

# Online Appendix

## Supervised Machine Learning for Eliciting Individual Demand

### A Literature on BDM Elicitation of WTP

Table A1: Previous Research Assessing Bias in WTPs Elicited from the BDM

| Paper                                         | Over/Same/Under Same                                            | Experiment Type | Design/Notes                                                                                                                                                                                                                                                   |
|-----------------------------------------------|-----------------------------------------------------------------|-----------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Wertenbroch and Skiera (2002)                 |                                                                 | Field and Lab   | Test the validity of BDM mechanism and second price auction through a purchase obligation for the participants. Across studies, look at both food and durable goods.                                                                                           |
| Noussair, Robin and Ruffieux (2004)           | Understatement                                                  | Lab             | BDM and Vickrey auction. The bias is measured as the difference between a bid and a valuation. Hypothetical goods.                                                                                                                                             |
| Kaas and Ruprecht (2006)                      | Understatement                                                  | Lab             | BDM, Vickrey auction, and hypothetical open-ended-question. Subjects' evaluation of the purchase occasion and revision of bids are used as indicators of over/under-bidding. Item is chocolate.                                                                |
| Wang, Venkatesh and Chatterjee (2007)         | Overstatement for one item, and understatement for another item | Lab             | BDM, incentive-compatible elicitation of the range in consumer's reservation prices, Vickrey auction, self-explication, TIOLI. TIOLI is benchmark. ICERANGE asks subjects prices for 100% buy, 50% buy, and 10% buy. Two items, chocolate and wine.            |
| Müller and Voigt (2010)                       | Overstatement                                                   | Field           | BDM and TIOLI. TIOLI is benchmark. Items are two best-selling spreads.                                                                                                                                                                                         |
| Miller, Hofstetter, Krohmer and Zhang (2011b) | Same                                                            | Online          | BDM, incentive aligned choice-based conjoint analysis, hypothetical open-ended question, hypothetical choice-based conjoint analysis, TIOLI. TIOLI is benchmark. Item is a new cleaning product.                                                               |
| de Meza and Reyniers (2013)                   | Overstatement                                                   | Field           | BDM, RBDM (the reframed BDM), and TIOLI. In RBDM, subjects choose between \$x and a candle with x increasing in successive rounds. Treatments include BDM, RBDMl(range: £0-3), RBDMh(range: £1-4), TIOLlh(buy decision at £3), and TIOLll(buy decision at £1). |
| Lehman (2015)                                 | Overstatement                                                   | Lab             | BDM and TIOLI. TIOLI is benchmark. BDM on 8 products and TIOLI in 16 situations (8 products x 2 prices).                                                                                                                                                       |
| Berry, Fischer and Guiteras (2020)            | Understatement                                                  | Field           | BDM and TIOLI. TIOLI is benchmark. Item is a water filter.                                                                                                                                                                                                     |

Notes: Over/Same/Under column lists WTP effect associated with BDM elicitation (e.g., understatement of true WTP). TIOLI stands for "take it or leave it" offer, which is the same as our Buy-Task.

## B Additional Information

### B.1 Food Items

Table B2: Food Items

|    | Food Item                        | Abbrev. |
|----|----------------------------------|---------|
| 1  | Cliff Barr Peanut Crunch         | BC      |
| 2  | Chex Mix                         | CM      |
| 3  | Coke                             | CK      |
| 4  | Godiva Dark Chocolate            | GC      |
| 5  | Green & Blacks Organic Chocolate | GB      |
| 6  | Hershey's Chocolate              | HS      |
| 7  | Justin's Peanut Butter Cup       | JP      |
| 8  | KIND Nuts & Spices               | KN      |
| 9  | Luna Choco Cupcake               | LC      |
| 10 | Naked Green Machine              | NG      |
| 11 | Naked Mango                      | NM      |
| 12 | Naturally Bare Banana            | NB      |
| 13 | Nature Valley Crunchy            | NV      |
| 14 | Organic Peeled Paradise          | OP      |
| 15 | Pretzel Crisps Original          | PC      |
| 16 | Pringles Original                | PO      |
| 17 | Red Bull                         | RB      |
| 18 | Simply Balanced Blueberries      | SB      |
| 19 | Starbuck's Frappuccino           | SF      |
| 20 | Vita Coco                        | VC      |

## B.2 Features

Features used are presented in groups below. Numbers in parentheses reflect the number of features for each description.

### Core Features

Total: 149

- Price variables of the item being sold (3):  $price_{ij}, price_{ij}^2, price_{ij}^3$
- Item indicators (19):  $Item_{i2}, \dots, Item_{i20}$
- Subject indicators (54):  $Subject_2, \dots, Subject_{55}$
- Interaction between Price of the item being sold and item indicators (19):  $price_{ij} \times Item_{i2}, \dots, price_{ij} \times Item_{i20}$
- Interaction between Price of the item being sold and subject indicators (54):  $price_{ij} \times Subject_2, \dots, price_{ij} \times Subject_{55}$

### Features Using WTP Data

Total: 76 Features

- WTP polynomial of the item being sold (3):  $WTP_{ij}, WTP_{ij}^2, WTP_{ij}^3$
- Interaction between WTP of the item being sold and item indicators (19):  $WTP_{ij} \times Item_{i2}, \dots, WTP_{ij} \times Item_{i20}$
- Interaction between WTP of the item being sold and subject indicators (54):  $WTP_{ij} \times Subject_2, \dots, WTP_{ij} \times Subject_{55}$

### Features Using OtherWTP Data

Total: 400 Features

- WTP on all the items (20):  $WTP_{i1}, \dots, WTP_{i20}$
- Interaction between WTP of each of the 20 items and each of the item indicators ( $19 \times 20 = 380$ ):  $WTP_{i1} \times Item_{i2}, \dots, WTP_{i1} \times Item_{i20}, \dots, WTP_{i20} \times Item_{i2}, \dots, WTP_{i20} \times Item_{i20}$

## Features Using Binary-Choice Data

Total: 211 Features

- Whether the good in question was chosen over other items (20):  $Choice_{ij1}, \dots, Choice_{ij20}$
- Fraction of time that the item was chosen over other items (20):  $Fraction_{i1}, \dots, Fraction_{i20}$
- Fraction of time that the item  $j$  being sold was chosen over other items (1):  $Fraction_{ij}$
- Interactions between Fraction of time that the item in question was chosen over other items and item indicators (19):  $Fraction_{ij} \times Item_{i2}, \dots, Fraction_{ij} \times Item_{i20}$
- Interactions between Fraction of time that the item in question was chosen over other items and subject indicators (54):  $Fraction_{ij} \times Subject_2, \dots, Fraction_{ij} \times Subject_{55}$
- Standard deviation for subject  $i$ 's 20  $Fraction_{ij}$  variables (and polynomial expansion) (3):  $stdFraction_i, stdFraction_i^2, stdFraction_i^3$
- Rank of each item by Fraction (20):  $Rank_{i1}, \dots, Rank_{i20}$
- Rank of the item in question, as determined by Fraction (1):  $Rank_{ij}$
- Interactions between Rank of the item in question and item indicators (19):  $Rank_{ij} \times Item_{i2}, \dots, Rank_{ij} \times Item_{i20}$
- Interactions between Rank of the item in question and subject indicators (54):  $Rank_{ij} \times Subject_2, \dots, Rank_{ij} \times Subject_{55}$

## Features Using Binary-Choice RT Data

Total: 87 Features

- Response time (RT) of the item being sold  $j$  against other items and polynomial expansion (40):  $RT_{ij1}, \dots, RT_{ij20}, RT_{ij1}^2, \dots, RT_{ij20}^2$
- Interactions between response time and choice variables (20):  $RT_{ij1} \times Choice_{ij1}, \dots, RT_{ij20} \times Choice_{ij20}$
- Interactions between squared response time and choice variables (20):  $RT_{ij1}^2 \times Choice_{ij1}, \dots, RT_{ij20}^2 \times Choice_{ij20}$

- Mean and standard deviation of RTs within person and polynomial expansion (6):

$$meanRT_i, meanRT_i^2, meanRT_i^3, sdRT_i, sdRT_i^2, sdRT_i^3$$

- For each item sold  $j$  (1):  $\sum_k \left[ \frac{\max RT_i - RT_{ijk}}{\max RT_i} \times (2 \times Choice_{ijk} - 1) \right]$ , where  $k$  is all other items (i.e., pairwise choices between item  $j$  and item  $k$ )

## C Additional Results

This section presents additional results to complement those included in the main text.

### C.1 Alternative Basic Comparison

Another natural starting point for the logit in Equation 1 in Section 4.1 would be to restrict  $\beta_1 = -\beta_2$ ,  $\zeta_k = -\delta_k$ , and  $\kappa_k = -\iota_k$  implying that the buy probability is increasing in consumer surplus, yielding:

$$\begin{aligned} buy_{ijt} = & \beta_0 + \beta_1(WTP_{ij} - p_{ijt}) + \sum_{k=2}^{20} 1\{k = j\} \cdot (\gamma_k + \delta_k(WTP_{ij} - p_{ijt})) \\ & + \sum_{k=2}^{55} 1\{k = i\} \cdot (\eta_k + \kappa_k(WTP_{ij} - p_{ijt})) + \epsilon_{ijt} \end{aligned}$$

We tried this as well. The performance of this model is very similar to the model in Equation (1) in the main text. For simplicity, we present the results of that model only given its greater flexibility.

### C.2 Test of Trending Demand Over Time

One possible concern is that people may have become hungrier over time or the constant exposure to pictures of food may have increased demand during the experiment. Or, the overexposure to food images may have reduced peoples' appetites. We can measure WTP within the BDM-Task and probability of purchase in the Buy-Task as a function of trial number (we do not observe demand in the Binary-Choice task). In the BDM-Task, using OLS, the effect of trial number is positive with a coefficient of 0.0095 and significant at  $p=0.08$ . This represents a 19% increase in WTP from the first trial to the 20th trial, which provides some weak evidence of increasing demand over time. In contrast, in the Buy-Task, using logit, the effect of trial number has a coefficient of -0.0024 and is significant at  $p=0.07$ . This represents an 18% decrease in the probability of a purchase between the first trial and 80th trial. Given the statistically insignificant trends at conventional levels and inconsistent pattern, there does not seem to be a clear trend in demand over time.

### C.3 Summary of Additional Tables and Figures

The following figures and tables are included as additional information.

Figure C1 displays the distribution of WTP for each of the 20 items and compares them to a typical market price.

Figure 3 in the main text provides a plot of purchase frequency as a function of WTP minus prices, across all items. Here, Figure C2 shows the same data, broken down item by item.

Figure C3 presents the full-sample results in the bar plot from the main text, Figure 7, as a heat map.

Table C3 presents all full-sample results for logit, lasso, and random forest, a subset of which are presented in the main text in Figure 7.

Figure C4 parallels Figure 4 in the main text for the logit models, but provides the full range of MSE performance for all training sample sizes.

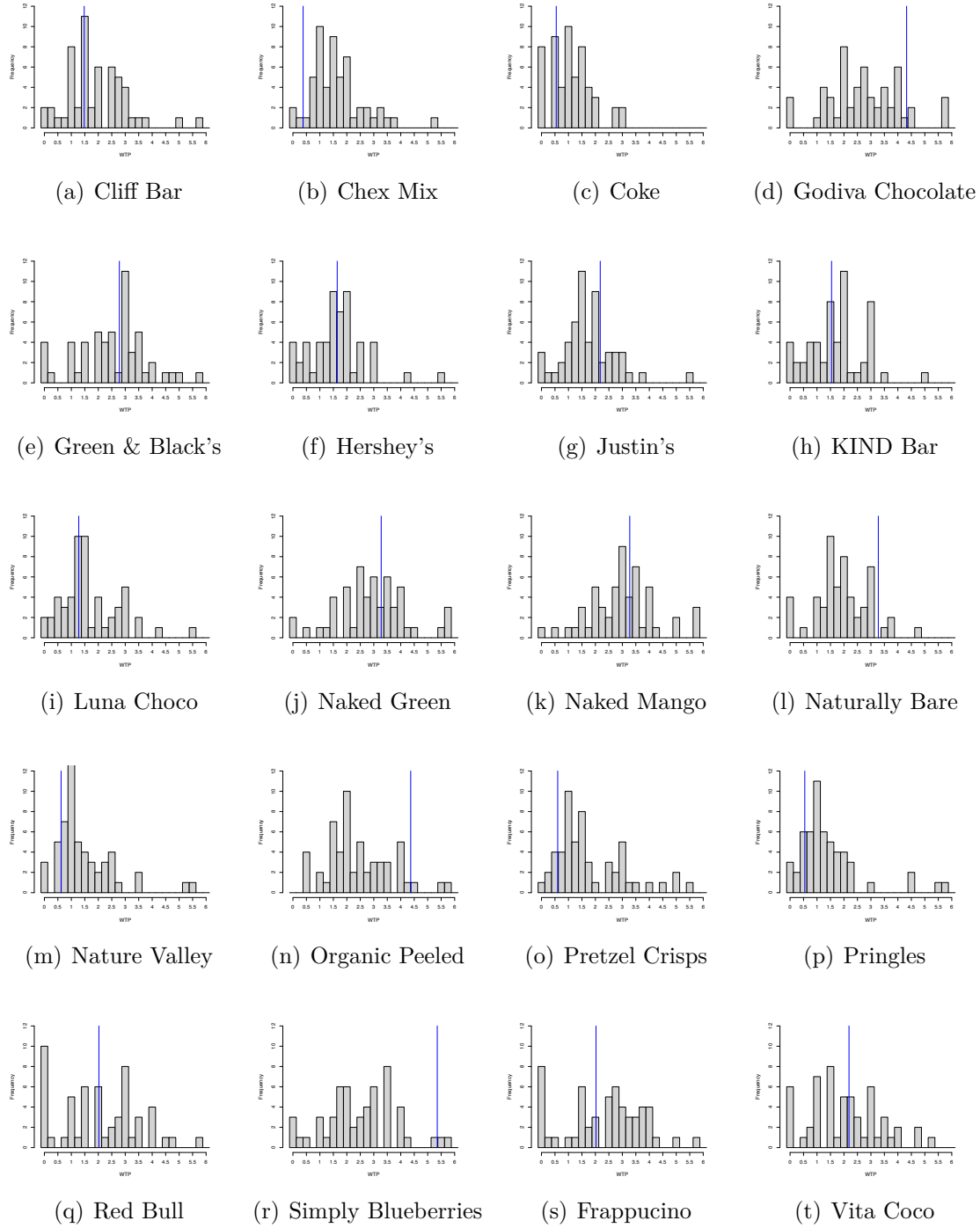
Figures C5 and C6 present prediction performance of SML using area under the curve (AUC) instead of MSE.

Figure C7 presents out-of-sample MSE for lasso and random forest models that include RT data from the Binary-Choice-Task, as well as corresponding models without the RT features included.

Table C4 presents the prediction performance of the different SML models in terms of classification accuracy. The table also includes false positive and false negative rates.

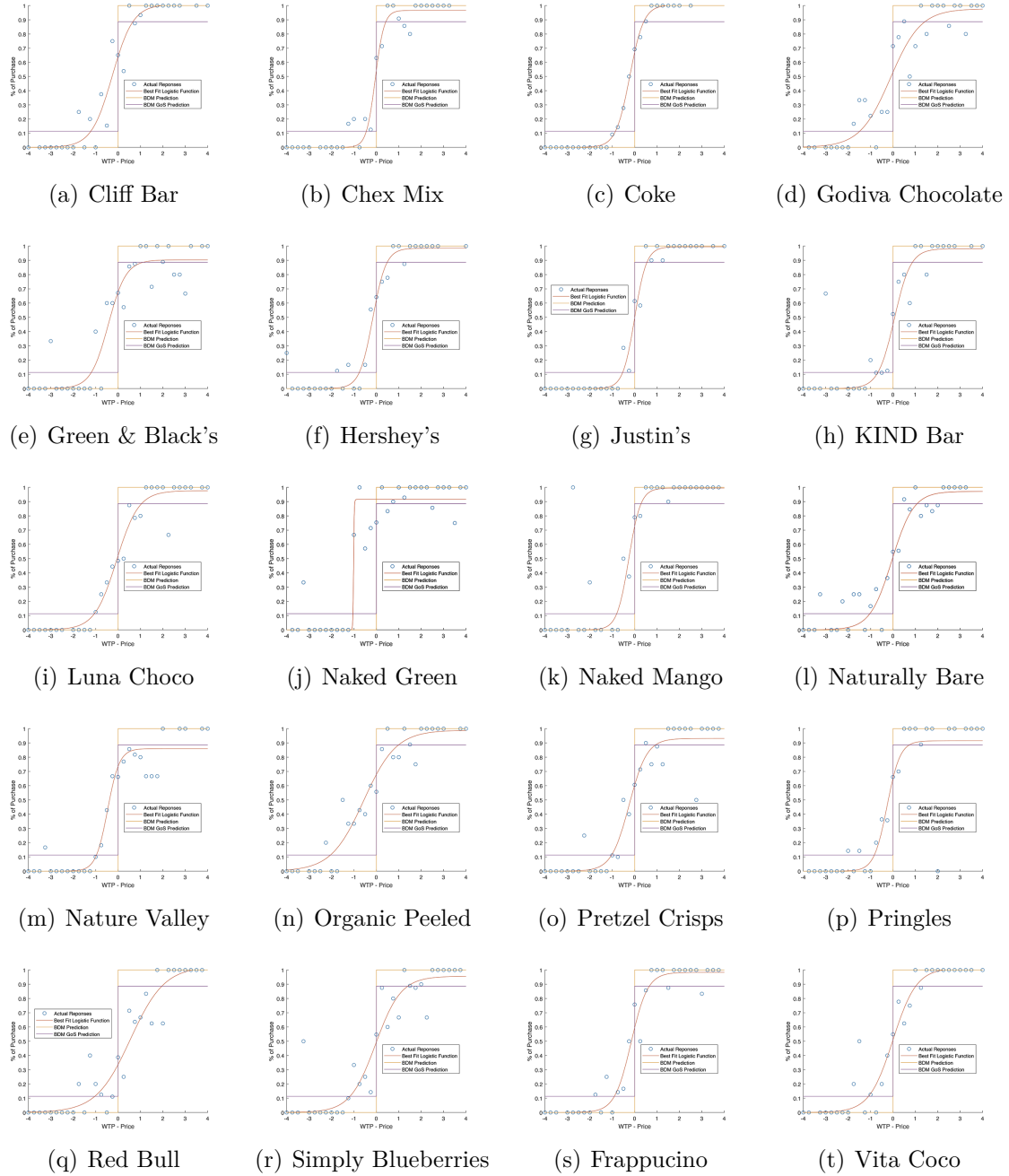


Figure C1: Histograms of WTP by Item



Notes: Blue vertical line indicates a typical market price.

Figure C2: Purchase Frequency as a Function of Surplus



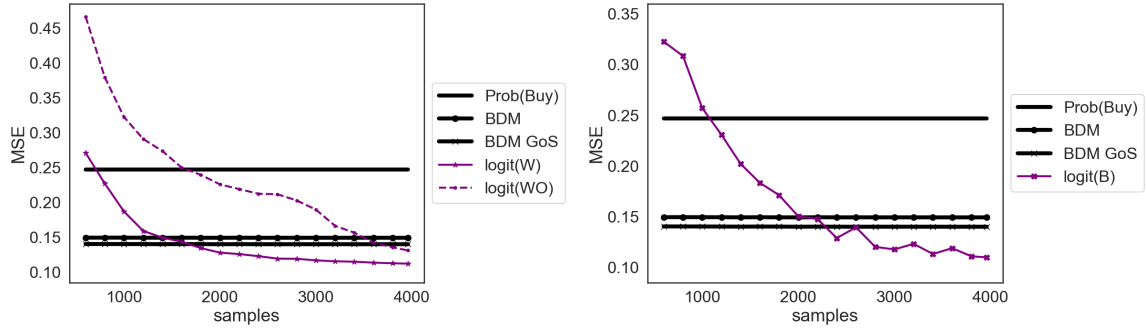
Notes: Each dot represents the probability of purchasing for a given bin with the specified consumer surplus. Items are also listed in Table B2.

Figure C3: Test Sample — Holding Out Observations vs. Holding Out Subjects

|            | MSE                     |                  |                 |
|------------|-------------------------|------------------|-----------------|
| lasso(W)   | 0.1170 (0.0013)         | 0.1294 (0.0024)  | 0.1206 (0.0018) |
| lasso(WO)  | 0.1147 (0.0013)         | 0.1415 (0.0039)  | 0.1192 (0.0018) |
| lasso(B)   | 0.1042 (0.0012)         | 0.1707 (0.0040)  | 0.1131 (0.0018) |
| lasso(WB)  | 0.0947 (0.0012)         | 0.1336 (0.0031)  | 0.0979 (0.0016) |
| lasso(WOB) | 0.0952 (0.0013)         | 0.1437 (0.0042)  | 0.0976 (0.0015) |
| rf(W)      | 0.1088 (0.0013)         | 0.1541 (0.0030)  | 0.1252 (0.0027) |
| rf(WO)     | 0.1026 (0.0012)         | 0.1326 (0.0027)  | 0.1283 (0.0025) |
| rf(B)      | 0.1010 (0.0012)         | 0.1436 (0.0027)  | 0.1125 (0.0017) |
| rf(WB)     | 0.0916 (0.0011)         | 0.1202 (0.0021)  | 0.0987 (0.0015) |
| rf(WOB)    | 0.0899 (0.0012)         | 0.1173 (0.0019)  | 0.0968 (0.0015) |
|            | Within&Between Subjects | Between-Subjects | Between-Items   |

Notes: Summary table of out-of-sample MSE results for high-dimensional methods, using the full available sample of features. Standard error across the  $N = 50$  runs is listed in parentheses.

Figure C4: Performance of Supervised Machine Learning with WTP and Binary-Choice Data



(a) Logit results with WTP data.

(b) Logit results with Binary-Choice data.

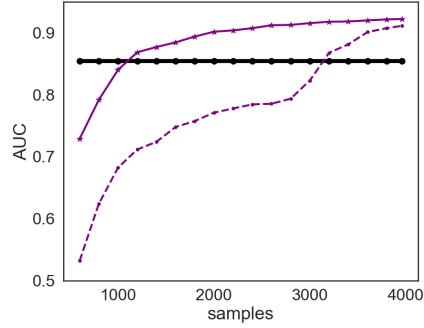
Notes: Out-of-sample MSE estimated on 440 hold-out observations. Sample size increases from 600 to 3960 in intervals of 200. Since samples are random, we repeat the estimation 50 times and MSE is averaged. This is a companion figure to Figure 4 in the main text.

Table C3: Test Sample — Holding Out Observations vs. Holding Out Subjects

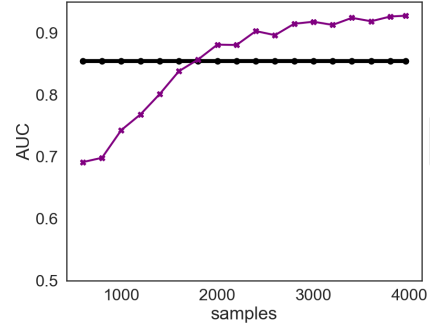
| Models      | Within&Between-Subjects MSE | Between-Subjects MSE | Between-Items MSE |
|-------------|-----------------------------|----------------------|-------------------|
| BDM         | 0.1494 (0.0019)             | 0.1458 (0.0037)      | 0.1469 (0.0024)   |
| BDM GoS     | 0.1402 (0.0015)             | 0.1372 (0.0029)      | 0.1380 (0.0020)   |
| logit(C)    | 0.1479 (0.0014)             | 0.1874 (0.0018)      | 0.1755 (0.0024)   |
| logit(W)    | 0.1123 (0.0015)             | 0.1312 (0.0024)      | 0.1206 (0.0018)   |
| logit(WO)   | 0.1312 (0.0023)             | 0.1977 (0.0053)      | 0.1206 (0.0018)   |
| logit(B)    | 0.1100 (0.0018)             | 0.3428 (0.0107)      | 0.5037 (0.0154)   |
| logit(BR)   | 0.1246 (0.0081)             | 0.4489 (0.0125)      | 0.4931 (0.0172)   |
| logit(WB)   | 0.1033 (0.0018)             | 0.2821 (0.0103)      | 0.4633 (0.0158)   |
| logit(WOB)  | 0.1982 (0.0107)             | 0.4968 (0.0119)      | 0.4819 (0.0128)   |
| logit(WOBR) | 0.2010 (0.0101)             | 0.5090 (0.0111)      | 0.4989 (0.0149)   |
| lasso(C)    | 0.1549 (0.0013)             | 0.1873 (0.0018)      | 0.1785 (0.0021)   |
| lasso(W)    | 0.1170 (0.0013)             | 0.1294 (0.0024)      | 0.1206 (0.0018)   |
| lasso(WO)   | 0.1147 (0.0013)             | 0.1415 (0.0039)      | 0.1192 (0.0018)   |
| lasso(B)    | 0.1042 (0.0012)             | 0.1707 (0.0040)      | 0.1131 (0.0018)   |
| lasso(BR)   | 0.1056 (0.0012)             | 0.1835 (0.0055)      | 0.1157 (0.0017)   |
| lasso(WB)   | 0.0947 (0.0012)             | 0.1336 (0.0031)      | 0.0979 (0.0016)   |
| lasso(WOB)  | 0.0952 (0.0013)             | 0.1437 (0.0042)      | 0.0976 (0.0015)   |
| lasso(WOBR) | 0.0959 (0.0012)             | 0.1512 (0.0047)      | 0.1036 (0.0017)   |
| rf(C)       | 0.1444 (0.0014)             | 0.2300 (0.0030)      | 0.1918 (0.0032)   |
| rf(W)       | 0.1088 (0.0013)             | 0.1541 (0.0030)      | 0.1252 (0.0027)   |
| rf(WO)      | 0.1026 (0.0012)             | 0.1326 (0.0027)      | 0.1283 (0.0025)   |
| rf(B)       | 0.1010 (0.0012)             | 0.1436 (0.0027)      | 0.1125 (0.0017)   |
| rf(BR)      | 0.1067 (0.0013)             | 0.1436 (0.0026)      | 0.1194 (0.0015)   |
| rf(WB)      | 0.0916 (0.0011)             | 0.1202 (0.0021)      | 0.0987 (0.0015)   |
| rf(WOB)     | 0.0899 (0.0012)             | 0.1173 (0.0019)      | 0.0968 (0.0015)   |
| rf(WOBR)    | 0.0930 (0.0012)             | 0.1171 (0.0022)      | 0.1024 (0.0014)   |

Notes: Summary table of out-of-sample MSE results for all three statistical methods, using the full available sample of features. Standard errors across the 50 runs are reported in parentheses.

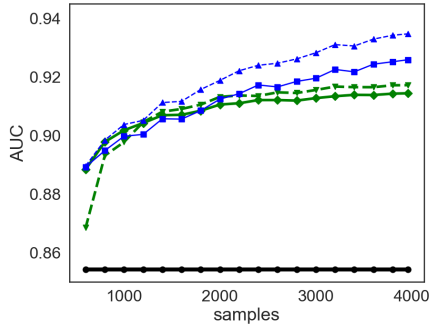
Figure C5: Performance (AUC) of Supervised Machine Learning using WTP Data



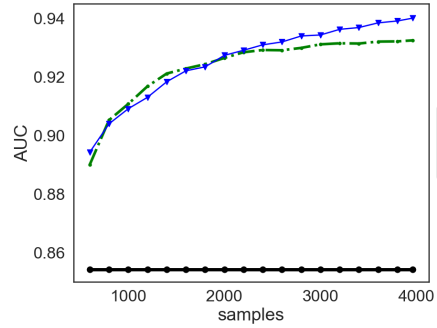
(a) Logit results with WTP data.



(b) Logit results with Binary-Choice data.



(c) Lasso and random forest results with WTP data.



(d) Lasso and random forest results with Binary-Choice data.

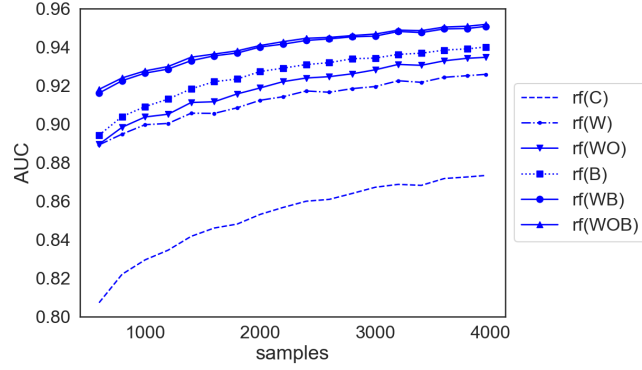
Notes: Out-of-sample AUC estimated on 440 hold-out observations. Sample size increases from 600 to 3960 in intervals of 200. Since samples are random, we repeat the estimation 50 times and AUC is averaged.

Table C4: Test Sample — Classification Accuracy

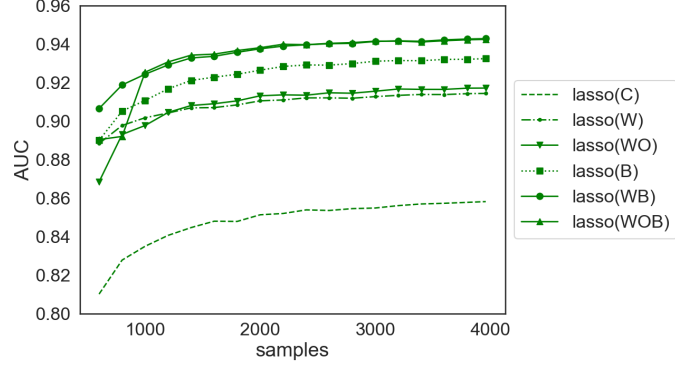
| Models      | Classification Accuracy | False Negative Rate | False Positive Rate |
|-------------|-------------------------|---------------------|---------------------|
| BDM         | 0.8086                  | 0.0731              | 0.3385              |
| BDM GoS     | 0.8086                  | 0.0731              | 0.3385              |
| logit(C)    | 0.7899                  | 0.1711              | 0.2583              |
| logit(W)    | 0.8406                  | 0.1237              | 0.2034              |
| logit(WO)   | 0.8354                  | 0.1412              | 0.1935              |
| logit(B)    | 0.8498                  | 0.1259              | 0.1799              |
| logit(BR)   | 0.8346                  | 0.1400              | 0.1965              |
| logit(WB)   | 0.8627                  | 0.1114              | 0.1691              |
| logit(WOB)  | 0.8018                  | 0.1831              | 0.2169              |
| logit(WOBR) | 0.7990                  | 0.1804              | 0.2259              |
| lasso(C)    | 0.7796                  | 0.1214              | 0.3430              |
| lasso(W)    | 0.8390                  | 0.0998              | 0.2365              |
| lasso(WO)   | 0.8404                  | 0.1126              | 0.2177              |
| lasso(B)    | 0.8499                  | 0.1151              | 0.1932              |
| lasso(BR)   | 0.8505                  | 0.1220              | 0.1833              |
| lasso(WB)   | 0.8661                  | 0.1002              | 0.1752              |
| lasso(WOB)  | 0.8668                  | 0.0975              | 0.1772              |
| lasso(WOBR) | 0.8682                  | 0.1008              | 0.1701              |
| rf(C)       | 0.7935                  | 0.1544              | 0.2712              |
| rf(W)       | 0.8461                  | 0.1016              | 0.2187              |
| rf(WO)      | 0.8599                  | 0.0897              | 0.2024              |
| rf(B)       | 0.8624                  | 0.0904              | 0.1961              |
| rf(BR)      | 0.8493                  | 0.1121              | 0.1986              |
| rf(WB)      | 0.8780                  | 0.0863              | 0.1659              |
| rf(WOB)     | 0.8767                  | 0.0873              | 0.1677              |
| rf(WOBR)    | 0.8713                  | 0.0981              | 0.1633              |

Notes: Summary table of out-of-sample classification accuracy, assuming a threshold of 50% is used to predict "buy" decisions. Models are within&between subject, using the full training sample-size possible (440 hold-out observations). False negatives correspond to incorrect predictions of "not buy" and false positives correspond to incorrect predictions of "buy."

Figure C6: Performance (AUC) of Supervised Machine Learning with All Combinations of Data



(a) Results for random forest algorithm.

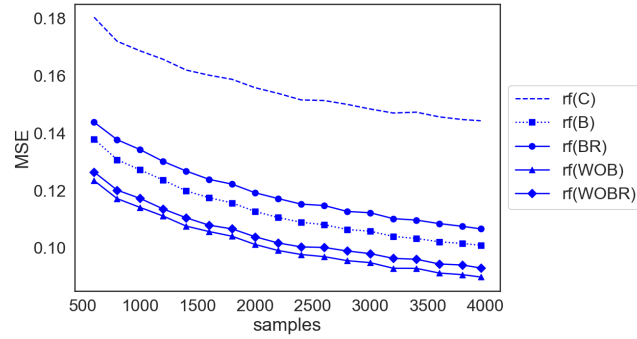


(b) Results for lasso algorithm.

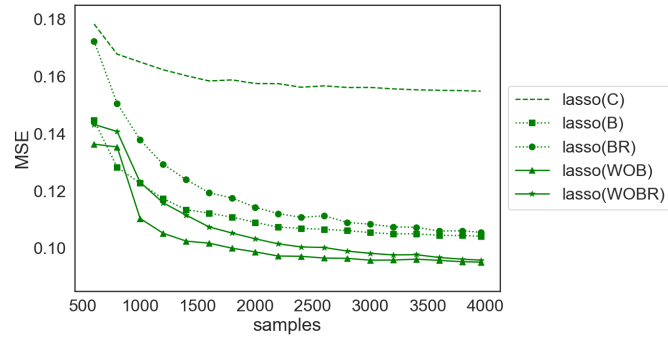
Notes: Out-of-sample AUC estimated on 440 hold-out observations. Sample size increases from 600 to 3960 in intervals of 200. Since samples are random, we repeat the estimation 50 times and AUC is averaged.



Figure C7: Performance of Supervised Machine Learning with RT Data



(a) Results for random forest algorithm.



(b) Results for lasso algorithm.

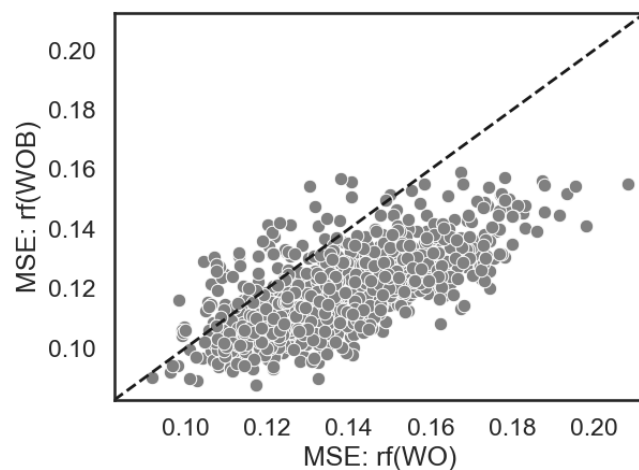
Notes: Out-of-sample MSE estimated on 440 hold-out observations. Sample size increases from 600 to 3960 in intervals of 200. Since samples are random, we repeat the estimation 50 times and MSE is averaged.

## C.4 Prediction Performance in Different Samples

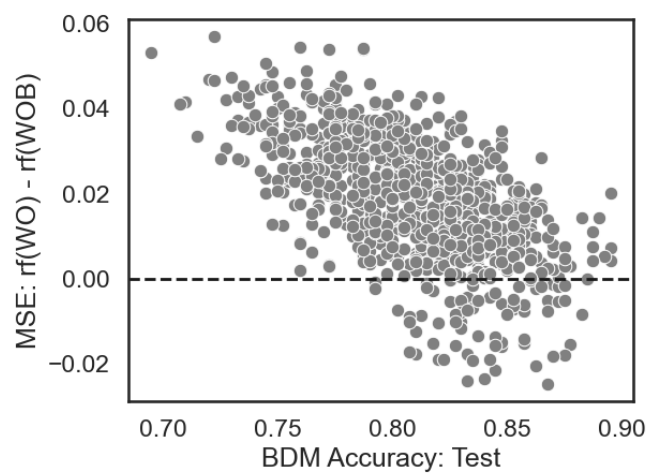
To further investigate how the different tasks can contribute to enhanced prediction, we repeated our between-subjects prediction exercise (as detailed in Section 4) 1000 times for both rf(WO) and rf(WOB). In each case, the prediction accuracy of the BDM (i.e., how often does a particular subject’s BDM correctly predict “buy” or “not buy”) was also recorded. The results of the 1000 random samples are summarized in Figure C8. In Figure C8(a) it is clear that in the overwhelming majority of cases, the MSE for rf(WOB) is smaller than it is for rf(WO), reflecting the added predictive power of the Binary-Choice Task data. This is consistent with the main results presented in Figure 7.

The plot also shows, though, that there is heterogeneity in how much rf(WOB) outperforms rf(WO) in prediction between-subjects. Figure C8(b) shows the MSE difference ( $\text{rf(WO)} - \text{rf(WOB)}$ ) plotted against the prediction accuracy of the BDM in the test set. Across the 1000 iterations, the prediction accuracy of the BDM in the test set ranges from 69.5% to 89.5%. In other words, there is substantial variation in how accurate the direct elicitation for WTP is in predicting subsequent purchase decisions. The plot shows a clear correlation between how much MSE is reduced by using rf(WOB) over rf(WO), when the BDM’s predictive accuracy decreases. This is a useful illustration. In the main results, it is shown that both SML and additional choice data can be utilized to improve predictions above and beyond those of direct elicitation. Here, we show that these gains can be larger in cases where the direct elicitation has lower predictive accuracy itself.

Figure C8: Prediction Performance of rf(WO) and rf(WOB) Between-Subjects



(a) Comparison of rf(WO) vs rf(WOB) MSE.



(b) Difference between MSE for rf(WO) and rf(WOB), by underlying test set BDM accuracy.

Notes: Plots show 1000 random test sets, with each dot representing a random test set. In (a), the plot is MSE rf(WO) on the horizontal axis and MSE rf(WOB) on the vertical axis. In (b), the plot is BDM prediction accuracy on the horizontal axis and MSE rf(WO) – MSE rf(WOB) on the vertical axis.

## **D Instrument**

### **Instructions and Quiz**

This section contains the text for instructions and the quiz given to subjects regarding the willingness-to-pay elicitation procedure.

Welcome. Thank you for participating in this experiment. This is an experiment about decision making. It should take approximately one hour.

At the end you will be paid your earnings in cash. By agreeing to participate, you have already earned a show-up fee of \$7. You have also stated that you like snacks and do not have any food allergies. You will earn a total of \$20, however this requires your participation through the entire experiment. Based on your choice, you may also receive a snack which you may pay for from your earnings. If you obtain a snack you will be given time at the end of the experiment to eat it. You have to have at least some of the snack before you leave.

Please make sure all of your personal belongings are below your desk. Please remain quiet for the rest of the experiment. If you have any questions, wait until the end of the instructions and ask.

The next few pages provide detailed instructions about the experiment. There is no deception in the experiment - we will do everything as outlined in the instructions.

There are four tasks in this experiment. The experimenter will read the instructions for each task just before you begin the task. One trial from the second, third, or fourth task will be randomly chosen to count for real stakes. On this trial your choice will determine what payoff and food you obtain.

You are welcome to ask any clarifying questions about the tasks or about the procedures.

## Part I

In this task, you will designate items at random to be your bonus items. There are two bonus items: Gold and Silver ones. Throughout the experiment, if you ever obtain your Gold item you will receive an additional \$4, and if you ever obtain your Silver item you will receive an additional \$2.

An example trial is shown below. You will see 20 cards on the screen, and each card has one of 20 snacks. First, you choose one of 20 cards by 'left clicking your mouse button' on the card. Second, you choose another card from 19 remaining cards. The items revealed will now be your bonus items. In this example, Milky Way is your Gold item, and Whoppers is your Silver item. During the experiment, you will see a gold border around the Gold item and a silver border around the Silver item in all subsequent tasks. When you evaluate the Gold item, indicated by the gold border, don't forget you get 4 additional dollars whenever you obtain the item. Similarly, you should not forget you get 2 additional dollars when you evaluate the Silver item with the silver border.



The basic steps to keep in mind in this task are:

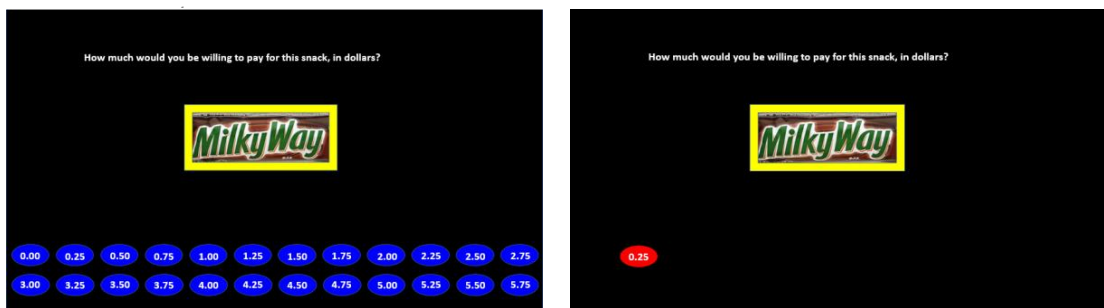
1. You will see 20 cards on the screen.
2. You will choose one of 20 cards by left clicking on the card.
3. You will choose one more card from 19 cards by left clicking on the card.
4. This will reveal your bonus items which will be henceforth indicated by a gold or silver border.
5. If you ever obtain the Gold item, you will receive an additional \$4.
6. If you ever obtain the Silver item, you will receive an additional \$2.

**Do you have any questions? Please raise your hand and ask any questions.**

## Part II

In this task, you will be asked about your willingness-to-pay for each snack. For example, a single trial will ask how much you are willing to pay to eat a Milky Way. Each snack is approximately a single serving.

In each trial, you will be shown an image of a snack. If Milky Way is your Gold item it will have a gold border. You can answer your willingness-to-pay by left clicking your mouse button on the monetary values at the bottom of the screen. You can choose your willingness-to-pay for that item from \$0 to \$5.75 in increments of \$0.25.



The screen will show you the amount you select. In this example above, \$0.25 is selected as the willingness-to-pay for Milky Way.

The computer will randomly select a price. You will obtain the snack as long as the random price is equal to or below your stated willingness-to-pay. Notice that it is optimal to state the maximum of what you would pay for this item. It is as if a friend was going to the store and asked you if you would like him to pick up a snack for you. There is a snack you want but you don't know the price. What would you do? You would inform your friend to only buy the snack so long as the price is equal to or below your true valuation of the snack. This task is logically equivalent. The procedure ensures that it is best for you truthfully reveal the highest price you are willing to pay.

As an example, imagine your true willingness-to-pay for a Dr. Pepper is \$3.00, but you untruthfully overstate that your willingness-to-pay is \$4.00. Then, if the random price is \$3.50, you would pay \$3.50 and get the Dr. Pepper even though the most you would be willing to pay is \$3.00. You would have wasted \$0.50. If the price were

below \$3 or above \$3.50 the outcome would have been the same as if you reported your true valuation. So you can only do worse if you give a willingness-to-pay above your true valuation. In contrast, if you understate your willingness-to-pay as \$2.00, and if the random price is \$2.50, you would be disappointed because you would not buy the Dr. Pepper even though the price is below your true valuation. If the price were below \$2.00 or above \$3.00 the outcome would have been the same as if you reported your true valuation. So you can only do worse if you give a willingness-to-pay below your true valuation.

Note that you cannot influence the purchase price with your stated willingness-to-pay, because the purchase price is completely random and independent of whatever you state.

The situation is analogous to having a friend go to the store to buy items on your behalf, but in which you don't know the prices. The optimal thing to do is to tell your friend to buy the Dr. Pepper only if the price is at your willingness to pay or lower (\$3.00). Saying anything else would have your friend not buying when you would have wanted it or buying at a price too high.

However, if you state willingness-to-pay for your Gold item, please remember your bonus item comes with \$4 in cash. Thus your Gold item should be worth whatever the value of that item is to you plus \$4.

Likewise, if you state willingness-to-pay for your Silver item, please remember your bonus item comes with \$2 in cash. Thus your Silver item should be worth whatever the value of that item is to you plus \$2.

Finally, you should treat every trial as if it is the only one that matters since only one trial will be chosen at random to count for real stakes. Please take each and every decision seriously.

The basic steps to keep in mind in this task are:

1. You will see a snack on the screen.



2. You should answer your maximum willingness-to-pay by left clicking your mouse button on one of the amounts from \$0 to \$5.75 in increments of \$0.25.
3. You are best off by selecting the maximum you would be willing to pay.
4. When you evaluate each snack, please do not forget you will get an additional \$4 for your Gold item and an additional \$2 for your Silver item.
5. You should treat every trial as if it is the only one that matters because you don't know which trial will be chosen.

**Do you have any questions? Please raise your hand or ask the experimenter any questions you have so far. The experimenter will tell you when you can start the experiment.**

## Quiz for Part II.

DATE \_\_\_\_\_ SUBJECT \_\_\_\_\_

Please answer the following four questions by circling the correct answer:

1. Imagine your true value for a Coke is \$2.00. What happens if you answer your willingness-to-pay for it is \$3.00?

- 1) You have no risk of paying more for the Coke than your true value.
- 2) You can influence the random price of a Coke by overstating your true value for it.
- 3) It's possible that you would pay a higher price than your true value for a Coke to receive it.

2. Imagine your true value for a Sprite is \$2.75. What happens if you answer your willingness-to-pay for it is \$2.00?

- 1) Your chance of receiving the Sprite is the same.
- 2) You lose the chance to get a Sprite if the random price is between \$2.00 and \$2.75.
- 3) You can strategically influence the random price of a Sprite by understating your true value for it.

3. Which of the following two statements is true?

- 1) You state your willingness-to-pay is \$2.00 and the random price is \$2.50. You receive a snack and pay \$2.50 for it.
- 2) You state your willingness-to-pay is \$2.00 and the random price is \$1.50. You receive a snack and pay \$1.50 for it.

4. Which of the following two statements is true?

- 1) You state your willingness-to-pay is \$3.25 and the random price is \$2.00. You do not receive the snack and you pay nothing.
- 2) You state your willingness-to-pay is \$3.25 and a random price is \$4.00. You do not receive the snack and you pay nothing.

5. Suppose MilkyWay is worth \$1.50 to you and it is your Gold item. So, if you were to receive a MilkyWay you would also get the cash bonus. Which of the following bids makes you the best off?"

- (a) \$1.50                      (b) \$3.50                      (c) \$5.50

6. Suppose Dr.Pepper is worth \$2.25 to you and it is your Silver item. Which of the following bids makes you the best off?"

- (a) \$2.25                      (b) \$4.25                      (c) \$6.25

**Please raise your hand to turn in your quiz when you are finished.**

### Part III

In this task, you will make decisions about which of two possible snacks to consume. For example, a single trial will ask whether you would prefer to eat Milky Way or Whoppers. Each of the snacks for this task is approximately a single serving. Over the course of the task, you will see each snack item several times.

In each trial, you will be shown two images, as in the example below. You will respond with your left and right index fingers, one for each button. You will only need to press the 'c' or 'm' button. Importantly, please use both of your hands in this task. The options on the left can be chosen with the 'c' button and the option on the right can be chosen with 'm' button.



The screen will show you the option you select. The example above shows the screen in which the choice is between Milky Way and Whoppers, with Whoppers being selected.

Since you don't know which trial will be chosen, you should treat every trial as if it is the only one that matters. Please treat each decision as a real choice.

The basic steps to keep in mind in this task are:

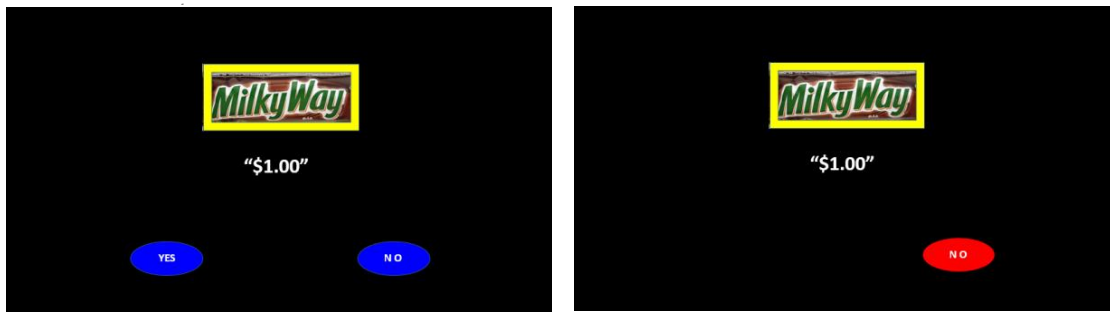
1. You will be shown a picture of two snack options.
2. Please use both index fingers to select which snack you prefer.
3. Again, please don't forget you will get the cash bonus for Gold or Silver items.

**Do you have any questions? Please raise your hand or ask the experimenter any questions you have so far. The experimenter will tell you when you can start the experiment.**

## Part IV

In this task, you will be asked whether you will buy each snack at a given price. For example, the screenshot below presents the choice to buy Milky Way for \$1.00. Over the course of the task, you will see each snack several times. Each of the snacks is approximately a single serving.

You will respond with your left and right index fingers, one for each button. You will only need to press the 'c' or 'm' button. Importantly, please use both of your hands in this task. To some participants, the options YES and NO will be on the opposite side. (No on the left and YES on the right.) The options on the left can be chosen with the 'c' button and the option on the right can be chosen with 'm' button.



Since you don't know which trial will be chosen, you should treat every trial as if it is the only one that matters.

The basic steps to keep in mind in this task are:

1. You will be shown a picture of a snack on the screen.
2. You will answer whether you would buy that snack at the given price.
3. By using both index fingers, please press 'c' if your answer is on the left, and press 'm' if your answer is on the right.
4. It will be best for you to respond honestly, and treat each decision as a real choice.
5. Again, please don't forget you will get the cash bonus for Gold or Silver items.

**Do you have any questions? Please raise your hand or ask the experimenter any questions you have so far. The experimenter will tell you when you can start the experiment.**

## **Screenshots**

This section contains several screen shots from the tasks and payment procedure.

**In this session, you will choose your own bonus items.**

**There are two bonus items: "Gold" and "Silver" ones.**

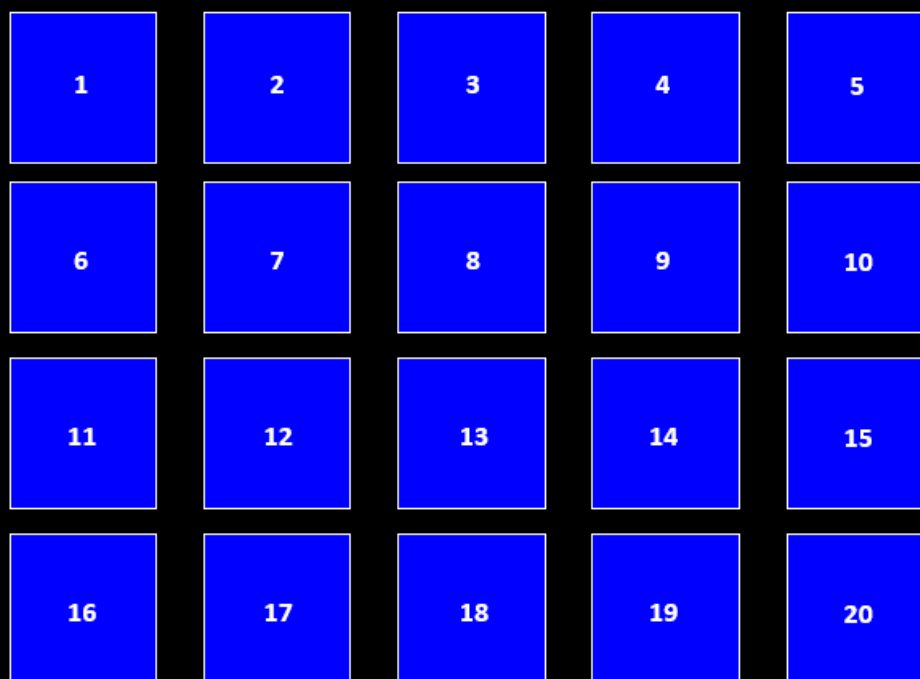
**If you get "Gold" item as your reward at the end of the experiment,  
you will get "4" additional dollars as well as the item itself.**

**Likewise, you will get "2" additional dollars as well as the item itself for "Silver" item.**

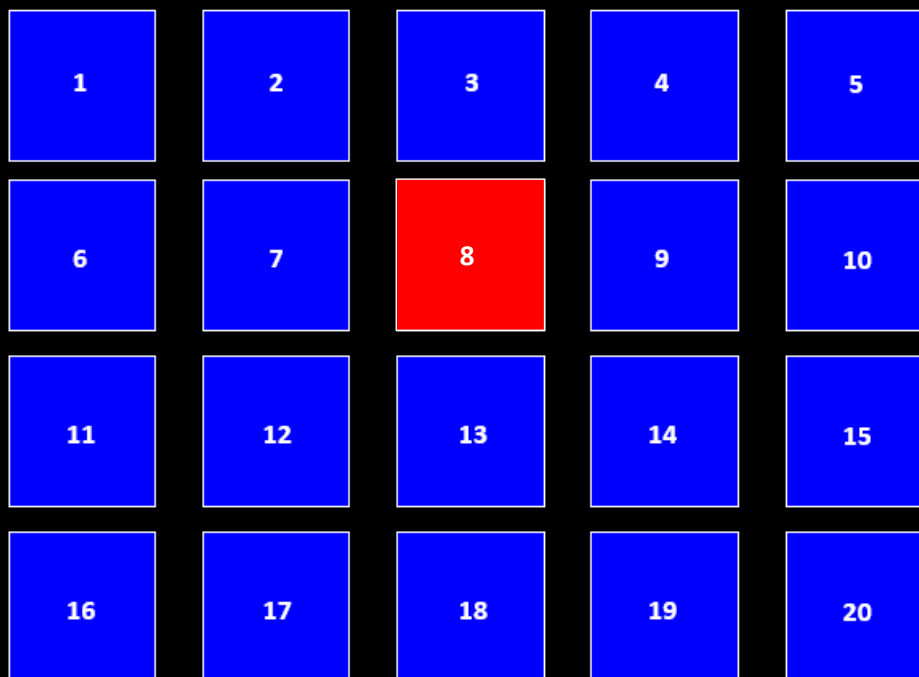
**Before starting this session, we will go over the instructions.**

**Please do not press SPACE before the experimenter says you can start.**

**Choose a card from a deck of 20 cards by clicking your mouse button.**



Choose one more card from a deck of 19 cards by clicking your mouse button.



Your Gold item is Hershey's.

Your Silver item is Justins Peanut Butter.



During the experiment, you will see a gold or silver border around each of these items.

If you receive Gold item as your reward, you will get 4 additional dollars.

If you receive Silver item as your reward, you will get 2 additional dollars.

Please do not forget this when you evaluate these items.

If you understand, please press SPACE to continue.

**This is the end of the bonus item selection.**

**Thank you very much!**

**Please do not press SPACE before the experimenter says you can start.**



In this session, you will see a picture of a snack several times.  
You should answer how much you are willing to pay for it.  
Please left click your mouse on the corresponding value.  
Before starting this session, we will go over the instruction.  
Please do not press SPACE before the experimenter says you can start.

How much would you be willing to pay for this snack, in dollars?



|      |      |      |      |      |      |      |      |      |      |      |      |
|------|------|------|------|------|------|------|------|------|------|------|------|
| 0.00 | 0.25 | 0.50 | 0.75 | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 | 2.75 |
| 3.00 | 3.25 | 3.50 | 3.75 | 4.00 | 4.25 | 4.50 | 4.75 | 5.00 | 5.25 | 5.50 | 5.75 |

How much would you be willing to pay for this snack, in dollars?



1.25

**This is the end of the task.**

**Please raise your hand when you finish.**

**Thank you very much!**

**Each trial will show two snacks.**

**Please pick the one you prefer.**

**If you prefer the left item, press "c" on the keyboard.**

**If you prefer the right item, press "m" on the keyboard.**

**Remember to please use both index fingers to respond.**

**Before starting this session, we will go over the instruction.**

**Please do not press SPACE before the experimenter says you can start.**

**Which one do you prefer?**



**Which one do you prefer?**



**This is the end of the task.**

**Please raise your hand when you finish.**

**Thank you very much!**

**You will see one of 20 different snacks several times.**

**In each trial, you should decide whether to buy a snack for a given price.**

**If your answer is on the left, press "c" on the keyboard.**

**If your answer is on the right, press "m" on the keyboard.**

**Before starting this session, we will go over the instructions.**

**Please do not press SPACE before the experimenter says you can start.**



**“\$1.00”**

**YES**

**NO**



**“\$1.00”**

**NO**

**This is the end of the task.**

**Please raise your hand when you finish.**

**Thank you very much!**

Now you will get a reward for this experiment.  
Please roll the dice in front of you.

If you get 1 or 2, you will receive the reward on your willingness-to-pay for a snack in the 1st session.  
If you get 3 or 4, you will receive the reward on your binary choice in the 2nd session.  
If you get 5 or 6, you will receive the reward on your buy/no buy decision in the 3rd session.

Which number did you get on your dice?: 3

You will get a reward on a binary choice in the 2nd session.

The decision selected was between the Bar Cliff Peanut Crunch and the Pringles Original.  
You chose the Pringles Original.  
You will receive your food item now.  
You must eat it before you leave the experiment.

THANK YOU FOR YOUR PARTICIPATION!