Taring the Multiple Price List: Imperceptive Preferences and the Reversing of the Common Ratio Effect

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Abstract

The Multiple Price List (MPL) is a common method of measuring preferences in economics experiments. Many studies have noticed that the design of the list can affect subject choices. Measuring these effects could allow researchers using MPLs to control for it, and thereby make better predictions of out-of-sample behavior. We study the effect of status quo bias on choices in MPLs. We propose a simple model of a constant utility bias towards the status quo. This model makes different predictions that the Koszegi and Rabin (2007) model of reference dependence. In particular, although the reference dependent model predicts the "common ratio effect," whereby subjects become less risk averse the riskier their choices are, we find instead that subjects exhibit the common ratio effect in one treatment, but the reverse common ratio effect - becoming more risk averse when facing riskier choices - in another, as predicted by our constant status quo bias model. We also estimate a parametric model and find that the constant status quo bias model fits better.

Keywords Risk preferences, Status-quo bias, Intransitive Indifference.

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1. Introduction

Decision makers exhibit a bias towards the status quo (Samuelson and Zeckhauser, 1988). This fact presents a confound for researchers trying to elicit preferences whenever a status quo is present. The gap between willingness-to-pay and willingness-to-accept, often called the "endowment effect" (Kahneman et al., 1990), is an example of this phenomenon. An individual may have some underlying "true" valuation of, say, a coffee mug. But the economist's estimate of that valuation varies according to whether the individual is currently holding the mug or not. Status quo bias is a fog that clouds the economist's picture of the individual's preferences.

We would like to somehow remove this fog from the picture. But first we must understand what it looks like. Though status quo bias hangs thick and heavy over economic data, there is no consensus on what model best describes it. This paper suggests such a model.

The model that describes our data best is very simple - each option has some utility value when it is not the status quo; when it is the status quo, its utility value increases by a constant, which we parameterize as ν. Note that, being a constant, ν does not depend in any way on the characteristics of either the status quo or the other options available. It is a fixed utility bonus that the status quo enjoys.

This model, though simple, generates interesting and testable predictions that differentiate it from other models. Appendix A describes the model and its implications in more depth, but a simple example will illustrate the most important implication. Since our experiment will involve choices over gambles, so will our example. This example will show that, with the right options set as status quo, our model can generate the "common ratio effect," a commonly observed pattern in which people are less risk averse when all their choices become more risky (Starmer, 2000; Camerer, 1995; Harless and Camerer, 1994), but also the less commonly observed "reverse common ratio effect," in which the opposite happens.

Suppose a risk-neutral experiment subject with utility function $u(x) = x$, and a ν, the bonus given to the status quo, of 1. Suppose the status quo is a gamble paying \$10 with 28 percent chance, and \$0 with 72 percent chance. The subject would prefer to have instead \$4 for sure, since $.28 * 10 + 1 < 4$. But if a 50 percent chance of getting zero were added to both sides (this is an example of all choices becoming more risky), then the subject would choose the riskier \$10 gamble, since $.14*10+1 > .5*4$. This apparent violation of the independence axiom is the common ratio effect.

But suppose instead that \$4 for sure were the status quo. The subject would prefer instead a 58% chance of \$10, since $4+1 > .58*10$. Now mix both sides with a 50% chance of winning zero, so that it is a choice between a 50% chance of winning \$4, and a 50% chance of winning nothing, vs. a 29% chance of winning \$10, and a 71% chance of winning nothing. The subject chooses the safer gamble, because $.5 * 4 + 1 > .29 * 10$. This is the reverse common ratio effect.

We run an experiment motivated by the above example. In one treatment, the riskier option is the status quo. In another treatment, the safer option is the status quo. In both cases, mixing in some chance of winning \$0 increases the bias towards the status quo, just as our model predicts.

Observe that these effects are not simply an implication of the subject liking the status quo more. Rather, the effects are comparative, describing when the status quo is decisive, and when it is not. The intuition is that since in our model the status quo is a fixed utility term, it will be more decisive in lower stakes decisions. When the 50% chance of winning zero is mixed in, the utility difference between the two options shrinks, and the status quo bias looms larger.

Our model is dogmatic in its simplicity, to the point of making silly predictions on some choices. For instance, if \$1 for sure were the status quo, the subject would keep it rather than choose \$1.25 instead. A richer model might also somehow describe the complexity of the options available, but that is beyond our scope.

But even our simple theory makes predictions that diverge from the current status quo of status quo modeling, which is to follow (Kahneman et al., 1991) in framing status quo bias as loss aversion, with the status quo as reference point. It's easy to see how this leads to a bias in favor of the status quo. All other options represent a loss - at least in some domain - and those losses are weighted more heavily than any gains, making alternative options less attractive.

The extension of the KT reference dependent model in Koszegi and Rabin (2007) makes testable predictions on the size of status quo bias as a function of the status quo and the alternative options presented (recall that in our model this bias is constant). Some of these are tested and supported in Sprenger (2010). But this model also cannot predict the reverse common ratio effect that we find, no matter how the status quo is gerrymandered. We also estimate a parametric model that nests our ν term inside a reference dependent model, and still estimate our ν term to be significantly different from zero.[1]

Sprenger (2010) is also important to us since the paper's experiment uses, as we do, a multiple price list to induce a status quo. The multiple price list is a page with a list of binary choice. One option, which we will call the "fixed option," is included in all these choices, while the other one (the "variable option" improves as the list progresses). Sprenger (2010) paper argues, as we do, that the salience of the fixed option gives the subject some sense of ownership of it, and therefore makes it the default, status quo choice.

We are not alone in finding a "reverse common ratio effect" - i.e., subjects exhibiting increased risk aversion when each side of a binary choice is mixed with a chance of earning \$0. Freeman et al. (2012) find the reverse common ratio effect when offering subjects multiple price lists, as we do, but not when offering binary choices. The authors attribute this discrepancy to the fact that MPLs are not incentive compatible when the independence axiom fails, a feature also articulated by Harrison and Swarthout (2012).[2] We are able to generate both the reverse com-

[1]The reverse common ratio effect contradicts proposition 1 in Koszegi and Rabin (2007) that establishes that a person do not become more risk averse as risk is added to lotteries and reference lotteries. The common ratio effect is predicted for correlated lotteries in Bordalo et al. (2012) if agents correct probabilities according to its salience. It is not predicted if lotteries are not correlated.

[2]For a simple example of how this could matter, suppose that the subject does have preferences consistent with the common ratio effect, and prefers \$x for sure to a 50-50 gamble over \$0 and \$y, but prefers a 50-50 gamble over \$0 and \$x to a 75-25 gamble over \$0 and \$y. Now suppose you have the subject make two choices, one between \$x for sure and a 50-50 gamble over \$0 and \$y, and another between \$0 for sure and \$0 for sure. You tell her you will then flip a coin to determine which of the two choices is paid. But of course you have now generated a choice between a 50-50 gamble over \$0 and \$x and a 75-25 gamble over \$0 and \$y.

mon ratio effect and the common ratio effect using multiple price lists, suggesting that MPLs themselves are not the problem. We also show in Appendix B that no standard version of cumulative prospect theory applied over the compound lotteries implied by each MPL can explain our data.

Blavatskyy (2010) finds the reverse common ratio effect in binary choice by starting with pairs that include a risky option that is much more attractive than the riskless option. Since most subjects choose the riskier option in this first choice, more subjects end up with the pattern of choosing a risky option in the first choice, and then the safer option in the compounded choice. Blavatskyy (2010) suggests that the error rate on this second choice might be higher because utility differences are smaller. Our explanation also uses changing stakes in that we claim the status quo bias embedded in a MPL is stronger when the stakes are lower. But the use of MPLs also allows us to elicit a more precise indifference point than if we used only binary questions.[3] We also do not change the relative attractiveness of the risky vs. the safe option across our two treatments, which is how Blavatskyy (2010) is able to generate a reverse common ratio effect.

Butler and Loomes (2011) do find evidence of the common ratio effect using a MPL. In their lists, the more risky option is always the one kept fixed. This evidence is therefore consistent with the data from our treatment where we do find the common ratio effect.

The paper is organized as follows. Section 2 describes experimental procedures. Section 3 presents the experimental results. Section 4 concludes.

2. Experiment

All sessions took place in February and March 2013 at the ICES laboratory at George Mason University. One hundred and ten subjects participated, with an

[3] Loomes (2005) points out that binary choice experiments might confound the effect of random choice and preferences. A random utility model with homoskedastic errors predicts that a population of risk averse agents might choose less risk aversely if scaling down the probability of good outcomes makes options harder to distinguish. Blavatskyy (2010) gives an example of the opposite effect.

average earning of \$7.46 (s.d. \$3.73).[4] Sessions lasted approximately 30 minutes, and were conducted entirely on pencil and paper. Subjects within each session were randomized into one of two treatments, which we call A and B. Full instructions can be found in the appendix.

Each of the two treatments included 15 Multiple Price Lists (MPLs). An MPL is simply a page with a list of binary choices - the subject is presented with two options and must choose which one she likes best. For each MPL, there is one "fixed option" - an option that is included in each one of the binary choices. This fixed option is pitted against a series of alternatives. We refer to the alternative to the fixed option as the "variable option." The variable option is always at its least appealing on the first choice, and then becomes more attractive as the subject moves down the list. Here are a few rows from the middle of one of the MPLs:

	Option A			Option B
6)	24% chance of \$10.00,	76% chance of \$0.00	*or*	\$3.00 for sure
7)	27% chance of \$10.00,	73% chance of \$0.00	*or*	\$3.00 for sure
8)	30% chance of \$10.00,	70% chance of \$0.00	*or*	\$3.00 for sure
9)	33% chance of \$10.00,	67% chance of \$0.00	*or*	\$3.00 for sure
10)	36% chance of \$10.00,	64% chance of \$0.00	*or*	\$3.00 for sure

At the conclusion of the experiment, we randomly draw one row from one task, and the subject receives whatever lottery she chose in that row [5].

Both treatments begin with the same three MPLs, each of which compares has a fixed option of a high-payoff, low-probability lottery, and a variable option of a sure amount. For instance, in MPL 1, in row 1 the subject chooses between a 5% chance of winning \$60, with a 95% chance of winning nothing, and \$0.50 for sure. In the final row, the subject chooses between the lottery and \$6.00 for sure. MPLs 2 and

[4] Two subjects are not included in the analysis because they did not complete the tasks.

[5] Both these randomizations were done by the throw of a die, with at least one subject observing the throw.

3 involve payoffs in the fixed lottery of \$80 and \$160, respectively. In each case, the row at which the subject switches from the fixed option to the variable option gives bounds on the subject's willingness-to-pay for the lottery.

Starting with MPL 4, the two treatments differ. In MPL 4, both treatments have \$3 for sure as the fixed option, while the variable option is a p per cent chance of earning \$10, with p increasing as the subject goes down the list. The only difference is that in treatment A, the fixed option is Option A (on the left hand side of the list), while in treatment B, the fixed option is Option B (on the right hand side). MPL 5 brings greater differences between the two treatments. Treatment A has a fixed option of a 66% chance of \$3 and a variable option a p per cent chance of winning \$10, with p increasing from a 2% at the top of the list to 30% at the bottom. Treatment B instead has a fixed option of a 20% chance of \$10, and a variable option of a p per cent chance of \$3, with p increasing from 50% at the top of the list to 76% at the bottom. Both MPLs have as their eighth row the (almost) risk-neutral choice between a 20% chance of \$10 and a 66% chance of \$3. MPL 6 is similar, except with all probabilities of winning cut in half, so that the fixed option in Treatment A is a 33% chance of \$3 in Treatment A, and the fixed option in Treatment B is a 10% chance of \$10 in Treatment B.

MPLs 7-9 and 10-12 follow the pattern of MPLs 4-6, starting with an option of a sure payment, then moving to smaller and smaller chances of winning the same amounts. The only differences are in payoffs and the amount of \$0 lottery mixed in to each option.

While in MPLs 4-12, the probability of winning a prize in the variable option changes across rows, in MPLs 13-15, the dollar amounts of the prizes themselves change. In Treatment A of MPL 13, the fixed option is \$4 for sure, while the variable option is a 40% chance of \$x, which varies across rows. MPL 14 is simply 50% of MPL 13, so that the fixed option as a 50% chance of \$4, and the variable option a 20% chance of \$x. MPL 15 is half again, so a fixed option of a 25% chance of \$4, versus a 10% chance of \$x. Similarly, in Treatment B, MPL 13 has a fixed option of a 40% chance of \$10, while Option B is a variable amount \$x for sure. Options in MPL 14 are then 50% chances of the options in MPL 13, and MPL 15 options half again.

Table 1 provides a summary of the choices offered in each MPL.

3. Results

Our model of status quo bias predicts that: (1) subjects will exhibit the common ratio effect in Treatment B, where the riskier options are fixed, (2) subjects will exhibit the reverse common ratio in Treatment A, where the safer options are fixed, and (3) the effect of the bias decreases with the stakes of the lottery - lower probability of non-zero outcomes and larger prizes. You can think of 1) and 2) as following from 3) and the existence of status quo bias on the fixed option: When we mix more of the zero-payoff lottery into each option in order to look for the common ratio effect, we descrease the stakes, and therefore increase the effect of status quo bias. When the fixed option is the riskier lottery, the increasing bias towards the fixed option looks like the common ratio effect. When the fixed option is the safer lottery, it looks like the reverse common ratio effect.

We now turn to the data to test these hypotheses. Each MPL gives us a a raw probability eqivalent - the probabilty of winning in the varying option that makes the subject indifferent between the varying option and the fixed option.[6][7] Above this probability, the subject certainly prefers the higher prize gamble. For instance,

[6]All the results are based on individual decisions that are consistent only. By this we mean that calculations and tests are performed using only those answers to MPLs that switched at most once. Seventy subjects made consistent choices in all 15 tasks and 15 subjects made consistent choices in 14 tasks. The average (s.d.) number of inconsistent tasks per subject is 1.47 (3.20).

[7]Of course, since we have a discrete list, the row where the subject switches from choosing the fixed option to the variable one gives only bounds on the point of indifference, not the point itself. The question then arises of what point to choose. Setting the indifference point at the last row where the fixed option was chosen, or the first row that the variable option was chosen, would confuse our comparisons across treatments. Since the difference in treatments is whether the fixed option is the risky or the safe one, in one treatment we would be choosing the upper bound on risk aversion, in the other treatment,the lower bound. To avoid this, we define the probability equivalent as the minimum probability on the higher prize gamble such that the subject prefers the higher prize gamble to the lower prize gamble. But even if we make the most conservative possible assumptions - that is, assume indifference at the point in the interval which minimizes our results - we still find our main effects.

a probability equivalent of 0.353 in MPL 4 (where \$3 for sure is the fixed option and \$10 with probability p is the varying option) means that, on average, subjects need to receive \$10 with probability 0.353 in order to prefer such lottery to receiving \$3 for sure. Figures 1, 2, and 3 graph these raw probability equivalents for each MPL in each Treatment.

Expected utility theory makes a sharp prediction on the relationship between probability equivalents within each figure. When we mix in a $\frac{1}{3}$ chance of winning zero on each side, probability equivalents should be reduced by $\frac{1}{3}$. For instance, if the subject were indifferent between a 36 percent chance of winning \$3 and having \$10 for sure, they should also be indifferent between a 24 percent chance of \$3 and a $\frac{2}{3}$ chance of winning \$10. The red lines in Figures 1-3 show this important benchmark. They show what an expected utility maximizer *would* choose, if she had a true probability equivalent equal to the sample mean in the first task of the triplet.

The blue lines represent the actual sample mean for each MPL. For Treatment A, on the left side of each panel, a higher number means more risk aversion - the subject requires a higher probability of winning the risky lottery to switch to it. For Treatment B, on the right side, a higher number means less risk aversion - the subject requires a higher probability of winning the *safer* lottery to switch to it. Our main result can be seen by the fact that the blue line lies to the right of the red one in each panel. This shows that on the second and third MPLs of each group, subjects require a better lottery to switch to the variable option than you would predict based on their responses in the first MPL, if you thought they were perfect expected utility maximizers.

Tables 2, 3 and 4 show statistical tests of the difference between the red and the blue lines. The top panel present data from Treatment A, with the safer option fixed; the bottom panel presents data from Treatment B, with the riskier lottery fixed. In order to make the numbers easy to compare, we have rescaled each probability equivalent so that they show what probability of winning the higher prize would make an expected utility maximizer indifferent between that lottery and winning the lower prize for sure, given her raw probability equivalent.

For instance, in Table 2, the first column just presents the raw probability equivalents, since this first MPL already finds an indifference point between some probability of winning the higher amount, in this case \$10, and a 100 percent chance of the lower amount, in this case \$3. The second column in Treatment A uses data from an MPL which has a 66 percent chance of winning \$3 as a fixed option. Suppose the subject is indifferent between this lottery and a 30 percent chance of \$10. If the subject were an expected utility maximizer, then this would say that $.66u(3) = .3u(10)$, which implies that $u(3) = \frac{100}{66}.3u(10)\ .45u(10)$. This probability on the right hand side then gives us what we were looking for - probability of winning \$10 would make an expected utility maximizer indifferent between that lottery and winning \$3 for sure, given that she was indifferrent between 66 percent chance of winning \$3 and a 30 percent chance of \$10. It is always calculated by taking the probability on the higher prize at the point of indifference, and multiplying it by the reciprocal of the probability on the lower prize. This is the statistic in column 2.

If subjects were expected utility maximizers, then the adjusted probability equivalent would be the same across treatments and across columns. The last row of the table presents the rank sum test of no treatment effects across each set of paired lotteries. We first observe that there are no statistically significant differences in pre-existing preferences across treatments. For the first column of each table (MPLs 4, 7, and 10) where the options given are exactly the same across treatments, we cannot reject the hypothesis that probability equivalents are the same.

In the second and third columns, we reject the hypothesis of no treatment effect with a p-value of less than 0.01 in ever case but one, in which the p-value is 0.0165. Clearly which option is kept fixed makes a difference in the elicitation of preferences.

We can look for the common ratio and reverse common ratio effect by comparing probability equivalents across columns within the same row. Again, for an expected utility maximizer, these numbers would all be the same. The stars next to each number classify the p-values of a rank sum test of no difference with the column to the right (for the right-most column, the comparison is with the left-most column). In the top half of Table 2, we see the probability equivalent increasing significantly - that is, the subjects are requiring a higher probability of winning \$10 in order to like that lottery just as much as the higher chance of winning \$3. This means that the subjects are getting more risk averse from the first MPL to the second and third - this is the reverse common ratio effect. As predicted by our model, this occurs when the fixed option is safer. In the bottom half of Table 2 we see the opposite - the probability equivalents are decrease from left to right, meaning the subjects exhibit the common ratio effect by becoming less risk averse. This occurs when the fixed option is riskier. Table 3 shows the same pattern.

Table 4 also suggest that, consistent with the theory, the distortion of preferences is smaller as payoffs are scaled up. In the same way that status quo bias has a larger effect when the stakes are scaled down by mixing in a zero-payoff lottery, the effect is smaller when stakes are increased to \$20 and \$8 rather than \$10 and \$3 or \$4. The results are consistent with subjects being unable or unwilling to distinguish among options as they become closer to each other, and defaulting in these cases to the fixed option.

Tasks 13 through 15 provide additional evidence in support of our model. In these MPLs, the right hand options vary in the dollar amounts of the prizes rather than the probability of winning. Because of the structure of these lists, we cannot calculate probability equivalents in a manner similar to the other triplets. However for each MPL, the two lotteries have one row in common: the risk neutral choice between \$4 with probability p and \$10 with probability $.4p$, where p is equal to $1, .5$, and .25 in MPLs 13,14, and 15, respectively.

Recall that the theory predicts that 1) an option will be chosen more often when it is fixed 2) the lower the "stakes" get (that is, the lower the p), the stronger the effect. Table 5 presents the data from these choices. The t-tests at the bottom of the columns represent tests on the differences within task, across treatment, while the others represent tests of differences within treatment, across tasks, in comparison to task 13.

Overall, subjects are quite risk loving in these tasks. In fact, subjects are even *more* risk loving in Treatment A, with the \$4 lottery fixed, in contradiction to the theory. However this switches in Tasks 14 and 15, since subjects become more risk averse in Treatment A and more risk loving in Treatment B. That is, their adherence to the fixed option strengthens as stakes decline, following the predictions of the theory.

These tasks also offer an opportunity for interesting within-subject comparisons with MPLs 7-9, where probabilities vary instead of payoffs. In Treatment A, MPL 7 fixes the sure payment of \$4. The same is true for MPL 13 which fixes \$4 and varies the prizes of a lottery that pays with 40 percent probability. Both tasks offer the same choice in row 8, between those two options. Despite the choices being identical, responses vary significantly ($p = 0.08$) across the two tasks. In task 7, 27 of the 53 subjects choose the sure \$4 payment. In task 13, only 18 choose the sure payment. In Treatment B, both tasks 7 and 13 fix a \$10 with 20% probability lottery, the only difference being that Task 7 varies probability of payoff, while Task 13 varies payoff amount. Here we find again a significant ($p = 0.041$) tendency towards risk taking in Task 13 vs. Task 7.

We next discuss results regarding preferences for gambling in low-probability high-payoff lotteries.

Table 6 present the average certainty equivalents for the lotteries paying \$60, \$80, or \$160 with 5% probability. As mentioned in the experimental design section, subjects in both treatments were asked these questions and they were presented in the same format. Table 6 shows that certainty equivalents are, on average, above the expected value of the lottery (\$3, \$4 and \$8). Subjects are, on average, risk loving over these lotteries. While the certainty equivalent of a lottery is not always significantly different from the expected value for each treatment separately, they are significantly above the expected value of the lottery across both treatments (p-value = 0.0002, 0.0101 and 0.0701 respectively). The proportion of subjects with certainty equivalents strictly larger than the expected value of the lottery confirms that risk loving behavior is modal in these lotteries. Finally, Table 6 shows that there are no statistically significant differences in risk preferences over these lotteries across treatments.

We also estimate a parametric model. The model we estimate is a random utility model with an added bias towards the fixed option. We estimate the amount of this bias, denoted ν, as well as other standard preference parameters such as the coefficient of relative risk aversion for our assumed CRRA utility function, and a parameter for probability weighting. Table 7 presents these results. Note that ν is significantly different from zero.

Figure 5 presents the distribution of ν, here estimated separately for each individual subject, by treatment. The two distributions are not signficiantly different from each other (two-sided t-test 0.49).[8]

Since the reference-dependent utility model of Koszegi and Rabin (2007) is both a popular model for risky choice in general and has been applied to choices from MPLs by Sprenger (2010), we also estimate a model with our status quo bias parameter ν nested inside a reference dependent model. We first estimate a model where we estimate one set of parameters for all subjects (Table 8, columns 1-3). We find a loss-aversion coefficient greater than one, as is standard, and still estimate our status quo bias parameter ν to be significantly greater than zero. We then estimate a model with only ν allowed to vary across subjects (columns 4-6). Here again we find the average estimate of ν across subjects (the SQ bias constant + individual dummy) to be positive and statistically different from zero.

Finally, we try to estimate all parameters at the individual level. Estimation for some subjects does not converge, since we are trying to estimate a model with several parameters on a limited amount of data. But the distribution of ν for the subjects that do converge is shown in Figures 2 and 3. Figure 2 shows the distribution of ν only those subjects with $|\nu| \leq 2$, while Figure 3 shows the distribution of ν for subjects with $|\nu| \leq 10$. In both cases, the distribution is shifted to the right of zero, showing that the status quo bias parameter estimate remains positive even when loss aversion is included in our model.

4. Discussion and Conclusion

We have proposed that status quo bias coupled with imperceptive preferences have unique behavioral implications. These behavioral patterns do not always coincide with received wisdom. In multiple price lists, subjects starting out with the fixed option continue to give a utility bonus to this option in all choices. The set of

[8]We could not estimate individual parameters for 6 subjects.

results from our experiment are consistent with this model, and inconsistent with any of the other models for risky choice, both those that propose a non-expected utility structure to preferences, such as the u-v model (Andreoni and Sprenger, 2012) or the reference dependence model.

The effects we find are not unique to risk preferences. Working with probability equivalents is particularly useful because we know how much we are scaling down the grid in utility terms for an expected utility maximizer. When a change in probability is reduced by one-half, the change in utils is also reduced by one-half. But the model that we have proposed can be applied to any multiple price list setting. For instance, consider time preferences. Suppose that you have two MPLs. The first is a \$50 payment in one month as the fixed option, and some payment today as the variable option. The second offers a \$50 payment in seven months as the fixed option, but some payment in six months as the variable option. Since the discounted payments in the second list offer lower utility levels, it will take a larger sooner payment to motivate the subject to switch from the fixed option to the sooner one, generating what appears as present bias.

Consider also two lists, each with a \$25 payment today as the fixed option. In one list, the variable option is a payment in one month, in the other, a payment in six months. Our model again predicts that the subject will appear more patient in the second list, as present bias would predict. The reason is that the initial "cost" of moving from the fixed present option to the variable later option is amortized over more periods in the six month list, similar to the "fixed cost" discounting model presented in Benhabib et al. (2010).[9]

Status quo bias does not encompass all of the ways in which list construction can affect preferences. For example, this model will not be able to generate the tendency

[9] To be precise, again let ϵ be the amount by which the subject must prefer the variable option in order to switch. A risk-neutral exponential discounter with discount factor δ then choses the switch point $\hat{x}_1$ to solve $25 + \nu = \delta x_1$. The experimenter, thinking that the subject is instead solving $25 = \delta x_1$, uses this relationship to estimate $\hat{\delta_1} = \frac{25}{x_1}$. Since in actuality $x_1 = \frac{25+\nu}{\delta}$, $\hat{\delta_1} = \delta\frac{25}{25+\nu}$. By similar reasoning, the δ estimated from the six-month list, $\hat{\delta}_6$, would be $\hat{\delta}_6 = \delta(\frac{25}{25+\nu})^{\frac{1}{6}} > \hat{\delta}_1$, so that there is the appearance of hyperbolic discounting.

to switch towards the middle of a list, nor the effects of changing the dimension along which the variable option varies, as in Eil (2012).[10] [11] Subjects also have a tendency to switch near the middle row of a MPL. Therefore the exact grid chosen for the variable option can skew preferences (Beauchamp et al., 2011; Harrison et al., 2005, 2007b; Andersen et al., 2006; Harrison et al., 2007a). Beauchamp et al. (2011) is in particular similar in spirit to our paper, as the authors show that they can generate or eliminate the appearance of reference dependence based on how they frame their MPLs.

Subjects also tend to express different preferences when facing MPLs as opposed to one-shot binary choices. This effect has been seen by the literature as a failure of the independence axiom and/or lottery reduction. Since typically each row in an MPL has a small chance of being selected for payment, the choice represents not simply a choice between the two lotteries described, but a choice between two lotteries describing all the possible outcomes in the experiment, differing only in the gambles described in the given row. When many choices are made, the researcher must then assume the independence axiom to infer that a subject's choice between one of two options in a given row would always represent their preference, regardless of whatever other kind of risk they face (Karni and Safra, 1987; Holt, 1986; Harrison and Swarthout, 2012). Freeman et al. (2012) explores this possibility of failure of this assumption and finds the common ratio effect for binary choice but the reverse

[10] Although it could resolve a result from Eil (2012) that the paper itself does not. The main result of the paper is that when subjects are asked how long they are willing to wait for a later payment of a fixed amount vs. a now payment of a fixed amount, they exhibit "future bias", in that their willingness to wait does not change enough as a function of the amount of the later payment. A secondary result is that they also look future biased when the now payment is shifted forward six months, although these MPLs mirror exactly the mixing in of the $0 for sure lottery in our paper here.

[11] Cubitt et al. (2004) shows a similar issue with what they call an "ordinal" design. Instead of choosing directly between Lottery A and Lottery B, subjects measure each lottery on a "yardstick." In one treatment, the yardstick measures dollars to be won for sure (the certainty equivalent). In another, it measures probability of winning a dollar amount (the probability equivalent). Importantly, in both cases, the subject simply gets the lottery that is ranked higher on the yardstick, so that the rankings imply the same consequences, no matter which yardstick is used. Still, there are significant treatment effects.

common ratio effect for MPL elicitation. However, Cubitt et al. (2004) presents evidence suggesting that preference reversals are not due to failure of either the independence axiom or lottery reduction. Our paper suggests the same.

So are we left with any hope for the Multiple Price List? Multiple price lists have many attractive qualities. They are relatively easy for subjects to understand. Researchers can gather a large amount of data for a relatively low cost by randomly selecting one choice for payment. At typical experimental stakes, however, subjects may not have very strong preferences between the options given, and might not expend the effort to select the choice that represents their true underlying preference. If "errors" in choice were independent of the choice given and unbiased, then more data would be the answer. But when errors are biased towards one option, and this bias is more significant in relative terms in some tasks than others, even broad patterns of choices in MPLs may not reflect underlying preferences.

We are also not alone in worrying about choice biases affecting estimates of preferences. In addition to all the papers on MPLs cited above, Cason and Plott (2014) shows that many subjects misunderstand the Becker-DeGroot-Marschak mechanism as a first-price auction, whereas it is actually a second-price auction. They argue that this confusion has led to much spurious theorizing about the preferences that drive subject behavior, when in fact the choices come from misunderstanding rather than preference. Chetty (2012) hypothesizes choice "frictions" that prevent people from reacting to a change in their environment when the utility cost of ignoring the change is small enough. He then derives bounds on what the true elasticities must be for a given elasticity estimate. In some sense, we are engaged in the complementary exercise - instead of assuming some amount of friction and deriving the effect on behavior, we estimate the effect of the friction on behavior, and use that estimate to back out what the level of friction must be.

Both of the papers described in the previous paragraph posit some "true" or "structural" preference parameters, that exist independent of the biases and frictions they describe confound. Cason and Plott (2014) argue forcefully that confusing a second-price auction for a first-price auction has nothing to do with a subject's preferences. That this misunderstanding represents a mistake rather than a choice.

Chetty (2012) is slightly less dogmatic, suggesting that "adjustment costs, inattentive agents, or status quo biases" or all of the above could be causing optimization frictions. But he still maintains the existence of structural parameters, and gives them primacy in welfare analysis. By contrast, Sprenger (2010) describes the endowment effect that he describes as a true change in the utility function. A preference, not a mistake or an obstacle to picking the best option - a change in the identity of the best option. We take no stand in this debate, but rather aim at a more humble and practical target - to better predict the subject's behavior when she faces a similar, but differently framed, decision. The change in behavior could be from preferences changing or from a bias moving in the opposite direction. All that matters to us is that we can describe the choice patterns. We certainly don't believe that we have found that the common ratio effect was a myth all along.

Status quo bias in MPLs is testable and measurable. Identifying the nature of these biases is important because it could help *correct* individual measures of preferences and extrapolate behavior to other context independently of the underlying decision theory.

There may be heterogeneity in the degree to which subjects are influenced by this sort of framing. The framing effect may also correlate with other behavior of interest and therefore cloud the vision of researchers interested in correlating, say, risk preferences, with other behavior. It may be that this has been a cause of some of the difficulty researchers have had in estimating risk preferences consistently within an individual across instruments, and also correlating measured risk preferences with risky field behavior. These are aspects of the instruments we use that we need to understand better, the same way that a doctor considers white coat syndrome or a patient's age when interpreting a blood pressure reading. Without such an understanding, the instrument's measurements are much less valuable.

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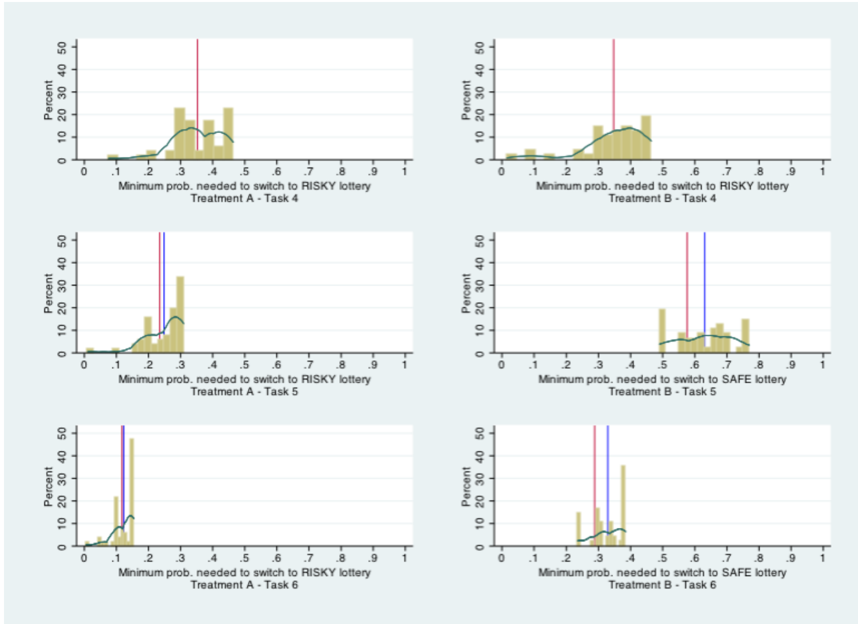

Figure 1. Lotteries based on $H = \$10, M = \$3, L = \$0$

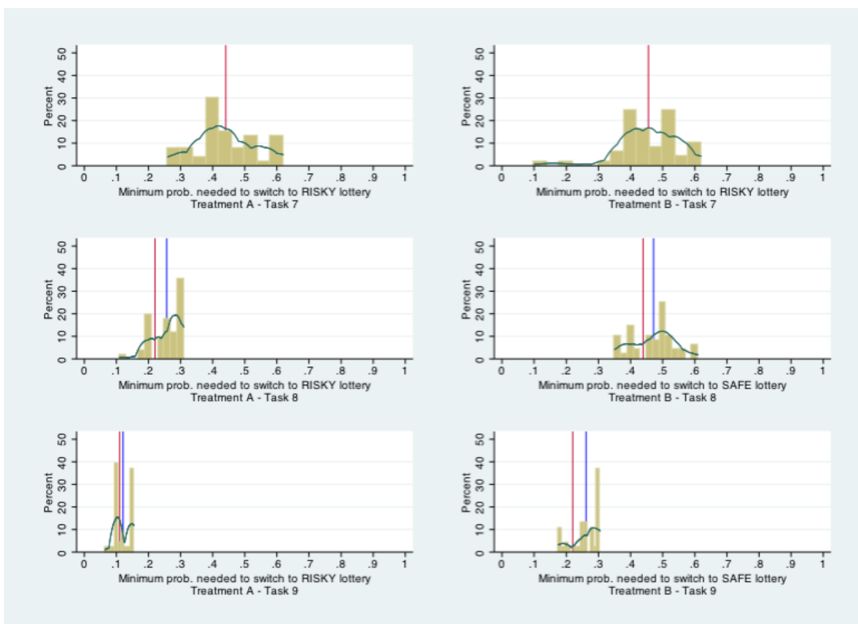

Figure 2. Lotteries based on $H = \$10, M = \$4, L = \$0$

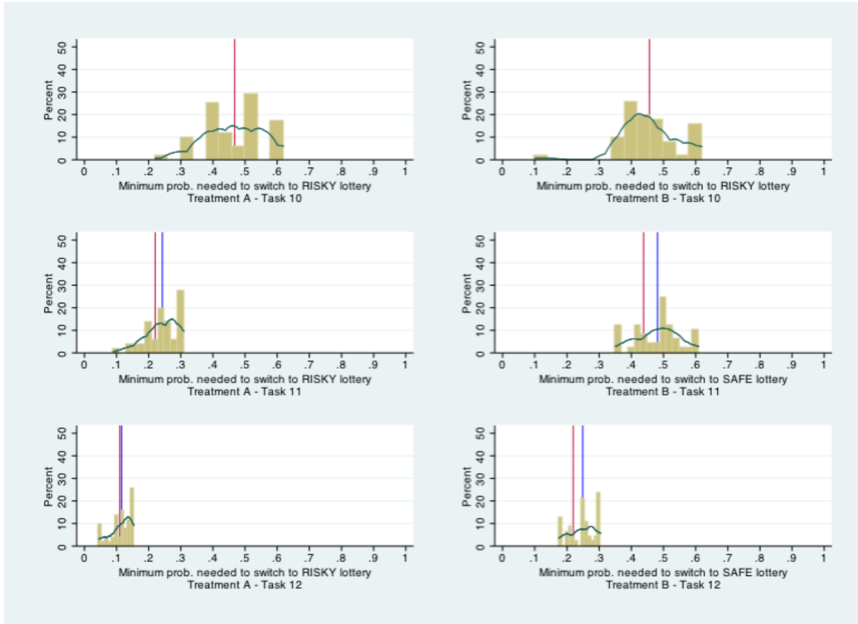

Figure 3. Lotteries based on $H = \$20$, $M = \$8$, $L = \$0$

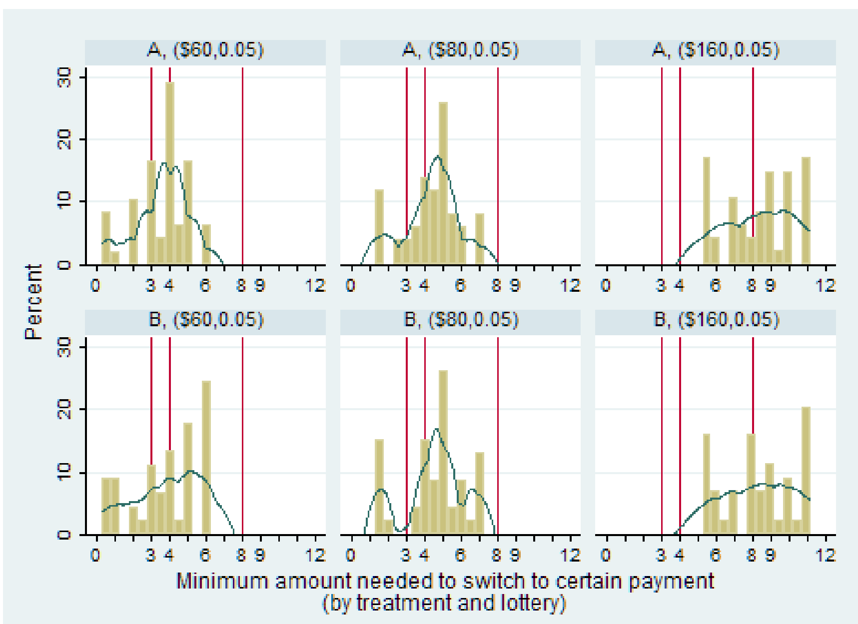

Figure 4. High stakes lotteries

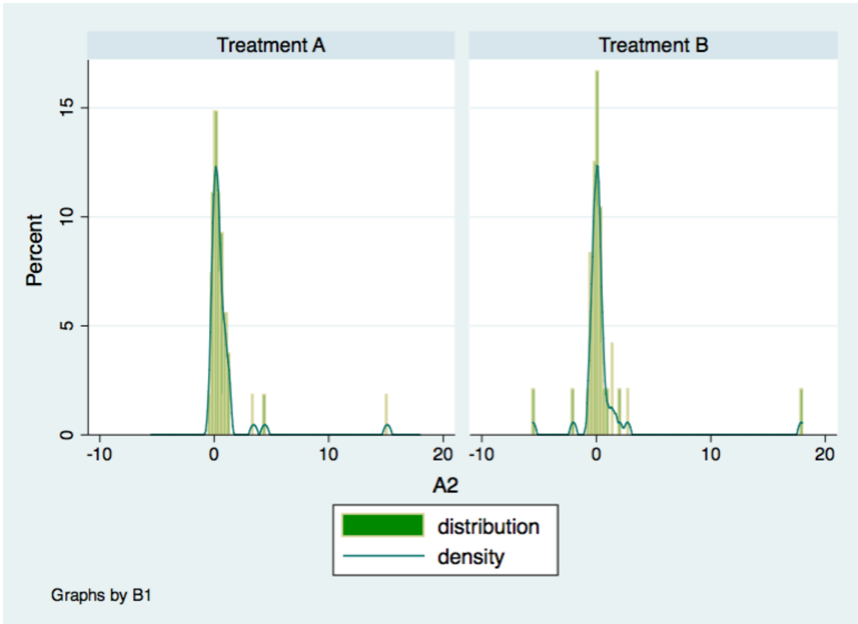

Figure 5. Distribution of Individually-Estimated Gamma by Treatment

Table 1: Task Descriptions Across Treatments.

	Treatment A			Treatment B		
	Fixed Option	Variable Option		Fixed Option	Variable Option	
Task Number		Variable	Fixed		Variable	Fixed
1	5% chance $60	Dollar amount	100% chance	5% chance $60	Dollar amount	100% chance
2	5% chance $80	Dollar amount	100% chance	5% chance $80	Dollar amount	100% chance
3	5% chance $160	Dollar amount	100% chance	5% chance $160	Dollar amount	100% chance
4	$3 for sure	Win prob	$10 prize	$3 for sure	Win prob	$10 prize
5	66% chance $3	Win prob	$10 prize	20% chance $10	Win prob	$3 prize
6	33% chance $3	Win prob	$10 prize	10% chance $10	Win prob	$3 prize
7	$4 for sure	Win prob	$10 prize	$4 for sure	Win prob	$10 prize
8	50% chance $4	Win prob	$10 prize	20% chance $10	Win prob	$4 prize
9	25% chance $4	Win prob	$10 prize	10% chance $10	Win prob	$4 prize
10	$8 for sure	Win prob	$20 prize	$8 for sure	Win prob	$20 prize
11	50% chance $8	Win prob	$20 prize	20% chance $20	Win prob	$8 prize
12	25% chance $8	Win prob	$20 prize	10% chance $20	Win prob	$8 prize
13	$4 for sure	Prize amount	40% chance	40% chance $10	Prize amount	100% chance
14	50% chance $4	Prize amount	20% chance	20% chance $10	Prize amount	50% chance
15	25% chance $4	Prize amount	10% chance	10% chance $10	Prize amount	25% chance

Table 2. Probability equivalents

Lotteries based on $H = \$10, M = \$3, L = \$0$

		Lottery		
Treatment A:	Fixed	(\$3,1) v.	(\$3,0.66) v.	(\$3,0.33) v.
	Variable	(\$10,0.3)	(\$10,0.2)	(\$10,0.1)
Mean		0.353***	0.377	0.372***
Standard deviation		0.080	0.091	0.101
% of risk takers+		11.32	13.73	11.80
Subjects++		53	51	51
Treatment B:	Fixed	(\$3,1) v.	(\$10,0.2) v.	(\$10,0.1) v.
	Variable	(\$10,0.3)	(\$3,0.66)	(\$3,0.33)
Mean		0.347**	0.331+	0.317***
Standard deviation		0.100	0.047	0.053
% of risk takers+		14.89	25.53	41.67
Subjects++		47	47	48
H_0:no-treatment effect		0.8421	0.0002	<0.0001
Rank sum test (p-value)				

*** p<0.01, ** p<0.05, * p<0.10, +p<0.15

+Probability equivalent less than 0.4.

++Only consistent choices within task.

Table 3. Probability equivalents

Lotteries based on $H = \$10, M = \$4, L = \$0$

		Lottery		
Treatment A:	Fixed	(\$4,1) v.	(\$4,0.5) v.	(\$4,0.25) v.
	Variable	(\$10,0.4)	(\$10,0.2)	(\$10,0.1)
Mean		0.441***	0.514	0.483*
Standard deviation		0.092	0.090	0.100
% of risk takers+		18.87	5.88	6.52
Subjects++		53	51	46
Treatment B:	Fixed	(\$4,1) v.	(\$10,0.2) v.	(\$10,0.1) v.
	Variable	(\$10,0.4)	(\$4,0.50)	(\$4,0.25)
Mean		0.456	0.449***	0.405***
Standard deviation		0.099	0.065	0.077
% of risk takers+		12.24	14.58	50.00
Subjects++		49	48	46
H_0:no-treatment effect		0.2440	0.0003	<0.0001
Rank sum test (p-value)				

*** p<0.01, ** p<0.05, * p<0.10, +p<0.15

+Probability equivalent less than 0.4.

++Only consistent choices within task.

Table 4. Probability equivalents

Lotteries based on $H = \$20, M = \$8, L = \$0$

		Lottery		
Treatment A:	Fixed	(\$8,1) v.	(\$8,0.5) v.	(\$8,0.25) v.
	Variable	(\$20,0.4)	(\$20,0.2)	(\$20,0.1)
Mean		0.468	0.485	0.463
Standard deviation		0.091	0.102	0.130
% of risk takers[+]		11.53	13.72	21.57
Subjects[++]		52	51	51
Treatment B:	Fixed	(\$8,1) v.	(\$20,0.2) v.	(\$20,0.1) v.
	Variable	(\$20,0.4)	(\$8,0.50)	(\$8,0.25)
Mean		0.456	0.439	0.426**
Standard deviation		0.090	0.066	0.077
% of risk takers[+]		11.76	20.40	34.04
Subjects[++]		51	49	47
H_0:no-treatment effect		0.4608	0.0029	0.0165
Rank sum test (p-value)				

*** p<0.01, ** p<0.05, * p<0.10, +p<0.15

[+]Probability equivalent less than 0.4.

[++]Only consistent choices within task.

Table 5. Fraction of subjects choosing \$10 in row 8 of Tasks 13-15

	Task 13 (\$4,1) v. (\$10,0.4)	Task 14 (\$4,0.5) v. (\$10,0.2)	Task 15 (\$4,0.25) v. (\$10,0.1)
Treatment A (\$4 lottery fixed)	0.660	0.521	0.500
H_0:no-scale effect (p-value)	–	0.158	0.105
Subjects+	45	47	49
Treatment B (\$10 lottery fixed)	0.578	0.596	0.693
H_0:no-scale effect (p-value)	–	0.862	0.248
Subjects+	51	51	51
H_0:no-treatment effect t-test (p-value)	0.408	0.466	0.053

*** $p<0.01$, ** $p<0.05$, * $p<0.10$, +$p<0.15$

+Only consistent choices within task.

Table 6. High stakes lotteries

	(\$60,0.05)	(\$80,0.05)	(\$160,0.05)
Treatment A			
Mean	3.55**	4.34+	8.36
Standard deviation	1.44	1.48	1.90
Percent of risk taking subjects	62.5	60.0	57.4
Subjects+	48	50	47
Treatment B			
Mean	3.81***	4.51**	8.38
Standard deviation	1.86	1.68	1.95
Percent of risk taking subjects	64.4	63.0	53.3
Subjects+	45	46	44
Test of no-treatment effect	0.3114	0.5460	0.9840
Rank sum test (p-value)			

H_0:Mean equals EV(L), *** p<0.01, ** p<0.05, * p<0.10, + p<0.15

+Only consistent choices within task.

Table 7. Parametric estimation (Decisions 4-12)

	(1)	(2)
σ^1	0.133 (0.000)	0.089 (0.000)
γ^2	0.985 (0.000)	1.033 (0.000)
τ^3	0.507 (0.000)	0.551 (0.000)
ν^3		0.184 (0.002)
Log-Likelihood	-6310.9	-6213.9
N	12,636	12,636
Individuals	108	108

clustered p-values in parentheses

[1] Utility function: $u(x) = \frac{x^{(1-\sigma)}}{1-\sigma}$

[2] Weighting function: $w(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{\frac{1}{\gamma}}}$

[3] Random utility model: $EU(L_A) = u(H_A)w(p_H) + u(L_A)(1 - w(p_H))$, $Pr(L_A \succeq L_B) = Pr(EU(L_A) + \nu + \tau\epsilon_A > EU(L_B) + \tau\epsilon_B)$

Table 8: ML estimates of Koszegi-Rabin model

Variable	Tasks included in estimations					
	4-12	1-12	1-15	4-12	1-12	1-15
η^1	1.432***	6.477***	5.370***	1.520***	3.178***	3.256***
	[0.214]	[0.694]	[0.444]	[0.519]	[0.572]	[0.334]
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
λ^1	1.095***	5.673***	4.931***	1.761*	2.671***	3.005***
	[0.317]	[0.638]	[0.556]	[0.939]	[0.608]	[0.398]
	(0.001)	(0.000)	(0.000)	(0.061)	(0.000)	(0.000)
τ^2	1.270***	1.155***	1.107***	1.129***	1.143***	1.081***
	[0.102]	[0.075]	[0.071]	[0.050]	[0.084]	[0.071]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SQ constant (ν)	0.417***	2.388***	1.948***	-0.961**	-2.284***	-1.923***
	[0.138]	[0.471]	[0.383]	[0.389]	[0.402]	[0.199]
	(0.003)	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)
				Individual dummies not shown		
Average of individual dummies + SQ constant (ν)				1.291***	1.452***	1.426***
				[0.317]	[0.289]	[0.189]
				(0.000)	(0.000)	(0.000)
Observations	12636	18144	22356	12636	18144	22356
log-likelihood	-6398.6	-9725.7	-12021.5	-5377.3	-8790.8	-10958.4

standard errors in brackets, p-values in parentheses

[1] All the estimations assume that the reference point is the lottery kept fixed in the MPL. For lotteries F and G, with F and G representing cumulative distributions over payoffs, the expected utility of lottery G given reference lottery F is: $Eu(G:F) = \int\int\{x + 1[x > y]\eta\lambda(y-x) + 1[x \leq y]\eta(y-x)\}dG(y)dF(x)$. Estimates of parameters η and λ are presented in the table above.

[2] Given the expected values of lottery L_A and L_B, the assumed random utility model is: $Pr(L_A \succeq L_B) = Pr(EU(L_A) + \nu + \tau\epsilon_A > EU(L_B) + \tau\epsilon_B)$

6. Appendix A

In this section we discuss the implications that imperceptive preferences, with indifference broken in favor of the status quo, have in the evaluation of risky prospects. Following the experimental design, we concentrate on simple lotteries $L \in M, L = (x, p)$ such that lottery L pays x ($x > 0$) with probability p and 0 with probability $1-p$. Whenever the set of preferences over lotteries $\succeq$ is complete and transitive, we say that utility function $U : M \to R$ represents preferences $\succeq$ if for all $L_i, L_j \in M$ we have that $L_i \succeq L_j$ if and only if $U(L_i) \geq U(L_j)$. Conversely, if such a representation of any preferences exists, then those preferences are transitive. More generally, preferences $\succeq$ might be composed of a transitive strict preference relation $\succ$ and an intransitive indifference relation $\sim$. A common argument why indifference relations might be intransitive is limited perception (Luce, 1956). We say that these preferences are represented by functions $U : M \to \mathbb{R}, V : M^2 \to R_+$ if $L_i \succ L_j$ if and only if $U(L_i) - U(L_j) > V(L_i, L_j)$ and $L_i \sim L_j$ if and only if $U(L_i) - U(L_j) \leq V(L_i, L_j)$. A binary relation that can be represented this way is said to have a numerical representation via utility function with error (Özbay and Filiz, 2005).

This framework accommodates several representations of preferences. A common representation is given by monotone and continuous functions $U(L) = u(x)p$ or $U(L) = u(x)g(p)$ and $V(L_i, L_j) = (\alpha U(L_i))^\beta (\alpha U(L_j))^\beta$ where $U : R \to R$ and $g : [0, 1] \to [0, 1]$ (Özbay and Filiz, 2005). Luce (1956) provides the necessary axioms of preferences such that they can be represented by functions $U(L) = u(x)p$ and $V(L_i, L_j) = \lambda > 0$.

Suppose that preferences over simple lotteries $L = (x, p)$ have a numerical representation via utility function with error such that $U(L) = u(x)p$ and $V(L_i, L_j) = \lambda > 0, \forall L_i, L_j \in M$. For lottery $L = (x, p)$, let $CE(L)$ be such that $u(CE(L)) = u(x)p$. For lottery $L = (x, p)$ and $L' = (y, 1)$ with $y > CE(L)$, let $q(L, y)$ be such that $u(y)q(L, y) = u(x)p$. We observe that if lottery $L(x, p)$ is held as the status-quo then,

i. $inf\{y : (y, 1) \succeq (x, p)\} > CE(x, p)$
ii. $inf\{q : (y, q) \succeq (x, p)\} > \frac{u(x)p}{u(y)}$ for $y > x$

In other words, a person with imperceptive preferences will ask strictly more than the certainty equivalent of the lottery if asked to sell it or, equivalently, will appear less risk averse than the true underlying preferences. At the same time, this person will look more risk averse than his underlying preferences would suggest if $y > x$ and asked for the probability equivalent of the lottery. This result holds whenever utility is increasing in x and p.

Let ν be the status quo bias introduced by limited perception. Equation (ii) implies that ν decreases as payoffs x and y are scaled up if λ is constant and u is concave. That is, the bias in measured preferences decreases as payoffs increase. More importantly, if function $V(.,.)$ is constant, equation (ii) implies that the bias in measured preferences increases as probabilities are scaled down. In particular, note that if $u(y)(q(L)+\nu) - u(x)p = \lambda$ for a given ν then $u(y)(\theta q(L)+\theta\nu) - u(x)\theta p < \lambda$ for any $\theta < 1$. This implies that the extra probability of winning y necessary to compensate for lottery $L = (x,p)$ increases as p decreases. Finally, equation (i) implies that even if a person has a concave utility function u it is possible that they will exhibit risk-loving preferences. The question is whether this behavior is more likely when probabilities of high outcomes are small or large. Suppose that function u is concave and $u(0) = 0$. Then the amount ν needed make $u(xp+\nu) - u(x)p \geq \lambda$ is increasing in p for all lotteries such that $xp = c > 0$.[12] This implies that whenever function V is constant, individuals are more likely to behave risk lovingly when probabilities are large not small. For this model to explain the tendency to gamble over low-probability high payoff lotteries and risk aversion over high probability low payoff lotteries function V needs to be decreasing in its arguments.[13]

To relate our experimental design, consider the situation in which a person is given the opportunity to exchange a lottery (x,p) for another lottery (y,q). These lotteries could include sure payments of money. We summarize predictions on behavior under

[12]To see this consider the equation $u(c+\epsilon) - u(\frac{c}{p})p = \lambda$ which defines ϵ as a function of the expected value of the lottery c and constant λ. Total differentiation of the equation implies that $\frac{d\nu}{dp} = \frac{u(\frac{c}{p}) - u'(\frac{c}{p})\frac{c}{p}}{u'(c+\nu)}$ which is positive if u is concave and $u(0) = 0$.

[13]The opposite results obtain if u is convex.

the joint assumption that function u is concave and function V is constant.

H1: Let $y > x$ and q such that $u(y)q = u(x)\theta$. If a person is asked to name the lowest q^* such that $L^* = (y, q^*)$ is preferred to lottery (x, θ) this number will be strictly larger than q. This bias will be proportionally larger as θ decreases. In other words, a person will appear more risk averse as θ decreases.

H2: Let $y > x$ and $p > q$ such that $u(y)q = u(x)p$. If a person is asked to name the lowest p^* such that $L^* = (x, p^*)$ is preferred to (y, q) this number will be strictly larger than q. The bias of the estimate of q will be proportionally larger as p decreases. In other words, a person will appear less risk averse as p decreases.

H3: Let $L = (x, p), x > 0$ and let $CE(L)$ be the certainty equivalent of lottery L. If a person is asked to name the lowest $CE(L)^*$ such that $CE(L)^*$ is preferred to (x, p) this number will be strictly larger than $CE(L)$. That is, a person will appear less risk averse in lotteries with large payoffs and low probabilities of winning than in lotteries with lower payoffs of the same expected value.

This discussion above shows that the empirical content of models with limited perception is not empty if coupled with a theory of what makes a lottery the status-quo.

7. Appendix B

Let L(eft) be the option that keeps the probability of a prize constant in the MPL and let R(ight) be the optionIn that increases the probability of the non-zero lottery. Let $p_{L,i}$ be the probability (a constant) of the non-zero prize in the i's row of lottery L and let $p_{R,i}$ be the probability (non-constant) of the non-zero prize in i's row in lottery R. A switching decision rule is a number $t \in \{1, ..., K+1\}$ that indicates the row at which the subject switches from lottery L to lottery R, with $K+1$ denoting never switching. Let x_L and x_R be the non-zero prizes of lotteries L and R. For instance $x_L = \$3$ and $x_R = \$10$ in Decision 5 of treatment A and $x_L = \$10$ and $x_R = \$3$ in Decision 5 of treatment B.

We can calculate the compound probabilities for non-zero prizes for switching rule t as follows:

$\Pr(x_L|t) = \frac{1}{K}\sum_1^{t-1} p_{L,t}$, with $\sum_1^0 p_{L,t} = 0$
$\Pr(x_R|t) = \frac{1}{K}\sum_t^{K} p_{R,t}$, with $\sum_{K+1}^K p_{R,t} = 0$

In treatment A we have that $x_R > x_L > 0$ and in treatment B we have that $x_L > x_R > 0$. We can summarize the corresponding compound lotteries L_t induced by decision rule t as:

$L_t = (x_R, \frac{1}{K}\sum_t^K p_{R,t}; x_L, \frac{1}{K}\sum_1^{t-1} p_{L,t}; 0, 1 - \frac{1}{K}\sum_1^{t-1} p_{L,t} - \frac{1}{K}\sum_t^K p_{R,t})$ for treatment A and

$L_t = (x_L, \frac{1}{K}\sum_1^{t-1} p_{L,t}; x_R, \frac{1}{K}\sum_t^K p_{R,t}; 0, 1 - \frac{1}{K}\sum_1^{t-1} p_{L,t} - \frac{1}{K}\sum_t^K p_{R,t})$ for treatment B.

Let $\theta \in (0,1)$ be the factor by which probabilities are reduced. By construction, we have that switching rule t will induce lotteries $L_t(\theta)$

$L_t(\theta) = (x_R, \frac{\theta}{K}\sum_t^K p_{R,t}; x_L, \frac{\theta}{K}\sum_1^{t-1} p_{L,t}; 0, 1 - \frac{\theta}{K}\sum_1^{t-1} p_{L,t} - \frac{\theta}{K}\sum_t^K p_{R,t})$ for treatment A and

$L_t(\theta) = (x_L, \frac{\theta}{K}\sum_1^{t-1} p_{L,t}; x_R, \frac{\theta}{K}\sum_t^K p_{R,t}; 0, 1 - \frac{\theta}{K}\sum_1^{t-1} p_{L,t} - \frac{\theta}{K}\sum_t^K p_{R,t})$ for treatment B.

In other words, the compound lotteries preserve the ratio of probabilities in each row of the triplets and in each corresponding switching rule.

If each row of a triplet is taken in isolation, then the CR and RCR are preference reversals. If we consider that subjects treat MPLs as compound lotteries, the the CR and CRC reject the hypothesis that the probability weighting function has global properties, but not necessarily preference stability. For instance, if a probability weighting function is subproportional (the assumption that subjects become less risk averse as θ decreases), then we should have that subjects become less risk averse in both treatments. In sum, allowing for compounding of lotteries would eliminate the preference reversal problem at the cost of abandoning global properties on behavior.