | 16 | 0.5 | 3 | 9.5 | 9.19 |
| Lottery 6 | 0.5 | 18 | 0.5 | 2 | 10 | 11.3 |

In Task 2, we decomposed Task 1 in order to create a multiple-price listing mechanism (as in Holt and Laury, 2002). Thus, subjects were presented with six choices among binary lotteries, obtained from combinations of the same lotteries shown in Task 1. Note that, unlike Holt and Laury—HL (2002), where the payoffs are kept constant and probabilities vary across decision rows, in our experiment, we keep probabilities always at 50-50 and the payoffs vary. Given that in Task 2, the binary lotteries are presented sequentially, we can observe if subject's preferences vary with respect to those expressed in Task 1. In our design, Task 2 allows us to observe deviations from predicted choices, based on choices in Task 1.

The estimation of preferences towards risk used in our analysis is based on the choices that subjects made in Task 2 (comparing to the ones made in Task 1). The experimental materials we used are reported in Appendix 1. As shown there, the tasks were relatively simple, so we anticipated no difficulties in regards to the quality of the information collected.

It is important to mention that, for roughly half of our sessions (61 observations), we used a different order in Task 2, which consisted in giving binary lotteries in the following order: lotteries 1 and 3, lotteries 2 and 4, lotteries 3 and 4, lotteries 1 and 6, lotteries 5 and 4, and lotteries 5 and 6. We wanted to test any order effects resulting from these variation. For the sake of space, we will only report results from the original Task 2 order (Order 1) (Appendix 2 reports the remaining results (Order 2)).

### *2.1 Preferences towards risk*

We estimated risk preferences from choices subjects made in Task 2, which involves six sequential choices between two binary lotteries. Appendix 1 shows the actual instructions and materials used in our experiment. Table 2 below shows the analysis of subjects' choice in Task 2.

As shown in columns 6, 11 and 12, the lottery on the right-hand side has a lower expected value and a higher risk than the lottery on the left-hand side in the first five rows, a relationship that is reversed in the last row. Table 2 shows a trade-off between expected gain and risk in subjects' decisions. The last column reports the Constant Relative Risk Aversion (CRRA) interval that results when a subject switches from choosing lottery "A" to lottery "B" in each of the rows. Our gambles do not consider a risk-loving range.

For example, if an individual switches to the right-hand side lottery in Choice 4, the degree of risk aversion implied ranges between 0.475 and 0.652 (average risk aversion coefficient of 0.563), which indicates a moderate degree of risk aversion.

**Table 2: Binary Lottery Choices in Task 2**

| | Lottery | Left | Right | EV | Risk | Lottery | Left | Right | EV | Risk | Diff. EV | CRRA interval ($r$)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Choice 1 | 1 | 7 | 7 | 7 | 0 | 2 | 10 | 6 | 8 | 2.83 | -1.0 | > 3.120 |
| Choice 2 | 2 | 10 | 6 | 8 | 2.83 | 3 | 12 | 5 | 8.5 | 4.95 | -0.5 | [0.985, 3.120] |
| Choice 3 | 3 | 12 | 5 | 8.5 | 4.95 | 4 | 14 | 4 | 9 | 7.07 | -0.5 | [0.652, 0.985] |
| Choice 4 | 4 | 14 | 4 | 9 | 7.07 | 5 | 16 | 3 | 9.5 | 9.19 | -0.5 | [0.475, 0.652] |
| Choice 5 | 5 | 16 | 3 | 9.5 | 9.19 | 6 | 18 | 2 | 10 | 11.31 | -0.5 | [0.360, 0.475] |
| Choice 6 | 6 | 18 | 2 | 10 | 11.3 | 1 | 7 | 7 | 7 | 0.00 | 3.0 | < 0.742 |

* Calculated as the $r$ in the CRRA utility $U(x) = \frac{x^{1-r}}{1-r}$ that makes a subject indifferent, in an expected utility sense, between lotteries considered in each decision row.

In addition to the CRRA coefficients, we can use the number of times the relatively safe lottery (the one on the left hand side in Choices 1 to 5, and the one on the right hand side in Choice 6) in our analysis, as in Holt and Laury (2002) and Jacobson and Petrie (2009). As mentioned earlier, for the other half of our sample, Table 2, shown in Appendix 2, is different (see Table 2A). We will use the corresponding CRRA coefficients in our analysis.

### 2.2 *Inconsistency measures*

Based on choices made in Task 1 and Task 2, we constructed two measures: a *local inconsistency ratio* (LIR), and a *global inconsistency* ratio (GIR). The intuition behind the LIR is to believe in that subject's choice in Task 1 reveals that this subject prefers explicitly *that* lottery. This means that whenever the selected lottery in Task 1 is available in a binary choice in Task 2, this subject will choose the lottery previously selected in Task 1. Thus, using this information we can construct the ratio of the number of times that a lottery available in Task 2 was chosen in Task 1, divided by the total number of times that such lottery was available in Task 2. The ratio is called local, because we do not assume that a subject's choice in Task 1 is always preferred to any other choice, but rather that whenever a subject has to choose between lotteries he chose before and something else, he will be consistent with what he has revealed as preferred.

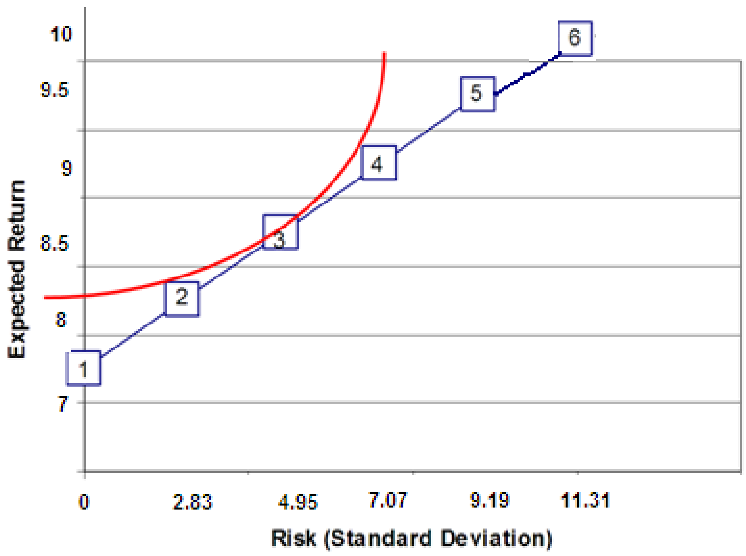
To illustrate the calculation of this ratio, let us consider the case of a subject who selected lottery 1 instead of the other five lotteries available in Task 1 (see Table 1). As shown in Table 2, lottery 1 may be selected twice in Task 2 (every single lottery in Task 1 can be selected twice during Task 2). Thus, our local inconsistency ratio is equal to 0.5 (1 minus the ratio 1 divided by 2) if our subject selected lottery 1 only once in Task 2, and is equal to 1, if our subject did not select lottery 1 ever in Task 2 (1 minus the ratio of 0 divided by 2). In the former case, we can label the subject as "half-locally inconsistent subject", and in the latter case, as "fully locally inconsistent subject". Finally, a subject is considered "fully locally consistent" when s/he shows a LIR of 0. This measurement is different from that of Jacobson & Petrie (2009)'s, which only considers the number of mistakes made by subjects.

On the other hand, the *global inconsistency* ratio assumes that subject's choice in Task 1 fully reveals his preferences. Therefore, we could infer from that selection, not only the preference of the selected lottery over the others, but also a complete *(global)* rank over all choices. If this is the case, then a subject's selection in Task 1 provides us with predictions of what s/he will choose anytime s/he faces binary lotteries involving the lottery selected in Task 1. Therefore, this second measure of inconsistency relies on additional assumptions about the transitivity of preferences. Because in Task 1 a subject makes one choice, such choice made implies five predicted binary choices for Task 2 (which involves 6 choices). Let us examine an example that illustrates the measure of global inconsistency. Figure 2 shows the expected return and risk involved in each of the lotteries available in Task 1 (shown in boxes), for a subject who selected lottery 3 (hence the indifference curve being tangent to such lottery).

As seen above, if lottery 3 is selected over the other five lotteries in Task 1, this means that:

1. Lottery 3 is preferred to lottery 2.
2. Lottery 3 is preferred to lottery 1.
3. Lottery 3 is preferred to lottery 4.
4. Lottery 3 is preferred to lottery 5.
5. Lottery 3 is preferred to lottery 6.

**Figure 2: Risk and Return of Lottery Choices**




Next, assuming transitivity in preferences, for a subject who chooses lottery 3 in Task 1, we have the following 5 lottery choices (predictions), which will be used to define our global inconsistency indicator in Task 2:

- Lottery 3 must be preferred to Lottery 2 in Task 2 (by condition 1 above).
- Lottery 2 must be preferred to Lottery 1 in Task 2 (by transitivity & condition 2 above).
- Lottery 3 must be preferred to Lottery 4 in Task 2 (by transitivity & condition 3 above).
- Lottery 4 must be preferred to Lottery 5 in Task 2 (by transitivity & condition 4 above).
- Lottery 5 must be preferred to Lottery 6 in Task 2 (by transitivity & condition 5 above).

Table 3 summarizes the predicted choices for a globally consistent subject who selected lottery 3 in Task 1:[4]

**Table 3: Example of choices made by a fully globally consistent subject**

| **Task 1** | **Task 2 – Choice 1** | **Task 2 – Choice 2** | **Task 2 – Choice 3** | **Task 2 – Choice 4** | **Task 2 – Choice 5** |
|---|---|---|---|---|---|
| Lottery 3 | Lottery 2 | Lottery 3 | Lottery 3 | Lottery 4 | Lottery 5 |

Note: There is no clear prediction for Choice 6 (lottery 6 versus lottery 1), without making further assumptions.

[4] See Appendix 3 for a complete set of examples of the other fully consistent choices.

To compute the GIR we divide the number of inconsistent choices over the total number of consistent choices to be made. Let us see Table 4 for an example of inconsistent choices that we may observe in our data.

**Table 4: Example of choices made by a globally inconsistent subject**

| Task 1 | Task 2 – Choice 1 | Task 2 – Choice 2 | Task 2 – Choice 3 | Task 2 – Choice 4 | Task 2 – Choice 5 |
|---|---|---|---|---|---|
| Lottery 3 | Lottery 2 | Lottery 2 | Lottery 4 | Lottery 5 | Lottery 5 |

As shown in Table 4, this subject made 3 inconsistent choices in Task 2 (Choices 2, 3 and 4—compare them with those made in Table 3). Therefore, this subject's global inconsistency ratio (GIR) is 0.6 (3 inconsistent choices divided by 5 consistent choices that had to be made). This subject, with a GIR of 0.6, is clearly more inconsistent than a subject with a GIR of 0.2, but less inconsistent than a subject with a GIR of 1.0.

For our analysis performed in sections 3 and 4, we create a dummy variable that takes the value of 1, if a subject's local inconsistency ratio is greater than 0.5, and 0, if such ratio is 0.[5] We will use both the GIR and LIR, as measures of preferences inconsistency.

## 3. Data

We conducted ten experimental sessions, with 120 undergraduate students, at the Universidad del Pacífico (Lima, Peru), a private university specialized in economics and business. Sessions were held in November 2012, June 2013 and May 2015. Subjects were paid a 3 Peruvian soles (S/. 3.00) show-up fee (equivalent to around 1 USD). In addition, subject's choices in Tasks 1 & 2 were incentivized.[6] On average, thus, subjects earned a total of approximately ten Peruvian soles (S/.10.00), or around 3 USD. The experimental sessions lasted, on average, about 15 minutes.[7]

We gathered information about sex, age, cumulative GPA, current semester at the University, career chosen, and courses taken in Mathematics and Economics. We also have information about the results from the CRT and three versions of the CRRA coefficients calculated from Task 2 (CRRA at the first switch from the lottery on the left

[5] The original LIR takes values of 0, 0.33, 0.50, 0.66 & 1.0. We use a dummy variable specification of the LIR (1 if it is greater than 0.5; and 0, if the LIR equals 0, 0.33 or 0.50) in our analysis.
[6] Incentives were provided as described in the instructions, shown in Appendix 1.
[7] Therefore, subjects' earnings per hour would be approximate USD 12, which is more than three times the amount they would have earned working in administrative tasks at the same university.

to the lottery on the right side; the CRRA at the last switch, and the average CRRA—from all switches made). In our analysis of the role of less reflective and risk-loving people on the probability of making inconsistent choices, we depart from the working hypothesis that, indeed, subjects with lower cognitive skills tend to make more choices that are inconsistent.

We next look at some descriptive statistics from our sample. As shown in Table 5, our subjects are mostly male (54%) and the average age is 18.4 years, meaning that our typical subject is at her third semester of undergraduate studies (we have a large proportion of new undergraduate students in the sample). The average cumulative GPA of our 120 subjects is about 13.59 (on a 0-to-20 scale), with a minimum of 10 and a maximum of 17.

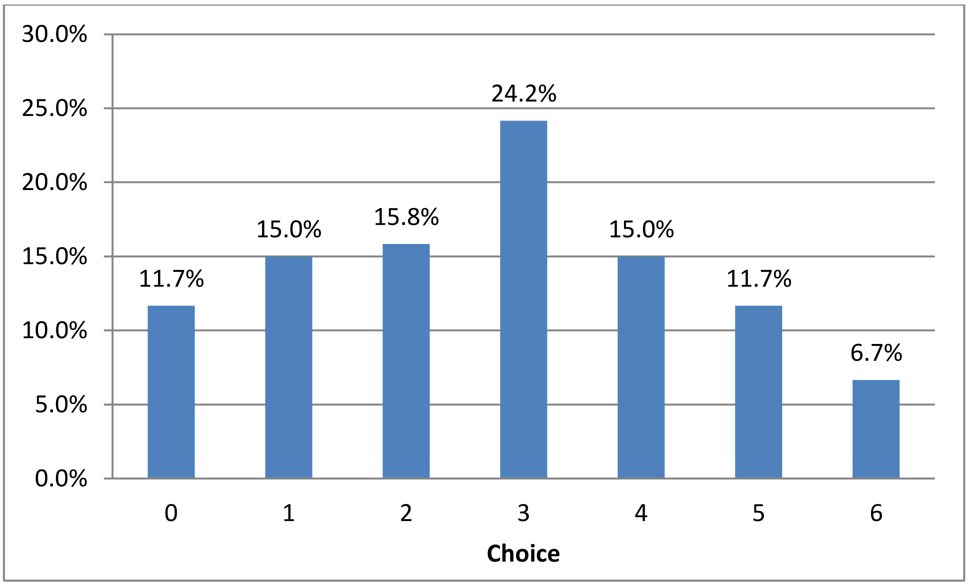
**Table 5: Summary statistics of participants**

| Variable | N | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Male | 120 | 0.542 | 1 | 0.500 | 0 | 1 |
| Age | 120 | 18.408 | 18 | 1.267 | 16 | 23 |
| Semester at University | 120 | 3.517 | 3 | 2.157 | 0 | 10 |
| Cumulative GPA | 98 | 13.592 | 13.51 | 1.362 | 10 | 17 |
| CRT (number of correct answers) | 120 | 1.4 | 1 | 1.118 | 0 | 3 |
| Number of safe choices, Task 2 | 120 | 2.775 | 3 | 1.732 | 0 | 6 |
| CRRA at First Switch | 120 | 1.038 | 0.788 | 1.028 | 0.475 | 4.502 |
| CRRA at Last Switch | 102 | 0.496 | 0.360 | 0.166 | 0.360 | 0.741 |
| CRRA Average Switch | 120 | 0.907 | 0.591 | 1.016 | 0.417 | 4.502 |
| Eckel-Grossman Global Inconsistency Ratio (GIR) | 120 | 0.351 | 0.333 | 0.266 | 0 | 1 |
| Local Inconsistency Ratio (LIR) | 120 | 0.117 | 0 | 0.322 | 0 | 1 |

Moreover, CRT results reveal that the average performance of our subjects is low: they answered an average of 1.4 questions correctly (out of 3 questions) which suggests that our typical subject tends to give impulsive rather than reflective answers. Questions included in the CRT (reported in Appendix 1, section III) have a logical, correct answer and an "impulsive" but incorrect one (for example: "A bat and a ball cost $1.10. The bat costs $1 more than the ball. How much does the ball cost?). The impulsive answer is 10 cents, but the correct one is 5 cents. As we will see below, the score on the CRT could be a good predictor of preferences inconsistency.

In terms of risk preferences, as seen in Table 5, on average, our subjects chose the safe choice 2.8 times (out of 6 safe choices, that is, in 46.25% of the choices), which means that our sample is just a bit more risk-loving than risk averse. Figure 3 shows the distribution of the number of safe choices made by our participants. The results using de CRRA coefficients (from Table 2) seem to confirm that our subjects are, on average, not very risk-averse: 0.50 if we consider the last switch, 0.91 is we consider the average switch and 1.04 if we consider the first switch. It is worth to mention that the percentage of subjects with multiple switching behavior in our sample is 85% (43.3% switched twice, 26.7% switched three times, 14.2% switched four times, and 0.8% switched five times). We will use different versions of the CRRA in our regression analysis.

**Figure 3: Percentage of safe choices made by participants in Task 2**




Finally, in terms of our measures of preference inconsistency, we show the GIR and the LIR in the last two rows of Table 5. As seen below, our subjects tend to be highly locally consistent (with a LIR sample average of only 0.117). However, subjects also reveal that they are more likely to be globally inconsistent (with a GIR sample average of 0.351). Considering the way that both indicators of consistency are measured, it seems harder for a given subject to be globally consistent rather than locally consistent.

## 4. Results

Who tends to make more choices that are inconsistent? Next two Tables report the correlates of our two inconsistency ratios (Tables 6 & 7: LIR and Tables 8 & 9: GIR). As mentioned earlier, we are particularly interested in the role of sex, cognitive ability and risk aversion on those choices. All regressions control for college experience, age, coursework in Economics and Mathematics, and major chosen. Tables 7 and 9 are the same regressions as Tables 6 and 8, respectively, except for the addition of a dummy variable for the change in the order of lotteries in Task 2.

From Table 6, we can see that females tend not to make choices that are more globally inconsistent than males in any of the eight specifications considered (columns 2 to 9). We also examined whether cognitive ability (measured by the CRT score and students' GPA) is correlated with locally inconsistent choices. As shown in Table 6, having a higher number of correct answers on the CRT is positively correlated with making fewer locally inconsistent choices (coefficients in all specifications are significant, at 5% or 10%), thus confirming that cognitive ability may be a good predictor of inconsistency. Similarly, the cumulative GPA is also significant (at 5%) in all specifications. Overall, these results suggest that being a more logical or reflexive individual is correlated with a higher the probability of making choices that are more consistent.

In terms of the role of risk aversion, it is not clear which way the relationship with preferences inconsistency should go, once we control for cognitive skills. In our case, the average CRRA, and the CRRA at the first switch from a safer lottery to a riskier one, are the only measures of risk that are (only marginally) significant (as seen in columns 5 & 7). The number of safe choices (see column 4) and the number of switches (column 9) are not significant. The aforementioned results remain mostly unaltered when we control for order effects (see Table 7), as expected (since the order only affects choices made in Task 2).

**Table 6: *Probit* Regression Results for LIR**

*(Marginal effects)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Age | -0.0201 | -0.0102 | -0.0116 | -0.0114 | -0.0215 | -0.0209 | -0.0087 | -0.0125 | -0.0081 |
| (years) | (0.0423) | (0.0305) | (0.0313) | (0.0302) | (0.0270) | (0.0276) | (0.0230) | (0.0300) | (0.0210) |
| Female | | | 0.0166 | 0.0270 | 0.0260 | 0.0287 | 0.0261 | 0.0419 | 0.0254 |
| (dummy) | | | (0.0406) | (0.0417) | (0.0357) | (0.0368) | (0.0310) | (0.0408) | (0.0286) |
| Correct CRT | -0.0526** | -0.0366* | -0.0366* | -0.0332* | -0.0312* | -0.0308* | -0.0317* | -0.0469* | -0.0306* |
| Answers | (0.0256) | (0.0216) | (0.0214) | (0.0199) | (0.0176) | (0.0175) | (0.0185) | (0.0241) | (0.0182) |
| Cumulative | | -0.0483** | -0.0479** | -0.0473** | -0.0463** | -0.0461** | -0.0459** | -0.0680** | -0.0434** |
| GPA | | (0.0213) | (0.0213) | (0.0209) | (0.0195) | (0.0195) | (0.0196) | (0.0288) | (0.0188) |
| Number of | | | | 0.0089 | | 0.0028 | | | |
| Safe choices | | | | (0.0102) | | (0.0092) | | | |
| Number of | | | | | 0.0281 | 0.0266 | | | |
| Switches | | | | | (0.0217) | (0.0222) | | | |
| CRRA | | | | | | | -0.0376* | | |
| (first switch) | | | | | | | (0.0218) | | |
| CRRA | | | | | | | | 0.0119 | |
| (last switch) | | | | | | | | (0.1240) | |
| CRRA (avg | | | | | | | | | -0.0440* |
| of switches) | | | | | | | | | (0.0236) |
| Term at | -0.0182 | -0.0350* | -0.0333* | -0.0304 | -0.0257 | -0.0252 | -0.0286 | -0.0415 | -0.0262 |
| School | (0.0250) | (0.0207) | (0.0202) | (0.0189) | (0.0172) | (0.0168) | (0.0204) | (0.0263) | (0.0199) |
| 1st course | -0.0145 | -0.0614 | -0.0599 | -0.0568 | -0.0569 | -0.0562 | -0.0469 | -0.0779 | -0.0447 |
| in Math | (0.1589) | (0.0573) | (0.0553) | (0.0564) | (0.0423) | (0.0433) | (0.0370) | (0.0549) | (0.0341) |
| 2nd course | -0.1079 | -0.1572 | -0.1574 | -0.1535 | -0.1399 | -0.1389 | -0.1115 | -0.1390 | -0.1049 |
| in Math | (0.1417) | (0.1329) | (0.1315) | (0.1324) | (0.1224) | (0.1232) | (0.1030) | (0.1156) | (0.0973) |
| 3rd course | -0.2400** | -0.2440** | -0.2386** | -0.2176** | -0.2107** | -0.2054* | -0.1713* | -0.2146** | -0.1583* |
| in Math | (0.1146) | (0.1130) | (0.1092) | (0.1089) | (0.1025) | (0.1054) | (0.0930) | (0.1024) | (0.0876) |
| 1st course in | -0.1820* | -0.2248** | -0.2202* | -0.2019* | -0.1861* | -0.1827* | -0.2224* | -0.2800** | -0.2107* |
| Economics | (0.1070) | (0.1135) | (0.1158) | (0.1051) | (0.1084) | (0.1036) | (0.1171) | (0.1287) | (0.1176) |
| 2nd course | -0.1045** | -0.1012** | -0.1001** | -0.0965** | -0.0838** | -0.0838** | -0.0893** | -0.1193*** | -0.0844** |
| in Econ | (0.0468) | (0.0433) | (0.0422) | (0.0391) | (0.0349) | (0.0344) | (0.0387) | (0.0450) | (0.0386) |
| 3rd course in | 0.0081 | -0.0193 | -0.0223 | -0.0245 | -0.0285 | -0.0291 | -0.0450 | -0.0789* | -0.0451 |
| Economics | (0.0798) | (0.0534) | (0.0539) | (0.0504) | (0.0402) | (0.0398) | (0.0304) | (0.0446) | (0.0281) |
| Business & | 0.0140 | 0.0800 | 0.0823 | 0.0741 | 0.0612 | 0.0592 | 0.1259 | 0.1867 | 0.1257 |
| Accounting[1/] | (0.1116) | (0.1286) | (0.1316) | (0.1278) | (0.1041) | (0.1047) | (0.1595) | (0.2109) | (0.1548) |
| Engineering[1] | 0.1712 | 0.3434* | 0.3595* | 0.3676* | 0.3477* | 0.3488* | 0.3884** | 0.4334* | 0.3780* |
| | (0.1487) | (0.1784) | (0.1877) | (0.1905) | (0.1962) | (0.1963) | (0.1981) | (0.2258) | (0.1956) |
| Pseudo R2 | 0.2084 | 0.2929 | 0.2946 | 0.3003 | 0.3173 | 0.3179 | 0.3217 | 0.3290 | 0.3300 |
| N | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 71 | 84 |

[1/] Omitted category: economics and finance.

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

## Table 7: *Probit* Regression Results for LIR with dummy for order effects

*(Marginal effects)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Age | -0.0112 | -0.0048 | -0.0058 | -0.0059 | -0.0180 | -0.0180 | -0.0063 | -0.0121 | -0.0066 |
| (years) | (0.0409) | (0.0298) | (0.0300) | (0.0292) | (0.0255) | (0.0266) | (0.0249) | (0.0311) | (0.0228) |
| Female | | | 0.0085 | 0.0164 | 0.0190 | 0.0190 | 0.0213 | 0.0257 | 0.0225 |
| (dummy) | | | (0.0385) | (0.0402) | (0.0336) | (0.0355) | (0.0327) | (0.0371) | (0.0302) |
| Correct CRT | -0.0517** | -0.0386* | -0.0387* | -0.0361* | -0.0331* | -0.0331* | -0.0343* | -0.0474* | -0.0329* |
| Answers | (0.0251) | (0.0224) | (0.0223) | (0.0209) | (0.0185) | (0.0185) | (0.0200) | (0.0244) | (0.0192) |
| Cumulative | | -0.0440** | -0.0439** | -0.0437** | -0.0422** | -0.0422** | -0.0451** | -0.0619** | -0.0436** |
| GPA | | (0.0194) | (0.0195) | (0.0194) | (0.0179) | (0.0179) | (0.0192) | (0.0285) | (0.0185) |
| Number of | | | | 0.0061 | | -0.0001 | | | |
| Safe choices | | | | (0.0110) | | (0.0102) | | | |
| Number of | | | | | 0.0282 | 0.0283 | | | |
| Switches | | | | | (0.0209) | (0.0212) | | | |
| CRRA | | | | | | | -0.0328 | | |
| (first switch) | | | | | | | (0.0204) | | |
| CRRA | | | | | | | | 0.1614 | |
| (last switch) | | | | | | | | (0.2098) | |
| CRRA (avg | | | | | | | | | -0.0401* |
| of switches) | | | | | | | | | (0.0224) |
| Term at | -0.0097 | -0.0274 | -0.0268 | -0.0253 | -0.0190 | -0.0190 | -0.0267 | -0.0361 | -0.0255 |
| School | (0.0270) | (0.0233) | (0.0232) | (0.0215) | (0.0196) | (0.0194) | (0.0221) | (0.0276) | (0.0210) |
| 1st course | -0.0270 | -0.0601 | -0.0596 | -0.0575 | -0.0570 | -0.0570 | -0.0499 | -0.0790 | -0.0477 |
| in Math | (0.1285) | (0.0538) | (0.0529) | (0.0544) | (0.0414) | (0.0418) | (0.0410) | (0.0563) | (0.0374) |
| 2nd course | -0.1029 | -0.1371 | -0.1378 | -0.1367 | -0.1277 | -0.1277 | -0.1095 | -0.1336 | -0.1048 |
| in Math | (0.1328) | (0.1245) | (0.1240) | (0.1253) | (0.1145) | (0.1151) | (0.1052) | (0.1154) | (0.1000) |
| 3rd course | -0.1874* | -0.1968* | -0.1956* | -0.1855* | -0.1751* | -0.1752* | -0.1611* | -0.1982* | -0.1534* |
| in Math | (0.1046) | (0.1068) | (0.1056) | (0.1026) | (0.0953) | (0.0964) | (0.0946) | (0.1034) | (0.0893) |
| 1st course in | -0.1504 | -0.1984* | -0.1974* | -0.1860* | -0.1600 | -0.1600 | -0.2095* | -0.2503* | -0.2041* |
| Economics | (0.1065) | (0.1129) | (0.1139) | (0.1040) | (0.1052) | (0.1029) | (0.1178) | (0.1303) | (0.1175) |
| 2nd course | -0.0901** | -0.0955** | -0.0954** | -0.0933** | -0.0782** | -0.0782** | -0.0908** | -0.1049** | -0.0868** |
| In Econ | (0.0441) | (0.0395) | (0.0393) | (0.0372) | (0.0335) | (0.0339) | (0.0381) | (0.0440) | (0.0373) |
| 3rd course in | 0.0048 | -0.0278 | -0.0295 | -0.0301 | -0.0301 | -0.0300 | -0.0467 | -0.0706* | -0.0471 |
| Economics | (0.0726) | (0.0487) | (0.0498) | (0.0485) | (0.0376) | (0.0375) | (0.0336) | (0.0429) | (0.0303) |
| Business & | 0.0288 | 0.0837 | 0.0855 | 0.0790 | 0.0623 | 0.0624 | 0.1189 | 0.1727 | 0.1215 |
| Accounting[1/] | (0.1136) | (0.1240) | (0.1283) | (0.1265) | (0.1013) | (0.1036) | (0.1530) | (0.1960) | (0.1512) |
| Engineering[1] | 0.2906 | 0.4144** | 0.4212** | 0.4214** | 0.4048* | 0.4048* | 0.4195** | 0.4615** | 0.4035* |
| | (0.1837) | (0.2050) | (0.2127) | (0.2133) | (0.2241) | (0.2249) | (0.2104) | (0.2327) | (0.2075) |
| Order 2 | 0.1146 | 0.0715 | 0.0696 | 0.0632 | 0.0563 | 0.0564 | 0.0328 | 0.0905 | 0.0224 |
| (dummy) | (0.0865) | (0.0782) | (0.0758) | (0.0760) | (0.0608) | (0.0630) | (0.0528) | (0.1142) | (0.0474) |
| Pseudo R-2 | 0.2401 | 0.3114 | 0.3119 | 0.3144 | 0.3334 | 0.3334 | 0.3269 | 0.3425 | 0.3328 |
| N | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 71 | 84 |

[1/] Omitted category: economics and finance.

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

In regards to our Global Inconsistency Ratio (GIR), we find that being female seems to be negatively correlated with making fewer choices that are globally inconsistent (see Table 8). On the other hand, unlike the case for the LIR, while the answers to the CRT are still, except for specification (6), negatively correlated with the GIR, this is no longer the case for the cumulative GPA. Moreover, the number of safe choices do appear negatively correlated with the GIR (see columns 4 & 6). The CRRA at the last switch also is significantly correlated with the GIR, though with a positive sign. This is a surprising result as it tells a different story than the number of safe choices. When we control for order effects (see Table 9), results regarding the coefficient of the CRRA variables are more intuitive (we find negative signs for the number of safe choices, the CRAA at the first switch and the average CRRA). Only one of our proxy variables for cognitive skills (cumulative GPA) is (marginally) significant (see columns 4 to 9).

**Table 8: *Probit* Regression Results for GIR**

*(Marginal effects)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Age | 0.0071 | -0.0045 | 0.0066 | -0.0076 | 0.0064 | -0.0101 | 0.0103 | 0.0008 | 0.0100 |
| (years) | (0.0488) | (0.0481) | (0.0468) | (0.0426) | (0.0470) | (0.0420) | (0.0456) | (0.0563) | (0.0454) |
| Female | | | -0.1525** | -0.1859*** | -0.1500* | -0.1811*** | -0.1473* | -0.1007 | -0.1454* |
| (dummy) | | | (0.0757) | (0.0691) | (0.0771) | (0.0677) | (0.0767) | (0.0791) | (0.0775) |
| Correct CRT | -0.0773* | -0.0723* | -0.0747** | -0.1041*** | -0.0739** | -0.1052*** | -0.0723* | -0.0231 | -0.0731* |
| Answers | (0.0395) | (0.0389) | (0.0379) | (0.0398) | (0.0377) | (0.0384) | (0.0380) | (0.0405) | (0.0379) |
| Cumulative | | -0.0467 | -0.0477 | -0.0483 | -0.0484 | -0.0487 | -0.0523 | -0.0451 | -0.0524 |
| GPA | | (0.0352) | (0.0335) | (0.0305) | (0.0339) | (0.0302) | (0.0344) | (0.0364) | (0.0343) |
| Number of | | | | -0.0523** | | -0.0593** | | | |
| Safe choices | | | | (0.0236) | | (0.0236) | | | |
| Number of | | | | | 0.0104 | 0.0445 | | | |
| Switches | | | | | (0.0367) | (0.0338) | | | |
| CRRA | | | | | | | -0.0274 | | |
| (first switch) | | | | | | | (0.0309) | | |
| CRRA | | | | | | | | 0.7355*** | |
| (last switch) | | | | | | | | (0.2855) | |
| CRRA (avg | | | | | | | | | -0.0301 |
| of switches) | | | | | | | | | (0.0314) |
| Term at | 0.0366 | 0.0328 | 0.0250 | 0.0245 | 0.0244 | 0.0228 | 0.0206 | -0.0064 | 0.0209 |
| School | (0.0429) | (0.0434) | (0.0409) | (0.0354) | (0.0413) | (0.0353) | (0.0406) | (0.0464) | (0.0406) |
| 1st course | 0.1080 | 0.0714 | 0.0660 | 0.0379 | 0.0670 | 0.0495 | 0.0705 | 0.1537 | 0.0642 |
| in Math | (0.2175) | (0.2528) | (0.2551) | (0.2287) | (0.2545) | (0.2048) | (0.2512) | (0.1427) | (0.2586) |
| 2nd course | 0.0467 | 0.0079 | 0.0463 | 0.0936 | 0.0541 | 0.1409 | 0.0649 | 0.1196 | 0.0591 |
| in Math | (0.2839) | (0.2875) | (0.2832) | (0.2214) | (0.2853) | (0.2125) | (0.2824) | (0.2473) | (0.2824) |
| 3rd course | 0.0286 | 0.0108 | -0.0176 | -0.1090 | -0.0115 | -0.0869 | 0.0161 | 0.0716 | 0.0132 |
| in Math | (0.2112) | (0.2134) | (0.2388) | (0.2283) | (0.2416) | (0.2211) | (0.2366) | (0.2077) | (0.2356) |
| 1st course in | -0.2289 | -0.2906 | -0.3068 | -0.4429 | -0.3089 | -0.4824* | -0.3412 | -0.4851 | -0.3343 |
| Economics | (0.3040) | (0.3007) | (0.2997) | (0.2895) | (0.3006) | (0.2916) | (0.3031) | (0.3372) | (0.3007) |
| 2nd course | -0.0149 | -0.1154 | -0.1360 | -0.3605 | -0.1465 | -0.4658 | -0.1976 | -0.2739 | -0.1944 |
| In Econ | (0.2784) | (0.3084) | (0.3146) | (0.3951) | (0.3191) | (0.4129) | (0.3475) | (0.3962) | (0.3414) |
| 3rd course in | 0.0050 | -0.0098 | 0.0086 | -0.0418 | 0.0012 | -0.0901 | -0.0236 | -0.0764 | -0.0205 |
| Economics | (0.1502) | (0.1575) | (0.1443) | (0.1537) | (0.1550) | (0.1801) | (0.1622) | (0.2155) | (0.1581) |
| Business & | 0.1600* | 0.1872** | 0.1525* | 0.1540** | 0.1511* | 0.1416** | 0.1655* | 0.1503* | 0.1658* |
| Accounting[1/] | (0.0916) | (0.0843) | (0.0902) | (0.0700) | (0.0903) | (0.0713) | (0.0861) | (0.0896) | (0.0859) |
| Engineering[1] | 0.1558** | 0.2054*** | 0.1782** | 0.1622*** | 0.1790** | 0.1587*** | 0.1915** | 0.1349 | 0.1937** |
| | (0.0778) | (0.0748) | (0.0802) | (0.0624) | (0.0801) | (0.0615) | (0.0791) | (0.0964) | (0.0789) |
| Pseudo R2 | 0.1438 | 0.1592 | 0.1935 | 0.2476 | 0.1941 | 0.2597 | 0.1987 | 0.2355 | 0.1996 |
| N | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 74 | 90 |

[1/] Omitted category: economics and finance.

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table 9:** ***Probit*** **Regression Results for GIR with a dummy for order effects**

*(Marginal effects)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Age | -0.0110 | -0.0247 | -0.0146 | -0.0194 | -0.0195 | -0.0270 | -0.0138 | -0.0200 | -0.0147 |
| (years) | (0.0510) | (0.0508) | (0.0471) | (0.0445) | (0.0462) | (0.0416) | (0.0406) | (0.0456) | (0.0401) |
| Female | | | -0.1342* | -0.1617** | -0.1200 | -0.1450** | -0.1187* | -0.0395 | -0.1153 |
| (dummy) | | | (0.0754) | (0.0704) | (0.0745) | (0.0669) | (0.0717) | (0.0621) | (0.0724) |
| Correct CRT | -0.0633 | -0.0575 | -0.0588 | -0.0854** | -0.0554 | -0.0846** | -0.0488 | -0.0013 | -0.0497 |
| Answers | (0.0389) | (0.0379) | (0.0370) | (0.0384) | (0.0345) | (0.0349) | (0.0320) | (0.0297) | (0.0320) |
| Cumulative | | -0.0524 | -0.0534 | -0.0530* | -0.0573* | -0.0560* | -0.0620* | -0.0537* | -0.0619* |
| GPA | | (0.0338) | (0.0329) | (0.0298) | (0.0331) | (0.0291) | (0.0316) | (0.0303) | (0.0316) |
| Number of | | | | -0.0407** | | -0.0477** | | | |
| Safe choices | | | | (0.0206) | | (0.0198) | | | |
| Number of | | | | | 0.0382 | 0.0594* | | | |
| Switches | | | | | (0.0353) | (0.0326) | | | |
| CRRA | | | | | | | -0.0634** | | |
| (first switch) | | | | | | | (0.0288) | | |
| CRRA | | | | | | | | 0.2178 | |
| (last switch) | | | | | | | | (0.2418) | |
| CRRA (avg | | | | | | | | | -0.0675** |
| of switches) | | | | | | | | | (0.0293) |
| Term at | 0.0187 | 0.0149 | 0.0077 | 0.0105 | 0.0057 | 0.0080 | -0.0049 | -0.0325 | -0.0046 |
| School | (0.0391) | (0.0384) | (0.0359) | (0.0338) | (0.0353) | (0.0322) | (0.0318) | (0.0333) | (0.0318) |
| 1st course | 0.1514 | 0.1273 | 0.1188 | 0.0829 | 0.1152 | 0.0788 | 0.1224 | 0.1380 | 0.1156 |
| in Math | (0.1435) | (0.1583) | (0.1561) | (0.1591) | (0.1546) | (0.1438) | (0.1179) | (0.0861) | (0.1253) |
| 2nd course | 0.0569 | 0.0274 | 0.0603 | 0.0888 | 0.0707 | 0.1206 | 0.0999 | 0.1141 | 0.0882 |
| in Math | (0.2665) | (0.2676) | (0.2573) | (0.2136) | (0.2549) | (0.2035) | (0.2286) | (0.1815) | (0.2279) |
| 3rd course | -0.0686 | -0.0821 | -0.0962 | -0.1563 | -0.0911 | -0.1512 | -0.0255 | 0.0523 | -0.0358 |
| in Math | (0.2311) | (0.2401) | (0.2550) | (0.2478) | (0.2577) | (0.2545) | (0.2242) | (0.1547) | (0.2257) |
| 1st course in | -0.2988 | -0.3897 | -0.3975 | -0.4891* | -0.4014 | -0.5295* | -0.4823* | -0.6691** | -0.4655 |
| Economics | (0.3055) | (0.3019) | (0.2969) | (0.2896) | (0.2934) | (0.2825) | (0.2871) | (0.3015) | (0.2849) |
| 2nd course | -0.0503 | -0.1967 | -0.2178 | -0.3889 | -0.2670 | -0.5317 | -0.4140 | -0.5364 | -0.4037 |
| In Econ | (0.3023) | (0.3566) | (0.3635) | (0.4124) | (0.3729) | (0.4044) | (0.4246) | (0.4620) | (0.4139) |
| 3rd course in | 0.0122 | -0.0222 | -0.0042 | -0.0413 | -0.0244 | -0.0930 | -0.0783 | -0.1809 | -0.0684 |
| Economics | (0.1523) | (0.1716) | (0.1553) | (0.1649) | (0.1637) | (0.1876) | (0.1723) | (0.2384) | (0.1646) |
| Business & | 0.1029 | 0.1387* | 0.1055 | 0.1258* | 0.0932 | 0.1042 | 0.1112 | 0.0859 | 0.1088 |
| Accounting[1/] | (0.0987) | (0.0836) | (0.0923) | (0.0683) | (0.0899) | (0.0644) | (0.0777) | (0.0653) | (0.0774) |
| Engineering[1] | 0.0540 | 0.1306 | 0.1067 | 0.1181* | 0.1062 | 0.1124* | 0.1200 | 0.0288 | 0.1226 |
| | (0.1123) | (0.0942) | (0.0984) | (0.0709) | (0.0952) | (0.0639) | (0.0827) | (0.1223) | (0.0813) |
| Order 2 | -0.2645** | -0.2683** | -0.2525** | -0.1844* | -0.2793** | -0.2090** | -0.3336*** | -0.4132*** | -0.3424*** |
| (dummy) | (0.1178) | (0.1201) | (0.1195) | (0.1036) | (0.1164) | (0.1065) | (0.1098) | (0.1317) | (0.1104) |
| Pseudo R2 | 0.2050 | 0.2245 | 0.2532 | 0.2856 | 0.2610 | 0.3077 | 0.2869 | 0.3326 | 0.2915 |
| N | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 74 | 90 |

[1/] Omitted category: economics and finance.

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 5. Conclusion

We design a lottery experiment in order to examine the correlates of inconsistent choices in risk. We find that women do not always tend to make fewer choices that are inconsistent than men when it comes to risky decisions. Interestingly, cognitive skills (as measured by the cumulative GPA and the CRT score) are strong predictors of locally inconsistent choices, but not as much of globally inconsistent choices (a result that reflects the greater difficulty of making globally consistent choices). Thus, the cumulative GPAs appear to have a stronger correlation with the probability of making fewer risky choices that are consistent than the CRT scores, once we control for order effects and risk preferences (see columns 4 to 9 of Tables 7 & 9), particularly for locally inconsistent choices. Moreover, we do not find a significant correlation between risk preferences and the LIR. On the contrary, once we control for order effects, risk preferences do seem correlated with a lower probability of making fewer choices that are globally inconsistent.

Although in future work, it would be interesting to examine the extent to which this experimentally observed (in-) consistent behavior can predict economic decisions; our study suggests that cognitive skills and risk preferences should be considered in such analysis.

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## Appendices

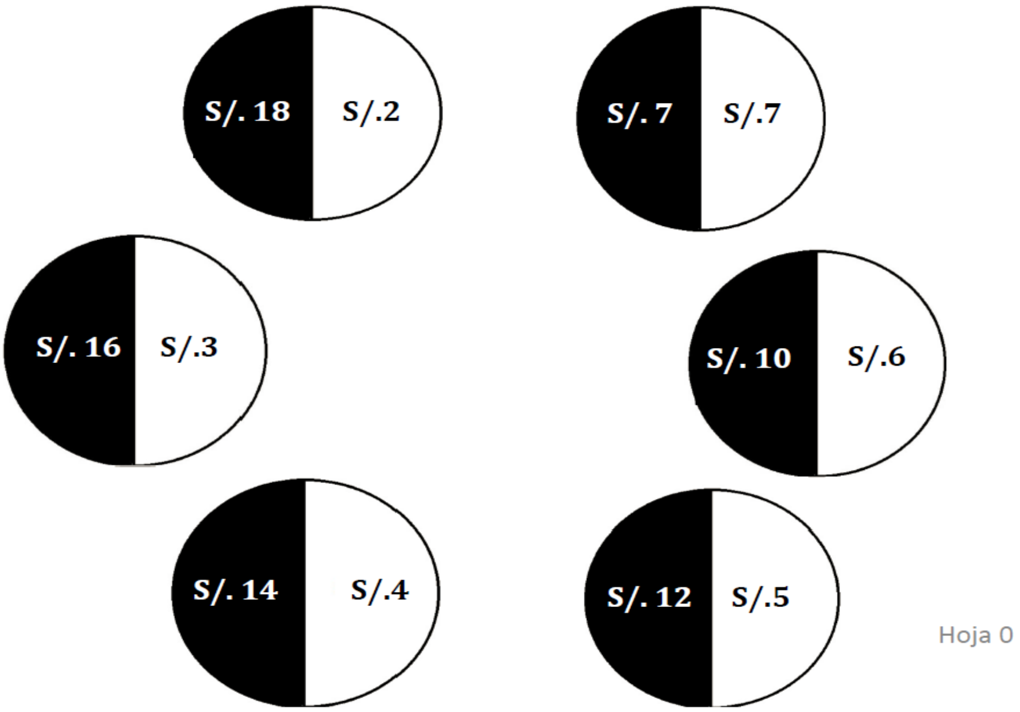
### Appendix 1
### 1A. Experimental Instructions

This session consists of two tasks. The final payment will be based on the decisions made in each task.

**Task 1**

In this task, you should choose one (1) out of the six (6) pies that are presented on the first worksheet (sheet 0). Each pie has two possible outcomes and each outcome in the pie has the same chance of being drawn. You should choose the pie that has the combination of the two possible results that you most prefer. This pie and the outcome resulting from a coin toss will determine your earnings from Task 1. If the coin lands on "heads", then the amount written in the black part of the pie of your choice will be paid; however, if the coin lands on "tails", then the amount written on the white part of the pie of your choice will be paid.

**0. Pies in Worksheet 0**



**Task 2 (Order 1)**

In this task, you have to perform a series of similar selections to Task 1. The difference is that, for each choice (1 to 6), there are only 2 pies. After you choose a pie for each sheet, we will proceed in two steps to calculate payment for this task. First, will we roll a dice to determine which sheet will be used for the coin toss. For example, if the dice lands on 1, we choose Sheet 1 to determine payments for the Task 2. Similarly, if the dice lands on 5, then Sheet 5 will be selected. It should be noted that in Task 2 the same procedure used in Task 1 will be followed to determine the amount of your payment. A coin will be tossed to determine the amount you will earn from Task 2. Thus, if the coin lands on "heads", then the amount in the black part of the chosen pie (in the Sheet chosen by the roll of the dice) will be paid. And, if the coin lands on "tails", then the amount in the white part of the chosen pie (in the chosen Sheet by the roll of the dice) will be paid.

The amounts you will earn from Task 1 and Task 2 will be determined at the end of the experiment. That is, after you select the preferred pie in both tasks. The assistant will individually assist you with a coin and a dice to perform the described process.

It is noteworthy that there are no right or wrong choices. Every single choice only reflects your preferences.

1. **Pies in Worksheet 1: lottery 1 versus lottery 2**

2. **Pies in Worksheet 2: lottery 2 versus lottery 3**


**3. Pies in Worksheet 3: lottery 3 versus lottery 4**


**4. Pies in Worksheet 4: lottery 4 versus lottery 5**

5. Pies in Worksheet 5: lottery 5 versus lottery 6


6. Pies in Worksheet 6: lottery 6 versus lottery 1


**Task 2 (Order 2)**

1. Pies in Worksheet 1: lottery 1 versus lottery 3
2. Pies in Worksheet 2: lottery 2 versus lottery 4
3. Pies in Worksheet 3: lottery 3 versus lottery 4
4. Pies in Worksheet 4: lottery 1 versus lottery 6
5. Pies in Worksheet 5: lottery 5 versus lottery 4
6. Pies in Worksheet 6: lottery 5 versus lottery 6

**1B. Survey questionnaire**

**Date: / / 201_**

*We would appreciate answering the following questions. If in doubt, notify attendees of activity.*

**I. General data**

1. Full name: ____________________________________________
2. How old are you? _______
3. In what semester are you studying? ________
4. What is your accumulated PGA? _______

**II. Understanding of the session:**

5. Do you think that instructions for today's activities were … :
   Too difficult ( ); Difficult ( ); Easy ( ); Too easy ( );

**III. CRT Test**

6. A bat and a ball cost $1.10. The bat costs $1 more than the ball. How much does the ball cost?
   -----10 cents -----50 cents -----5 cents
7. If 5 machines take five minutes to manufacture 5 cell phones, how much it would take 100 machines to make 100 cell phones?
   -----10 minutes -----5 minutes -----100 minutes
8. In a lake, there is a floating island. Every day, this island doubles its size. If it takes 48 days for the island to cover the entire lake, how many days, it will take to cover half the lake?
   -----47 days -----10 days -----24 days

## Appendix 2

### Table 2A: Binary Lottery Choices in Task 2 (Order 2)

| | Lottery | Left | Right | EV | Risk | Lottery | Left | Right | EV | Risk | Diff. EV | CRRA ($r$) Interval* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Choice 1 | 1 | 7 | 7 | 7 | 0.00 | 3 | 12 | 5 | 8.5 | 4.95 | -1.5 | > 2.050 |
| Choice 2 | 2 | 10 | 6 | 8 | 2.83 | 4 | 14 | 4 | 9 | 7.07 | -1.0 | [0.788, 2.050] |
| Choice 3 | 3 | 12 | 5 | 8.5 | 4.95 | 4 | 14 | 4 | 9 | 7.07 | -0.5 | [0.650, 0.788] |
| Choice 4 | 1 | 7 | 7 | 7 | 0.00 | 6 | 18 | 2 | 10 | 11.31 | -3.0 | [0.741, 0.650] |
| Choice 5 | 5 | 16 | 3 | 9.5 | 9.19 | 4 | 14 | 4 | 9 | 7.07 | 0.5 | [0.476, 0.741] |
| Choice 6 | 5 | 16 | 3 | 9.5 | 9.19 | 6 | 18 | 2 | 10 | 11.31 | -0.5 | < 0.359 |

* Calculated as the $r$ in the CRRA utility $U(x) = \frac{x^{1-r}}{1-r}$ that makes a subject indifferent, in an expected utility sense, between lotteries considered in each decision row.

**Appendix 3**

**Examples of fully consistent choices for lotteries 1, 2, 4, 5 and 6**

**(Order 1)**

**Figure 3A: Risk and Return of Lottery Choices – Lottery 1**

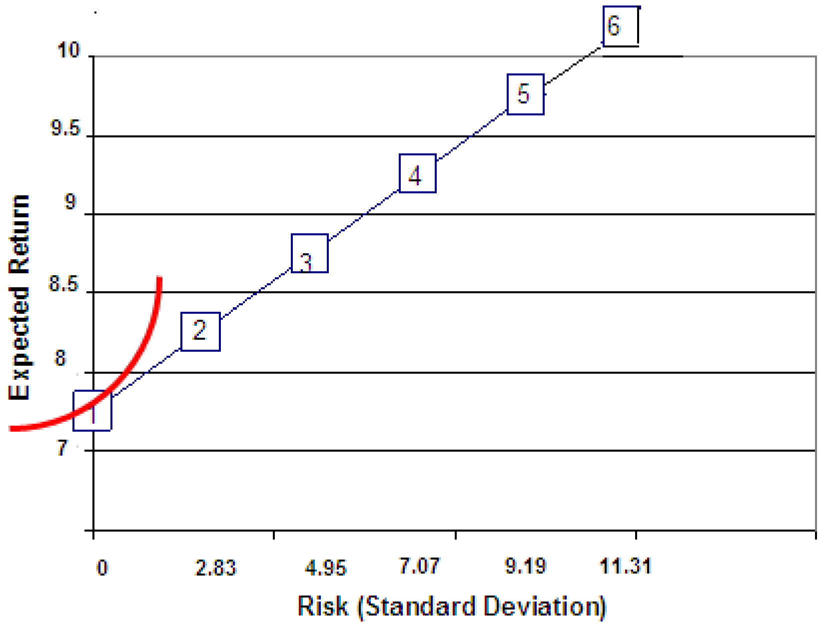



**Table 3A: Example of choices made by a fully consistent subject – Lottery 1**

| **Task 1** | **Task 2 – Choice 1** | **Task 2 – Choice 2** | **Task 2 – Choice 3** | **Task 2 – Choice 4** | **Task 2 – Choice 5** |
|---|---|---|---|---|---|
| Lottery 1 | Lottery 1 | Lottery 2 | Lottery 3 | Lottery 4 | Lottery 5 |

**Figure 3B: Risk and Return of Lottery Choices – Lottery 2**

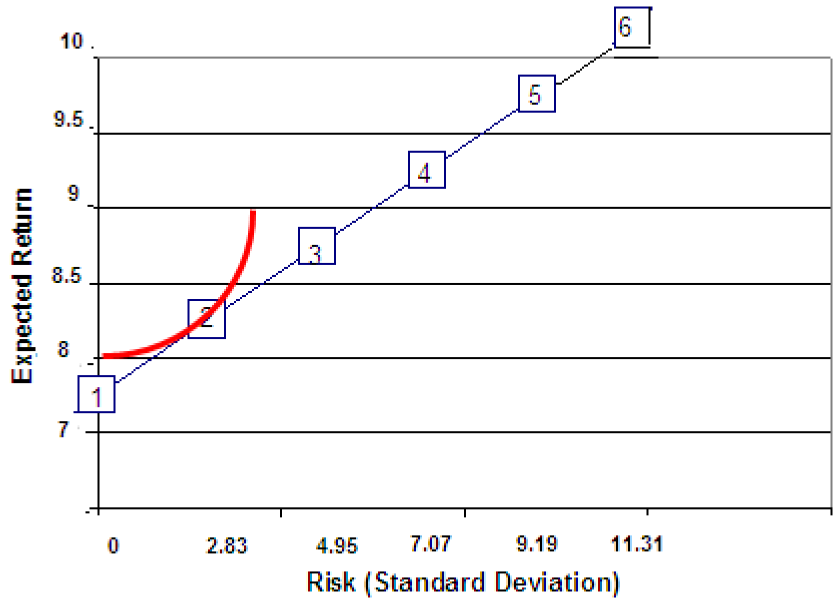



**Table 3B: Example of choices made by a fully consistent subject – Lottery 2**

| **Task 1** | **Task 2 – Choice 1** | **Task 2 – Choice 2** | **Task 2 – Choice 3** | **Task 2 – Choice 4** | **Task 2 – Choice 5** |
|---|---|---|---|---|---|
| Lottery 2 | Lottery 2 | Lottery 2 | Lottery 3 | Lottery 4 | Lottery 5 |

**Figure 3C: Risk and Return of Lottery Choices – Lottery 4**

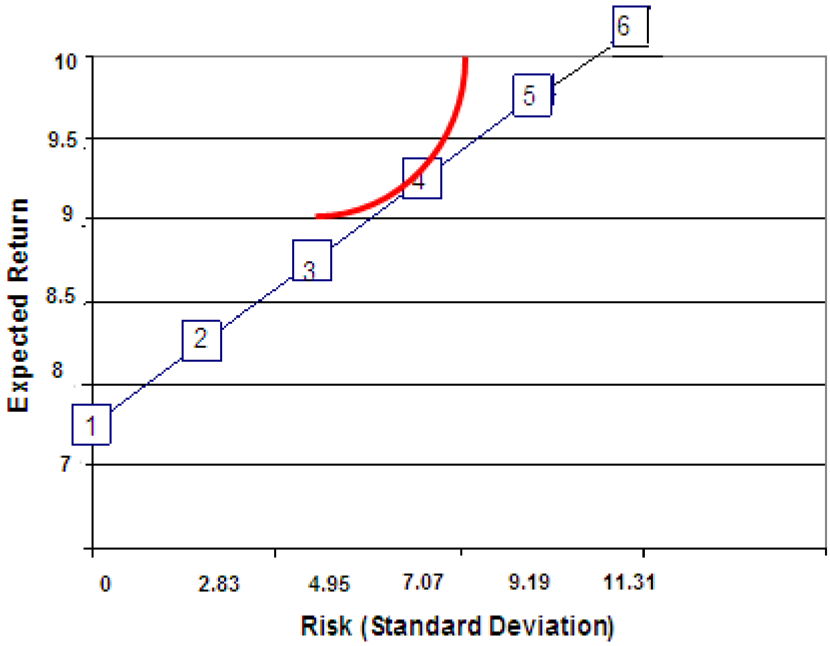



**Table 3C: Example of choices made by a fully consistent subject – Lottery 4**

| Task 1 | Task 2 – Choice 1 | Task 2 – Choice 2 | Task 2 – Choice 3 | Task 2 – Choice 4 | Task 2 – Choice 5 |
|---|---|---|---|---|---|
| Lottery 4 | Lottery 2 | Lottery 3 | Lottery 4 | Lottery 4 | Lottery 5 |

**Figure 3D: Risk and Return of Lottery Choices – Lottery 5**

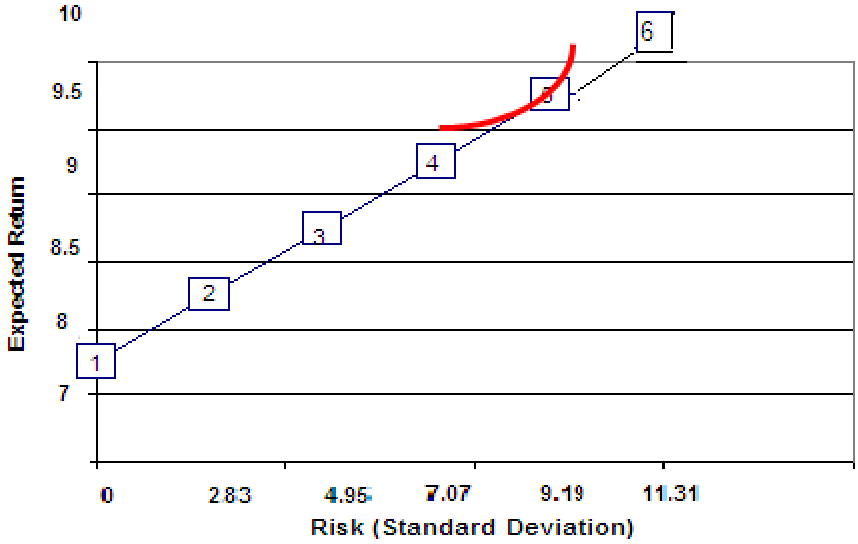



**Table 3D: Example of choices made by a fully consistent subject – Lottery 5**

| Task 1 | Task 2 – Choice 1 | Task 2 – Choice 2 | Task 2 – Choice 3 | Task 2 – Choice 4 | Task 2 – Choice 5 |
|---|---|---|---|---|---|
| Lottery 5 | Lottery 2 | Lottery 3 | Lottery 4 | Lottery 5 | Lottery 5 |

**Figure 3E: Risk and Return of Lottery Choices – Lottery 6**

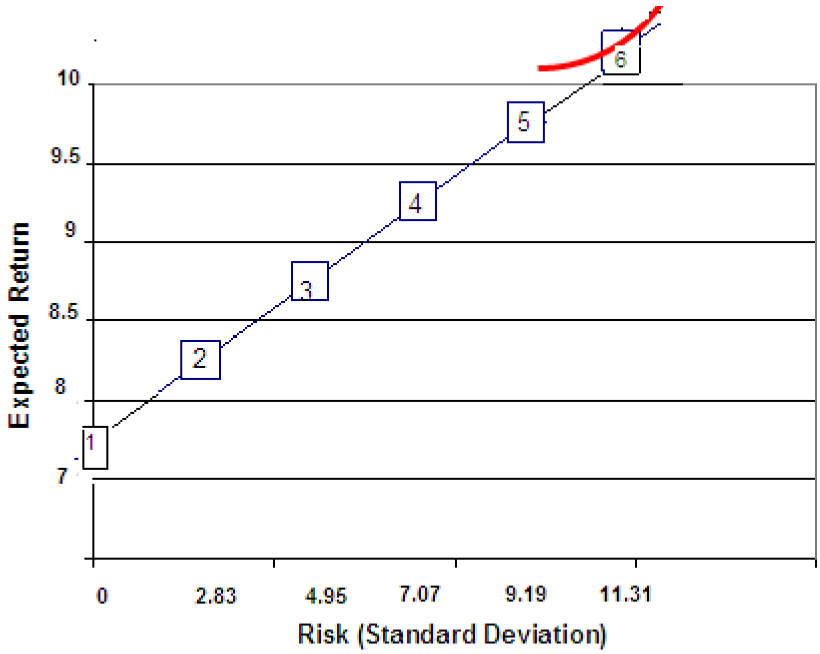



**Table 3E: Example of choices made by a fully consistent subject – Lottery 6**

| **Task 1** | **Task 2 – Choice 1** | **Task 2 – Choice 2** | **Task 2 – Choice 3** | **Task 2 – Choice 4** | **Task 2 – Choice 5** |
|---|---|---|---|---|---|
| Lottery 6 | Lottery 2 | Lottery 3 | Lottery 4 | Lottery 5 | Lottery 6 |