Online Appendix 4 to "Narrow Bracketing and Dominated Choices": Model estimates separated by background characteristics

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This appendix considers the background characteristics of the decisionmakers in the survey sample. The panel is designed to be representative of the general U.S. population and we have a variety of relevant characteristics in the data set. We separate the data set into pairs of subsamples according to a series of criteria (e.g. male/female respondents), and for each of these subsamples we re-estimate the model of the previous subsection. Online Appendix 5 complements the analysis with a series of behavioral regressions, projecting the respondents' choices on their personal characteristics. This allows to check whether the differences between subgroups that we find in the model estimations are significantly reflected in the frequencies of accepting/rejecting certain lotteries and in the rate of violating dominance. The regression framework is also useful because for some of the explanatory variables it is important to include control variables. We will cross-refer to the regression results when discussing statistical significance of difference between the subsamples.

We use the following binary variables to create subsamples of the data, with numbers in parentheses indicating the numbers of individuals in each category who made at least one lottery choice (1109 in total): gender (532 male/577 female), age weakly below/strictly above the median age of 45 (548/561), "white, non-hispanic"/other as the self-reported racial/ethnic background[1] (815/294), household income weakly above/strictly below the median income[2] (576/533), complete/incomplete set of correct answers to all three of our numerical questions (174/935), self-reported attendance of a mathematics course in college (397/712), bachelor degree or higher/no bachelor degree (306/803).

Table OA4.1 reports the parameter estimates and standard deviations for all seven pairs of subsamples, as well as the obtained log-likelihoods, of the model presented in Section 4 of the paper. Figures OA4.1 through OA4.7 show the estimated preferences. For a comparison, the

[1] In the full data set, the racial/ethnic background is coded as a categorical dummy with five categories.

[2] Household income is measured in 20 brackets. The median category is the bracket [40,000; 49,999].

estimates for the full data set are repeated in the first column of the table, and the preferences are depicted in Figure 4.1 of the paper. The last row of Table OA4.1 shows the percentage of participants in each subsample that made at least one A and D choice combination in one of the four examples.[3]

	All data	Gender		Age		Racial/ethnic background	
		male	female	<=45	>45	white	non-white
θ	0.1196	0.2120	0.0001	0.1565	0.0866	0.1272	0.0352
	(0.0491)	(0.0622)	(0.0019)	(0.0689)	(0.0881)	(0.0542)	(0.1217)
r_+	0.0014	0.0010	0.0017	0.0012	0.0017	0.0015	0.0009
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0006)
γ_+	0.0740	0.0812	0.0617	0.0673	0.0796	0.0772	0.0544
	(0.0109)	(0.0149)	(0.0159)	(0.0134)	(0.0146)	(0.0122)	(0.0149)
r_-	0.0005	0.0006	0.0004	0.0005	0.0006	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
γ_-	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.0133	0.0159	0.0113	0.0142	0.0125	0.0149	0.0101
	(0.0012)	(0.0019)	(0.0013)	(0.0018)	(0.0024)	(0.0014)	(0.0025)
$obs.$	1109	532	577	548	561	815	294
ll^*	-1926.4	-913.2	-1009.6	-949.9	-975.3	-1381.2	-537.5
% A and D	50.1	49.3	50.8	46.7	53.3	53.3	41.7

Table OA4.1: Parameter estimates (st. dev. in parentheses) with x_0=0, data separated by variables.

[3] For ease of interpretation in the light of the estimation results, this percentage is calculated using only the narrow presentations of the four examples, not the broad presentation cases.

	Household income		Math answers		College math course		Educational degree	
	>=40,000	<40,000	3 correct	<=2 correct	attended	not attended	bachelor	below bachelor
θ	0.1539	0.0627	0.0928	0.1133	0.1615	0.0880	0.176	0.1082
	(0.0681)	(0.0577)	(0.1334)	(0.0471)	(0.0697)	(0.0666)	(0.0705)	(0.0449)
r_+	0.0012	0.0017	0.0008	0.0016	0.0014	0.0014	0.0013	0.0015
	(0.0003)	(0.0007)	(0.0004)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
γ_+	0.0608	0.0876	0.0454	0.0815	0.0751	0.0718	0.0547	0.0834
	(0.0116)	(0.0201)	(0.0150)	(0.0127)	(0.0160)	(0.0143)	(0.0158)	(0.0139)
r_-	0.0004	0.0006	0.0003	0.0006	0.0005	0.0005	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
γ_-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.0163	0.0109	0.0201	0.0126	0.0159	0.0121	0.0170	0.0122
	(0.0019)	(0.0015)	(0.0044)	(0.0012)	(0.0022)	(0.0014)	(0.0026)	(0.0013
$obs.$	576	533	174	935	397	712	306	803
ll^*	-967.9	-951.7	-282.1	-1639.7	-679.0	-1245.3	-516.7	-1406.2
% A and D	50.4	49.8	46.8	51.6	52.7	48.6	52.0	49.4

Table OA4.1 (ctd.): Parameter estimates (st. dev. in parentheses) with x_0=0, data separated by variables.

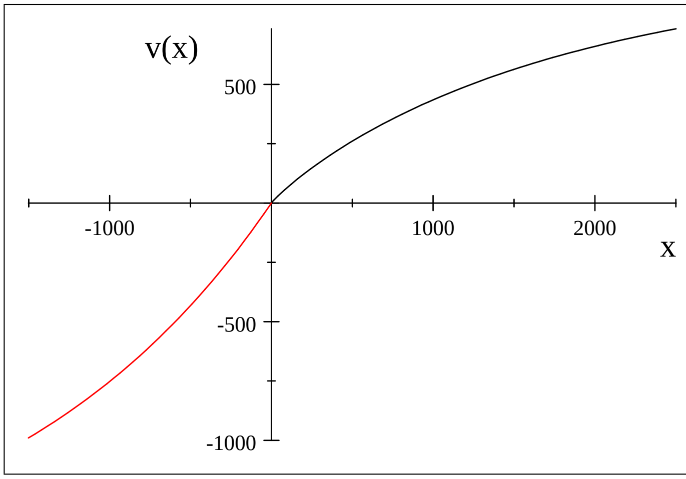

Figure OA4.1a: Estimated $v(\cdot)$, male respondents

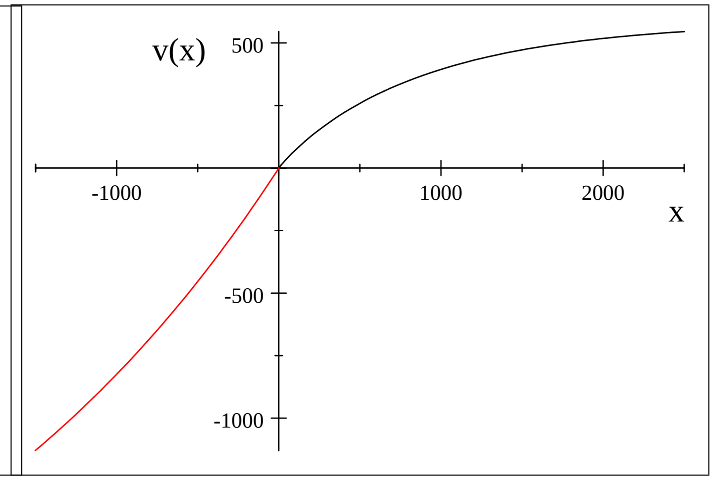

Figure OA4.1b: Estimated $v(\cdot)$, female respondents

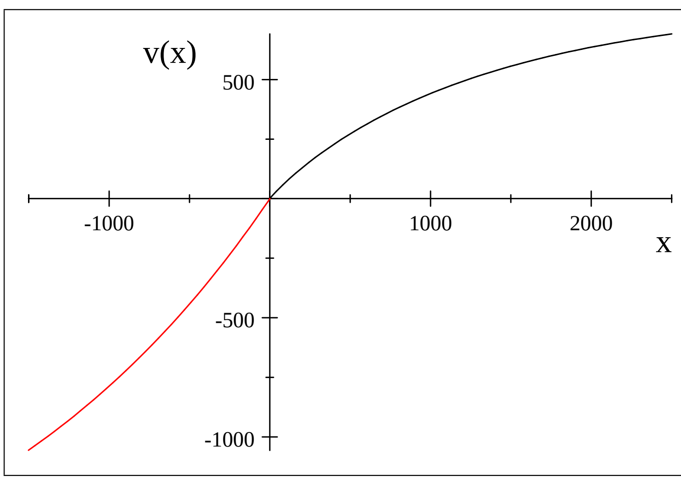

Figure OA4.2a: Estimated $v(\cdot)$, respondents $\leq$45 years

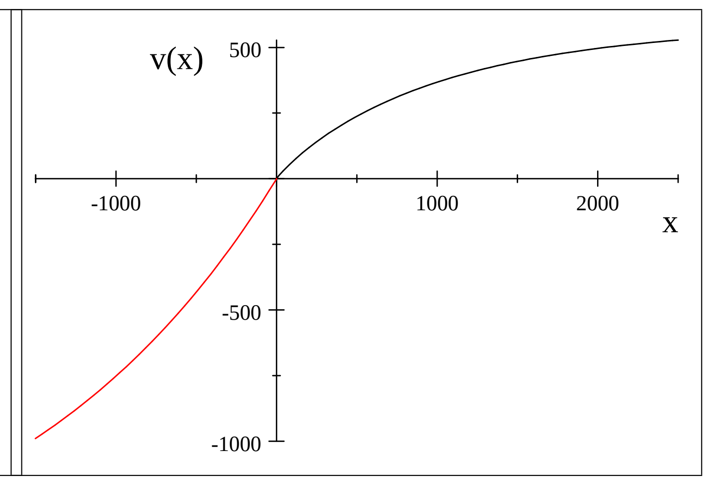

Figure OA4.2b: Estimated $v(\cdot)$, respondents $>$45 years

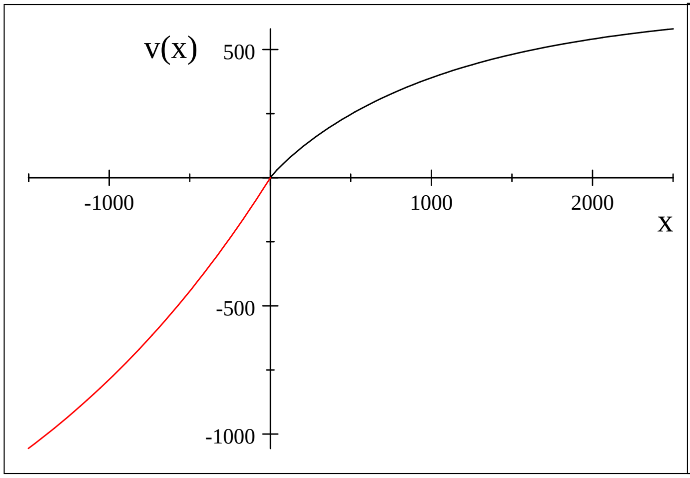

Figure OA4.3a: Estimated $v(\cdot)$, white respondents

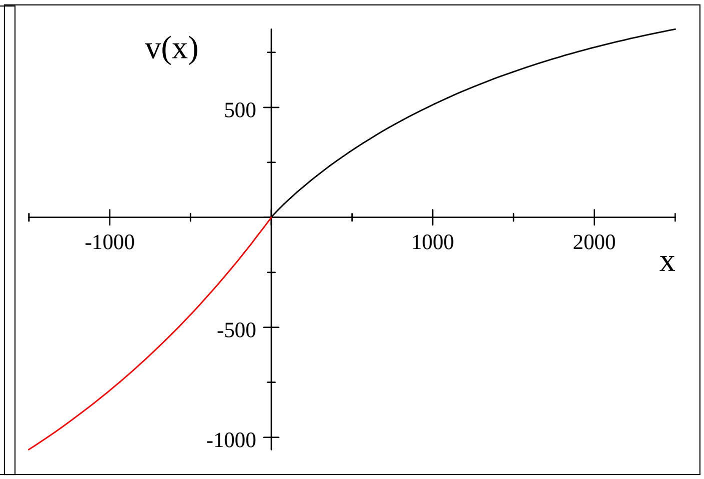

Figure OA4.3b: Estimated $v(\cdot)$, nonwhite respondents

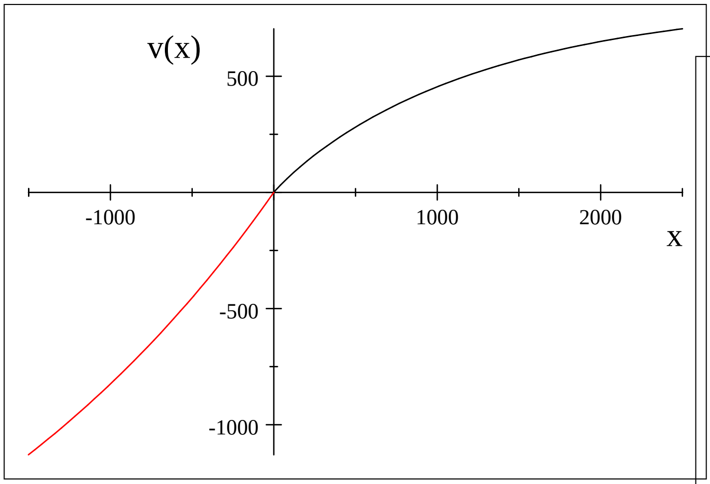

Figure OA4.4a: Estimated $v(\cdot)$, higher-income respondents.

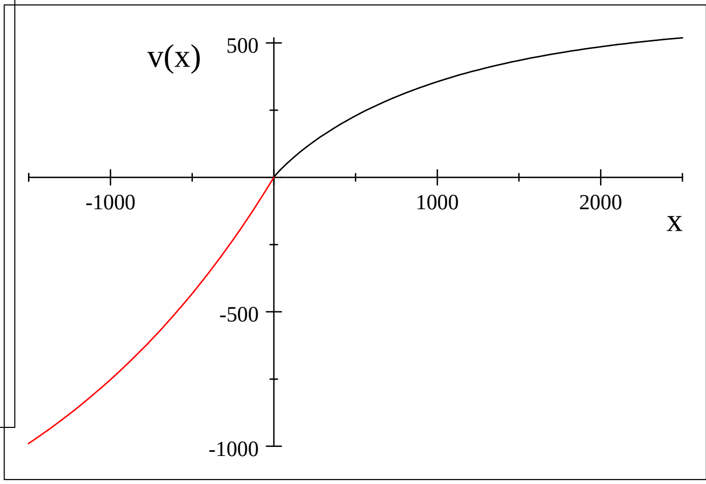

Figure OA4.4b: Estimated $v(\cdot)$, lower-income respondents

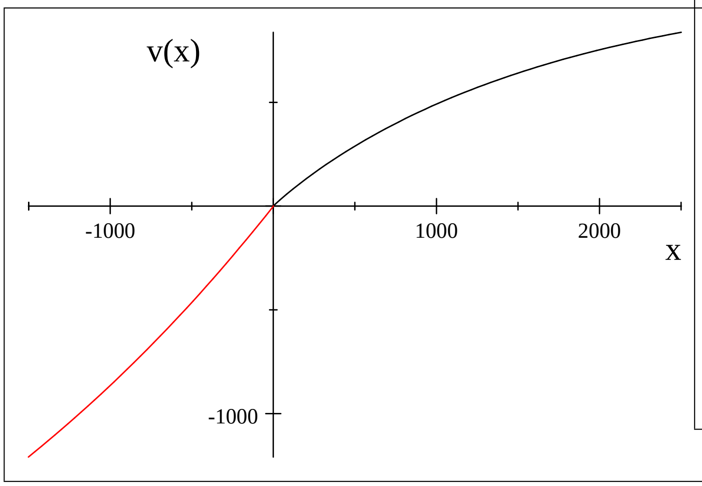

Figure OA4.5a: Estimated $v(\cdot)$, math-skilled respondents

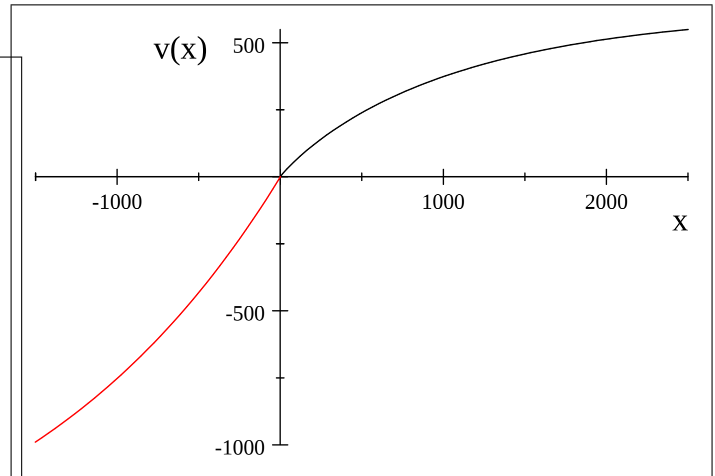

Figure OA4.5b: Estimated $v(\cdot)$, less math-skilled respondents

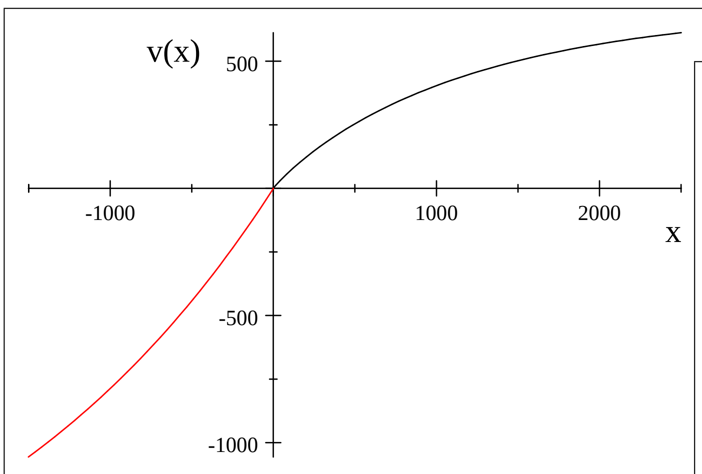

Figure OA4.6a: Estimated $v(\cdot)$, math-educated respondents

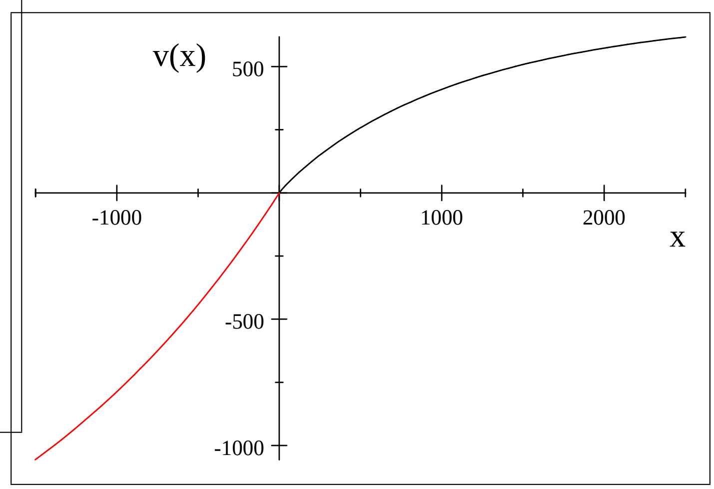

Figure OA4.6b: Estimated $v(\cdot)$, non-math-educated resp.

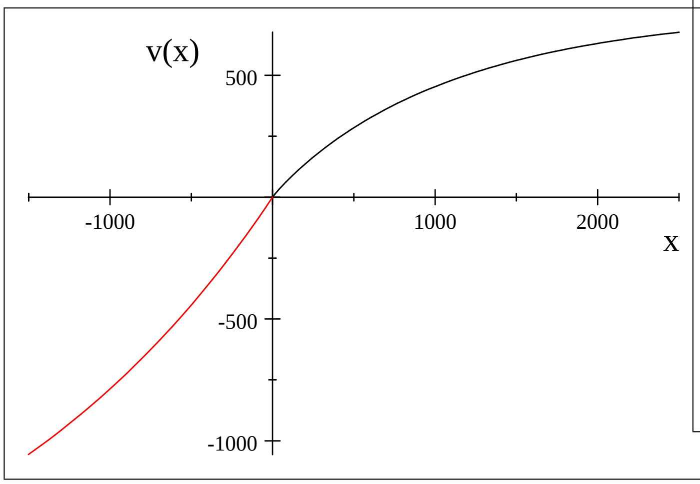

Figure OA4.7a: Estimated v(·), respondents with bachelor

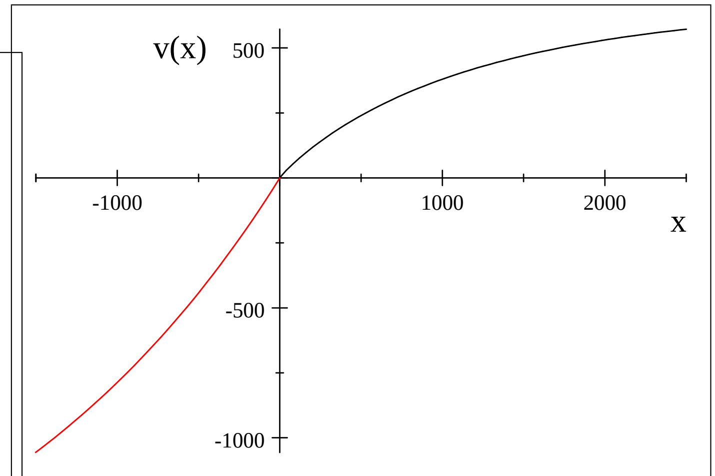

Figure OA4.7b: Estimated v(·), respondents without bachelor

The estimation results and the figures show that the findings of Section 4 of the paper are largely robust to the inclusion of background characteristics. All estimated preferences have essentially the same shape, and the estimated prevalence of broad bracketing (θ) lies below 0.22 in all subsamples. Likewise, almost all other parameter estimates are statistically indistinguishable between the pairs of subsamples. In a separate, unreported set of estimates, we also ran the analogous regressions without the restriction that $x_0 = 0$. The results are qualitatively identical to the ones presented here. In particular, all estimated preferences have the shape of prospect theory's value function – although the unrestricted model would allow for much more flexibility – and with a single exception, all estimates of θ lie below 0.3.[4]

But despite this robustness, there are some noticable differences between the subgroups. For example, male respondents have a significantly higher estimate of θ than female respondents. (In fact, women do not seem to integrate the choices at all, according to our estimates.) However, as

[4]The exception is the subsample of non-white respondents, whose estimate of θ lies at 0.4 without the restriction. This difference under the more general model may also help to explain the behavioral differences between this subgroup and its comparison group, as described later in the main text of this appendix. Other differences between the more general estimation and the one with $x_0 = 0$ were minor.

indicated in the table's last row and confirmed in the the regressions of Online Appendix 5, this difference is not strong enough to generate significant differences in the violation rates – respondents of both genders have virtually identical frequencies of dominance violations. The reason may lie in the stronger convexity of men's utilities in the domain below zero, which leads them to have a slightly higher rate of accepting unbalanced risks.

Older respondents appear to be more loss averse, as the slope of their valuation function is steeper below zero. Their frequency of making a dominated choice is 14% higher than that of younger respondents, but this difference, too, is mostly insignificant in the regression analysis of Online Appendix 5.

A stronger and more significant effect appears between white and non-white respondents. Non-whites are much more risk neutral towards lotteries around zero and in the domain above zero. This help them to avoid dominance violations, which is reflected in the fact that their violation rate is smaller than that of whites by 22%. The regressions in Online Appendix 5 indicate that this is mostly due to a strong difference in the behavior of hispanics.

Further differences are in the more risk-neutral preferences for the groups of high-income and math-skilled respondents, relative to their comparison groups. But again, the differences do not carry over to a statistically reliable effect on behavior: dominance violation rates for high-income respondents are almost identical to those of low-income respondents and about 9% lower for the resondents who gave 3 correct mathematics answers, but none of this is significant in logistic regressions. This discussion partially confirms recent studies by Benjamin, Brown and Shapiro (2006), Frederick (2006) and Dohmen et al (2007) who find that risk preferences change systematically with measures of IQ or mathematics skills.[5] Our evidence is consistent with these findings in that we also find more risk neutrality among the math-skilled respondents; but we do not find any robust effect on behavior, a discrepancy that may be due to the different pools of participants and/or to the different behavioral outcome variables. It is also worth pointing out that between the more and the less math-skilled respondents, we find no significant difference in θ. Hence, it appears that

[5] Their measures are comparable to our three numerical questions – one of our questions is equivalent to a question that is used in Frederick (2006) and Benjamin, Brown and Shapiro (2006).

it is not a question of numerical complexity that determines whether or not the decisionmakers integrate several choices into a joint choice problem. Even math-skilled respondents are susceptible to narrow bracketing, and therefore to making dominated choices.