Scope Sensitivity & Charitable Giving

I. Introduction

A. What was the purpose of your study?

1. We are interested in studying charitable giving patterns, specifically what methods help people to overcome the scope insensitivity bias as it relates to charitable giving and the impact of their money.
2. We are specifically studying the use of a math/calculation activity as a potential means of reducing scope insensitivity. Several previous studies explored the difference between scope sensitivity in participants who completed ‘calculation’ versus ‘emotional’ activities (Hsee & Rottenstreich, 2004; Hasford et al., 2015).

B. What was your hypothesis of results?

1. We believed that participants who complete the math activity would have a more consistent willingness to pay per life than participants who complete the grammar activity. Therefore, their accuracy scores should be lower (closer to zero).

C. What was the motivation for studying this topic and why is it useful?

1. Identifying strategies to help people overcome the scope insensitivity bias could help charities to elicit more donations or help people to more effectively allocate their charitable giving.

D. Why is this topic important?

1. Scope insensitivity is a very common but easily avoidable bias.
2. It could have large impacts on the amount of money people are willing to donate and the optimal allocation of their donations.
3. Past literature has identified that scope insensitivity exists, but there is less agreement about the best ways to overcome it.

E. How does it contribute to the literature already written on this topic?

1. Prior literature has established that people are scope insensitive (they demonstrate the scope insensitivity bias) when making charitable giving decisions. Our study confirms the existence of this bias.
2. Prior literature has established that the order questions are asked in scope sensitivity studies could affect results. We varied the question order to control for this (Bateman et al. 2004; Carson & Mitchell 1995).
3. We investigate altruistic scope insensitivity for humans, turtles, and birds which occurs in fewer studies and may give more comprehensive results (Desvousges et al., 2010).
4. We control for demographic variables like education and race to account for differences in scope sensitivity between groups (Kogut et al., 2015; Dickert et al., 2015).

II. Literature Review

A. Imas, A., & Loewenstein, G. (2018, May). Is altruism sensitive to scope? The role of tangibility. In *AEA Papers and Proceedings* (Vol. 108, pp. 143-47).

1. This study focused on the role of tangibility in scope sensitivity and altruism. They found that scope sensitivity “depends critically on its tangibility” and that increasing tangibility causes people to become more sensitive to scope.

B. Hasford, J., Farmer, A., & Waites, S. F. (2015). Thinking, feeling, and giving: the effects of scope and valuation on consumer donations. *International Journal of Research in Marketing*, *32*(4), 435-438.
   1. This study replicated Hsee and Rottenstreich (2004). They studied the role of scope sensitivity on donation behavior. They found that people were more sensitive to scope when they made donations based on calculations and less sensitive to scope when they made donations based on emotion. Our study is similar in that it studies the role of scope sensitivity on charitable donations.

C. Hsee, C. K., & Rottenstreich, Y. (2004). Music, pandas, and muggers: on the affective psychology of value. *Journal of Experimental Psychology: General*, *133*(1), 23.
   1. This is an early and heavily cited paper that studied the difference between emotion-based and calculation-based valuation.
   2. Studies valuations based on calculation vs valuation based on feeling.
   3. Finds that feelings-based valuations lead to less scope sensitivity, whereas calculation-based evaluations "reveal relatively more constant sensitivity to scope."
   4. Our study looks at calculation but uses a grammar activity rather than an 'emotional' activity.

D. Bateman, I. J., Cole, M., Cooper, P., Georgiou, S., Hadley, D., & Poe, G. L. (2004). On visible choice sets and scope sensitivity. *Journal of environmental economics and management*, *47*(1), 71-93.
   1. This study contributes to the literature by studying the presentation of choices and information in scope sensitivity studies. They believe that there is a significant difference between studies that use a stepwise model (presenting options one at a time) and studies that present the entire choice set at once. They find that scope sensitivity "is substantially and significantly affected by the order in which goods are presented" when the stepwise model is used.

E. Baron, J., & Greene, J. (1996). Determinants of insensitivity to quantity in valuation of public goods: Contribution, warm glow, budget constraints, availability, and prominence. *Journal of Experimental Psychology: Applied*, *2*(2), 107.
   1. Explored how people value public goods and found "insensitivity to numerical quantity."
   2. Lit review that identifies several types/mechanisms of scope insensitivity: warm glow, budget constraints.
   3. Performed 11 different studies of various public goods to look for evidence of different mechanisms.

F. Cameron, C. D., & Payne, B. K. (2011). Escaping affect: how motivated emotion regulation creates insensitivity to mass suffering. *Journal of personality and social psychology*, *100*(1), 1.
   1. Offers a theory for why people experience/use scope insensitivity specifically when dealing with mass suffering.
   2. 'Collapse of compassion' effect occurs when people are overwhelmed by large numbers of people suffering and feel less compassion.

G. Fetherstonhaugh, D., Slovic, P., Johnson, S., & Friedrich, J. (1997). Insensitivity to the value of human life: A study of psychophysical numbing. *Journal of Risk and uncertainty*, *14*(3), 283-300.
   1. Find evidence for 'psychophysical numbing' - the phenomenon that increasing numbers of lives at risk cause people to exhibit "diminished sensitivity in valuing lifesaving interventions."
   2. Basically evidence for scope insensitivity without using the same language.
   3. Specific to value of human life.

H. Kogut, T., Slovic, P., & Västfjäll, D. (2015). Scope insensitivity in helping decisions: Is it a matter of culture and values?. *Journal of Experimental Psychology: General*, *144*(6), 1042.
   1. Finds that "The singularity effect of identifiable victims refers to people's greater willingness to help a single concrete victim compared with a group of victims experiencing the same need."
   2. Look at differences between individualist and collectivist cultures.

I. Carson, R. T., & Mitchell, R. C. (1995). Sequencing and nesting in contingent valuation surveys. Journal of environmental economics and Management, 28(2), 155-173.
   1. Finds issues with common experimental designs of contingent valuation surveys.
   2. Order of options presented can affect results.
   3. Finds evidence against/lack of evidence for scope insensitivity.
   4. Rationale for mixing up the ordering of our questions.

J. Dickert, S., Västfjäll, D., Kleber, J., & Slovic, P. (2015). Scope insensitivity: The limits of intuitive valuation of human lives in public policy. *Journal of Applied Research in Memory and Cognition*, *4*(3), 248-255.
   1. Evidence that people exhibit diminishing marginal utility in regards to number of lives saved.
   2. Focus on the psychological processes involved in scope insensitivity and inconsistent valuation of life.
   3. Motivation for studying this topic.

K. Bateman, I. J., Cooper, P., Georgiou, S., Navrud, S., Poe, G. L., Ready, R. C., Riera, P., Ryan, M., & Vossler, C. A. (2005). Economic valuation of policies for managing acidity in remote mountain lakes: Examining validity through scope sensitivity testing. *Aquatic Sciences*, *67*(3), 274–291. https://doi.org/10.1007/s00027-004-0744-3
   1. Participants were scope sensitive to environmental changes that they cared about. When participants don't really care, they are not scope sensitive. Whether participants in a focus group care can be determined by qualitative analysis.

L. Hsee, C. K., Zhang, J., Lu, Z. Y., & Xu, F. (2013). Unit Asking. *Psychological Science*, *24*(9), 1801–1808. https://doi.org/10.1177/0956797613482947
   1. "Unit-asking," (asking donors to choose a hypothetical amount to donate to help one person before they decide how much to donate for everyone) significantly increases scope sensitivity, and with it, group donations.

M. Small, D. A., Loewenstein, G., & Slovic, P. (2007). Sympathy and callousness: The impact of deliberative thought on donations to identifiable and statistical victims.

Organizational Behavior and Human Decision Processes, *102*(2), 143–153. https://doi.org/10.1016/j.obhdp.2006.01.005

   1. When teaching or priming people to notice the scope insensitive difference between their valuation of individuals vs. groups, they decrease giving to identifiable victims and maintain but do not increase giving to groups.

N. Dunn, E. W., & Ashton-James, C. (2008). On emotional innumeracy: Predicted and actual affective responses to grand-scale tragedies. *Journal of Experimental Social Psychology*, *44*(3), 692–698. https://doi.org/10.1016/j.jesp.2007.04.011

   1. People expect that they will be emotionally scope sensitive (e.g. feel worse about a disaster that kills 1000 people than one that kills 5), but they are not, unless numbers are translated into concrete images.

O. Harel, I., & Kogut, T. (2021). The Effect of the Number and Identification of Recipients on Organ-Donation Decisions. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.794422

   1. Participants who learned about more people that were saved by the organs of a donor do not increase willingness to donate.

P. Erlandsson, A., Västfjäll, D., Sundfelt, O., & Slovic, P. (2016). Argument-inconsistency in charity appeals: Statistical information about the scope of the problem decrease helping toward a single identified victim but not helping toward many non-identified victims in a refugee crisis context. *Journal of Economic Psychology*, *56*, 126–140. https://doi.org/10.1016/j.joep.2016.06.007

   1. Statistical information may not affect or have a slightly positive impact on willingness to help groups. When statistical information is combined with emotional arguments, donations can decrease.

Q. Chang, H. H., & Hung, I. W. (2018). Mirror, Mirror on the Retail Wall: Self-Focused Attention Promotes Reliance on Feelings in Consumer Decisions. *Journal of Marketing Research*, *55*(4), 586–599. https://doi.org/10.1509/jmr.15.0080

   1. When donors have greater self-focused attention, scope insensitivity is amplified in both a hypothetical study and a real-life donation.

R. Dickert, S., Kleber, J., Peters, E., & Slovic, P. (2011). Numeracy as a precursor to pro-social behavior: The impact of numeracy and presentation format on the cognitive mechanisms underlying donation decisions. *Scholarsbank.uoregon.edu*. http://hdl.handle.net/1794/22050

   1. Less numerate people change their donation choices when numeric presentation format is changed more than numerate individuals. The mental image of victims influenced less numerate people only. Estimated impact was correlated with donation amounts for all.

S. Dickert, S., Västfjäll, D., Kleber, J., & Slovic, P. (2012). Valuations of human lives: normative expectations and psychological mechanisms of (ir)rationality. *Synthese*, *189*(S1), 95–105. https://doi.org/10.1007/s11229-012-0137-4

   1. Scope insensitivity can be explained by the mechanisms that influence emotional reactions.

T. Czajkowski, M., & Hanley, N. (2009). Using Labels to Investigate Scope Effects in Stated Preference Methods. *Environmental and Resource Economics*, *44*(4), 521–535. https://doi.org/10.1007/s10640-009-9299-z

1. Labels affect scope sensitivity ("controlling for the effects of a label—in this case, national park designation—leads to significant increase in the scope sensitivity of welfare measures.").

U. Desvousges, W., Johnson, F. R., Dunford, R., Boyle, K., Hudson, S., & Wilson, K. N. (2010). *Measuring Nonuse Damages Using Contingent Valuation: An Experimental Evaluation of Accuracy*. https://doi.org/10.3768/rtipress.2009.bk.0001.1009

1. Found inconsistent per-life valuations of migratory waterfowl and questioned contingent valuation methodology in specific contexts.

III. Experimental Design: Describe your experimental design: please see resources I posted in the project modules, especially https://www.statisticshowto.com/experimental-design/.

A. Sampling technique:

1. **Desired sample size by level and treatment:**
   a) In our proposal, we planned to have sixty total participants with roughly thirty in each treatment group. We were able to collect data for a total of 77 participants but only used 65 in our regressions. We removed one response because the respondent stated that they were under the age of 18 and 11 that were incomplete.
2. **Describe each treatment.**
   a) Subjects were assigned either to a math activity (treatment) or to a grammar activity (control).
   b) In the math activity, participants completed simple multiple-choice math questions designed to get them to do 'scaling' activities.
   c) In the grammar activity, participants completed multiple-choice questions about grammatical structure and errors.
3. **How did you assign subjects to treatments?**
   a) Our survey software randomly assigned subjects to either the math activity or the grammar activity. A roughly equal number of participants were assigned to the treatment and control activities over the course of the experiment.
4. **Did you use a within or between subjects design?**
   a) We are using a between-subjects design to compare the consistency of the math participants with the consistency of the grammar participants.
   b) We are collecting within-subjects data, but this is not ultimately what we are comparing in the analysis. We used our within-subjects data (different valuation calculations) to calculate our
5. **Could your experiment be easily replicated and verified by another researcher?**
   a) Our experiment could easily be replicated. It was in part a replication (with modifications) of earlier studies that also explored the effect of performing calculations on scope sensitivity in altruistic contexts.

B. Describe the methodology fully:

1. **What independent and dependent variables did you record from your experiments?**
    a) The primary independent variable is the math activity intervention. Additional independent variables tested are annual income, essential spending, non-essential spending, charity-givers, and demographic info such as age, gender and race.
    b) The dependent variable is the scope-scaling accuracy score.
2. **How do you define each?**
    a) The math activity intervention is a binary variable equal to one if the participant was randomly assigned to the treatment group; equal to zero if randomly assigned to the control group.
    b) The “accuracy score” was calculated using the valuations provided by participants. The formula is described in the analysis document. Lower scores indicate more consistency between a participant’s per-life valuations. The accuracy score is separate from the activity score, which indicates what proportion of the grammar or math activity questions the participant got correct.
    c) Income, essential spending, and non-essential spending were numeric values provided by the participants. The exact question wording is available in our survey content in the appendix.
    d) We used dummy variables to include our gender and race variables.
    e) We used binary variables to indicate whether a participant responded ‘yes’ (1) or ‘no’ (0) to the questions about their charity donation behavior.
3. **Do you potentially have any confounding variables that should be addressed?**
    a) We controlled for confounding variables such as income or education level by including them in our regressions.
4. **What methods did you use to record these data?**
    a) We used a Qualtrics survey to collect data.
5. **Do you encounter any issues in getting clean data?**
    a) Yes, there were issues with having participants answer honestly. Additionally, given that we asked hypothetical questions and were not available to consult, some participants may have been confused and therefore not answered accurately.
6. **How did you statistically test your data to determine your results?**
    a) We ran a multivariate linear regression in STATA.
7. **How did you present your results so that they are clear?**
    a) We will use the relevant tables and other outputs from STATA to show significant and non-significant variables.
8. **What were the limitations of your study?**
    a) Since the grammar activity was more difficult than the math activity, it serves as an imperfect control to compare with.
        (1) Frustration from knowing fewer correct answers may affect

willingness to pay.

(2) Non-response bias – more participants who received the grammar activity chose to not complete the survey compared with participants who received the math activity.

b) Our results cannot be generalized to the United States population due to a disproportionate number of young people, men, and people with some higher education.

c) Incomplete/insufficient responses result in not meeting the Central Limit Theorem's requirement of 30 minimum responses for approximately normal distribution.

(1) Results from comparisons between the 6 different form types might not accurately reflect the true nature of the differences.

C. Ethics

1. Were there any ethical concerns for participants?

a) We do not believe there are any ethical concerns for participants. We made efforts to inform them about the nature of the study as much as possible and reduce any risk of distress.

2. Were participants subjected to any risk above minimal risk?

a) No, participants were not subjected to any risk above minimal risk. They were easily able to withdraw from the survey at any time and for any reason.

3. Was there any deception of participants involved in the study?

a) We were intentionally vague about the purpose of our study, but otherwise did not deceive participants in any way.

D. Additional materials/appendices

1. Attach a list of materials needed and descriptions.(These may need to be part of the methodology or they may work best in the appendix.)

a) No materials were needed for the survey itself. We used Qualtrics to create the survey and distributed it online and using fliers with a QR code.

2. Attach any surveys/questionnaires/tasks that participants will participate in.

a) Please see appendix III for the survey our participants filled out.

IV. Results

A. What does your data show?

1. Our data analysis showed that the independent variables we chose to run a regression on are NOT significantly related to our dependent variable (scope-scaling accuracy) in any way. Additionally, we eliminated order bias.

B. Here is where you include any charts, stats, graphs or other representations of your data. I encourage you to use Tableau, Excel, PPT, etc to show your results in a visually pleasing way. If you used regression analysis, this is the place to put the regression tables.

1. We ran multiple different types of regressions. Please see appendix II for all of the STATA output tables and our analysis.

V. Conclusions

A. What can we conclude from the work?

1. In conclusion, we cannot confidently say that participating in a relevant mathematical activity before answering scope-scaling questions will nudge individuals into more accurately adjusting their WTP for donations to charities of various causes.

B. What were the limitations of the study and thus what do we need to consider when interpreting results?

1. Sample size.
2. Mostly college students.
3. Results may have been impacted by the specifics of the questions (e.g. perhaps people are less sympathetic to birds, sea turtles, etc.).

C. What other questions remain to be answered?

1. How do different ‘victims’ affect valuations and why?
2. How would the introduction of budget constraints change participant responses?
3. Would participant answers change if social pressures were introduced (i.e. if the questions were asked by a person rather than a survey)?

D. What is the importance of the work done? Any policy implications based on the conclusions?

1. Further research is needed to determine the impact of calculation exercises on scope sensitivity. Given that our results show no statistically significant effect, there are no notable policy implications at this time.
2. Our study is consistent with earlier literature which indicates that people are insensitive to scope. Policies should be scope-sensitive and correct for this bias.

Appendices

Appendix I. Descriptive Statistics

Per-Life Valuations

		Mean	Median	Mode	Minimum	Maximum
Bird	Small	$14.17	$.03	$0	$0	$500
	Medium	$7.89	$.10	$.001	$0	$500
	Large	$6.83	$.001	$.001	$0	$500
Turtle	Small	$365	$1.25	$100	$0	$25,000
	Medium	$75.67	$.50	$5	$0	$5,000
	Large	$16.93	$.10	$.05	$0	$1,000
Human	Small	$144,044	$50	$100	$0	$10,000,000
	Medium	$78,744	$5	$5	$0	$5,000,000
	Large	$1,421	$.62	$.25	$0	$50,000

	Grammar Activity	Math Activity	Differential
Bird	7.24	.356	20.33
Turtle	351	4.83	72.67
Human	144,478	562	257.08

Appendix II: STATA Analysis

Section 1: Analysis on Overall Accuracy Score

Overall accuracy score (accuracy_score) is a measurement of participants' response accuracy in keeping their per life valuations proportional with increasing quantities of lives by averaging the differences between each of their per life valuations from small to medium and from medium to large scope questions for all three life forms: birds, turtles, and humans. A score of zero indicates that the participant's valuations were perfectly proportional. The higher the score, the less accurate the participant's valuations were.

Sample Calculation

1) Participant Responses

Small: Amount willing to pay to save 200 birds: $20

Medium: Amount willing to pay to save 2,000 birds: $25

Large: Amount willing to pay to save 20,000 birds: $40

2) Per Life Valuations

Small: $20 / 200 birds = $.10 per bird

Medium: $25 / 2,000 birds = $.0125 per bird

Large:$40 / 20,000 birds = $.002 per bird

3) Difference Calculations

Absolute value of the small valuation minus the medium valuation: $.10 -$.0125 = $.0875

Absolute value of the medium valuation minus the large valuation: $.0125 - $.002 = $.0105

4) Score calculation

Average difference: ($.0875 + $.0105) / 2 = .098

This number was multiplied by 1,000 to avoid reporting the small decimals that were often present and are known to confuse readers.

This participant's accuracy score would be 980.

The process was repeated for the turtle and human questions, then added for each participant to calculate their final accuracy score.

Figure 1: Overall Participant Accuracy - Full Regression & F-Test of Joint Significance on Form Type

Source	SS	df	MS			
				Number of obs	=	56
				F(25, 30)	=	1.05
Model	1.1973e+11	25	4.7890e+09	Prob > F	=	0.4449
Residual	1.3681e+11	30	4.5602e+09	R-squared	=	0.4667
				Adj R-squared	=	0.0223
Total	2.5653e+11	55	4.6642e+09	Root MSE	=	67529

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	8472.273	28731.34	0.29	0.770	-50204.96	67149.5
activity_score	-99053.63	55956.62	-1.77	0.087	-213332.3	15225.04
msl	11901.72	43419.91	0.27	0.786	-76773.57	100577
slm	42641.45	52416.1	0.81	0.422	-64406.51	149689.4
lsm	78482.87	41263.98	1.90	0.067	-5789.428	162755.2
lms	18148.85	42723.91	0.42	0.674	-69105.02	105402.7
mls	37229.37	41669.54	0.89	0.379	-47871.18	122329.9
age	-1925.927	1470.559	-1.31	0.200	-4929.21	1077.355
male	1011.532	36085.67	0.03	0.978	-72685.23	74708.3
female	12718.43	39643.89	0.32	0.751	-68245.19	93682.06
black_or_africanamerican	153082.1	78527.84	1.95	0.061	-7293.166	313457.3
hispanic_or_latnix	43857.23	88413.99	0.50	0.623	-136708.2	224422.7
asian_or_pacificislander	4844.862	82230.5	0.06	0.953	-163092.2	172781.9
white	29012.99	71031	0.41	0.686	-116051.7	174077.6
completed_graduate_degree	11102.31	72262.06	0.15	0.879	-136476.5	158681.1
completed_bachelors_degree	-49449.56	71250.94	-0.69	0.493	-194963.4	96064.27
current_undergrad	-27039.02	69490.08	-0.39	0.700	-168956.7	114878.7
high_school_diploma	-46371.96	76262.28	-0.61	0.548	-202120.3	109376.4
incomplete_high_school	-99954.99	120014.9	-0.83	0.412	-345058.1	145148.2
current_graduatestu	32972.46	89924.72	0.37	0.716	-150678.3	216623.3
annual_income	.1004359	.096951	1.04	0.309	-.0975645	.2984363
ess_spend	.0048393	.0946893	0.05	0.960	-.1885421	.1982207
noness_spend	-.3178271	.6232201	-0.51	0.614	-1.590612	.9549582
charity_past	31483.45	78368.24	0.40	0.691	-128565.9	191532.8
charity_future	-24536.2	43137.88	-0.57	0.574	-112635.5	63563.09
_cons	66758.68	99845.27	0.67	0.509	-137152.6	270669.9

```
. test msl slm lsm lms mls

 ( 1)  msl = 0
 ( 2)  slm = 0
 ( 3)  lsm = 0
 ( 4)  lms = 0
 ( 5)  mls = 0

       F(  5,    30) =    1.11
            Prob > F =    0.3761
```

```
. di invFtail(5, 30, .05)
2.5335545
```

Since the calculated F-static of 1.11 is less than the calculated critical F-statistic of 2.5335545, and it has a corresponding p-value of 0.3761, which is greater than the critical p-value of 0.05, I fail to reject the null hypothesis at alpha levels of 0.05. Given the sample, there is insufficient evidence to conclude that the different form types MSL, SLM, LSM, LMS, and MLS are jointly significant. Therefore, form type does not have a jointly significant effect on accuracy score.

Figure 2: Figure 1 Regression without Form Type

Source	SS	df	MS			
Model	9.1124e+10	19	4.7960e+09	Number of obs	=	56
Residual	1.6541e+11	36	4.5947e+09	F(19, 36)	=	1.04
				Prob > F	=	0.4413
				R-squared	=	0.3552
				Adj R-squared	=	0.0149
Total	2.5653e+11	55	4.6642e+09	Root MSE	=	67784

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	22195.29	27359.46	0.81	0.423	-33292.27	77682.85
activity_score	-114852.9	53983.39	-2.13	0.040	-224336.2	-5369.489
male	1237.704	34017.96	0.04	0.971	-67753.92	70229.33
female	17425.82	35972.71	0.48	0.631	-55530.21	90381.86
black_or_africanamerican	143350.7	71725.09	2.00	0.053	-2114.484	288816
hispanic_or_latnix	29461.35	84349.29	0.35	0.729	-141606.9	200529.6
asian_or_pacificislander	19730.17	74682.7	0.26	0.793	-131733.4	171193.7
white	35796.8	61419.41	0.58	0.564	-88767.54	160361.1
completed_graduate_degree	3579.479	68681.5	0.05	0.959	-135713.1	142872
completed_bachelors_degree	-49143.76	67086.25	-0.73	0.469	-185201	86913.46
current_undergrad	-1363.863	67343.39	-0.02	0.984	-137942.6	135214.9
high_school_diploma	-21550.61	71611.25	-0.30	0.765	-166784.9	123683.7
incomplete_high_school	-56448.27	109967	-0.51	0.611	-279471.8	166575.2
current_graduatestu	22857.48	86714.53	0.26	0.794	-153007.7	198722.7
annual_income	.0934475	.0898351	1.04	0.305	-.0887465	.2756414
ess_spend	-.0002035	.0789491	-0.00	0.998	-.1603197	.1599127
noness_spend	-.4501691	.5778402	-0.78	0.441	-1.622083	.7217451
charity_past	7032.408	61954.26	0.11	0.910	-118616.6	132681.5
charity_future	1709.464	39204.18	0.04	0.965	-77800.31	81219.23
_cons	30563.76	88824.75	0.34	0.733	-149581.2	210708.7

Figure 3: Condensed Education Regression without Form Type & F-Test of Joint Significance on Charity Variables

Condensed education variable: other_education2 = other_education + incomplete_high_school + current_graduatestu + high_school_diploma

Source	SS	df	MS			
Model	8.8342e+10	16	5.5214e+09	Number of obs	=	56
Residual	1.6819e+11	39	4.3126e+09	F(16, 39)	=	1.28
				Prob > F	=	0.2575
				R-squared	=	0.3444
				Adj R-squared	=	0.0754
Total	2.5653e+11	55	4.6642e+09	Root MSE	=	65670

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	19465.93	25068.38	0.78	0.442	-31239.64	70171.51
activity_score	-104570.3	49912.73	-2.10	0.043	-205528.3	-3612.292
male	2012.905	32228.55	0.06	0.951	-63175.49	67201.3
female	20832.27	34274.55	0.61	0.547	-48494.55	90159.09
black_or_africanamerican	123291.9	62952.59	1.96	0.057	-4041.697	250625.5
hispanic_or_latnix	-6083.965	68699.19	-0.09	0.930	-145041.2	132873.3
asian_or_pacificislander	1566.865	65923.1	0.02	0.981	-131775.2	134908.9
white	18059.94	52042.31	0.35	0.730	-87205.57	123325.5
completed_graduate_degree	10126.03	33730.83	0.30	0.766	-58101.01	78353.07
completed_bachelors_degree	-39010.05	33681.64	-1.16	0.254	-107137.6	29117.49
current_undergrad	6084.222	37827.41	0.16	0.873	-70428.94	82597.38
annual_income	.0838594	.085847	0.98	0.335	-.0897826	.2575013
ess_spend	-.0152337	.0720981	-0.21	0.834	-.1610659	.1305986
noness_spend	-.3950996	.552589	-0.71	0.479	-1.512816	.7226173
charity_past	12331.25	46504.8	0.27	0.792	-81733.58	106396.1
charity_future	668.8173	35449.89	0.02	0.985	-71035.35	72372.98
_cons	29813.93	79014.67	0.38	0.708	-130008.3	189636.2

```
. test charity_past charity_future

 ( 1)  charity_past = 0
 ( 2)  charity_future = 0

       F(  2,    39) =    0.04
            Prob > F =    0.9646

. di invFtail(2, 39, .05) // 3.2380961
3.2380961
```

Education was condensed because the number of participants characterized by the incomplete_high_school, current_graudatestu, and high_school_diploma variables are less than 5 each. After condensing the variables, the number of participants denoted by other_education2 is 12.
Since the calculated F-static of 0.04 is less than the calculated critical F-statistic of 3.23, and it has a corresponding p-value of 0.9646 which is greater than the critical p-value of 0.05, I fail to reject the null hypothesis at alpha levels of 0.05. Given the sample, there is insufficient evidence to conclude that the charity variables: charity_past and charity_future, are jointly significant. Therefore, the charity variables do not have a jointly significant effect on accuracy score.

Figure 4: Figure 3 Regression without Charity Variables & F-Test of Joint Significance on Spending Variables

Source	SS	df	MS			
Model	5.9238e+12	14	4.2313e+11	Number of obs	=	67
Residual	1.8761e+13	52	3.6079e+11	F(14, 52)	=	1.17
				Prob > F	=	0.3232
Total	2.4685e+13	66	3.7401e+11	R-squared	=	0.2400
				Adj R-squared	=	0.0354
				Root MSE	=	6.0e+05

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-31603.39	199287.8	-0.16	0.875	-431503.7	368296.9
activity_score	-203274.3	389296.1	-0.52	0.604	-984454.2	577905.5
male	-87062.19	261287.7	-0.33	0.740	-611374.2	437249.9
female	-261350	267887.6	-0.98	0.334	-798905.8	276205.9
black_or_africanamerican	271997.8	533144.6	0.51	0.612	-797835.1	1341831
hispanic_or_latnix	145600.5	540198.1	0.27	0.789	-938386.2	1229587
asian_or_pacificislander	1129637	547904.4	2.06	0.044	30186.67	2229088
white	295343.7	460131.1	0.64	0.524	-627976.8	1218664
completed_graduate_degree	291205.5	263013.7	1.11	0.273	-236570.1	818981.1
completed_bachelors_degree	-18290.97	259358	-0.07	0.944	-538730.8	502148.8
current_undergrad	-452329	313023	-1.45	0.154	-1080456	175797.6
annual_income	-.2545899	.6994035	-0.36	0.717	-1.658046	1.148866
ess_spend	.0940515	.6459308	0.15	0.885	-1.202104	1.390206
noness_spend	-4.383928	4.961549	-0.88	0.381	-14.34	5.572149
_cons	60563.69	494173	0.12	0.903	-931066.9	1052194

```
( 1)  ess_spend = 0
( 2)  noness_spend = 0

       F(  2,    52) =    0.39
            Prob > F =    0.6786

. di invFtail(2, 52, .05) // 3.175141
3.175141
```

Since the calculated F-static of 0.39 is less than the calculated critical F-statistic of 3.23, and it has a corresponding p-value of 0.6786 that is greater than the critical p-value of 0.05, I fail to reject the null hypothesis at alpha levels of 0.05. Given the sample, there is insufficient evidence to conclude that the spending variables: ess_spend and noness_spend, are jointly significant. Therefore, the spending variables do not have a jointly significant effect on accuracy score.

Figure 5: Figure 4 Regression without the Spending variables & F-Tests of Joint Significance on Ethnicity and Gender

Source	SS	df	MS			
Model	5.6419e+12	12	4.7016e+11	Number of obs	=	67
Residual	1.9043e+13	54	3.5265e+11	F(12, 54)	=	1.33
				Prob > F	=	0.2277
				R-squared	=	0.2286
				Adj R-squared	=	0.0571
Total	2.4685e+13	66	3.7401e+11	Root MSE	=	5.9e+05

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-39395.94	195729.5	-0.20	0.841	-431810.1	353018.2
activity_score	-151807.3	379891.9	-0.40	0.691	-913444.8	609830.2
male	-117431.4	253113.4	-0.46	0.645	-624893.3	390030.4
female	-254386	258076.9	-0.99	0.329	-771799	263027
black_or_africanamerican	210623.1	447846	0.47	0.640	-687254.1	1108500
hispanic_or_latnix	98054.02	481375.1	0.20	0.839	-867045	1063153
asian_or_pacificislander	1076360	468869.8	2.30	0.026	136332.8	2016388
white	226531	372617.3	0.61	0.546	-520521.6	973583.6
completed_graduate_degree	248517.2	249673.7	1.00	0.324	-252048.5	749082.9
completed_bachelors_degree	-21195.29	253797.5	-0.08	0.934	-530028.6	487638.1
current_undergrad	-466129	305547	-1.53	0.133	-1078714	146455.9
annual_income	-.2493751	.6910017	-0.36	0.720	-1.63475	1.136
_cons	103211.2	448986.4	0.23	0.819	-796952.3	1003375

```
( 1)  black_or_africanamerican = 0
( 2)  hispanic_or_latnix = 0
( 3)  asian_or_pacificislander = 0
( 4)  white = 0

      F(  4,    54) =    2.61
           Prob > F =    0.0452
```

```
( 1)  completed_graduate_degree = 0
( 2)  completed_bachelors_degree = 0
( 3)  current_undergrad = 0

      F(  3,    54) =    2.74
           Prob > F =    0.0520
```

```
( 1)  male = 0
( 2)  female = 0

      F(  2,    54) =    0.61
           Prob > F =    0.5468
```

Since the calculated F-statistics for education and gender are both less than their respective calculated critical F-statistics of 2.78 and 3.17 respectively, and both of their calculated p-values are greater than the critical p-value of 0.05, I fail to reject the null hypotheses at alpha levels of 0.05. Given the sample, there is insufficient evidence to conclude that the education and gender variables are respectively jointly significant. Therefore, the variables do not have a significant effect on accuracy score.

Alternatively, since the calculated F-static for the ethnicity variables is 2.61, which is greater than the calculated critical F-statistic of 2.54, and the calculated p-value of 0.0452 is less than the critical p-value of 0.05, there is evidence that the null hypothesis is incorrect. Given the sample, there is evidence that the ethnicity variables are jointly significant.

Figure 6: Figure 5 without the Education and Gender Variables & F-Test of Joint Significance on Ethnicity

Source	SS	df	MS			
				Number of obs	=	67
				F(7, 59)	=	0.95
Model	2.5089e+12	7	3.5841e+11	Prob > F	=	0.4732
Residual	2.2176e+13	59	3.7587e+11	R-squared	=	0.1016
				Adj R-squared	=	-0.0049
Total	2.4685e+13	66	3.7401e+11	Root MSE	=	6.1e+05

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-30466.32	201540.7	-0.15	0.880	-433748.2	372815.6
activity_score	-384505.5	378321.4	-1.02	0.314	-1141525	372513.7
black_or_africanamerican	60315.41	438056.6	0.14	0.891	-816233.7	936864.5
hispanic_or_latnix	-127545.8	476228	-0.27	0.790	-1080476	825384.3
asian_or_pacificislander	489789.5	412711.3	1.19	0.240	-336043.9	1315623
white	36098.28	371441.2	0.10	0.923	-707153.8	779350.3
annual_income	-.0645761	.6900283	-0.09	0.926	-1.44532	1.316167
_cons	281193.3	403841.8	0.70	0.489	-526892.3	1089279

```
( 1)  black_or_africanamerican = 0
( 2)  hispanic_or_latnix = 0
( 3)  asian_or_pacificislander = 0
( 4)  white = 0

       F(  4,    59) =    1.27
            Prob > F =    0.2905
```

Since the calculated F-static of 1.27 is less than the calculated critical F-statistic of 2.53, and it has a corresponding p-value of 0.2905 that is greater than the critical p-value of 0.05, I fail to reject the null hypothesis at alpha levels of 0.05. Given the sample, there is insufficient evidence to conclude that the ethnicity variables are jointly significant. Therefore, the ethnicity variables do not have a jointly significant effect on accuracy score.

Figure 7: Activity Variables Only Regression

Source	SS	df	MS			
				Number of obs	=	77
				F(2, 74)	=	0.73
Model	4.7665e+11	2	2.3833e+11	Prob > F	=	0.4869
Residual	2.4266e+13	74	3.2792e+11	R-squared	=	0.0193
				Adj R-squared	=	-0.0072
Total	2.4743e+13	76	3.2556e+11	Root MSE	=	5.7e+05

accuracy_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-102635.9	158156.5	-0.65	0.518	-417769.6	212497.8
activity_score	-129779.5	274875.7	-0.47	0.638	-677481.3	417922.2
_cons	219965.8	184267.8	1.19	0.236	-147195.8	587127.3

Since the base regression T-statistics are small, the calculated T-test p-values are greater than the critical p-value of 0.05, and 0 is within the 95% confidence intervals for all three variables, there is insufficient evidence to conclude significance in the sample for a relationship between participants taking the intervention, their respective activity score, and the scope sensitivity measurement, accuracy score.

Note: After identified bad responses and outliers were removed, **no significant change occurred** to the results, so those regressions have been omitted to reduce redundancy. Also, since no significance has been identified, additional tests such as tests for heteroscedasticity have not been applied.

Section 2: Analysis on the Accuracy Scores for Birds, Turtles, and Humans

SUMMARY

```
Contains data from ScopeSensitivityData.dta
 Observations:          77
    Variables:          67                  21 Nov 2022 21:23
```

FIGURE 8: Accuracy Score For Birds Linear-Linear Regression Model

Source	SS	df	MS
Model	27985.93	25	1119.4372
Residual	32050.8491	30	1068.36164
Total	60036.779	55	1091.5778

Number of obs	=	56
F(25, 30)	=	1.05
Prob > F	=	0.4473
R-squared	=	0.4661
Adj R-squared	=	0.0213
Root MSE	=	32.686

accuracy_bird	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	4.605184	13.90668	0.33	0.743	-23.79604	33.00641
activity_score	-47.61178	27.08438	-1.76	0.089	-102.9255	7.701901
msl	4.835984	21.0163	0.23	0.820	-38.08503	47.757
slm	18.98458	25.37068	0.75	0.460	-32.82926	70.79842
lsm	37.07708	19.97278	1.86	0.073	-3.712785	77.86694
lms	8.421516	20.67942	0.41	0.687	-33.8115	50.65453
mls	18.22337	20.16908	0.90	0.373	-22.96739	59.41413
age	-.9047687	.7117868	-1.27	0.213	-2.358431	.5488939
male	.2896857	17.46635	0.02	0.987	-35.38136	35.96073
female	6.377469	19.18862	0.33	0.742	-32.81091	45.56585
black_or_africanamerican	73.05328	38.0094	1.92	0.064	-4.572277	150.6788
hispanic_or_latnix	18.35578	42.79454	0.43	0.671	-69.04233	105.7539
asian_or_pacificislander	1.595348	39.80158	0.04	0.968	-79.69032	82.88102
white	12.149	34.38075	0.35	0.726	-58.06586	82.36385
completed_graduate_degree	5.276859	34.97661	0.15	0.881	-66.15492	76.70863
completed_bachelors_degree	-23.25382	34.4872	-0.67	0.505	-93.68609	47.17844
current_undergrad	-12.77147	33.63491	-0.38	0.707	-81.46311	55.92017
high_school_diploma	-21.03341	36.91282	-0.57	0.573	-96.41944	54.35262
incomplete_high_school	-46.98847	58.09016	-0.81	0.425	-165.6244	71.64747
current_graduatestu	14.44663	43.52577	0.33	0.742	-74.44486	103.3381
annual_income	.0000466	.0000469	0.99	0.329	-.0000493	.0001424
ess_spend	7.42e-08	.0000458	0.00	0.999	-.0000935	.0000937
noness_spend	-.0001496	.0003017	-0.50	0.624	-.0007656	.0004665
charity_past	13.85426	37.93215	0.37	0.717	-63.61353	91.32205
charity_future	-11.45895	20.87979	-0.55	0.587	-54.10117	31.18328
_cons	34.45097	48.32756	0.71	0.481	-64.24708	133.149

```
 ( 1)  msl = 0
 ( 2)  slm = 0
 ( 3)  lsm = 0
 ( 4)  lms = 0
 ( 5)  mls = 0

       F(  5,    30) =    1.09
            Prob > F =    0.3869
```

In the regression seen above (Figure 8), there are no t-values greater than the critical value of 1.96 and there are no p-values less than the critical value of 0.05 which means we can not say that any of these variables have a significant relationship with the dependent variable, ‘accuracy_bird.’ Additionally, with an R-squared value of 0.466, we can infer that perhaps a linear-linear model is not that best fit. Therefore, I tested additional regression models to see if they held any compelling results. Additionally, we can see that form-type is not significant due to the joint-significance test outputting a F-stat of 1.09 which is less than the critical value of 1.96 and a p-value of 0.387 which is greater than the critical value of 0.05. This means that the order in which the scope-scaling questions was not significant.

FIGURE 9: Accuracy Score for Birds Log-Linear Regression Model

Source	SS	df	MS			
				Number of obs	=	49
				F(25, 23)	=	1.73
Model	221.73369	25	8.86934759	Prob > F	=	0.0956
Residual	118.00934	23	5.13084088	R-squared	=	0.6527
				Adj R-squared	=	0.2751
Total	339.74303	48	7.07797979	Root MSE	=	2.2651

logAccBird	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	2.390472	1.172294	2.04	0.053	-.0346022	4.815546
activity_score	-4.685881	2.166572	-2.16	0.041	-9.167776	-.203986
msl	-.8249306	1.624583	-0.51	0.616	-4.185637	2.535776
slm	-1.001989	2.023733	-0.50	0.625	-5.188399	3.184421
lsm	-.0994972	1.83866	-0.05	0.957	-3.903054	3.70406
lms	-.6118081	1.631194	-0.38	0.711	-3.986189	2.762573
mls	2.56119	1.540024	1.66	0.110	-.6245937	5.746973
age	.0697553	.0606206	1.15	0.262	-.055648	.1951586
male	-.5771318	1.277904	-0.45	0.656	-3.220677	2.066414
female	-.1988645	1.361153	-0.15	0.885	-3.014624	2.616895
black_or_africanamerican	1.024456	2.910573	0.35	0.728	-4.996523	7.045434
hispanic_or_latnix	-5.218494	3.857036	-1.35	0.189	-13.19738	2.760392
asian_or_pacificislander	-2.215328	2.923814	-0.76	0.456	-8.263699	3.833043
white	-2.409281	2.478214	-0.97	0.341	-7.535857	2.717296
completed_graduate_degree	1.670214	3.859847	0.43	0.669	-6.314487	9.654916
completed_bachelors_degree	-1.100568	3.865159	-0.28	0.778	-9.096258	6.895122
current_undergrad	.9661223	3.601915	0.27	0.791	-6.485007	8.417251
high_school_diploma	1.415269	3.797162	0.37	0.713	-6.439759	9.270297
incomplete_high_school	.1619286	4.917802	0.03	0.974	-10.01132	10.33518
current_graduatestu	-2.230741	4.239025	-0.53	0.604	-10.99983	6.538351
annual_income	-4.68e-06	3.90e-06	-1.20	0.243	-.0000128	3.39e-06
ess_spend	-9.69e-06	3.35e-06	-2.89	0.008	-.0000166	-2.76e-06
noness_spend	-.0000227	.0000462	-0.49	0.628	-.0001183	.0000729
charity_past	1.194547	2.942731	0.41	0.689	-4.892956	7.282051
charity_future	1.624165	1.935792	0.84	0.410	-2.380326	5.628657
_cons	-3.053699	3.849352	-0.79	0.436	-11.01669	4.909292

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

      F(  5,    23) =    2.32
           Prob > F =    0.0759
```

The R-squared value for this regression (Figure 9) is 0.653, which is worse than before. This means the log-linear model is a worse fit for our data. There are two variables that show a significant relationship with the dependent variable: ‘activity_score’ and ‘ess_spend’. This implies that the performance on the activity (math or grammar) correlates with the participants’ ability to accurately scale scope when it comes to donations that would hypothetically save birds. It also implies that essential spending is significantly related. However, since this model does not fit the data well, I am not confident in these findings. Another thing to note is that the variable ‘math_activity’ is very close to being significant, but since the p-value of 0.053 is greater than the critical value of 0.05, it is not significant. Finally, a joint-significance test for form-type shows that the order in which we asked the scope-scaling questions doesn't matter.

FIGURE 10: Accuracy for Bird Linear-Log Regression Model

Source	SS	df	MS			
Model	29189.0836	25	1167.56334	Number of obs	=	54
Residual	30801.0762	28	1100.03843	F(25, 28)	=	1.06
				Prob > F	=	0.4368
				R-squared	=	0.4866
				Adj R-squared	=	0.0281
Total	59990.1598	53	1131.88981	Root MSE	=	33.167

accuracy_bird	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	9.923922	14.88192	0.67	0.510	-20.56031	40.40816
logActSco	-32.45932	16.03382	-2.02	0.053	-65.30311	.3844646
msl	8.910138	21.2028	0.42	0.678	-34.52183	52.34211
slm	25.484	27.06829	0.94	0.355	-29.96289	80.93088
lsm	41.46734	20.29791	2.04	0.051	-.1110347	83.04572
lms	18.98086	21.69759	0.87	0.389	-25.46464	63.42635
mls	27.1275	21.73037	1.25	0.222	-17.38515	71.64014
age	-.8063643	.7609198	-1.06	0.298	-2.365038	.7523093
male	.8497028	18.98016	0.04	0.965	-38.0294	39.7288
female	7.110119	21.62413	0.33	0.745	-37.18491	51.40515
black_or_africanamerican	66.72075	34.3542	1.94	0.062	-3.650635	137.0921
hispanic_or_latnix	17.01262	43.11474	0.39	0.696	-71.30393	105.3292
asian_or_pacificislander	-4.703642	43.26542	-0.11	0.914	-93.32885	83.92156
white	4.243399	33.25013	0.13	0.899	-63.86641	72.35321
completed_graduate_degree	-2.845055	38.58505	-0.07	0.942	-81.88294	76.19283
completed_bachelors_degree	-28.46234	37.48376	-0.76	0.454	-105.2443	48.31965
current_undergrad	-15.5453	35.12006	-0.44	0.661	-87.48548	56.39488
high_school_diploma	-26.50126	39.01692	-0.68	0.503	-106.4238	53.42127
incomplete_high_school	-42.75856	77.24975	-0.55	0.584	-200.9975	115.4804
current_graduatestu	5.784874	43.38689	0.13	0.895	-83.08913	94.65888
logAnnInc	3.50538	6.132917	0.57	0.572	-9.057332	16.06809
logEssSpe	-1.719862	6.379845	-0.27	0.789	-14.78838	11.34866
logNEssSpe	1.283684	5.29303	0.24	0.810	-9.558596	12.12596
charity_past	15.93713	40.52092	0.39	0.697	-67.0662	98.94047
charity_future	-13.68042	21.45875	-0.64	0.529	-57.63668	30.27584
_cons	-42.15555	81.48322	-0.52	0.609	-209.0663	124.7553

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

F(  5,    28) =    1.18
     Prob > F =    0.3446
```

The regression seen in Figure 10 has an R-squared value of 0.487 which is better than the log-linear regression model, but slightly worse than the linear-linear regression model. In this model, there are no significant variables as all have t-scores above the critical value of 1.96 and p-values below the critical value of 0.05. Additionally, the form type is not significant.

FIGURE 11: Accuracy for Birds Log-Log Regression Model

Source	SS	df	MS
Model	212.017025	25	8.480681
Residual	123.46468	21	5.87927049
Total	335.481705	46	7.29308055

Number of obs	=	47
F(25, 21)	=	1.44
Prob > F	=	0.1986
R-squared	=	0.6320
Adj R-squared	=	0.1939
Root MSE	=	2.4247

logAccBird	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	1.997192	1.354835	1.47	0.155	-.8203411	4.814726
logActSco	-2.241399	1.294431	-1.73	0.098	-4.933317	.4505182
msl	.6244443	1.848924	0.34	0.739	-3.220603	4.469492
slm	1.824678	2.416129	0.76	0.459	-3.199936	6.849293
lsm	.9538382	1.9979	0.48	0.638	-3.201022	5.108699
lms	.906763	1.961357	0.46	0.649	-3.172103	4.985629
mls	4.313914	1.909713	2.26	0.035	.3424477	8.28538
age	-.0300483	.0734026	-0.41	0.686	-.1826973	.1226008
male	-1.671888	1.43378	-1.17	0.257	-4.653596	1.30982
female	-.9585592	1.609252	-0.60	0.558	-4.305181	2.388063
black_or_africanamerican	1.672254	2.916624	0.57	0.572	-4.393198	7.737707
hispanic_or_latnix	-6.40283	4.629719	-1.38	0.181	-16.03086	3.225197
asian_or_pacificislander	-3.395672	3.710784	-0.92	0.371	-11.11267	4.321326
white	-2.359901	2.787242	-0.85	0.407	-8.156289	3.436487
completed_graduate_degree	-.0390465	4.397529	-0.01	0.993	-9.184208	9.106115
completed_bachelors_degree	-2.055524	4.392776	-0.47	0.645	-11.1908	7.079755
current_undergrad	-.9064357	3.916052	-0.23	0.819	-9.050313	7.237441
high_school_diploma	.3154014	4.235516	0.07	0.941	-8.492837	9.12364
incomplete_high_school	-5.668148	6.738067	-0.84	0.410	-19.68073	8.344429
current_graduatestu	-2.417283	4.678551	-0.52	0.611	-12.14686	7.312297
logAnnInc	-.6720118	.5112259	-1.31	0.203	-1.735164	.3911408
logEssSpe	-.7322098	.5654079	-1.30	0.209	-1.90804	.4436202
logNEssSpe	1.09437	.4490617	2.44	0.024	.1604949	2.028245
charity_past	3.808791	3.290118	1.16	0.260	-3.033384	10.65097
charity_future	1.218737	2.119937	0.57	0.571	-3.189914	5.627388
_cons	.0501115	6.746951	0.01	0.994	-13.98094	14.08116

(1) msl = 0
(2) slm = 0
(3) lsm = 0
(4) lms = 0
(5) mls = 0

F(5, 21) = 1.92
Prob > F = 0.1336

Figure 11 shows a poorly-fitted model where the variable 'logNEssSpe' is significant. This variable is the self-reported money spent on non-essential things every month. However, due to the R-squared value of 0.632, I am not confident that any impactful conclusion can be drawn from this correlation. Additionally, the form-type is once again, not significant.

FIGURE 12: Accuracy Score for Turtles Linear-Linear Regression Model

Source	SS	df	MS			
				Number of obs	=	56
				F(25, 30)	=	1.05
Model	66062366.3	25	2642494.65	Prob > F	=	0.4421
Residual	75273619.6	30	2509120.65	R-squared	=	0.4674
				Adj R-squared	=	0.0236
Total	141335986	55	2569745.2	Root MSE	=	1584

accuracy_turtle	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	203.5939	673.9458	0.30	0.765	-1172.787	1579.975
activity_score	-2300.624	1312.564	-1.75	0.090	-4981.238	379.9892
msl	258.2219	1018.493	0.25	0.802	-1821.818	2338.262
slm	961.5671	1229.515	0.78	0.440	-1549.437	3472.571
lsm	1816.803	967.9216	1.88	0.070	-159.9564	3793.563
lms	406.0081	1002.167	0.41	0.688	-1640.689	2452.706
mls	851.1637	977.4346	0.87	0.391	-1145.024	2847.352
age	-44.86621	34.49464	-1.30	0.203	-115.3137	25.58123
male	19.58356	846.4548	0.02	0.982	-1709.108	1748.275
female	292.5893	929.9194	0.31	0.755	-1606.559	2191.738
black_or_africanamerican	3616.037	1842.013	1.96	0.059	-145.8554	7377.929
hispanic_or_latnix	1005.303	2073.91	0.48	0.631	-3230.187	5240.793
asian_or_pacificislander	107.4012	1928.865	0.06	0.956	-3831.868	4046.67
white	666.267	1666.161	0.40	0.692	-2736.488	4069.022
completed_graduate_degree	249.0075	1695.038	0.15	0.884	-3212.722	3710.737
completed_bachelors_degree	-1151.244	1671.32	-0.69	0.496	-4564.534	2262.047
current_undergrad	-633.0571	1630.016	-0.39	0.700	-3961.994	2695.879
high_school_diploma	-1074.636	1788.87	-0.60	0.553	-4727.996	2578.724
incomplete_high_school	-2318.414	2815.167	-0.82	0.417	-8067.753	3430.925
current_graduatestu	746.2108	2109.348	0.35	0.726	-3561.652	5054.073
annual_income	.0023381	.0022742	1.03	0.312	-.0023064	.0069826
ess_spend	.0001031	.0022211	0.05	0.963	-.0044331	.0046392
noness_spend	-.0074751	.0146188	-0.51	0.613	-.0373306	.0223804
charity_past	725.2012	1838.269	0.39	0.696	-3029.046	4479.448
charity_future	-548.4603	1011.877	-0.54	0.592	-2614.989	1518.069
_cons	1566.165	2342.052	0.67	0.509	-3216.943	6349.274

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

       F(  5,    30) =    1.09
            Prob > F =    0.3846
```

Figure 12 shows no significant variables - either the t-score is less than 1.96 or the p-value is greater than 0.05 or both. Additionally, the joint-significance test for form-type shows that the order in which we asked the questions did not have a significant effect in this model. The R-squared value of 0.467 could be better, so different regression models were tested just like for birds.

FIGURE 13: Accuracy for Turtles Log-Linear Regression Model

Source	SS	df	MS			
Model	143.308956	25	5.73235824	Number of obs	=	49
Residual	129.326018	23	5.62287035	F(25, 23)	=	1.02
				Prob > F	=	0.4837
Total	272.634974	48	5.67989529	R-squared	=	0.5256
				Adj R-squared	=	0.0100
				Root MSE	=	2.3713

logAccTurtle	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	1.351119	1.191712	1.13	0.269	-1.114125	3.816363
activity_score	-3.214001	2.220769	-1.45	0.161	-7.808011	1.380009
msl	1.000688	1.585374	0.63	0.534	-2.278909	4.280284
slm	2.094692	2.01636	1.04	0.310	-2.076465	6.26585
lsm	1.324814	1.669128	0.79	0.435	-2.128039	4.777668
lms	.1331214	1.604592	0.08	0.935	-3.18623	3.452473
mls	1.852582	1.591553	1.16	0.256	-1.439796	5.14496
age	-.0129828	.0574347	-0.23	0.823	-.1317956	.1058299
male	-.768191	1.35264	-0.57	0.576	-3.56634	2.029958
female	-.6425891	1.475205	-0.44	0.667	-3.694283	2.409105
black_or_africanamerican	.48089	2.841332	0.17	0.867	-5.396852	6.358632
hispanic_or_latnix	-1.49446	4.407812	-0.34	0.738	-10.61271	7.623793
asian_or_pacificislander	-1.206148	3.006153	-0.40	0.692	-7.424849	5.012554
white	-1.658287	2.543553	-0.65	0.521	-6.920028	3.603453
completed_graduate_degree	2.91928	4.062348	0.72	0.480	-5.484327	11.32289
completed_bachelors_degree	.5869016	4.026796	0.15	0.885	-7.743161	8.916964
current_undergrad	.3374147	3.78949	0.09	0.930	-7.501743	8.176572
high_school_diploma	1.331002	4.206225	0.32	0.755	-7.370236	10.03224
incomplete_high_school	-2.20111	5.102559	-0.43	0.670	-12.75656	8.354336
current_graduatestu	-.6500828	4.497045	-0.14	0.886	-9.952929	8.652764
annual_income	-2.19e-06	4.19e-06	-0.52	0.606	-.0000109	6.48e-06
ess_spend	-3.93e-06	3.47e-06	-1.13	0.270	-.0000111	3.26e-06
noness_spend	.0000145	.000022	0.66	0.516	-.0000311	.0000602
charity_past	2.708809	3.180653	0.85	0.403	-3.870873	9.28849
charity_future	.6405126	2.171157	0.30	0.771	-3.850869	5.131894
_cons	-1.20518	4.248219	-0.28	0.779	-9.993292	7.582931

(1) msl = 0
(2) slm = 0
(3) lsm = 0
(4) lms = 0
(5) mls = 0

F(5, 23) = 0.60
Prob > F = 0.6991

Figure 13 shows an R-squared value of 0.526 which is higher than the linear-linear model shown in Figure 12. There are no significant variables in this model. The form-type is also not significant.

FIGURE 14: Accuracy for Turtles Linear-Log Regression Model

Source	SS	df	MS
Model	68818312.4	25	2752732.49
Residual	72419492.4	28	2586410.44
Total	141237805	53	2664864.24

Number of obs	=	54
F(25, 28)	=	1.06
Prob > F	=	0.4340
R-squared	=	0.4873
Adj R-squared	=	0.0294
Root MSE	=	1608.2

accuracy_turtle	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	467.2425	721.6121	0.65	0.523	-1010.913	1945.398
logActSco	-1568.343	777.4666	-2.02	0.053	-3160.911	24.22489
msl	447.6921	1028.106	0.44	0.667	-1658.288	2553.672
slm	1249.061	1312.519	0.95	0.349	-1439.513	3937.634
lsm	2021.836	984.2288	2.05	0.049	5.734816	4037.937
lms	909.2699	1052.098	0.86	0.395	-1245.856	3064.395
mls	1277.395	1053.688	1.21	0.236	-880.9863	3435.776
age	-38.9048	36.89637	-1.05	0.301	-114.4836	36.67399
male	54.96929	920.3324	0.06	0.953	-1830.246	1940.185
female	346.3308	1048.536	0.33	0.744	-1801.499	2494.16
black_or_africanamerican	3268.646	1665.807	1.96	0.060	-143.6042	6680.896
hispanic_or_latnix	933.7041	2090.598	0.45	0.659	-3348.692	5216.1
asian_or_pacificislander	-223.242	2097.905	-0.11	0.916	-4520.605	4074.121
white	253.7999	1612.271	0.16	0.876	-3048.788	3556.388
completed_graduate_degree	-152.6904	1870.957	-0.08	0.936	-3985.172	3679.791
completed_bachelors_degree	-1414.315	1817.556	-0.78	0.443	-5137.41	2308.781
current_undergrad	-756.3885	1702.943	-0.44	0.660	-4244.708	2731.931
high_school_diploma	-1342.676	1891.898	-0.71	0.484	-5218.054	2532.701
incomplete_high_school	-2003.728	3745.776	-0.53	0.597	-9676.603	5669.147
current_graduatestu	305.2902	2103.794	0.15	0.886	-4004.137	4614.717
logAnnInc	185.8105	297.3801	0.62	0.537	-423.345	794.966
logEssSpe	-82.39654	309.3534	-0.27	0.792	-716.0783	551.2852
logNEssSpe	55.42194	256.6546	0.22	0.831	-470.3112	581.1551
charity_past	798.3225	1964.826	0.41	0.688	-3226.441	4823.086
charity_future	-654.6818	1040.517	-0.63	0.534	-2786.085	1476.721
_cons	-2257.415	3951.054	-0.57	0.572	-10350.78	5835.952

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

       F(  5,    28) =    1.17
            Prob > F =    0.3491
```

Figure 14 has an R-squared value of 0.487 which is lower than the log-linear model, but higher than the linear-linear model. In this model, there are no significant variables and the form-type is not jointly-significant.

FIGURE 15: Accuracy for Turtles Log-Log Regression Model

Source	SS	df	MS			
				Number of obs	=	47
				F(25, 21)	=	1.66
Model	180.085363	25	7.20341454	Prob > F	=	0.1202
Residual	90.9860421	21	4.33266867	R-squared	=	0.6643
				Adj R-squared	=	0.2648
Total	271.071406	46	5.89285664	Root MSE	=	2.0815

logAccTurtle	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	1.995626	1.117935	1.79	0.089	-.3292462	4.320498
logActSco	-2.11451	1.121414	-1.89	0.073	-4.446619	.2175992
msl	1.730633	1.379636	1.25	0.223	-1.138477	4.599743
slm	3.273706	1.831316	1.79	0.088	-.5347228	7.082136
lsm	1.614652	1.437858	1.12	0.274	-1.375539	4.604842
lms	.9119443	1.467462	0.62	0.541	-2.139809	3.963698
mls	3.388437	1.483621	2.28	0.033	.3030786	6.473796
age	-.0258573	.0530687	-0.49	0.631	-.1362198	.0845052
male	-.9527688	1.250141	-0.76	0.454	-3.55258	1.647042
female	-.2811015	1.432017	-0.20	0.846	-3.259143	2.69694
black_or_africanamerican	-.3557943	2.257886	-0.16	0.876	-5.051325	4.339737
hispanic_or_latnix	-5.424208	4.380958	-1.24	0.229	-14.53491	3.686492
asian_or_pacificislander	-4.134926	3.004892	-1.38	0.183	-10.38394	2.114089
white	-3.369449	2.215517	-1.52	0.143	-7.976868	1.23797
completed_graduate_degree	.5597183	3.74237	0.15	0.883	-7.222966	8.342402
completed_bachelors_degree	-1.259781	3.705797	-0.34	0.737	-8.966408	6.446847
current_undergrad	-1.024625	3.354281	-0.31	0.763	-8.000235	5.950984
high_school_diploma	.5809849	3.775408	0.15	0.879	-7.270406	8.432375
incomplete_high_school	-5.555745	5.542428	-1.00	0.328	-17.08185	5.970364
current_graduatestu	-2.26056	3.973921	-0.57	0.575	-10.52478	6.003661
logAnnInc	-.487912	.4831795	-1.01	0.324	-1.492739	.5169148
logEssSpe	-.7490753	.4413037	-1.70	0.104	-1.666817	.168666
logNEssSpe	1.167161	.385447	3.03	0.006	.3655801	1.968742
charity_past	3.727913	2.889256	1.29	0.211	-2.280624	9.73645
charity_future	.8143469	1.987676	0.41	0.686	-3.319251	4.947945
_cons	.7576473	6.008095	0.13	0.901	-11.73687	13.25216

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

      F(  5,    21) =    1.55
           Prob > F =    0.2182
```

Figure 15 shows an R-squared value of 0.664 for the log-log regression model. There are no significant variables and the form-type is not significant.

FIGURE 16: Accuracy Score for Humans Linear-Linear Regression Model

Source	SS	df	MS
Model	1.1479e+11	25	4.5917e+09
Residual	1.2933e+11	30	4.3111e+09
Total	2.4413e+11	55	4.4387e+09

Number of obs	=	56
F(25, 30)	=	1.07
Prob > F	=	0.4305
R-squared	=	0.4702
Adj R-squared	=	0.0287
Root MSE	=	65659

accuracy_human	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	8515.35	27935.6	0.30	0.763	-48536.76	65567.46
activity_score	-94429.09	54406.85	-1.74	0.093	-205542.7	16684.53
msl	9214.129	42217.36	0.22	0.829	-77005.22	95433.47
slm	38581.06	50964.39	0.76	0.455	-65502.11	142664.2
lsm	74156.38	40121.14	1.85	0.074	-7781.918	156094.7
lms	15894.77	41540.63	0.38	0.705	-68942.52	100732.1
mls	34242.58	40515.46	0.85	0.405	-48501.03	116986.2
age	-1873.294	1429.831	-1.31	0.200	-4793.398	1046.81
male	976.3334	35086.24	0.03	0.978	-70679.33	72632
female	12007	38545.92	0.31	0.758	-66714.27	90728.26
black_or_africanamerican	153995.8	76352.94	2.02	0.053	-1937.665	309929.3
hispanic_or_latnix	42639.81	85965.28	0.50	0.624	-132924.7	218204.3
asian_or_pacificislander	6091.672	79953.05	0.08	0.940	-157194.2	169377.6
white	29078.99	69063.73	0.42	0.677	-111968	170126
completed_graduate_degree	10138.53	70260.7	0.14	0.886	-133353	153630
completed_bachelors_degree	-47173.09	69277.58	-0.68	0.501	-188656.8	94310.6
current_undergrad	-26487.44	67565.49	-0.39	0.698	-164474.6	111499.7
high_school_diploma	-44146.93	74150.12	-0.60	0.556	-195581.7	107287.8
incomplete_high_school	-95682.9	116691	-0.82	0.419	-333997.7	142631.9
current_graduatestu	30920.98	87434.18	0.35	0.726	-147643.4	209485.4
annual_income	.0966818	.0942659	1.03	0.313	-.0958348	.2891984
ess_spend	.0063248	.0920668	0.07	0.946	-.1817007	.1943504
noness_spend	-.2975383	.6059595	-0.49	0.627	-1.535073	.939996
charity_past	29622.57	76197.76	0.39	0.700	-125994	185239.2
charity_future	-21719.88	41943.13	-0.52	0.608	-107379.2	63939.43
_cons	63415.41	97079.97	0.65	0.519	-134848.3	261679.1

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

       F(  5,    30) =    1.08
            Prob > F =    0.3906
```

Figure 16 shows an R-squared value of 0.47 which could be better. The same testing of different models was done for humans just like for birds and turtles. In this model, there are no significant variables and the form-type is not significant.

FIGURE 17: Accuracy for Humans Log-Linear Regression Model

Source	SS	df	MS			
				Number of obs	=	51
				F(25, 25)	=	2.55
Model	302.984557	25	12.1193823	Prob > F	=	0.0114
Residual	118.856937	25	4.75427749	R-squared	=	0.7182
				Adj R-squared	=	0.4365
Total	421.841494	50	8.43682988	Root MSE	=	2.1804

logAccHuman	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-.615857	1.023163	-0.60	0.553	-2.723101	1.491387
activity_score	-2.321542	1.99075	-1.17	0.255	-6.421567	1.778484
msl	-.3263497	1.464276	-0.22	0.825	-3.342082	2.689382
slm	3.698738	1.733581	2.13	0.043	.1283613	7.269115
lsm	3.45532	1.414527	2.44	0.022	.5420465	6.368593
lms	2.231372	1.49068	1.50	0.147	-.8387417	5.301485
mls	1.970899	1.46504	1.35	0.191	-1.046408	4.988206
age	-.1486152	.0605512	-2.45	0.021	-.2733227	-.0239077
male	.7189088	1.226242	0.59	0.563	-1.806585	3.244402
female	.3310105	1.335051	0.25	0.806	-2.418579	3.0806
black_or_africanamerican	4.566173	2.714983	1.68	0.105	-1.02544	10.15779
hispanic_or_latnix	1.93884	3.121078	0.62	0.540	-4.489141	8.366822
asian_or_pacificislander	1.440407	2.772054	0.52	0.608	-4.268744	7.149558
white	-.5893536	2.32715	-0.25	0.802	-5.382208	4.203501
completed_graduate_degree	1.67135	2.550461	0.66	0.518	-3.581421	6.924122
completed_bachelors_degree	-1.240227	2.412642	-0.51	0.612	-6.209157	3.728703
current_undergrad	-3.371748	2.384928	-1.41	0.170	-8.2836	1.540105
high_school_diploma	-2.771144	3.05489	-0.91	0.373	-9.062808	3.52052
incomplete_high_school	-7.696371	4.017848	-1.92	0.067	-15.97128	.578542
current_graduatestu	-1.409274	3.052051	-0.46	0.648	-7.69509	4.876542
annual_income	4.98e-06	3.76e-06	1.32	0.197	-2.77e-06	.0000127
ess_spend	6.90e-07	3.33e-06	0.21	0.838	-6.17e-06	7.55e-06
noness_spend	.0000341	.0000202	1.69	0.103	-7.37e-06	.0000757
charity_past	2.793822	2.729259	1.02	0.316	-2.827191	8.414836
charity_future	-.6031866	1.92174	-0.31	0.756	-4.561085	3.354711
_cons	5.4296	3.753479	1.45	0.160	-2.300835	13.16004

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

      F(  5,    25) =    3.06
           Prob > F =    0.0274
```

Figure 17 shows one significant variable, ‘age’, and form-type turns out to be jointly-significant. Unfortunately, with an R-squared value of 0.718, this is a poor fit for the data. This leads me to the same lack of confidence in a compelling conclusion as before. However, if we ignored the R-squared value these results would imply that age and the order in which we asked the questions has a statistically significant correlation with the dependent variable ‘logAccHuman’.

FIGURE 18: Accuracy for Humans Linear-Log Regression Model

Source	SS	df	MS			
				Number of obs	=	54
				F(25, 28)	=	1.08
Model	1.1965e+11	25	4.7859e+09	Prob > F	=	0.4212
Residual	1.2430e+11	28	4.4393e+09	R-squared	=	0.4905
				Adj R-squared	=	0.0355
Total	2.4395e+11	53	4.6028e+09	Root MSE	=	66628

accuracy_human	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	19391.78	29896.08	0.65	0.522	-41847.56	80631.13
logActSco	-64421.14	32210.11	-2.00	0.055	-130400.6	1558.273
msl	17037.7	42594	0.40	0.692	-70212.17	104287.6
slm	50712.63	54377.11	0.93	0.359	-60673.83	162099.1
lsm	82907.64	40776.18	2.03	0.052	-618.5685	166433.9
lms	36809.87	43587.98	0.84	0.406	-52476.05	126095.8
mls	51960.86	43653.83	1.19	0.244	-37459.95	141381.7
age	-1649.684	1528.601	-1.08	0.290	-4780.881	1481.513
male	2304.945	38128.98	0.06	0.952	-75798.72	80408.61
female	14190.86	43440.41	0.33	0.746	-74792.79	103174.5
black_or_africanamerican	139046.2	69013.66	2.01	0.054	-2321.873	280414.3
hispanic_or_latnix	39139.41	86612.59	0.45	0.655	-138278.4	216557.3
asian_or_pacificislander	-8057.959	86915.3	-0.09	0.927	-186095.9	169980
white	11453.95	66795.72	0.17	0.865	-125370.9	148278.8
completed_graduate_degree	-7513.425	77512.95	-0.10	0.923	-166291.5	151264.7
completed_bachelors_degree	-58637.53	75300.58	-0.78	0.443	-212883.8	95608.72
current_undergrad	-32330.6	70552.19	-0.46	0.650	-176850.2	112189
high_school_diploma	-55560.13	78380.53	-0.71	0.484	-216115.4	104995.1
incomplete_high_school	-80804.02	155185.9	-0.52	0.607	-398688	237079.9
current_graduatestu	12246.89	87159.3	0.14	0.889	-166290.8	190784.6
logAnnInc	7583.461	12320.33	0.62	0.543	-17653.59	32820.51
logEssSpe	-3066.769	12816.38	-0.24	0.813	-29319.93	23186.4
logNEssSpe	2548.341	10633.09	0.24	0.812	-19232.56	24329.24
charity_past	33651.26	81401.89	0.41	0.682	-133093	200395.5
charity_future	-26112.23	43108.18	-0.61	0.550	-114415.3	62190.88
_cons	-96135.82	163690.5	-0.59	0.562	-431440.6	239168.9

(1) msl = 0
(2) slm = 0
(3) lsm = 0
(4) lms = 0
(5) mls = 0

F(5, 28) = 1.16
Prob > F = 0.3511

Figure 18 shows a much better fit than the model in Figure 17 with an R-squared value of 0.491, but this is still a worse fit than the linear-linear model seen in Figure 16. In this model there are no significant variables and the form-type is not significant.

FIGURE 19: Accuracy for Humans Log-Log Regression Model

Source	SS	df	MS			
Model	325.419995	25	13.0167998	Number of obs	=	49
Residual	94.4688368	23	4.10734073	F(25, 23)	=	3.17
				Prob > F	=	0.0035
				R-squared	=	0.7750
				Adj R-squared	=	0.5305
Total	419.888832	48	8.747684	Root MSE	=	2.0267

logAccHuman	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
math_activity	-1.003437	.9918516	-1.01	0.322	-3.055238	1.048364
logActSco	-1.096761	1.039751	-1.05	0.302	-3.24765	1.054128
msl	-.5363466	1.401514	-0.38	0.705	-3.435598	2.362905
slm	4.112183	1.721761	2.39	0.026	.5504486	7.673916
lsm	3.824753	1.369676	2.79	0.010	.9913619	6.658144
lms	2.669569	1.523124	1.75	0.093	-.4812522	5.820391
mls	1.972661	1.485417	1.33	0.197	-1.100158	5.04548
age	-.2008611	.055257	-3.64	0.001	-.315169	-.0865533
male	.8776305	1.218723	0.72	0.479	-1.643489	3.39875
female	.1792185	1.374614	0.13	0.897	-2.664388	3.022825
black_or_africanamerican	4.816417	2.19349	2.20	0.038	.2788375	9.353996
hispanic_or_latnix	1.610761	3.052877	0.53	0.603	-4.704597	7.926119
asian_or_pacificislander	1.864519	2.887918	0.65	0.525	-4.109594	7.838632
white	-.3633658	2.206486	-0.16	0.871	-4.927831	4.201099
completed_graduate_degree	.8688461	2.501619	0.35	0.732	-4.306147	6.043839
completed_bachelors_degree	-1.571433	2.376121	-0.66	0.515	-6.486813	3.343946
current_undergrad	-4.034984	2.250505	-1.79	0.086	-8.690509	.6205414
high_school_diploma	-2.427798	2.872743	-0.85	0.407	-8.370521	3.514924
incomplete_high_school	-3.214788	5.236455	-0.61	0.545	-14.04722	7.617645
current_graduatestu	-1.332275	2.743634	-0.49	0.632	-7.007914	4.343363
logAnnInc	.0013849	.4234105	0.00	0.997	-.8745065	.8772763
logEssSpe	.4969056	.4115065	1.21	0.240	-.3543605	1.348172
logNEssSpe	.4511853	.3657644	1.23	0.230	-.305456	1.207827
charity_past	4.370695	2.678347	1.63	0.116	-1.169888	9.911277
charity_future	-.9732251	1.799999	-0.54	0.594	-4.696807	2.750356
_cons	-2.120864	5.851036	-0.36	0.720	-14.22465	9.982926

```
( 1)  msl = 0
( 2)  slm = 0
( 3)  lsm = 0
( 4)  lms = 0
( 5)  mls = 0

      F(  5,    23) =    4.23
           Prob > F =    0.0071
```

Figure 19 shows another poorly-fit model with an R-squared value of 0.775. However, if we ignore this, we see that ‘age’, ‘black_or_africanamerican’ are significant variables and form-type is jointly-significant. Again, it is difficult to jump to any compelling conclusions due to the poor fit, but worth mentioning.

```
/*********************************************************************************
*****

ECON4803: Behavioral Economics - Scope Sensitivity Semester Project
@authors Ethan Nguyen-Tu and Jacqueline Chambers
@version 1.0.2
@date 22 November 2022

**********************************************************************************
****/
clear
set more off
*Working Directory
capture cd "\\Client\C$\Users\jacki\OneDrive\Desktop\Documents\Georgia Tech\Fall 2022\ECON 4803 -
Behavioral Econ\Project\STATA"
use ScopeSensitivityData.dta, clear

clear
capture cd "C:\Users\enguyentu3\Downloads\ScopeSensitivity"
import excel "ScopeSensitivityResults.xls", firstrow case(preserve)




**# CLEAN DATA #**
describe
summarize
* check gender count
count if black_or_africanamerican == 1 // 6
count if hispanic_or_latnix == 1 // 5
count if asian_or_pacificislander == 1 // 12
count if white  == 1 // 46
* check education count
count if completed_graduate_degree == 1 // 20
count if completed_bachelors_degree == 1 // 19
count if current_undergrad == 1 // 23
count if high_school_diploma == 1 // 4
count if incomplete_high_school == 1 // 1
count if current_graduatestu == 1 // 2
count if other_education == 1 // 5
// Combine high_school_diploma, incomplete_high_school, and current_graduatestu with other_education
generate other_education2 = other_education + incomplete_high_school + current_graduatestu +
high_school_diploma
count if other_education2 == 1 // 12
* check charity count
count if charity_past == 1 // 66
count if charity_future == 1 // 53
```

```
**# REGRESSION #**


** Overall Accuracy Score Regression Framework **

/* Figure 1
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: sml
  Gender: other_gender
  Ethnicity: other_race
  Education: other_education
*/
reg accuracy_score math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test form type significance
test msl slm lsm lms mls // msl slm lsm lms mls are are not jointly significant
di invFtail(5, 30, .05) // 2.5335545


/* Figure 2
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: other_gender
  Ethnicity: other_race
  Education: other_education
*/
reg accuracy_score math_activity activity_score male female black_or_africanamerican
hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future


/* Figure 3
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: other_gender
  Ethnicity: other_race
  Education: other_education2
*/
```

```
reg accuracy_score math_activity activity_score male female black_or_africanamerican
hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad annual_income ess_spend noness_spend charity_past
charity_future

* Test charity variables significance
test charity_past charity_future
di invFtail(2, 39, .05) // 3.2380961


/* Figure 4
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: other_gender
  Ethnicity: other_race
  Education: other_education2
  Charity: charity_past & charity_future
*/
reg accuracy_score math_activity activity_score male female black_or_africanamerican
hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad annual_income ess_spend noness_spend

test ess_spend noness_spend
di invFtail(2, 52, .05) // 3.175141


/* Figure 5
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: other_gender
  Ethnicity: other_race
  Education: other_education2
  Charity: charity_past & charity_future
  Spending: ess_spend & noness_spend
*/
reg accuracy_score math_activity activity_score male female black_or_africanamerican
hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad annual_income

* Test Ethnicity
test black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white
di invFtail(4, 54, .05) // 2.5429175

* Test Education
test completed_graduate_degree completed_bachelors_degree current_undergrad
di invFtail(3, 54, .05) // 2.7757624

* Test Gender
test male female
```

```
di invFtail(2, 54, .05) // 3.168246


/* Check Regression 1
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: all
  Ethnicity: other_race
  Education: other_education2
  Charity: all
  Spending: all
*/
reg accuracy_score math_activity activity_score black_or_africanamerican hispanic_or_latnix
asian_or_pacificislander white completed_graduate_degree completed_bachelors_degree
current_undergrad annual_income


/* Figure 6
DEPENDENT VARIABLE: accuracy_score
Variables Left Out:
  Form Type: all
  Gender: all
  Ethnicity: other_race
  Education: all
  Charity: all
  Spending:all
*/
reg accuracy_score math_activity activity_score black_or_africanamerican hispanic_or_latnix
asian_or_pacificislander white annual_income

* Test Ethnicity
test black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white
di invFtail(4, 59, .05) // 2.5279066


* Figure 7 - Base Regression
reg accuracy_score math_activity activity_score

/* Overall Accuracy Score Conclusion
Cannot conclude significance.
*/



** Bird Regression Framework **

* linear-linear model
* variables left out: sml, other_gender, other_race, other_education
* dependent var: accuracy_bird
```

```
reg accuracy_bird math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* log-linear model
* independent vars: no change
* dependent var: logAccBird
generate logAccBird = ln(accuracy_bird)
reg logAccBird math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* linear-log model & log-log model
/* independent vars:
logActSco - newly generated
logAnnInc - newly generated
logEssSpe - newly generated
logNEssSpe - newly generated
*/
generate logActSco = ln(activity_score)
generate logAnnInc = ln(annual_income)
generate logEssSpe = ln(ess_spend)
generate logNEssSpe = ln(noness_spend)
* dependent var: accuracy_bird
reg accuracy_bird math_activity logActSco msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression

* dependent var: logAccBird
reg logAccBird math_activity logActSco msl slm lsm lms mls age male female black_or_africanamerican
hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
```

```
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression



** Turtle Regression Framework **

* linear-linear model
* independent variables left out: sml, other_gender, other_race, other_education
* dependent var: accuracy_turtle
reg accuracy_turtle math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* log-linear model
* independent vars: no change
* dependent var: logAccTurtle
generate logAccTurtle = ln(accuracy_turtle)
reg logAccTurtle math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* linear-log & log-log
* independent vars: no change
* dependent var: accuracy_turtle
reg accuracy_turtle math_activity logActSco msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
```

```
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression

* dependent var: logAccTurtle
reg logAccTurtle math_activity logActSco msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression



** Human Regression Framework **

* linear-linear model
* variables left out: sml, other_gender, other_race, other_education
* dependent var: accuracy_human
reg accuracy_human math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* log-linear model
* independent vars: no change
* dependent var: logAccHuman
generate logAccHuman = ln(accuracy_human)
reg logAccHuman math_activity activity_score msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu annual_income ess_spend noness_spend charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is significant in this regression!


* linear-log & log-log
* independent vars: no change
* dependent var: accuracy_human
```

```
reg accuracy_human math_activity logActSco msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are not jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is not significant in this regression


* dependent var: logAccHuman
reg logAccHuman math_activity logActSco msl slm lsm lms mls age male female
black_or_africanamerican hispanic_or_latnix asian_or_pacificislander white completed_graduate_degree
completed_bachelors_degree current_undergrad high_school_diploma incomplete_high_school
current_graduatestu logAnnInc logEssSpe logNEssSpe charity_past charity_future

* Test 'form type' significance
test msl slm lsm lms mls // msl slm lsm lms mls are jointly significant
di invFtail(5, 30, .05) // 2.5335545
// form type is significant in this regression!



// Uncomment below if new variables have been added or variables have been modified
*export excel using "ScopeSensitivityResults.xls", firstrow(variables) keepcellfmt replace

// END OF DOCUMENT
```

Appendix III: Bibliography

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Appendix IV: Survey Content

Georgia Tech

Consent Form - A

Thank you for considering participation in our study! We are completing this study as a class project for ECON 4803, taught by Dr. Whitney Buser at Georgia Tech's School of Economics. We are interested in studying patterns related to charitable giving. To participate, you will complete a short survey consisting of 27 questions that is expected to take no more than 30 minutes total. We will not collect any personally identifying information, and you will remain anonymous. We do not anticipate that you will incur any risks from participating. At any time, you can choose to close the survey and not continue.

By continuing, you agree to the following:
1) I am between the ages of 18 and 65.
2) I have read and understand the provided information.
3) I understand that my participation is voluntary and that I can withdraw my participation at any time and for any reason.
4) I voluntarily agree to participate in this study.

- ◯ I agree to the above statements.
- ◯ I do not agree to the above statements.

Mathematical Activity - B

Please carefully read and answer the following 4 questions.

A rice cooker has a capacity of 12 cups of fully-cooked rice. Uncooked rice triples in volume when cooked. How much uncooked rice can be put into the rice cooker without making it overflow when cooked?

- ◯ 3 cups
- ◯ 4 cups
- ◯ 9 cups
- ◯ 14 cups

An ant can lift about 50 times its body weight. If humans had the same capability, how much weight would a 200 pound person be able to lift?

- ◯ 250 pounds
- ◯ 1,250 pounds
- ◯ 10,000 pounds
- ◯ 150,000 pounds

An essay is written on an 11 inch tall sheet of paper. There are 1 inch margins on the top and bottom of the page. If each line of text takes up ½ th of an inch, how many lines of text can fit on the page?

- ◯ 18 lines
- ◯ 72 lines
- ◯ 924 lines
- ◯ 6724 lines

The rate at which air is blown through a tuba determines the volume of the sound emitted from it. This relationship can be represented using the equation Volume (in decibels) = 12 X Rate. If the rate is 4, what is the volume?

- ◯ 0.8 decibels
- ◯ 48 decibels
- ◯ 100 decibels
- ◯ 4000 decibels

Linguistic Activity - C

Please carefully read and answer the following 4 questions.

Select the number of commas missing from this sentence:
Sarah Jolene, and Mary set out on a walk and they encountered a large statue.

- 1
- 2
- 3
- 4

Name the error in this sentence:
This activity, known as “doing a donut,” is when a driver drifts a car in a circular, often leaving skid marks on the asphalt.

- Mixed construction
- Parallelism
- Naked “this”
- Inverted structure

Select the word that should be capitalized in this sentence:
The oak flooring was installed on a tuesday during the spring of 2017.

- Oak
- Tuesday
- Spring
- Installed

Name the term that applies to the word “bicycle” in this sentence:
The proud owner of the new bicycle beamed at his creation.

- Verb
- Objective complement
- Article
- Object of the preposition

Contingent Valuation - D_SML

The next 9 questions will consist of 3 short prompts followed by 3 questions each. Please read each prompt and answer the questions accurately to the best of your ability. The questions asked are purely hypothetical and will not have any effect in the real world.

“At least 102 species of birds are known to have been harmed by the BP oil spill [in 2010], including black skimmers, brown pelicans, clapper rails, common loons, laughing gulls, northern gannets and several species of tern” (krüg). Consider a hypothetical scenario in which birds are dying due to oil spills, but your donation would guarantee the lives of many birds.

How much would you be willing to pay (in US dollars) to prevent oil spills with certainty and therefore save the lives of around 2,000 birds?

How much would you be willing to pay (in US dollars) to prevent oil spills with certainty and therefore save the lives of around 20,000 birds?

How much would you be willing to pay (in US dollars) to prevent oil spills with certainty and therefore save the lives of around 200,000 birds?

“Plastic waste is everywhere, on the surface of the ocean, underwater and on the beach. It is estimated that more than 1,000 turtles die every year after getting entangled in plastic, and this number is almost certainly a gross underestimate” (Lipponen). Now, consider a hypothetical scenario in which an earth clean-up campaign launched globally could effectively remove all plastic waste from the ocean.

How much would you be willing to donate (in US dollars) to this campaign if you knew with certainty that your donation would save the lives of around 40 sea turtles?

How much would you be willing to donate (in US dollars) to this campaign if you knew with certainty that your donation would save the lives of around 200 sea turtles?

How much would you be willing to donate (in US dollars) to this campaign if you knew with certainty that your donation would save the lives of around 1,000 sea turtles?

“The global prevalence, morbidity and mortality related to childhood asthma among children has increased significantly over the last 40 years” (Serebrisky). Consider a hypothetical scenario in which increasing the cost of healthcare would definitely reduce the number of childhood deaths related to asthma per year.

How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 1 next year?

How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 20 next year?

How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 400 next year?

Contingent Valuation - D_SLM

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Contingent Valuation - D_MSL

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Contingent Valuation - D_MLS

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How much would you be willing to donate (in US dollars) to this campaign if you knew with certainty that your donation would save the lives of around 1,000 sea turtles?

How much would you be willing to donate (in US dollars) to this campaign if you knew with certainty that your donation would save the lives of around 40 sea turtles?

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Contingent Valuation - D_LMS

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How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 1 next year?

Contingent Valuation - D_LSM

The next 9 questions will consist of 3 short prompts followed by 3 questions each. Please read each prompt and answer the questions accurately to the best of your ability. The questions asked are purely hypothetical and will not have any effect in the real world.

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How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 1 next year?

How much would you be willing to pay (in US dollars) for this healthcare to reduce the number of childhood deaths by 20 next year?

Demographic Questions - E

What is your age in years?

Which of the following best describes your gender identity?

- ◯ Female
- ◯ Male

- Transgender female
- Transgender male
- Nonbinary
- Other. Please specify:
- Prefer not to say.

Which of the following best describes your ethnic or racial identity?

- Hispanic or Latnix
- White
- Black or African American
- Native American or Alaska Native
- Asian or Pacific Islander
- Other. Please specify:
- Prefer not to say.

Which of the following best describes your level of education?

- Incomplete High School
- High School Diploma
- Current Undergraduate
- Completed Bachelor's Degree
- Current Graduate Student
- Completed Graduate Degree
- Other. Please specify:
- Prefer not to say.

What is your annual household income in US dollars? Here, we are defining household income as the pre-tax, cash income of family members or other individuals sharing most living expenses. If you are a student but your parents or other family members pay for over half of your living expenses, please include their income in your household income. Use your best estimate.

On average, how much do you spend on essential expenses per month in US dollars? Here, we are defining essential expenses as anything necessary to maintain your basic well-being. This includes rent or a mortgage payment, utilities, transportation costs, insurance, groceries, tuition, required textbooks, and any medical expenses. Use your best estimate.

On average, how much do you spend on non-essential expenses per month in US dollars? Non-essential expenses include anything you purchased primarily for enjoyment. Some examples might be restaurant meals, entertainment expenses, or any non-essential travel, material goods, and clothing. Use your best estimate.

Have you ever donated to a charity in the past? The amount does not matter.

- Yes
- No

Do you have plans to donate to at least one charity at some point in your future?

- Yes
- No

Appendix V: Raw Data

response_id	math_activity	activity_score	SML	MSL	SLM	LSM	LMS	MLS	consistent_order	birds_S	birds_M	birds_L	perlife_bird_S	perlife_bird_M	perlife_bird_L	perlife_bird_avg	perlife_bird_avg_thousand	diff_bird_SM	diff_bird_ML
D1018-FSLM-NR4-A57-GFemale-I100000	0.000	0.750	0.000	0.000	1.000	0.000	0.000	0.000	0	50.000	100.000	100.000	0.025	0.005	0.001	0.010	10.167	0.020	0.005
D1018-FSML-NR4-A30-GMale-I25000	0.000	0.500	1.000	0.000	0.000	0.000	0.000	0.000	1	100.000	1000.000	10000.000	0.050	0.050	0.050	0.050	50.000	0.000	0.000
D1018-FSML-NR4-A57-GMale-I100000	0.000	0.500	1.000	0.000	0.000	0.000	0.000	0.000	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1024-FMLS-NR4-A19-GMale-I25000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	20.000	100.000	500.000	0.010	0.005	0.003	0.006	5.833	0.005	0.003
D1025-FMLS-NR4-A30-GMale-I200000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	1.000	0	5000.000	10000.000	11000.000	2.500	0.500	0.055	1.018	1018.333	2.000	0.445
D1025-FMLS-NR4-A35-GMale-I180000	0.000	0.250	0.000	0.000	0.000	0.000	0.000	1.000	0	2000.000	2000.000	1500.000	1.000	0.100	0.008	0.369	369.167	0.900	0.093
D1025-FMSL-NR4-A44-GMale-I88787	0.000	0.250	0.000	1.000	0.000	0.000	0.000	0.000	0	76.000	78.000	75.000	0.038	0.004	0.000	0.014	14.092	0.034	0.004
D1025-FSML-NR4-A25-GFemale-I4000	0.000	0.250	1.000	0.000	0.000	0.000	0.000	0.000	1	100.000	100.000	50.000	0.050	0.005	0.000	0.018	18.417	0.045	0.005
D1025-FSML-NR4-A36-GMale-I126000	0.000	0.500	1.000	0.000	0.000	0.000	0.000	0.000	1	2000.000	20000.000	200000.000	1.000	1.000	1.000	1.000	1000.000	0.000	0.000
D1110-FSML-NR4-A18-GMale-I50000	0.000	0.250	1.000	0.000	0.000	0.000	0.000	0.000	1	20.000	20.000	50.000	0.010	0.001	0.000	0.004	3.750	0.009	0.001
D1111-FLMS-NR4-A20-GNonbinary-I0	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	25.000	25.000	25.000	0.013	0.001	0.000	0.005	4.625	0.011	0.001
D1111-FLMS-NR4-A22-GFemale-I100000	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	25.000	100.000	100.000	0.013	0.005	0.001	0.006	6.000	0.008	0.005
D1111-FLSM-NR4-A23-GNonbinary-I30000	0.000	0.500	0.000	0.000	0.000	1.000	0.000	0.000	0	25.000	2000.000	200.000	0.013	0.100	0.001	0.038	37.833	0.088	0.099
D1111-FMLS-NR4-A19-GMale-I450000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	20.000	200.000	2000.000	0.010	0.010	0.010	0.010	10.000	0.000	0.000
D1111-FMLS-NR6-A42-GMale-I65000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	1.000	0			1000000.000	0.000	0.000	5.000	1.667	1666.667	0.000	5.000
D1111-FSLM-NR4-A20-GMale-I60000	0.000	0.500	0.000	0.000	1.000	0.000	0.000	0.000	0	6.000	25.000	100.000	0.003	0.001	0.001	0.002	1.583	0.002	0.001
D1111-FSLM-NR4-A40-GMale-I200000	0.000	0.750	0.000	0.000	1.000	0.000	0.000	0.000	0	20.000	50.000	100.000	0.010	0.003	0.001	0.004	4.333	0.008	0.002
D1112-FMLS-NR4-A31-GTransgender male-I180900	0.000	0.500	0.000	0.000	0.000	0.000	0.000	1.000	0	5200.000	5200.000	5200.000	2.600	0.260	0.026	0.962	962.000	2.340	0.234
D1112-FMSL-NR4-A24-GFemale-I55000	0.000	0.500	0.000	1.000	0.000	0.000	0.000	0.000	0	40.000	40.000	60.000	0.020	0.002	0.000	0.007	7.433	0.018	0.002
D1113-FLSM-NR4-A39-GFemale-I147000	0.000	0.250	0.000	0.000	0.000	1.000	0.000	0.000	0	1000000.000	1000000.000	1000000.000	500.000	50.000	5.000	185.000	185000.000	450.000	45.000
D1113-FMSL-NR4-A36-GFemale-I75000	0.000	0.750	0.000	1.000	0.000	0.000	0.000	0.000	0	100.000	1000.000	1000.000	0.050	0.050	0.005	0.035	35.000	0.000	0.045
D1115-FSLM-NR8-A18-GMale-I	0.000	0.750	0.000	0.000	1.000	0.000	0.000	0.000	0	20.000	30.000	50.000	0.010	0.002	0.000	0.004	3.917	0.009	0.001
D1117-FLMS-NR12-A-G-I	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	100.000	2000.000	1000.000	0.050	0.100	0.005	0.052	51.667	0.050	0.095
D1117-FLMS-NR4-A31-GFemale-I30000	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	50.000	50.000	25.000	0.025	0.003	0.000	0.009	9.208	0.023	0.002
D1117-FLMS-NR4-A32-GFemale-I29000	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	20000.000	200000.000	2000000.000	10.000	10.000	10.000	10.000	10000.000	0.000	0.000
D1117-FLMS-NR4-A57-GFemale-I150000	0.000	0.250	0.000	0.000	0.000	0.000	1.000	0.000	1	80000.000	750000.000	750000.000	40.000	37.500	3.750	27.083	27083.333	2.500	33.750
D1117-FLSM-NR4-A43-GMale-I44000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	500.000	500.000	500.000	0.250	0.025	0.003	0.093	92.500	0.225	0.023
D1117-FLSM-NR8-A20-GFemale-I	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	1000.000	15000.000	15000.000	0.500	0.750	0.075	0.442	441.667	0.250	0.675
D1117-FMLS-NR4-A27-GNonbinary-I80000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	1.000	0	1500.000	1500.000	1500.000	0.750	0.075	0.008	0.278	277.500	0.675	0.068
D1117-FSLM-NR12-A-G-I	0.000	0.500	0.000	0.000	1.000	0.000	0.000	0.000	0	50.000	70.000	100.000	0.025	0.004	0.001	0.010	9.667	0.022	0.003
D1117-FSLM-NR4-A28-GFemale-I40000	0.000	0.250	0.000	0.000	1.000	0.000	0.000	0.000	0	5.000	10.000	10.000	0.003	0.001	0.000	0.001	1.017	0.002	0.000
D1117-FSML-NR4-A57-GMale-I150000	0.000	0.500	1.000	0.000	0.000	0.000	0.000	0.000	1	1000000.000	10000000.000	100000000.000	500.000	500.000	500.000	500.000	500000.000	0.000	0.000
D1117-FSML-NR8-A26-GFemale-I	0.000	0.750	1.000	0.000	0.000	0.000	0.000	0.000	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D112-FLMS-NR4-A20-GMale-I500000	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	1.000	10.000	100.000	0.001	0.001	0.001	0.001	0.500	0.000	0.000
D112-FSML-NR4-A30-GPrefer not to say.-I100000	0.000	0.250	1.000	0.000	0.000	0.000	0.000	0.000	1	10000.000	10000.000	10000.000	5.000	0.500	0.050	1.850	1850.000	4.500	0.450
D116-FLMS-NR4-A31-GFemale-I93000	0.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	600.000	1200.000	1200.000	0.300	0.060	0.006	0.122	122.000	0.240	0.054
D117-FLSM-NR4-A53-GMale-I100000	0.000	0.750	0.000	0.000	0.000	1.000	0.000	0.000	0	100.000	100.000	100.000	0.050	0.005	0.001	0.019	18.500	0.045	0.005
D119-FMSL-NR4-A18-GFemale-I170000	0.000	0.250	0.000	1.000	0.000	0.000	0.000	0.000	0	30.000	100.000	110.000	0.015	0.005	0.001	0.007	6.850	0.010	0.004
D1018-FMSL-NR4-A27-GFemale-I43000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	10.000	50.000	100.000	0.005	0.003	0.001	0.003	2.667	0.003	0.002
D1020-FLMS-NR4-A21-GMale-I600000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1	0.000	25.000	100.000	0.000	0.001	0.001	0.001	0.583	0.001	0.001
D1020-FLSM-NR4-A22-GFemale-I20000	1.000	0.750	0.000	0.000	0.000	1.000	0.000	0.000	0	5500.000	6000.000	5000.000	2.750	0.300	0.025	1.025	1025.000	2.450	0.275
D1024-FLSM-NR4-A18-GMale-I150000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	50.000	50.000	50.000	0.025	0.003	0.000	0.009	9.250	0.023	0.002
D1024-FSLM-NR4-A28-GFemale-I56000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	1000.000	1000.000	1000.000	0.500	0.050	0.005	0.185	185.000	0.450	0.045
D1025-FLMS-NR4-A34-GMale-I145000	1.000	0.750	0.000	0.000	0.000	0.000	1.000	0.000	1	100.000	300.000	200.000	0.050	0.015	0.001	0.022	22.000	0.035	0.014
D1025-FLMS-NR4-A35-GMale-I149999	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1	450.000	200.000	250.000	0.225	0.010	0.001	0.079	78.750	0.215	0.009
D1025-FLSM-NR4-A45-GMale-I145000	1.000	0.500	0.000	0.000	0.000	1.000	0.000	0.000	0	500.000	700.000	1000.000	0.250	0.035	0.005	0.097	96.667	0.215	0.030
D1025-FMSL-NR4-A34-GMale-I135000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	500.000	1500.000	1500.000	0.250	0.075	0.008	0.111	110.833	0.175	0.068
D1025-FSML-NR4-A35-GMale-I100000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	7000.000	80000.000	16000.000	3.500	4.000	0.080	2.527	2526.667	0.500	3.920
D1025-FSML-NR4-A37-GMale-I11000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1110-FLMS-NR4-A35-GNonbinary-I190000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1	1000.000	1000.000	1000.000	0.500	0.050	0.005	0.185	185.000	0.450	0.045
D1110-FLSM-NR4-A21-GFemale-I125000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	50.000	500.000	500.000	0.025	0.025	0.003	0.018	17.500	0.000	0.023
D1110-FSLM-NR4-A61-GFemale-I250000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	50.000	50.000	50.000	0.025	0.003	0.000	0.009	9.250	0.023	0.002
D1110-FSML-NR4-A23-GTransgender female-I7000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	50.000	50.000	50.000	0.025	0.003	0.000	0.009	9.250	0.023	0.002
D1111-FLMS-NR4-A19-GPrefer not to say.-I1320	1.000	0.250	0.000	0.000	0.000	0.000	1.000	0.000	1	100.000	100.000	100.000	0.050	0.005	0.001	0.019	18.500	0.045	0.005
D1111-FLSM-NR13-A44-GMale-I	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0			1.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000
D1111-FMSL-NR4-A21-GMale-I31000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	1500.000	1500.000	1500.000	0.750	0.075	0.008	0.278	277.500	0.675	0.068
D1111-FMSL-NR8-A-GPrefer not to say.-I	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1111-FSML-NR4-A19-GMale-I60000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	150.000	200.000	300.000	0.075	0.010	0.002	0.029	28.833	0.065	0.009
D1112-FLMS-NR4-A33-GFemale-I11000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1	5.000	35.000	30.000	0.003	0.002	0.000	0.001	1.467	0.001	0.002
D1112-FMLS-NR4-A19-GFemale-I3724.48	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	20000.000	20000.000	20000.000	10.000	1.000	0.100	3.700	3700.000	9.000	0.900
D1112-FSLM-NR4-A20-GNonbinary-I100000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	20.000	25.000	50.000	0.010	0.001	0.000	0.004	3.833	0.009	0.001
D1113-FLSM-NR4-A32-GMale-I260000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1113-FLSM-NR4-A62-GFemale-I50000	1.000	0.750	0.000	0.000	0.000	1.000	0.000	0.000	0	0.000	10.000	0.000	0.000	0.001	0.000	0.000	0.167	0.001	0.001
D1113-FMLS-NR4-A34-GFemale-I250000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	1000.000	100.000	1000.000	0.500	0.005	0.005	0.170	170.000	0.495	0.000
D1113-FSML-NR4-A31-GMale-I130000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	75.000	100.000	100.000	0.038	0.005	0.001	0.014	14.333	0.033	0.005
D1114-FLSM-NR8-A19-GPrefer not to say.-I	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0	0.650	0.880	0.950	0.000	0.000	0.000	0.000	0.125	0.000	0.000
D1116-FMLS-NR4-A22-GMale-I150000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	400.000	500.000	700.000	0.200	0.025	0.004	0.076	76.167	0.175	0.022
D1117-FMSL-NR4-A43-GMale-I45000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	500.000	500.000	5.000	0.250	0.025	0.000	0.092	91.675	0.225	0.025
D1117-FSLM-NR4-A22-GFemale-I300000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	10.000	15.000	20.000	0.005	0.001	0.000	0.002	1.950	0.004	0.001
D1117-FSLM-NR8-A30-GFemale-I	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	3000.000	3500.000	5000.000	1.500	0.175	0.025	0.567	566.667	1.325	0.150
D1117-FSML-NR12-A-G-I	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1	9000.000	5000.000	20000.000	4.500	0.250	0.100	1.617	1616.667	4.250	0.150
D1117-FSML-NR4-A45-GMale-I80000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1	1000.000	3000.000	5000.000	0.500	0.150	0.025	0.225	225.000	0.350	0.125
D112-FSLM-NR4-A21-GMale-I300000	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0	50.000	450.000	1000.000	0.025	0.023	0.005	0.018	17.500	0.003	0.018
D115-FMSL-NR4-A28-GFemale-I135000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0	500.000	500.000	500.000	0.250	0.025	0.003	0.093	92.500	0.225	0.023
D116-FMLS-NR4-A25-GMale-I210000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	20.000	200.000	400.000	0.010	0.010	0.002	0.007	7.333	0.000	0.008
D118-FSLM-NR4-A7-GMale-I7	1.000	0.250	0.000	0.000	1.000	0.000	0.000	0.000	0	7.000	7.000	7.000	0.004	0.000	0.000	0.001	1.295	0.003	0.000
D119-FMLS-NR4-A18-GMale-I12000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0	100.000	5000.000	10000.000	0.050	0.250	0.050	0.117	116.667	0.200	0.200

response_id	math_activity	accuracy_bird	turtle_S	turtle_M	turtle_L	perlife_turtle_S	perlife_turtle_M	perlife_turtle_L	perlife_turtle_avg [1]	perlife_turtle_avg_thousand	diff_turtle_SM	diff_turtle_ML	accuracy_turtle	human_S	human_M	human_L
D1018-FSLM-NR4-A57-GFemale-I100000	0.000	0.012	50.000	100.000	100.000	1.250	0.500	0.100	0.617	616.667	0.750	0.400	0.575	300.000	200.000	300.000
D1018-FSML-NR4-A30-GMale-I25000	0.000	0.000	100.000	500.000	2500.000	2.500	2.500	2.500	2.500	2500.000	0.000	0.000	0.000	100.000	2000.000	4000.000
D1018-FSML-NR4-A57-GMale-I100000	0.000	0.000	20.000	20.000	20.000	0.500	0.100	0.020	0.207	206.667	0.400	0.080	0.240	100.000	100.000	100.000
D1024-FMLS-NR4-A19-GMale-I25000	0.000	0.004	10.000	50.000	75.000	0.250	0.250	0.075	0.192	191.667	0.000	0.175	0.088	10.000	20.000	50.000
D1025-FMLS-NR4-A30-GMale-I200000	0.000	1.223	200.000	1000.000	1500.000	5.000	5.000	1.500	3.833	3833.333	0.000	3.500	1.750	500.000	10000.000	15000.000
D1025-FMLS-NR4-A35-GMale-I180000	0.000	0.496	1500.000	1500.000	1500.000	37.500	7.500	1.500	15.500	15500.000	30.000	6.000	18.000	2500.000	2500.000	2500.000
D1025-FMSL-NR4-A44-GMale-I88787	0.000	0.019	65.000	67.000	56.000	1.625	0.335	0.056	0.672	672.000	1.290	0.279	0.785	5.000	45.000	7.000
D1025-FSML-NR4-A25-GFemale-I4000	0.000	0.025	100.000	100.000	50.000	2.500	0.500	0.050	1.017	1016.667	2.000	0.450	1.225	50.000	100.000	250.000
D1025-FSML-NR4-A36-GMale-I126000	0.000	0.000	400.000	200.000	1000.000	10.000	1.000	1.000	4.000	4000.000	9.000	0.000	4.500	2000.000	1000.000	4000.000
D1110-FSML-NR4-A18-GMale-I50000	0.000	0.005	40.000	40.000	60.000	1.000	0.200	0.060	0.420	420.000	0.800	0.140	0.470	50.000	100.000	200.000
D1111-FLMS-NR4-A20-GNonbinary-I0	0.000	0.006	25.000	15.000	25.000	0.625	0.075	0.025	0.242	241.667	0.550	0.050	0.300	15.000	15.000	25.000
D1111-FLMS-NR4-A22-GFemale-I100000	0.000	0.006	15.000	20.000	50.000	0.375	0.100	0.050	0.175	175.000	0.275	0.050	0.163	100.000	100.000	100.000
D1111-FLSM-NR4-A23-GNonbinary-I30000	0.000	0.093	15.000	30.000	100.000	0.375	0.150	0.100	0.208	208.333	0.225	0.050	0.138	10.000	20.000	30.000
D1111-FMLS-NR4-A19-GMale-I450000	0.000	0.000	0.400	2.000	10.000	0.010	0.010	0.010	0.010	10.000	0.000	0.000	0.000	4000.000	80000.000	1600000.000
D1111-FMLS-NR6-A42-GMale-I65000	0.000	2.500	200.000	1000.000	5000.000	5.000	5.000	5.000	5.000	5000.000	0.000	0.000	0.000	50000.000	1000000.000	20000000.000
D1111-FSLM-NR4-A20-GMale-I60000	0.000	0.001	5.000	6.000	15.000	0.125	0.030	0.015	0.057	56.667	0.095	0.015	0.055	500.000	200.000	600.000
D1111-FSLM-NR4-A40-GMale-I200000	0.000	0.005	200.000	50.000	5000.000	5.000	0.250	5.000	3.417	3416.667	4.750	4.750	4.750	20.000	250.000	10000.000
D1112-FMLS-NR4-A31-GTransgender male-I180900	0.000	1.287	1000.000	1000.000	1500.000	25.000	5.000	1.500	10.500	10500.000	20.000	3.500	11.750	95.000	500.000	600.000
D1112-FMSL-NR4-A24-GFemale-I55000	0.000	0.010	20.000	40.000	50.000	0.500	0.200	0.050	0.250	250.000	0.300	0.150	0.225	1.000	40.000	40.000
D1113-FLSM-NR4-A39-GFemale-I147000	0.000	247.500	1000000.000	1000000.000	1000000.000	25000.000	5000.000	1000.000	10333.333	10333333.333	20000.000	4000.000	12000.000	1000000.000	20000000.000	1000000.000
D1113-FMSL-NR4-A36-GFemale-I75000	0.000	0.023	400.000	2000.000	1000.000	10.000	10.000	1.000	7.000	7000.000	0.000	9.000	4.500	100.000	100.000	500.000
D1115-FSLM-NR8-A18-GMale-I	0.000	0.005	5.000	7.300	10.000	0.125	0.037	0.010	0.057	57.167	0.089	0.027	0.058	100.000	500.000	1000.000
D1117-FLMS-NR12-A-G-I	0.000	0.073	20.000	50.000	500.000	0.500	0.250	0.500	0.417	416.667	0.250	0.250	0.250	50.000	100.000	400.000
D1117-FLMS-NR4-A31-GFemale-I30000	0.000	0.012	25.000	25.000	50.000	0.625	0.125	0.050	0.267	266.667	0.500	0.075	0.288	25.000	50.000	50.000
D1117-FLMS-NR4-A32-GFemale-I29000	0.000	0.000	400.000	20000.000	10000.000	10.000	100.000	10.000	40.000	40000.000	90.000	90.000	90.000	20.000	300.000	50000.000
D1117-FLMS-NR4-A57-GFemale-I150000	0.000	18.125	100000.000	100000.000	200000.000	2500.000	500.000	200.000	1066.667	1066666.667	2000.000	300.000	1150.000	0.000	0.000	0.000
D1117-FLSM-NR4-A43-GMale-I44000	0.000	0.124	500.000	500.000	500.000	12.500	2.500	0.500	5.167	5166.667	10.000	2.000	6.000	100.000	200.000	1000.000
D1117-FLSM-NR8-A20-GFemale-I	0.000	0.463	200.000	200.000	1000.000	5.000	1.000	1.000	2.333	2333.333	4.000	0.000	2.000	200.000	200.000	0.000
D1117-FMLS-NR4-A27-GNonbinary-I80000	0.000	0.371	500.000	2000.000	2500.000	12.500	10.000	2.500	8.333	8333.333	2.500	7.500	5.000	500.000	2000.000	3000.000
D1117-FSLM-NR12-A-G-I	0.000	0.012	20.000	20.000	30.000	0.500	0.100	0.030	0.210	210.000	0.400	0.070	0.235	2.000	5.000	10.000
D1117-FSLM-NR4-A28-GFemale-I40000	0.000	0.001	20.000	3.000	30.000	0.500	0.015	0.030	0.182	181.667	0.485	0.015	0.250	1.000	7.000	5.000
D1117-FSML-NR4-A57-GMale-I150000	0.000	0.000	400.000	800.000	1200.000	10.000	4.000	1.200	5.067	5066.667	6.000	2.800	4.400	10000000.000	100000000.000	9999999.000
D1117-FSML-NR8-A26-GFemale-I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D112-FLMS-NR4-A20-GMale-I500000	0.000	0.000	0.040	0.200	1.000	0.001	0.001	0.001	0.001	1.000	0.000	0.000	0.000	1000.000	20000.000	400000.000
D112-FSML-NR4-A30-GPrefer not to say.-I100000	0.000	2.475	1000.000	10000.000	10000.000	25.000	50.000	10.000	28.333	28333.333	25.000	40.000	32.500	100.000	2000.000	10000.000
D116-FLMS-NR4-A31-GFemale-I93000	0.000	0.147	100.000	200.000	800.000	2.500	1.000	0.800	1.433	1433.333	1.500	0.200	0.850	200.000	400.000	1200.000
D117-FLSM-NR4-A53-GMale-I100000	0.000	0.025	100.000	100.000	100.000	2.500	0.500	0.100	1.033	1033.333	2.000	0.400	1.200	100.000	100.000	100.000
D119-FMSL-NR4-A18-GFemale-I170000	0.000	0.007	20.000	50.000	60.000	0.500	0.250	0.060	0.270	270.000	0.250	0.190	0.220	10.000	10.000	20.000
D1018-FMSL-NR4-A27-GFemale-I43000	1.000	0.002	15.000	25.000	50.000	0.375	0.125	0.050	0.183	183.333	0.250	0.075	0.163	5.000	10.000	25.000
D1020-FLMS-NR4-A21-GMale-I600000	1.000	0.001	0.000	0.000	25.000	0.000	0.000	0.025	0.008	8.333	0.000	0.025	0.013	100.000	250.000	500.000
D1020-FLSM-NR4-A22-GFemale-I20000	1.000	1.363	3000.000	1000.000	10000.000	75.000	5.000	10.000	30.000	30000.000	70.000	5.000	37.500	800.000	1500.000	2000.000
D1024-FLSM-NR4-A18-GMale-I150000	1.000	0.012	15.000	20.000	50.000	0.375	0.100	0.050	0.175	175.000	0.275	0.050	0.163	40.000	200.000	400.000
D1024-FSLM-NR4-A28-GFemale-I56000	1.000	0.248	500.000	1000.000	1000.000	12.500	5.000	1.000	6.167	6166.667	7.500	4.000	5.750	1500.000	1000.000	2000.000
D1025-FLMS-NR4-A34-GMale-I145000	1.000	0.025	40.000	40.000	120.000	1.000	0.200	0.120	0.440	440.000	0.800	0.080	0.440	6.000	8.000	48.000
D1025-FLMS-NR4-A35-GMale-I149999	1.000	0.112	220.000	120.000	100.000	5.500	0.600	0.100	2.067	2066.667	4.900	0.500	2.700	240.000	120.000	120.000
D1025-FLSM-NR4-A45-GMale-I145000	1.000	0.123	500.000	300.000	5000.000	12.500	1.500	5.000	6.333	6333.333	11.000	3.500	7.250	2000.000	480.000	900.000
D1025-FMSL-NR4-A34-GMale-I135000	1.000	0.121	500.000	1000.000	1000.000	12.500	5.000	1.000	6.167	6166.667	7.500	4.000	5.750	500.000	400.000	400.000
D1025-FSML-NR4-A35-GMale-I100000	1.000	2.210	2000.000	5000.000	1000.000	50.000	25.000	1.000	25.333	25333.333	25.000	24.000	24.500	10000.000	100000.000	10000000.000
D1025-FSML-NR4-A37-GMale-I11000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	2.000	5.000
D1110-FLMS-NR4-A35-GNonbinary-I190000	1.000	0.248	200.000	500.000	500.000	5.000	2.500	0.500	2.667	2666.667	2.500	2.000	2.250	50.000	500.000	1000.000
D1110-FLSM-NR4-A21-GFemale-I125000	1.000	0.011	5.000	5.000	50.000	0.125	0.025	0.050	0.067	66.667	0.100	0.025	0.063	5.000	10.000	500.000
D1110-FSLM-NR4-A61-GFemale-I250000	1.000	0.012	50.000	50.000	50.000	1.250	0.250	0.050	0.517	516.667	1.000	0.200	0.600	0.000	0.000	0.000
D1110-FSML-NR4-A23-GTransgender female-I7000	1.000	0.012	40.000	100.000	100.000	1.000	0.500	0.100	0.533	533.333	0.500	0.400	0.450	0.000	20.000	100.000
D1111-FLMS-NR4-A19-GPrefer not to say.-I1320	1.000	0.025	100.000	100.000	100.000	2.500	0.500	0.100	1.033	1033.333	2.000	0.400	1.200	100.000	100.000	100.000
D1111-FLSM-NR13-A44-GMale-I	1.000	0.000			1.000	0.000	0.000	0.001	0.000	0.333	0.000	0.001	0.001			1.000
D1111-FMSL-NR4-A21-GMale-I31000	1.000	0.371	3000.000	3000.000	3000.000	75.000	15.000	3.000	31.000	31000.000	60.000	12.000	36.000	0.000	0.000	10.000
D1111-FMSL-NR8-A-GPrefer not to say.-I	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1111-FSML-NR4-A19-GMale-I60000	1.000	0.037	30.000	100.000	200.000	0.750	0.500	0.200	0.483	483.333	0.250	0.300	0.275	30.000	40.000	100.000
D1112-FLMS-NR4-A33-GFemale-I11000	1.000	0.001	5.000	19.000	45.000	0.125	0.095	0.045	0.088	88.333	0.030	0.050	0.040	1.000	10.000	50.000
D1112-FMLS-NR4-A19-GFemale-I3724.48	1.000	4.950	400.000	2000.000	10000.000	10.000	10.000	10.000	10.000	10000.000	0.000	0.000	0.000	100.000	200.000	4000.000
D1112-FSLM-NR4-A20-GNonbinary-I100000	1.000	0.005	10.000	10.000	15.000	0.250	0.050	0.015	0.105	105.000	0.200	0.035	0.118	0.000	5.000	20.000
D1113-FLSM-NR4-A32-GMale-I260000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1113-FLSM-NR4-A62-GFemale-I50000	1.000	0.001	10.000	100.000	10.000	0.250	0.500	0.010	0.253	253.333	0.250	0.490	0.370	25.000	50.000	2.000
D1113-FMLS-NR4-A34-GFemale-I250000	1.000	0.248	1000.000	1000.000	1000.000	25.000	5.000	1.000	10.333	10333.333	20.000	4.000	12.000	15.000	500.000	1000.000
D1113-FSML-NR4-A31-GMale-I130000	1.000	0.019	40.000	60.000	80.000	1.000	0.300	0.080	0.460	460.000	0.700	0.220	0.460	0.000	10.000	10.000
D1114-FLSM-NR8-A19-GPrefer not to say.-I	1.000	0.000	1.000	2.000	2.000	0.025	0.010	0.002	0.012	12.333	0.015	0.008	0.012	0.020	0.780	3.000
D1116-FMLS-NR4-A22-GMale-I150000	1.000	0.098	300.000	400.000	600.000	7.500	2.000	0.600	3.367	3366.667	5.500	1.400	3.450	150.000	1000.000	5000.000
D1117-FMSL-NR4-A43-GMale-I45000	1.000	0.125	500.000	500.000	500.000	12.500	2.500	0.500	5.167	5166.667	10.000	2.000	6.000	200.000	200.000	200.000
D1117-FSLM-NR4-A22-GFemale-I300000	1.000	0.002	10.000	15.000	20.000	0.250	0.075	0.020	0.115	115.000	0.175	0.055	0.115	7.000	5.000	20.000
D1117-FSLM-NR8-A30-GFemale-I	1.000	0.738	1000.000	5000.000	10000.000	25.000	25.000	10.000	20.000	20000.000	0.000	15.000	7.500	10000.000	25000.000	50000.000
D1117-FSML-NR12-A-G-I	1.000	2.200	250.000	500.000	10000.000	6.250	2.500	10.000	6.250	6250.000	3.750	7.500	5.625	1550.000	10000.000	600000.000
D1117-FSML-NR4-A45-GMale-I80000	1.000	0.238	2000.000	1000.000	1500.000	50.000	5.000	1.500	18.833	18833.333	45.000	3.500	24.250	500.000	1000.000	1500.000
D112-FSLM-NR4-A21-GMale-I300000	1.000	0.010	75.000	85.000	250.000	1.875	0.425	0.250	0.850	850.000	1.450	0.175	0.813	500.000	1000.000	5000.000
D115-FMSL-NR4-A28-GFemale-I135000	1.000	0.124	200.000	450.000	650.000	5.000	2.250	0.650	2.633	2633.333	2.750	1.600	2.175	150.000	100.000	800.000
D116-FMLS-NR4-A25-GMale-I210000	1.000	0.004	50.000	200.000	300.000	1.250	1.000	0.300	0.850	850.000	0.250	0.700	0.475	0.000	100.000	200.000
D118-FSLM-NR4-A7-GMale-I7	1.000	0.002	7.000	7.000	7.000	0.175	0.035	0.007	0.072	72.333	0.140	0.028	0.084	7.000	7.000	7.000
D119-FMLS-NR4-A18-GMale-I12000	1.000	0.200	10.000	10.000	50.000	0.250	0.050	0.050	0.117	116.667	0.200	0.000	0.100	5.000	5.000	10.000

response_id	math_activity	perlife_human_S	perlife_human_M	perlife_human_L	perlife_human_avg	perlife_human_avg_thousand	perlife_unit_avg	perlife_unit_avg_thousand	diff_human_SM	diff_human_ML	accuracy_human	accuracy_score	age	male
D1018-FSLM-NR4-A57-GFemale-I100000	0.000	300.000	10.000	0.750	103.583	103583.333	34.737	34736.722	290.000	9.250	149.625	150.212	57.000	0.000
D1018-FSML-NR4-A30-GMale-I25000	0.000	100.000	100.000	10.000	70.000	70000.000	24.183	24183.333	0.000	90.000	45.000	45.000	30.000	1.000
D1018-FSML-NR4-A57-GMale-I100000	0.000	100.000	5.000	0.250	35.083	35083.333	11.763	11763.333	95.000	4.750	49.875	50.115	57.000	1.000
D1024-FMLS-NR4-A19-GMale-I25000	0.000	10.000	1.000	0.125	3.708	3708.333	1.302	1301.944	9.000	0.875	4.938	5.029	19.000	1.000
D1025-FMLS-NR4-A30-GMale-I200000	0.000	500.000	500.000	37.500	345.833	345833.333	116.895	116895.000	0.000	462.500	231.250	234.223	30.000	1.000
D1025-FMLS-NR4-A35-GMale-I180000	0.000	2500.000	125.000	6.250	877.083	877083.333	297.651	297650.833	2375.000	118.750	1246.875	1265.371	35.000	1.000
D1025-FMSL-NR4-A44-GMale-I88787	0.000	5.000	2.250	0.018	2.423	2422.500	1.036	1036.197	2.750	2.233	2.491	3.295	44.000	1.000
D1025-FSML-NR4-A25-GFemale-I4000	0.000	50.000	5.000	0.625	18.542	18541.667	6.526	6525.583	45.000	4.375	24.688	25.937	25.000	0.000
D1025-FSML-NR4-A36-GMale-I126000	0.000	2000.000	50.000	10.000	686.667	686666.667	230.556	230555.556	1950.000	40.000	995.000	999.500	36.000	1.000
D1110-FSML-NR4-A18-GMale-I50000	0.000	50.000	5.000	0.500	18.500	18500.000	6.308	6307.917	45.000	4.500	24.750	25.225	18.000	1.000
D1111-FLMS-NR4-A20-GNonbinary-I0	0.000	15.000	0.750	0.063	5.271	5270.833	1.839	1839.042	14.250	0.688	7.469	7.775	20.000	0.000
D1111-FLMS-NR4-A22-GFemale-I100000	0.000	100.000	5.000	0.250	35.083	35083.333	11.755	11754.778	95.000	4.750	49.875	50.044	22.000	0.000
D1111-FLSM-NR4-A23-GNonbinary-I30000	0.000	10.000	1.000	0.075	3.692	3691.667	1.313	1312.611	9.000	0.925	4.963	5.193	23.000	0.000
D1111-FMLS-NR4-A19-GMale-I450000	0.000	4000.000	4000.000	4000.000	4000.000	4000000.000	1333.340	1333340.000	0.000	0.000	0.000	0.000	19.000	1.000
D1111-FMLS-NR6-A42-GMale-I65000	0.000	50000.000	50000.000	50000.000	50000.000	50000000.000	16668.889	16668888.889	0.000	0.000	0.000	2.500	42.000	1.000
D1111-FSLM-NR4-A20-GMale-I60000	0.000	500.000	10.000	1.500	170.500	170500.000	56.853	56852.750	490.000	8.500	249.250	249.306	20.000	1.000
D1111-FSLM-NR4-A40-GMale-I200000	0.000	20.000	12.500	25.000	19.167	19166.667	7.529	7529.222	7.500	12.500	10.000	14.755	40.000	1.000
D1112-FMLS-NR4-A31-GTransgender male-I180900	0.000	95.000	25.000	1.500	40.500	40500.000	17.321	17320.667	70.000	23.500	46.750	59.787	31.000	0.000
D1112-FMSL-NR4-A24-GFemale-I55000	0.000	1.000	2.000	0.100	1.033	1033.333	0.430	430.256	1.000	1.900	1.450	1.685	24.000	0.000
D1113-FLSM-NR4-A39-GFemale-I147000	0.000	1000000.000	1000000.000	2500.000	667500.000	667500000.000	226006.111	226006111.111	0.000	997500.000	498750.000	510997.500	39.000	0.000
D1113-FMSL-NR4-A36-GFemale-I75000	0.000	100.000	5.000	1.250	35.417	35416.667	14.151	14150.556	95.000	3.750	49.375	53.898	36.000	0.000
D1115-FSLM-NR8-A18-GMale-I	0.000	100.000	25.000	2.500	42.500	42500.000	14.187	14187.028	75.000	22.500	48.750	48.812	18.000	1.000
D1117-FLMS-NR12-A-G-I	0.000	50.000	5.000	1.000	18.667	18666.667	6.378	6378.333	45.000	4.000	24.500	24.823		0.000
D1117-FLMS-NR4-A31-GFemale-I30000	0.000	25.000	2.500	0.125	9.208	9208.333	3.161	3161.403	22.500	2.375	12.438	12.737	31.000	0.000
D1117-FLMS-NR4-A32-GFemale-I29000	0.000	20.000	15.000	125.000	53.333	53333.333	34.444	34444.444	5.000	110.000	57.500	147.500	32.000	0.000
D1117-FLMS-NR4-A57-GFemale-I150000	0.000	0.000	0.000	0.000	0.000	0.000	364.583	364583.333	0.000	0.000	0.000	1168.125	57.000	0.000
D1117-FLSM-NR4-A43-GMale-I44000	0.000	100.000	10.000	2.500	37.500	37500.000	14.253	14253.056	90.000	7.500	48.750	54.874	43.000	1.000
D1117-FLSM-NR8-A20-GFemale-I	0.000	200.000	10.000	0.000	70.000	70000.000	24.258	24258.333	190.000	10.000	100.000	102.463	20.000	0.000
D1117-FMLS-NR4-A27-GNonbinary-I80000	0.000	500.000	100.000	7.500	202.500	202500.000	70.370	70370.278	400.000	92.500	246.250	251.621	27.000	0.000
D1117-FSLM-NR12-A-G-I	0.000	2.000	0.250	0.025	0.758	758.333	0.326	326.000	1.750	0.225	0.988	1.235		0.000
D1117-FSLM-NR4-A28-GFemale-I40000	0.000	1.000	0.350	0.013	0.454	454.167	0.212	212.283	0.650	0.338	0.494	0.745	28.000	0.000
D1117-FSML-NR4-A57-GMale-I150000	0.000	10000000.000	5000000.000	24999.998	5008333.333	5008333332.500	1669612.800	1669612799.722	5000000.000	4975000.003	4987500.001	4987504.401	57.000	1.000
D1117-FSML-NR8-A26-GFemale-I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	26.000	0.000
D112-FLMS-NR4-A20-GMale-I500000	0.000	1000.000	1000.000	1000.000	1000.000	1000000.000	333.334	333333.833	0.000	0.000	0.000	0.000	20.000	1.000
D112-FSML-NR4-A30-GPrefer not to say.-I100000	0.000	100.000	100.000	25.000	75.000	75000.000	35.061	35061.111	0.000	75.000	37.500	72.475	30.000	0.000
D116-FLMS-NR4-A31-GFemale-I93000	0.000	200.000	20.000	3.000	74.333	74333.333	25.296	25296.222	180.000	17.000	98.500	99.497	31.000	0.000
D117-FLSM-NR4-A53-GMale-I100000	0.000	100.000	5.000	0.250	35.083	35083.333	12.045	12045.056	95.000	4.750	49.875	51.100	53.000	1.000
D119-FMSL-NR4-A18-GFemale-I170000	0.000	10.000	0.500	0.050	3.517	3516.667	1.265	1264.506	9.500	0.450	4.975	5.202	18.000	0.000
D1018-FMSL-NR4-A27-GFemale-I43000	1.000	5.000	0.500	0.063	1.854	1854.167	0.680	680.056	4.500	0.438	2.469	2.634	27.000	0.000
D1020-FLMS-NR4-A21-GMale-I600000	1.000	100.000	12.500	1.250	37.917	37916.667	12.642	12641.861	87.500	11.250	49.375	49.389	21.000	1.000
D1020-FLSM-NR4-A22-GFemale-I20000	1.000	800.000	75.000	5.000	293.333	293333.333	108.119	108119.444	725.000	70.000	397.500	436.363	22.000	0.000
D1024-FLSM-NR4-A18-GMale-I150000	1.000	40.000	10.000	1.000	17.000	17000.000	5.728	5728.083	30.000	9.000	19.500	19.675	18.000	1.000
D1024-FSLM-NR4-A28-GFemale-I56000	1.000	1500.000	50.000	5.000	518.333	518333.333	174.895	174895.000	1450.000	45.000	747.500	753.498	28.000	0.000
D1025-FLMS-NR4-A34-GMale-I145000	1.000	6.000	0.400	0.120	2.173	2173.333	0.878	878.444	5.600	0.280	2.940	3.405	34.000	1.000
D1025-FLMS-NR4-A35-GMale-I149999	1.000	240.000	6.000	0.300	82.100	82100.000	28.082	28081.806	234.000	5.700	119.850	122.662	35.000	1.000
D1025-FLSM-NR4-A45-GMale-I145000	1.000	2000.000	24.000	2.250	675.417	675416.667	227.282	227282.222	1976.000	21.750	998.875	1006.248	45.000	1.000
D1025-FMSL-NR4-A34-GMale-I135000	1.000	500.000	20.000	1.000	173.667	173666.667	59.981	59981.389	480.000	19.000	249.500	255.371	34.000	1.000
D1025-FSML-NR4-A35-GMale-I100000	1.000	10000.000	5000.000	25000.000	13333.333	13333333.333	4453.731	4453731.111	5000.000	20000.000	12500.000	12526.710	35.000	1.000
D1025-FSML-NR4-A37-GMale-I11000	1.000	1.000	0.100	0.013	0.371	370.833	0.124	123.611	0.900	0.088	0.494	0.494	37.000	1.000
D1110-FLMS-NR4-A35-GNonbinary-I190000	1.000	50.000	25.000	2.500	25.833	25833.333	9.562	9561.667	25.000	22.500	23.750	26.248	35.000	0.000
D1110-FLSM-NR4-A21-GFemale-I125000	1.000	5.000	0.500	1.250	2.250	2250.000	0.778	778.056	4.500	0.750	2.625	2.699	21.000	0.000
D1110-FSLM-NR4-A61-GFemale-I250000	1.000	0.000	0.000	0.000	0.000	0.000	0.175	175.306	0.000	0.000	0.000	0.612	61.000	0.000
D1110-FSML-NR4-A23-GTransgender female-I7000	1.000	0.000	1.000	0.250	0.417	416.667	0.320	319.750	1.000	0.750	0.875	1.337	23.000	0.000
D1111-FLMS-NR4-A19-GPrefer not to say.-I1320	1.000	100.000	5.000	0.250	35.083	35083.333	12.045	12045.056	95.000	4.750	49.875	51.100	19.000	0.000
D1111-FLSM-NR13-A44-GMale-I	1.000	0.000	0.000	0.003	0.001	0.833	0.000	0.389	0.000	0.003	0.001	0.002	44.000	1.000
D1111-FMSL-NR4-A21-GMale-I31000	1.000	0.000	0.000	0.025	0.008	8.333	10.429	10428.611	0.000	0.025	0.013	36.384	21.000	1.000
D1111-FMSL-NR8-A-GPrefer not to say.-I	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
D1111-FSML-NR4-A19-GMale-I60000	1.000	30.000	2.000	0.250	10.750	10750.000	3.754	3754.056	28.000	1.750	14.875	15.187	19.000	1.000
D1112-FLMS-NR4-A33-GFemale-I11000	1.000	1.000	0.500	0.125	0.542	541.667	0.210	210.489	0.500	0.375	0.438	0.479	33.000	0.000
D1112-FMLS-NR4-A19-GFemale-I3724.48	1.000	100.000	10.000	10.000	40.000	40000.000	17.900	17900.000	90.000	0.000	45.000	49.950	19.000	0.000
D1112-FSLM-NR4-A20-GNonbinary-I100000	1.000	0.000	0.250	0.050	0.100	100.000	0.070	69.611	0.250	0.200	0.225	0.347	20.000	0.000
D1113-FLSM-NR4-A32-GMale-I260000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	32.000	1.000
D1113-FLSM-NR4-A62-GFemale-I50000	1.000	25.000	2.500	0.005	9.168	9168.333	3.141	3140.611	22.500	2.495	12.498	12.868	62.000	0.000
D1113-FMLS-NR4-A34-GFemale-I250000	1.000	15.000	25.000	2.500	14.167	14166.667	8.223	8223.333	10.000	22.500	16.250	28.498	34.000	0.000
D1113-FSML-NR4-A31-GMale-I130000	1.000	0.000	0.500	0.025	0.175	175.000	0.216	216.444	0.500	0.475	0.488	0.966	31.000	1.000
D1114-FLSM-NR8-A19-GPrefer not to say.-I	1.000	0.020	0.039	0.008	0.022	22.167	0.012	11.542	0.019	0.032	0.025	0.037	19.000	0.000
D1116-FMLS-NR4-A22-GMale-I150000	1.000	150.000	50.000	12.500	70.833	70833.333	24.759	24758.722	100.000	37.500	68.750	72.298	22.000	1.000
D1117-FMSL-NR4-A43-GMale-I45000	1.000	200.000	10.000	0.500	70.167	70166.667	25.142	25141.669	190.000	9.500	99.750	105.875	43.000	1.000
D1117-FSLM-NR4-A22-GFemale-I300000	1.000	7.000	0.250	0.050	2.433	2433.333	0.850	850.094	6.750	0.200	3.475	3.592	22.000	0.000
D1117-FSLM-NR8-A30-GFemale-I	1.000	10000.000	1250.000	125.000	3791.667	3791666.667	1270.744	1270744.444	8750.000	1125.000	4937.500	4945.738	30.000	0.000
D1117-FSML-NR12-A-G-I	1.000	1550.000	500.000	1500.000	1183.333	1183333.333	397.067	397066.667	1050.000	1000.000	1025.000	1032.825		0.000
D1117-FSML-NR4-A45-GMale-I80000	1.000	500.000	50.000	3.750	184.583	184583.333	67.881	67880.556	450.000	46.250	248.125	272.613	45.000	1.000
D112-FSLM-NR4-A21-GMale-I300000	1.000	500.000	50.000	12.500	187.500	187500.000	62.789	62789.167	450.000	37.500	243.750	244.573	21.000	1.000
D115-FMSL-NR4-A28-GFemale-I135000	1.000	150.000	5.000	2.000	52.333	52333.333	18.353	18353.056	145.000	3.000	74.000	76.299	28.000	0.000
D116-FMLS-NR4-A25-GMale-I210000	1.000	0.000	5.000	0.500	1.833	1833.333	0.897	896.889	5.000	4.500	4.750	5.229	25.000	1.000
D118-FSLM-NR4-A7-GMale-I7	1.000	7.000	0.350	0.018	2.456	2455.833	0.843	843.154	6.650	0.333	3.491	3.577	7.000	1.000
D119-FMLS-NR4-A18-GMale-I12000	1.000	5.000	0.250	0.025	1.758	1758.333	0.664	663.889	4.750	0.225	2.488	2.788	18.000	1.000

response_id	math_activity	female	other_gender [2]	black_or_africanamerican	hispanic_or_latnix	asian_or_pacificislander	white	other_race [3]	completed_graduate_degree	completed_bachelors_degree	current_undergrad	high_school_diploma
D1018-FSLM-NR4-A57-GFemale-I100000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
D1018-FSML-NR4-A30-GMale-I25000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
D1018-FSML-NR4-A57-GMale-I100000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
D1024-FMLS-NR4-A19-GMale-I25000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1025-FMLS-NR4-A30-GMale-I200000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1025-FMLS-NR4-A35-GMale-I180000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1025-FMSL-NR4-A44-GMale-I88787	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1025-FSML-NR4-A25-GFemale-I4000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000
D1025-FSML-NR4-A36-GMale-I126000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1110-FSML-NR4-A18-GMale-I50000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1111-FLMS-NR4-A20-GNonbinary-I0	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1111-FLMS-NR4-A22-GFemale-I100000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1111-FLSM-NR4-A23-GNonbinary-I30000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1111-FMLS-NR4-A19-GMale-I450000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1111-FMLS-NR6-A42-GMale-I65000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
D1111-FSLM-NR4-A20-GMale-I60000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
D1111-FSLM-NR4-A40-GMale-I200000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
D1112-FMLS-NR4-A31-GTransgender male-I180900	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1112-FMSL-NR4-A24-GFemale-I55000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1113-FLSM-NR4-A39-GFemale-I147000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
D1113-FMSL-NR4-A36-GFemale-I75000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1115-FSLM-NR8-A18-GMale-I	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1117-FLMS-NR12-A-G-I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1117-FLMS-NR4-A31-GFemale-I30000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1117-FLMS-NR4-A32-GFemale-I29000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1117-FLMS-NR4-A57-GFemale-I150000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
D1117-FLSM-NR4-A43-GMale-I44000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1117-FLSM-NR8-A20-GFemale-I	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1117-FMLS-NR4-A27-GNonbinary-I80000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1117-FSLM-NR12-A-G-I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1117-FSLM-NR4-A28-GFemale-I40000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
D1117-FSML-NR4-A57-GMale-I150000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000
D1117-FSML-NR8-A26-GFemale-I	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D112-FLMS-NR4-A20-GMale-I500000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D112-FSML-NR4-A30-GPrefer not to say.-I100000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000
D116-FLMS-NR4-A31-GFemale-I93000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D117-FLSM-NR4-A53-GMale-I100000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D119-FMSL-NR4-A18-GFemale-I170000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1018-FMSL-NR4-A27-GFemale-I43000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
D1020-FLMS-NR4-A21-GMale-I600000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1020-FLSM-NR4-A22-GFemale-I20000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1024-FLSM-NR4-A18-GMale-I150000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
D1024-FSLM-NR4-A28-GFemale-I56000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1025-FLMS-NR4-A34-GMale-I145000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1025-FLMS-NR4-A35-GMale-I149999	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1025-FLSM-NR4-A45-GMale-I145000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1025-FMSL-NR4-A34-GMale-I135000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1025-FSML-NR4-A35-GMale-I100000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
D1025-FSML-NR4-A37-GMale-I11000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
D1110-FLMS-NR4-A35-GNonbinary-I190000	1.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1110-FLSM-NR4-A21-GFemale-I125000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1110-FSLM-NR4-A61-GFemale-I250000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1110-FSML-NR4-A23-GTransgender female-I7000	1.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1111-FLMS-NR4-A19-GPrefer not to say.-I1320	1.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1111-FLSM-NR13-A44-GMale-I	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1111-FMSL-NR4-A21-GMale-I31000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1111-FMSL-NR8-A-GPrefer not to say.-I	1.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000
D1111-FSML-NR4-A19-GMale-I60000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
D1112-FLMS-NR4-A33-GFemale-I11000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
D1112-FMLS-NR4-A19-GFemale-I3724.48	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1112-FSLM-NR4-A20-GNonbinary-I100000	1.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000
D1113-FLSM-NR4-A32-GMale-I260000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D1113-FLSM-NR4-A62-GFemale-I50000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000
D1113-FMLS-NR4-A34-GFemale-I250000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1113-FSML-NR4-A31-GMale-I130000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D1114-FLSM-NR8-A19-GPrefer not to say.-I	1.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
D1116-FMLS-NR4-A22-GMale-I150000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1117-FMSL-NR4-A43-GMale-I45000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1117-FSLM-NR4-A22-GFemale-I300000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D1117-FSLM-NR8-A30-GFemale-I	1.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
D1117-FSML-NR12-A-G-I	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D1117-FSML-NR4-A45-GMale-I80000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D112-FSLM-NR4-A21-GMale-I300000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000
D115-FMSL-NR4-A28-GFemale-I135000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
D116-FMLS-NR4-A25-GMale-I210000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
D118-FSLM-NR4-A7-GMale-I7	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D119-FMLS-NR4-A18-GMale-I12000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000

response_id	math_activity	incomplete_high_school	current_graduatestu	other_education [4]	annual_income	ess_spend	noness_spend	charity_past	charity_future
D1018-FSLM-NR4-A57-GFemale-I100000	0.000	0.000	0.000	0.000	100000.000	5000.000	600.000	1.000	0.000
D1018-FSML-NR4-A30-GMale-I25000	0.000	0.000	0.000	0.000	25000.000	1600.000	400.000	1.000	0.000
D1018-FSML-NR4-A57-GMale-I100000	0.000	0.000	0.000	0.000	100000.000	3000.000	700.000	1.000	1.000
D1024-FMLS-NR4-A19-GMale-I25000	0.000	0.000	0.000	0.000	25000.000	200.000	100.000	1.000	1.000
D1025-FMLS-NR4-A30-GMale-I200000	0.000	0.000	0.000	0.000	200000.000	20000.000	2000.000	1.000	1.000
D1025-FMLS-NR4-A35-GMale-I180000	0.000	0.000	0.000	0.000	180000.000	5000.000	1000.000	1.000	1.000
D1025-FMSL-NR4-A44-GMale-I88787	0.000	0.000	0.000	0.000	88787.000	6765.000	7566.000	1.000	1.000
D1025-FSML-NR4-A25-GFemale-I4000	0.000	0.000	0.000	0.000	4000.000	500.000	250.000	1.000	1.000
D1025-FSML-NR4-A36-GMale-I126000	0.000	0.000	0.000	0.000	126000.000	150000.000	120000.000	1.000	1.000
D1110-FSML-NR4-A18-GMale-I50000	0.000	0.000	0.000	0.000	50000.000	100.000	100.000	1.000	1.000
D1111-FLMS-NR4-A20-GNonbinary-I0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
D1111-FLMS-NR4-A22-GFemale-I100000	0.000	0.000	0.000	0.000	100000.000	2000.000	1000.000	1.000	1.000
D1111-FLSM-NR4-A23-GNonbinary-I30000	0.000	0.000	0.000	0.000	30000.000	1200.000	600.000	1.000	1.000
D1111-FMLS-NR4-A19-GMale-I450000	0.000	0.000	0.000	0.000	450000.000	1500.000	50.000	1.000	1.000
D1111-FMLS-NR6-A42-GMale-I65000	0.000	0.000	0.000	0.000	65000.000	2500.000	1000.000	1.000	0.000
D1111-FSLM-NR4-A20-GMale-I60000	0.000	0.000	0.000	1.000	60000.000	3000.000	400.000	0.000	1.000
D1111-FSLM-NR4-A40-GMale-I200000	0.000	0.000	0.000	0.000	200000.000	3000.000	2000.000	1.000	1.000
D1112-FMLS-NR4-A31-GTransgender male-I180900	0.000	0.000	0.000	0.000	180900.000	500.000	150.000	1.000	1.000
D1112-FMSL-NR4-A24-GFemale-I55000	0.000	0.000	0.000	0.000	55000.000	850.000	200.000	1.000	1.000
D1113-FLSM-NR4-A39-GFemale-I147000	0.000	0.000	0.000	0.000	147000.000	5000.000	2000.000	1.000	1.000
D1113-FMSL-NR4-A36-GFemale-I75000	0.000	0.000	0.000	0.000	75000.000	4250.000	1500.000	1.000	1.000
D1115-FSLM-NR8-A18-GMale-I	0.000	0.000	0.000	0.000				0.000	
D1117-FLMS-NR12-A-G-I	0.000	0.000	0.000	0.000				0.000	
D1117-FLMS-NR4-A31-GFemale-I30000	0.000	0.000	0.000	0.000	30000.000	1300.000	100.000	1.000	
D1117-FLMS-NR4-A32-GFemale-I29000	0.000	0.000	0.000	0.000	29000.000	1100.000	300.000	1.000	
D1117-FLMS-NR4-A57-GFemale-I150000	0.000	0.000	0.000	0.000	150000.000	2000.000	750.000	1.000	
D1117-FLSM-NR4-A43-GMale-I44000	0.000	0.000	0.000	0.000	44000.000	2200.000	400.000	1.000	
D1117-FLSM-NR8-A20-GFemale-I	0.000	0.000	0.000	0.000				0.000	
D1117-FMLS-NR4-A27-GNonbinary-I80000	0.000	0.000	0.000	1.000	80000.000	3500.000	900.000	1.000	
D1117-FSLM-NR12-A-G-I	0.000	0.000	0.000	0.000				0.000	
D1117-FSLM-NR4-A28-GFemale-I40000	0.000	0.000	0.000	1.000	40000.000	2000.000	500.000	1.000	
D1117-FSML-NR4-A57-GMale-I150000	0.000	0.000	0.000	0.000	150000.000	4000.000	1000.000	1.000	
D1117-FSML-NR8-A26-GFemale-I	0.000	0.000	0.000	0.000				0.000	
D112-FLMS-NR4-A20-GMale-I500000	0.000	0.000	0.000	0.000	500000.000	2000.000	5000.000	1.000	1.000
D112-FSML-NR4-A30-GPrefer not to say.-I100000	0.000	0.000	0.000	0.000	100000.000	3000.000	1000.000	1.000	1.000
D116-FLMS-NR4-A31-GFemale-I93000	0.000	0.000	0.000	0.000	93000.000	3500.000	1500.000	1.000	1.000
D117-FLSM-NR4-A53-GMale-I100000	0.000	0.000	0.000	0.000	100000.000	1000.000	1000.000	1.000	1.000
D119-FMSL-NR4-A18-GFemale-I170000	0.000	0.000	0.000	0.000	170000.000	3000.000	500.000	1.000	1.000
D1018-FMSL-NR4-A27-GFemale-I43000	1.000	0.000	0.000	0.000	43000.000	1600.000	50.000	1.000	1.000
D1020-FLMS-NR4-A21-GMale-I600000	1.000	0.000	0.000	0.000	600000.000	3000.000	200.000	1.000	1.000
D1020-FLSM-NR4-A22-GFemale-I20000	1.000	0.000	0.000	0.000	20000.000	2000.000	2000.000	1.000	1.000
D1024-FLSM-NR4-A18-GMale-I150000	1.000	0.000	0.000	0.000	150000.000	200.000	20.000	1.000	1.000
D1024-FSLM-NR4-A28-GFemale-I56000	1.000	0.000	0.000	0.000	56000.000	2000.000	300.000	1.000	1.000
D1025-FLMS-NR4-A34-GMale-I145000	1.000	0.000	0.000	0.000	145000.000	400.000	350.000	1.000	1.000
D1025-FLMS-NR4-A35-GMale-I149999	1.000	0.000	0.000	0.000	149999.000	5000.000	2000.000	1.000	1.000
D1025-FLSM-NR4-A45-GMale-I145000	1.000	0.000	0.000	0.000	145000.000	50000.000	60000.000	1.000	1.000
D1025-FMSL-NR4-A34-GMale-I135000	1.000	0.000	0.000	0.000	135000.000	20000.000	5000.000	1.000	1.000
D1025-FSML-NR4-A35-GMale-I100000	1.000	0.000	0.000	0.000	100000.000	30000.000	20000.000	1.000	1.000
D1025-FSML-NR4-A37-GMale-I11000	1.000	0.000	0.000	1.000	11000.000	770.000	130.000	1.000	0.000
D1110-FLMS-NR4-A35-GNonbinary-I190000	1.000	0.000	0.000	0.000	190000.000	7000.000	2000.000	1.000	1.000
D1110-FLSM-NR4-A21-GFemale-I125000	1.000	0.000	0.000	0.000	125000.000	2000.000	250.000	1.000	1.000
D1110-FSLM-NR4-A61-GFemale-I250000	1.000	0.000	0.000	0.000	250000.000	12000.000	500.000	1.000	1.000
D1110-FSML-NR4-A23-GTransgender female-I7000	1.000	0.000	0.000	0.000	7000.000	1000.000	200.000	1.000	0.000
D1111-FLMS-NR4-A19-GPrefer not to say.-I1320	1.000	0.000	0.000	0.000	1320.000	1319.000	0.000	1.000	1.000
D1111-FLSM-NR13-A44-GMale-I	1.000	0.000	0.000	0.000				1.000	1.000
D1111-FMSL-NR4-A21-GMale-I31000	1.000	0.000	0.000	0.000	31000.000	1100.000	200.000	1.000	1.000
D1111-FMSL-NR8-A-GPrefer not to say.-I	1.000	0.000	0.000	0.000				1.000	1.000
D1111-FSML-NR4-A19-GMale-I60000	1.000	0.000	1.000	0.000	60000.000	1500.000	100.000	1.000	1.000
D1112-FLMS-NR4-A33-GFemale-I11000	1.000	0.000	1.000	0.000	11000.000	700.000	100.000	1.000	1.000
D1112-FMLS-NR4-A19-GFemale-I3724.48	1.000	0.000	0.000	0.000	3724.480	2000.000	100.000	1.000	1.000
D1112-FSLM-NR4-A20-GNonbinary-I100000	1.000	0.000	0.000	0.000	100000.000	6000.000	1000.000	0.000	1.000
D1113-FLSM-NR4-A32-GMale-I260000	1.000	0.000	0.000	0.000	260000.000	3000.000	500.000	1.000	1.000
D1113-FLSM-NR4-A62-GFemale-I50000	1.000	0.000	0.000	0.000	50000.000	1200200.000	200.000	1.000	1.000
D1113-FMLS-NR4-A34-GFemale-I250000	1.000	0.000	0.000	0.000	250000.000	10000.000	2000.000	1.000	1.000
D1113-FSML-NR4-A31-GMale-I130000	1.000	0.000	0.000	0.000	130000.000	3000.000	2000.000	1.000	1.000
D1114-FLSM-NR8-A19-GPrefer not to say.-I	1.000	0.000	0.000	1.000				0.000	
D1116-FMLS-NR4-A22-GMale-I150000	1.000	0.000	0.000	0.000	150000.000	10000.000	800.000	1.000	
D1117-FMSL-NR4-A43-GMale-I45000	1.000	0.000	0.000	0.000	45000.000	2100.000	400.000	1.000	
D1117-FSLM-NR4-A22-GFemale-I300000	1.000	0.000	0.000	0.000	300000.000	1200.000	300.000	1.000	
D1117-FSLM-NR8-A30-GFemale-I	1.000	0.000	0.000	0.000				0.000	
D1117-FSML-NR12-A-G-I	1.000	0.000	0.000	0.000				0.000	
D1117-FSML-NR4-A45-GMale-I80000	1.000	0.000	0.000	0.000	80000.000	3500.000	750.000	1.000	
D112-FSLM-NR4-A21-GMale-I300000	1.000	0.000	0.000	0.000	300000.000	600.000	300.000	1.000	1.000
D115-FMSL-NR4-A28-GFemale-I135000	1.000	0.000	0.000	0.000	135000.000	3000.000	1500.000	1.000	1.000
D116-FMLS-NR4-A25-GMale-I210000	1.000	0.000	0.000	0.000	210000.000	5000.000	2000.000	1.000	1.000
D118-FSLM-NR4-A7-GMale-I7	1.000	1.000	0.000	0.000	7.000	7.000	7.000	0.000	1.000
D119-FMLS-NR4-A18-GMale-I12000	1.000	0.000	0.000	0.000	12000.000	3500.000	50.000	1.000	1.000

[1] (perLifeTurtleS + perLifeTurtleM + perLifeTurtleL) / 3

[2] includes PreferNotToSay, TransF, TransM, and NonBinary

[3] includes PreferNotToSay, Indian, and NativeAmerican/AlaskaNative

[4] Contains PreferNotToSay, Complete Associate Degree, and Incomplete Degree