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Responding Linearly in Nonlinear Problems: Application to Earth's Climate

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Chapter 2

RESPONDING LINEARLY IN NONLINEAR PROBLEMS: APPLICATION TO EARTH'S CLIMATE

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ABSTRACT

Past research has shown that a majority of peopleexhibit robust linear thinking for nonlinear changes in theirdecision environment. We argue that linear thinkingcould be particularly problematic in the case of interpreting carbon-dioxide's (CO_2) lifetime in the earth's atmosphere.

Participants from policy and non-policy backgrounds were asked to rank five ranges of CO_2 percentages to be removed from the atmosphere according to their impact on CO_2's lifetime in two separate conditions: Aid and no-Aid. In the Aid condition, participants were provided with a descriptive decision aid through instructions that might enable them to answer the problem correct, while this aid was absent in the no-Aid condition.

Two problems were presented to each participant in random order: Linear, where a ranking based upon linear thinking yielded a correct rank order; and Nonlinear, where a ranking based upon linear thinking yielded an incorrect rank order. Results reveal that a majority of participants from both backgrounds responded linearly on both problems and although the decision aid had no effect on participants' correct responses, it enabled policy backgrounds to move away from responding according to linear thinking. We discuss implications of these findings on policymaking about climate change.

Keywords: Carbon-dioxide gas's lifetime; linear thinking; climate change; aid; nonlinear problems

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INTRODUCTION

According to Galileo Galilei (Galilei, 1638), Aristotle believed that the speed with which an object falls is *linearly* related to its weight. Thus, comparing dropping a ball weighting 100 kg and another weighting 1 kg from the same height, the heavier ball will fall 100 times faster. Responding *linearly* as Aristotle did refers to a function, f(x) = *a**x, where f(x) is a person's decision response, x is a change in the decision environment, and *a*is different from zero[1] (Freudenthal, 1983). Many centuries later, Galileo proved Aristotle's reasoning aswrong, but it is unclear whether our tendency to respond linearly to nonlinear problems has been solved.

Currently, there is burgeoning amount of evidence that a majority of people think linearly when encountering nonlinear problems in their decision environment (Cronin,Gonzalez, and Sterman, 2009; Dörner,Kimber, and Kimber, 1997; Dutt and Gonzalez, 2009a; Larrick and Soll, 2008; Van Dooren, De Bock, Janssens, and Verschaffel, 2007). For example, more than 90% of students at the end of elementary schoolresponded "170 seconds" to the question: "John's best time to run 100 meters is 17 seconds. How long will it take him to run 1 kilometer?" (Greer, 1993). Similarly, many people wrongly believe that "3,500 calories consumed is a pound,"or for every 3,500 "extra" calories consumed, you will gain one pound (Chow, 2010).[2] In fact, the tendency to respond linearly has been shown to pervasively affect human judgment in global problems involving serious socio-economic consequences such as those concerning the earth's climate (Dutt and Gonzalez, 2009a; Sterman, 2008; Sterman and Booth Sweeney, 2007). For example, Dutt and Gonzalez (2009b) have shown that when university students were asked to estimate the shape of a carbon-dioxide (CO_2) accumulation and given linear changes in CO_2 emissions and absorption over time, a majority drewa linear shape fortheaccumulation that was similar to the linear shape of CO_2 emissions overtime. Similarly, Sterman and Booth Sweeney (2007) and Sterman (2008) have shown thatpeople often misperceive the dynamics of CO_2 accumulation; assuming that if one is to increase the accumulation, then CO_2 emissions should increase as well in a shapesimilar to the accumulation. This tendency to respond linearly is also related to people's level of educationin science and technology (STEM) (Dutt and Gonzalez, 2009b), where people with backgrounds in STEM seem to respond less linearly compared to non-STEM backgrounds.

A prediction that the shape of an accumulation "looks like" the shape of the inflow is anexample of robust linear thinking called the *correlation heuristic*(CH) (Cronin et al., 2009). According to Cronin et al. (2009),the proportion of participantsrelying onthe CH increased as the nonlinear relationship between the inflow, outflow, and accumulation became more complex.

In the case of the earth's climate, people may underestimate the extent of the nonlinear increase in CO_2 accumulation (Dutt and Gonzalez, 2010). That is because the shape of CO_2 emissions (inflow) has been increasing about linearly overtime (IPCC, 2007), and peoplemight think that the accumulation will also increase linearly. In practice, an assumption of linear increase will underestimate the actual increase. Furthermore, such underestimations could undermine the urgency of the climate problem and encourage deferment of human

[1] If a = 0, then the relationship is constant (= 0) rather than linear. For a constant relationship, a person's decision response is independent of environmental changes.

[2] The actual relationship between the changes in body weight over time is nonlinear, and is a function of a person's food intake and the difference of one's current body weight from a reference body weight (Chow, 2010).

actions, leading to *wait-and-see*behavior (Dutt and Gonzalez, 2009a; Sterman, 2008; Sterman and Booth Sweeney, 2007).

It has been argued that overreliance on linear thinking is partly due to its simplicity (Fischbein, 1999; Freudenthal, 1983; Lesh, Post, and Behr, 1988; Rouche, 1989). For example, Rouche (1989) argued that "it is the idea of proportionality that comes immediately in the mind, because undoubtedly there are no functions that are moresimple than the linear ones" (pg. 17). Similarly, Freudenthal (1983) commented that "linearity is such a suggestive property of relations that one readily yields to the seduction to deal with each numerical relation as though it were linear" (pg. 267).

Furthermore, literature on heuristics and biases show that simple linear models lead to approximate correct responses that are more accurate than even expert judgments (Dawes, 1979; Goldberg, 1970). For example, Dawes (1979) gives the example of predicting something as abstract as "professional self-actualization." Given students' graduate record examination, grade point average, and letters of recommendation, one could create a simple linear model to predict the students' professional self-actualization (self-actualization was measured for a set of students based upon their achievementpost-graduation from the university).

When Dawes and Corrigan (1974) applied different linear models to five different datasets to predict the criterion, an equal weighting linear model (the simplest assumption of linearity) out performed all other competing models. Thus, simple linear assumptions can be accurate in many situations, and people depend upon it because it yields an accurate answer in many situations.

Concrete interventions can help reduce linear thinking in both simple and complex nonlinear problems (Cronin et al., 2009; Larrick and Soll, 2008; Garcia-Retamero, Galesic, Gigerenzer, 2010). For example, a physical representation of a nonlinear problem that uses pictures as "metaphors" helped participants reduce their reliance on linear thinking and increased their accuracy (Dutt and Gonzalez, 2010). Although theseinterventions seem to be effective in reducing reliance on linear thinking, they require people to *change* their cognitive thought processes in nonlinear problems, where such a change might at times become very difficult or even impossible to attain (Klayman and Brown, 1993).

This chapter demonstrates robust reliance on linear thinking in a nonlinear environmental problem. It tests concrete interventionsto help people respond correctly *without changing* their tendency to think linearly.[3] One intervention is to presenta nonlinear problem in a way wherelinear thinking results in a correct response. Some research has shown that a change in the information context can enable people to make correct responses without influencing their natural thought process (Klayman and Brown, 1993; Payne, Bettman, and Schkade, 1999). Another intervention is to encourage participants through instruction to think nonlinearly; an intervention that tries to change a participant's thought process. Recent research has shown that a *nudge* given in the form of written instructionsmight enable better decisions (Thaler and Sunstein, 2008). Furthermore, we evaluate whether participants' policy backgrounds influence their reliance on linear thinking in these problems. Because decisions about environmental problems are made by policymakers, it is important to determine if the participant's background in politics, business, economics, and law influence their thinking

[3] We discuss other problems in the discussion section where linear thinking could result in a correct response based upon the problem's presentation.

compared to non-policy backgrounds. According to Nordhaus (1994), the policy background is highly representative of the backgrounds possessed by policymakers who decide on environmental issues facing the world.

The Nonlinear CO_2 Lifetime Problem

The lifetime of CO_2 in the atmosphere (in units of years) is the time it takes to remove a certain mass of CO_2 from the atmosphere. CO_2 lifetime is naturally affected by the yearly percentage of CO_2 removed ("percent-removed" hereafter) by natural processes like absorption by oceans and photosynthesis in plants (IPCC, 2007). A large percent-removed is desirable because larger quantities of accumulated CO_2 leads to climate changeand increasing average temperature (IPCC, 2007). Figure 1 exemplifies CO_2's lifetime in the atmosphere as a nonlinear function of its percent-removed:the lifetime of CO_2 in the atmosphere (units: years) = 100 / percent-removed (units: percent per year).

As shown in Figure 1, a decrease in the percent-removed corresponds to a nonlinear increase in CO_2 lifetime. In addition, the percent-removed is expected to decrease in future years, as oceans and plants are expected to have a reduced ability to absorb CO_2, resulting in a large increase in atmospheric CO_2 lifetime (Cramer et al. 2001; Joos et al. 2001; Matear and Hirst, 1999; Sarmiento and Quéré, 1996).

Given the nonlinear relationship between the percent-removed and CO_2 lifetime, the equal range of reduction in percent-removed may result in a very large or very small increase in CO_2 lifetime, depending on where the range falls on the non-linear curve (see Figure 1). For example, apercent-removed reduction from 0.3 to 0.1 (i.e., 0.2 range) per year results in a 667 years increase for CO_2 lifetime. A reduction from 0.8 to 0.6 (i.e., a similar 0.2 range) per year, however, results in only a 42 years lifetime increase.

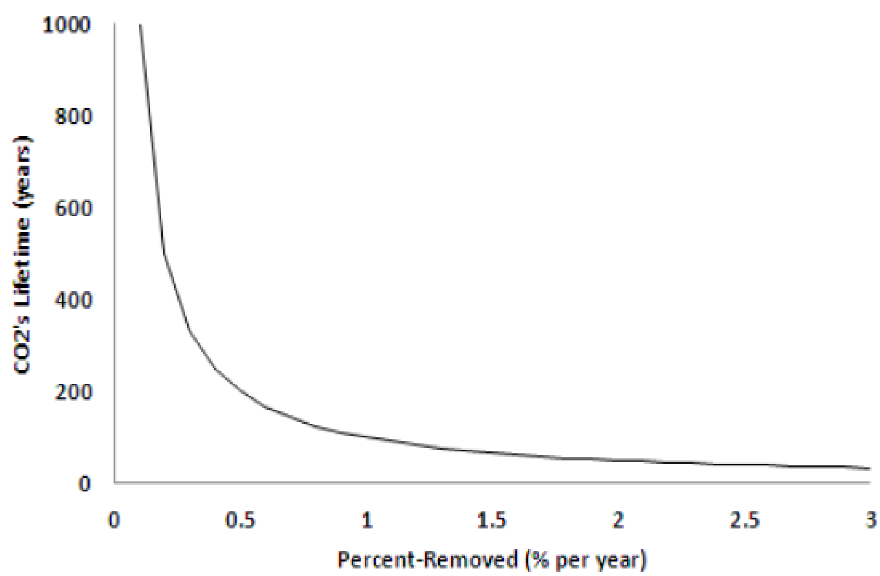

Figure 1. The nonlinear relationship between CO_2's lifetime and percent-removed in the CO_2 lifetime problem.

Consistent with the substantial evidence of human linear thinking in nonlinear problems, we expect that participants will think linearly when asked to judge the effect of a decrease in CO_2's percent-removed on an increase in CO_2 lifetime: they would believe that the *largest*reduction inpercent-removed would result in the *largest* increase in lifetime. Thus, we expect:

– *H1a*: A larger proportion of linear responsesthan nonlinear responses.

Furthermore, we expect that by presenting a problem where a linear response leads to a correct response, we will enable participants to make correct responses even when relying on linear thinking (Klayman and Brown, 1993; Payne et al., 1999). We accomplish this by changing the presentation of information in the decision environment. This manipulation is strictly in the decision environment, not a treatment to change participants' thought processes. Such anapproach has also been suggested in other judgment research (Larrick, 2004; Klayman and Brown, 1993; Payne et al., 1999). In other cases, however, linear thinking would lead to incorrect responses. Thus, we hypothesize that:

– *H1b*: Theproportion of correct responses will be greater when the correct response in the problem is aligned with linear thinking compared to when it is not.

Furthermore, an other way to enable participants make better decisionsis to provide them witha descriptive aid through instruction (Thaler and Sunstein, 2008). The aidcould be in the form of a statement that suggeststo convert aCO_2'spercent-removed value toa CO_2'slifetimevalue (where CO_2's lifetime = 100 / percent-removed as seenin Figure 1) and make it simplerfor them to calculate the linear increase in CO_2's lifetime. UsingCO_2's lifetime information will help a person reduce the nonlinear problem to a linear one, making it easy to answer the problem correctly.

It is to be noted that unlike the above manipulation that changed a person's decision environment, this aid manipulation is aimed at changing a person's linear thought process. Thus, we hypothesize that:

– *H2:* The proportion of correct responses will be greater for those who are given anaid than those who are not given an aid.

Finally, according to Dutt and Gonzalez, (2009b), a greater proportion of STEMs provided correct responses in nonlinear problems compared to non-STEMs. A possible reason for this finding is that STEMs possess greater expertise inmathematical problem solving (Chi, 2006). For example, Chase and Simon (1973) found that expertise and skill in chess enabled participantsto recognize significant patterns and remember them easily. Similarly, experience in mathematical problem solving might enable STEMs to respond appropriately in nonlinear problems.

Currently, there is dearth ofresearch that directly investigates people with policy backgrounds' linear responses in nonlinear problems. If policy backgrounds possess some expertise in policymaking, then theyshould respond more accurately in the CO_2 lifetime problem. Thus, we expect:

- *H3:* A larger proportion of correct responses by those with policy backgrounds compared to those with non-policy backgrounds.

METHODS

Participants

Sixty-seven participants participated in this experiment and were recruited using an online advertisement. Twenty-three participants were from a policy background, and possessed or were pursuing degrees in political science (N=3), business (N=2), economics (N=5), policy (N=9), and law (N=4). The rest of the participants (N=44) had non-policy backgrounds. Thirty-threeparticipants were females. Ages ranged from 18 to 52 years (Mean= 25, SD= 6).

Forty-nine percent of participants were either enrolled in a graduate degree or had completed a graduate degree in the past. Forty-four percent of participants with a policy background and fifty-two percent of participants with a non-policy background were either enrolled in a graduate degree or had completed a graduate degree in the past, respectively. All sixty-seven participants reported knowing some information about climate change through television, radio, newspaper, magazine, movie, or a talk with family or friends. Ten and thirteen participants with policy backgrounds were randomly assigned to the no-Aid and Aid conditions, respectively. Twenty-five and nineteen participants with non-policy backgrounds were randomly assigned to the no-Aid and Aid conditions, respectively. All participants received a flat compensation of $5 in the experiment, which lasted for about 10 minutes.

Materials and Procedure

Each participant was presented with two problems in random order. One of the problems is aligned correctly with linear thinking (Linear) while the other problem is not (Nonlinear)."Aligning correctly" with linear thinking meant that the problem was presented such that a linear response would yield a correct response, while “aligning incorrectly” meant that the problem was presented such that a linear response would yield an incorrect response.

Each problem consisted offive ranges of decreasing values of CO_2 percent-removed per year, with a From (status-quo and higher) and a To (future and lower) value. Participants were asked to rank the percent-removed ranges from the one that would cause the largest increase in CO_2 lifetime (rank 1) to the smallest increase (rank 5) (see Figure 2 for full instructions). Participants were also requested toclearly show their math in the space provided.

Participants were randomly assigned to one of two conditions, Aid or no-Aid. In the Aid condition, participants were given the following statement as part of the instructions: “For calculations, the climate scientist has suggested that you translate the yearly percentage of CO_2 removed values (in percentage of CO_2 per year) into the lifetime that CO_2 stays in the atmosphere (in years).” This sentence was omitted from the instructions for participants assigned to the no-Aid condition.

Aid Condition, Linear Problem

The table below gives you the pairs of "From" and "To" yearly percentage of CO_2 removed values. Please rank order these values in terms of their detriment to Earth's climate from 1 to 5:

- Use 1 for the **most** detrimental pair: the pair that would cause the most increase of lifetime of CO_2 in the atmosphere.
- Use 5 for the **least** detrimental pair: the pair that would cause the least increase of lifetime of CO_2 in the atmosphere.

You are allowed to use a computer screen calculator, in case you need one. But you also need to clearly show your work (i.e. your mathematical formulation) in the space provided below the table. For calculations, the climate scientist has suggested that you translate the yearly percentage of CO_2 removed values (in percentage of CO_2 per year) into the lifetime that CO_2 stays in the atmosphere (in years).

Pairs		Rank
From	To	(1 to 5)
1.9% per year now	0.5% per year in future	
2.1% per year now	0.1% per year in future	
2.0% per year now	0.3% per year in future	
1.7% per year now	1.1% per year in future	
1.6% per year now	0.9% per year in future	

Please clearly show your work i.e. the math you did for getting the ranks in the table above (you are allowed to use a computer screen calculator for any calculations):

Aid Condition, Nonlinear Problem

The table below gives you the pairs of "From" and "To" yearly percentage of CO_2 removed values. Please rank order these values in terms of their detriment to Earth's climate from 1 to 5:

- Use 1 for the **most** detrimental pair: the pair that would cause the most increase of lifetime of CO_2 in the atmosphere.
- Use 5 for the **least** detrimental pair: the pair that would cause the least increase of lifetime of CO_2 in the atmosphere.

You are allowed to use a computer screen calculator, in case you need one. But you also need to clearly show your work (i.e. your mathematical formulation) in the space provided below the table. For calculations, the climate scientist has suggested that you translate the yearly percentage of CO_2 removed values (in percentage of CO_2 per year) into the lifetime that CO_2 stays in the atmosphere (in years).

Pairs		Rank
From	To	(1 to 5)
0.3% per year now	0.1% per year in future	
0.8% per year now	0.5% per year in future	
2.2% per year now	1.1% per year in future	
0.9% per year now	0.2% per year in future	
2.1% per year now	1.2% per year in future	

Please clearly show your work i.e. the math you did for getting the ranks in the table above (you are allowed to use a computer screen calculator for any calculations):

Figure 2. The climate problems, Linear and Nonlinear, presented to the participants in the Aid condition. The same problems were presented in the no-Aid condition, except that the statement instructing the participant to convert the percent-removed to CO_2's lifetime was omitted.

The ranks and math shown by participants were used to classify the type of procedure they used to respond (linear or nonlinear). Only one sequence of ranks from 1 to 5is correct response in each problem, however, participants could enter different sequence of ranks by following different rank-order rules. Table 1 provides five different linear rank-order rules that participants could follow in each problem (numbered from 1 to 5) as a result of linear thinking. We made use of these five rules to classify a participant's ranking as being a linear response.

Table 1. Different linear rank orders of the percent-removed ranges in the Linear and Nonlinear problems

Linear Problem									
From	To	Proportional Change	Delta Change	Correct Change in Years	Correct Rule (1)	Difference Rule (2)	Addition Rule (3)	Ratio Rule (4)	Proportional Rule (5)
2.1	0.1	0.95	2.0	952	1	1	1	1	1
2.0	0.3	0.85	1.7	283	2	2	2	2	2
1.9	0.5	0.74	1.4	147	3	3	3	3	3
1.6	0.9	0.44	0.7	49	4	4	4	4	4
1.7	1.1	0.35	0.6	32	5	5	5	5	5
Nonlinear Problem									
From	To	Proportional Change	Delta Change	Correct Change in Years	Correct Rule (1)	Difference Rule (2)	Addition Rule (3)	Ratio Rule (4)	Proportional Rule (5)
2.2	1.1	0.50	1.1	46	4	1	5	3	3
0.9	0.2	0.78	0.7	389	2	3	2	1	1
2.1	1.2	0.43	0.9	36	5	2	4	4	4
0.3	0.1	0.67	0.2	667	1	5	1	2	2
0.8	0.5	0.38	0.3	75	3	4	3	5	5

The From and To values are given to participants (in Figure 2). The next three columns: "Proportional Change," "Delta Change," and "Correct Change in Years" are used to calculate five possible linear rules: "Correct Rule," "Difference Rule," "Addition Rule," "Ratio Rule," and "Proportional Rule." Proportional Change refers to the relative change in the percent-removed given by the formula (From - To) / From. Delta Change refers to the difference between the From and To values of apercent-removed range. Correct Change in Years refers to the correct values of CO_2 lifetime that could be obtained by using the formula, 100/To - 100/From. The Correct Rule was the correct rank order obtained through the Correct Change in Years column. The other four rules represent different forms of linear-thinking response: the Difference Rule is the rank order obtained based on the Delta Change column; the Addition Rule is the rank order obtained by the addition of From and To values; the Ratio Rule is the rank order obtained based on the ratio of From/To; and the Proportional Rule is the rank order obtained using Proportional Change. In the Linear problem, all of the other four rank-order rules are the same as the Correct Rule (or correct response), but not in the Nonlinear problem. Participants' responses were classified according to the rule they appeared to follow, or as "other"if their ranks did not correspond to any of the fivelinear rules (i.e., their responses were nonlinear-incorrect responses). If a participant ranked according to linear response or the Correct Rule in the Linear problem, then this ranking would lead her to a correct response. In contrast, a participant could only get a correct response on the Nonlinear problem by following the Correct Rule. Therefore, following a linear response on the Nonlinear problem could not have produced a correct response.

RESULTS

Two independent raters coded each participant's response as belonging to one the five rank rules (given in Table 1) or as"other". Inter-rater reliability for the two independent raters revealed satisfactory amounts of agreement between the two, Kappa, Correct = 0.94 (p< 0.001), 95% CI[4] (0.89, 1.00); Kappa, Difference = 0.97 (p< 0.001), 95% CI (0.92, 1.00); Kappa, Addition = 1.00 (p < .001), 95% CI (1.00, 1.00); Kappa, Ratio = 0.92 (p< 0.001), 95% CI (0.81, 1.00); Kappa, Proportion = 0.92 (p< 0.001), 95% CI (0.81, 1.00); and Kappa, Other = 0.93 (p< 0.001), 95% CI (0.80, 1.00). These categorizations were used for subsequent analysis of responses after resolving any inconsistency between raters through direct meeting and active discussion.

Proportion of Linear Responses within Each Problem (H1a)

To test H1a, we compared the proportion of linear responses to other (nonlinear) responses within the Linear and Nonlinear problems in the Aid and no-Aid conditions for policy and non-policy backgrounds. Table 2 shows the proportion of correct responses, linear responses, and otherresponses for participants in both problems and both conditions. A non-zero correct response in the Linear problem was only due to linear thinking, and there were 0% correct responses in the Nonlinear problem.

[4] 95% Confidence interval.

Table 2. Proportion of participants following a correct, linear, and other response in the experiment

Response	Policy Backgrounds				Non-policy Backgrounds			
	Aid		No-Aid		Aid		No-Aid	
	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)
Correct	62	00	50	00	63	00	72	00
Linear	62	54	80	80	84	79	92	88
Other	38	46	20	20	16	21	08	12

For participants with non-policy backgrounds, the proportion of linear responses was significantly greater than the proportion of other (nonlinear) responses, regardless of the problem or condition: In the Aid condition and Linear problem (84%>16%):$\chi^2(1)=17.789$, $p<.001$, $r=.68$; In the Aid condition and Nonlinear problem (79%>21%): χ^2 (1) =12.737, p <.001, $r=.58$; In the no-Aid condition and Linear problem (92%>8%): χ^2 (1)=35.280, $p<.001$, $r=.84$; and in the no-Aid condition and Nonlinear problem (88%>12%): χ^2 (1)=28.880, p <.001, $r=.76$.

These results supports hypothesis H1a. For participants with policy backgrounds, the proportion of linear responses was significantly greater than the proportion of other (nonlinear) responses in the no-Aid condition's Linear (80%>20%) (χ^2 (1)=7.200, $p<.01$, $r=.60$) and Nonlinear problem (80%>20%)(χ^2 (1)=7.200, $p<.01$, $r=.60$). However, there was no difference between the proportion of linear responses and other responsesin the Aid condition's Linear and Nonlinear problem (Linear problem: linear response (62%) = other response (38%) with χ^2 (1)=1.385, *ns*, r =.23; Non-linear problem: linear response (54%)=other response (46%) with χ^2 (1)=0.154, *ns*, $r=.08$).

Therefore, an aid helped participants with policybackgrounds to relylessonlinear responses.Support forhypothesis H1a is present in the problem without Aid, but not in the problem with Aid.

Proportion of Correct and Linear Responses between Linear and Nonlinear problems (H1b)

To test H1b, we compared the proportion of correct responses between each problem in each condition for policy and non-policy backgrounds, respectively. For non-policy backgrounds, the proportion of correct responses was significantly greater for the Linear problem compared to the Nonlinear problem in both conditions (see Table 2) (Aid: 63% > 0% with χ^2 (1)=17.538, $p<.001$, $r = .68$; no-Aid: 72% > 0% with χ^2 (1) = 28.125, $p<.001$, $r=.75$).

Similarly, for policy backgrounds, the proportion of correct responses was significantly greater for the Linear problem compared to the Nonlinear problem in both conditions (Aid: 62% > 0% with χ^2 (1) = 13.765, $p<.001$, $r=.73$; no-Aid: 50% > 0% with χ^2 (1) = 6.667, $p<.01$, $r = .58$). These results support H1b.

Furthermore, regardless of the background, the proportion of participants giving linear responses was no different between each problem in both conditions (see Table 2) (For non-policy background: Aid: 84% = 79% with χ^2 (1) = 0.175, *ns*, *r* = .07; no-Aid: 92% = 88% with χ^2 (1) = 0.222, *ns*, *r*=.07. For policy background: Aid: 62% = 54% with χ^2 (1) = 0.158, *ns*, *r*=.08; no-Aid: 80% = 80% with χ^2 (1) = 0.000, *ns*, *r* = .00). These results show that the difference in correct responses between problems was due to the participants' persistent reliance on linear reasoning, regardless of their backgrounds and any aid.

Proportion of Correct and Linear Responses between Aid and No-Aid conditions (H2)

To test H2, we compared the proportion of correct responses between the Aid and no-Aid conditions in the Linear and Nonlinear problems for non-policy and policy backgrounds. Aid had no effect on the proportion of correct responsesin the Linear problem (for non-policy background: Aid: 63% = no-Aid: 72% with χ^2 (1) = 0.389, *ns*, *r* = .09; for policy background: Aid: 62% = no-Aid: 50% with χ^2 (1) = 0.878, *ns*, *r* = .20) or in the Nonlinear problem (for non-policy background: Aid: 0% = no-Aid: 0% with χ^2 (1) = no-statistic[5], *ns*, *r* = no-statistic; for policy background: Aid: 0% = no-Aid: 0% with χ^2 (1) = no-statistic, *ns*, *r* = no-statistic). Again, Aid had no effect on the proportion of linear responses in the Linear problem (for non-policy background: Aid: 84% = no-Aid: 92% with χ^2 (1) = 0.650, *ns*, *r* = .12; for policy background: Aid: 62% = no-Aid: 80% with χ^2 (1) = 0.910, *ns*, *r* = .20) or in the Nonlinear problem (for non-policy background: Aid: 79% = no-Aid: 88% with χ^2 (1) = 0.661, *ns*, *r*=.12; for policy background: Aid: 54% = no-Aid: 80% with χ^2 (1) = 1.704, *ns*, *r* = .27). Thus, Aid had noinfluence on participants'reliance on linear or correct responses. These results do not support hypothesis H2.

Effects of Educational backgrounds

Finally, to test hypothesis H3, we compared the proportion of correct responses between policy and non-policy backgrounds in each problem in the Aid and no-Aid conditions, respectively. Overall, there was no difference for participants withpolicy and non-policy backgrounds. This finding holds in the Aid condition for the Linear problem (Correct response: 62% = 63% with χ^2 (1) = 0.126, *ns*, *r* = .06; Linear response:62% = 84% with χ^2 (1) = 2.116, *ns*, *r* = .26) and for the Nonlinear problem(Correct response: 0% = 0%with χ^2 (1) = no-statistic, *ns*, *r* = no-statistic; Linear response: 54% = 79% with χ^2 (1) = 2.264, *ns*, *r* = 0.27). This finding also holds in the no-Aid condition for the Linear problem (Correct response: 50% = 72% with χ^2 (1) = 1.534, *ns*, *r* = .21; Linear response: 80% = 92% with χ^2 (1) = 1.016, *ns*, *r* = .17) and for the Nonlinear problem (Correct response: 0% = 0% with χ^2 (1) = no-statistic, *ns*, *r*= no-statistic; Linear response: 80% = 88% with χ^2 (1) = 0.373, *ns*, *r*=.10). When taken together, these resultsdo not support hypothesis H3.

[5] Because there is no participant in the Nonlinear problem who gave a correct response, there is no statistic to report for the comparison due to the absence of data.

GENERAL DISCUSSION

This research shows that people's linear thinking is pervasive while making judgments in nonlinear environmental problems. Our manipulation of aligning correct responses with linear thinking proved highly effective. Changing the information in the problemto align with a person's dominant decision-making strategy (which in this case is responding linearly) can be an effective way of improving their decision making (Klayman and Brown, 1993; Payne et al., 1999). Moreover, the important point to note is that the alignment manipulation does not change their thought processes in any way. The manipulation is simply meant to make use of these linear cognitive processes to help participants understand nonlinear problems in the way they naturally are inclined to and thus enable them to correctly respond. Furthermore, our results agree withprior evidence of linear thinking in environmental problems concerning inferences about CO_2 accumulation (Sterman, 2008; Sterman and Booth Sweeney, 2007).

Our results also indicate thata majority of participants with non-policy backgrounds responded linearly in problems with or without instructional aid and regardless of whether or not correct response was aligned with linear thinking. There could be a number of reasons for this over reliance amongst participants with non-policy backgrounds. First, it could simply be because linear responses are the simplest response to come to mind (Fischbein, 1999; Freudenthal, 1983; Lesh, Post, and Behr, 1988; Rouche, 1989). Second, literature has shown that even simple linear models lead to correct approximate responses in many cases that are more accurate than expert judgments (Dawes, 1979; Goldberg, 1970). Linear thinking offers two crucial benefits of being simple and/orit producing accurate and good enough answers in many problems, while avoiding more complicated nonlinear rules.

Furthermore, in our results, participants with policy backgrounds still relied on linear thinking and were not able to provide correct responses. But they were able to make some use of the instructional aid, which helped them to move away from linear thinking to other nonlinear or incorrect types of response. Although we can only currently speculate, one reason may be that it is challenging to *change* participants' cognitive thought processes to enable better decisions (Klayman and Brown, 1993) and the aid was not inadequate in producing this change.

A second reason could be on account of the aid's effectiveness itself: adescriptive aid that provided participants with the exact relationship between CO_2 lifetime and percent-removed might have been more effective. Still, participants with policy backgrounds, just like those with non-policy backgrounds, are limited by their cognitive capacity (Sterman and Booth Sweeney, 2007) and are thus unable to utilize the aid effectively. We plan to investigate these explanations as part of future research.

It is expected that the yearly percentage of CO_2 removed from the atmosphere will decrease in future years, resulting ina large increase in CO_2 lifetime (Cramer et al., 2001; Joos et al. 2001; Matear and Hirst, 1999; Sarmiento and Quéré, 1996). As this change will be detrimental to the earth's climate, accurate human assessment of the nonlinear relationship between the percent-removed and CO_2 lifetime is important. When participants were given a problem where a linear response would lead to an incorrect answer, none of the participants in the experiment correctly ranked the decreasing percent-removed ranges in the problem. They ultimately underestimate the most detrimental changes in CO_2 lifetime. This inaccurate assessment could be a possible reason for wait-and-see policies for climate change.

Finally, aligning a nonlinear problem with linear mental models is a manipulation that may also be useful in many other important problems. For example, an intervention similar to the one tested here could be attempted for reducing the dispersal of a commodity (e.g., pollution in river) by giving people choices about the taxes they pay per unit of dispersing the commodity. For example, consider a certain tax per kilogram on pollution created in a river (units: $/Kg of pollution) aimed at reducing pollution. Polluters, like large industrial factories on the river's banks, could be offered different taxation choices, where they are charged with a smaller tax now and a larger tax in the near future for each policy. A range of tax increases could be designed in such a way that the smallest increase for the same amount of total pollution appears the most attractive to polluters according to their linear thinking. But in fact, the smallest increase has the maximum potential to reduce river pollution. Our future endeavor in this research will be to extend the problem alignment intervention to other nonlinear problems faced in daily life.

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