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The Longevities of Policy-Shifts and Memories Due to Single Feedback Numbers

Edward L. Munnich (emunnich@usfca.edu)
University of San Francisco, Psychology Department, 2130 Fulton Street, San Francisco, CA 94117

Michael A. Ranney (ranney@cogsci.berkeley.edu)
University of California, Graduate School of Education, 4533 Tolman Hall, Berkeley, CA 94720-1670

Mandy L. N. Bachman (mandybachman@hotmail.com)
University of California, Graduate School of Education, 4533 Tolman Hall, Berkeley, CA 94720-1670

Abstract

What proportion of people in the U.S. are imprisoned? Would knowing this number affect one's views on U.S. justice? Policy-makers, voters, and consumers need a sense of such quantities to help shape effective policies, and schools must prepare students for such roles. Our past research has documented changes in individuals' numerical concepts—and often their views on issues—after they received a single critical number. In the experiment, we examined eighth grade students within the Numerically-Driven Inferencing paradigm (NDI), using an experimental method (EPIC) in which participants: *Estimate* policy-relevant quantities, state *Preferences* for these, briefly receive actual quantities as feedback to *Incorporate*, and offer preferences again that may exhibit any policy *Changes*. Students were then asked (post-EPIC) to recall the actual number and indicate their current preference for the quantity—either eight or 84 days after they received the feedback. Memory for the actual values was considerable after eight days, and still evident after 12 weeks. Further, feedback-triggered policy shifts were also evident after both eight and 84 days post-feedback. Therefore, recall and policy shifts spawned by minimalist interventions—briefly viewed solitary numbers—can have substantial longevities.

Keywords: Belief Revision; Conceptual Change; Decision Making; Estimation; Mental Models; Reasoning.

Please write down an answer to the following: Out of every 1000 U.S. residents, how many are currently incarcerated (in prison, jail, or juvenile hall)? Next, reflect on how you reached your estimate. Now, think of what you would *prefer* the number to be. The true number is seven per thousand; does learning this actual statistic change your preference (whether massively or modestly)? Finally, to the extent that your preference changed, how do you think your new preference would persist or fade as you have time to digest the number over the coming days or months? This last question is the present work's main focus.

Individuals differ greatly in their preferences for policy-relevant statistics, but there are some common patterns. While some may protest that incarceration is an issue of justice, and not "just" one of numbers, rhetoricians know that a well-placed number can often sway opinion. If a newspaper reports that Country X has achieved domestic tranquility without incarcerating a single person, most of us would likely react with some mix of hopefulness that there might be ways of accomplishing this in our own country, and/or suspicion that the full truth was not told. Similarly, a report that *half* of Country Y's population is incarcerated would likely provoke disbelief that such a large proportion of people could be guilty of noteworthy crimes, and likely outrage at a government that would yield such a situation. In both examples, most readers would find the numbers surprising, and—were the source of the numbers credible—this surprise might provoke them to revise some of their beliefs, and perhaps to become more or less active regarding an issue.

Along these lines, Ranney, Cheng, Nelson, and Garcia de Osuna (2001) and Munnich, Ranney, Nelson, Garcia de Osuna, and Brazil (2003) have reported feedback-triggered *policy shifts*––changes in preference that are *disproportionate* in regards to contemporaneous beliefs about the value's magnitude. To illustrate by way of contrast, suppose a person thought that six people per 1000 were incarcerated and preferred the number to double to 12 per 1000; finding out that the true number is seven would not be very surprising, and might lead to only a *proportional rescaling* of the preference (i.e., still preferring a doubling, thus 14). However, those whose estimates are off by larger amounts often undergo policy shifts: Say, one initially thought one out of every 1000 were incarcerated and preferred that the number be three; upon learning that the correct number was seven, a common response is to indicate a revised preference that the number *remain at seven*. In this case, it would certainly be correct to note a shift in preference from three to seven, but this would miss the more interesting point that the participant has made a notable policy shift—initially preferring a tripling of the incarceration rate, but shifting to a status quo policy after receiving feedback. Such policy shifts suggest that people have implicit beliefs about plausible ranges for a quantity (cf. Ranney et al.'s, 2001, "non-surprise intervals"), and evidence contradicting such beliefs yield surprise, leading them to change their beliefs and desires regarding the focal issue. We assess a numerical policy (e.g., a wish to halve—or triple—a quantity) by eliciting one's preference (e.g., "What would you prefer the number to be?") and dividing it by what one believes the value to be. (See Garcia de Osuna, Ranney, & Nelson, 2004, for more discussion of the qualitative and quantitative natures of such surprise-triggered shifts, regarding the topic of abortion).

A host of experiments based on the Numerically-Driven Inferencing paradigm (NDI; Ranney et al., 2001) have now shown marked policy shifts resulting from a single number (including Garcia de Osuna et al., 2004; Lurie & Ranney, 2005; Munnich et al., 2003; Ranney et al., 2001), and therefore contrast with findings discussed by Chinn and Brewer (1993), among others, which indicated that conceptual changes are difficult to effect. Going beyond the *existence* of policy shifts, this paper addresses how *durable* policy shifts are: Do those who shift policies immediately after receiving feedback maintain the new policies over time? It could be that we feel obliged to express shock when we hear surprising numbers, but we might later return to our usual ways of thinking. Were this the case, then what appear to be policy shifts may be relatively transient experimental effects. On the other hand, to the extent that policy shifts persist, they provide evidence of stable, substantive, belief revision resulting from the receipt of a single, surprising, feedback number.

Theoretical Framework

NDI builds on work in many fields, including estimation, attitude, conceptual change, mental models, and judgment and decision-making (although NDI deals with base rates directly—not through Bayesian analyses). For instance, NDI builds on studies regarding the numerical concepts a person has, as indicated by the estimates one produces. Estimates have been found to draw on a variety of sources, including category information (e.g., Huttenlocher, Hedges, & Prohaska, 1988), relevant "seed" numbers (e.g., Brown & Siegler, 2001), and underlying magnitude representations (e.g., Dehaene & Marques, 2002). However, NDI goes beyond the numerical-concepts literature to consider how such notions of quantities relate to *preferences* and *attitudes* on a variety of issues. Specifically, our group examines how understandings of relevant numerical information (e.g., the incarceration rate) affect public policy opinions (e.g., what would one *prefer* the incarceration rate to be, and why?). We suppose that qualitative attitudes have some—albeit not necessarily direct—relationships with relevant quantities, and we aim to explore the nature of those connections. By focusing on people's conceptions of quantities, NDI can shed light on how such concepts interact with people's initial attitudes, and the extent to which learning true values shapes subsequent attitudes.

Even when considering the same issue, one can arrive at strikingly different estimates and policies, depending on the issue's framing (cf. Schwarz, 1999). When Munnich et al. (2003) asked for the number of abortions per million live births, the median response was 33.5 times too low. (Indeed, Ranney et al., 2001, with a larger sample, found it to be 67 times too low.) If their estimates were so far off, how were participants' preferences impacted? Rather than discount the feedback, they showed an overall policy shift—a 64% more reductive policy than they had initially indicated. In contrast, when participants estimated the number of abortions per million fertile women, the median estimate was much more accurate—half the actual number—so for this item variant, rather than shift policies, people more often just rescaled their preferences to adjust to their new understanding of the number. In other words, when a quantity (e.g., an abortion rate) is framed in different ways, accuracy in estimating the quantity is affected, and this strongly influences people's preferences after they learn the true number.

More broadly, NDI has ties to work in scientific conceptual change, including the Theory of Explanatory Coherence (TEC; e.g., Ranney & Thagard, 1988; Thagard, 1989). TEC describes change as spawned by incoherence and inter-idea conflicts, such that people try to revise their beliefs in order to increase global coherence. For example, Ranney, Schank, Mosmann, and Montoya (1993; based on a misconception noted by Keysar, 1990) found that most participants initially believed that Berlin lay *on* the East/West German border, but revised their beliefs as they incrementally received information that could be used to disconfirm the "on-the-border" hypotheses. (E.g., they were told/reminded of the Berlin airlift, the Western Allies' agreement to halt their troops far west of Berlin, Berlin's location within united Germany, and the northern and southern ends of the border.) With each successive piece of evidence, participants moved toward a more accurate view of Berlin's location relative to the border, suggesting that they modified their belief networks to maintain coherence in the face of the new information. In this vein, and relating to studies on metacognitions about one's estimates (e.g., Soll & Klayman, 2004, on overconfidence), Munnich, Ranney, and Appel (2004) found that a curriculum that fosters counterarguments to one's own initial estimates can lead to improved estimations of novel quantities.

Numeracy and Policy: Elicitation and Hypotheses

According to TEC, accepted evidence that is critical and germane carries considerable weight in our belief systems. Within NDI, we seek to understand when and how a *special* kind of proposition that meets these criteria—numerical evidence—can catalyze knowledge-transformations. To address NDI, Ranney and colleagues have developed various methods, including EPIC (Estimate-Prefer-Incorporate-Change; see the top four cells of Table 1): (1) Participants *estimate* a quantity that is relevant to an issue; for instance, we asked our (California) students for the number of U.S. citizens registered to vote per 1000 18-24 year olds. (2) Participants indicate what they *prefer* the quantity to be. (3) Participants later receive correct base rate feedback to *incorporate* (507 of every thousand 18-24 year olds are registered). Finally, (4) participants indicate again what they prefer the quantity to be—telling us whether their preferences *changed* after learning the actual number. We have found that, to the extent that feedback is surprising, it generally leads to nontrivial belief revision (e.g., Lurie & Ranney, 2005). However, previous studies of EPIC-induced changes have focused on rather short periods of time (e.g., under two hours in Ranney et al., 2001), so an obvious extension is to note what happens with numerical conceptions and policies over longer periods.

Numerical Recall First we consider how well participants recall numbers they receive as feedback after some delay. Had students *not* received any feedback, we would expect their subsequent estimates to be randomly distributed around their original estimates; this would also be the case if they fully forgot the feedback they received. On the other hand, if they recall numbers that show distributional movement (relative to initial estimates) in the direction of the feedback they received, the result would show some memory of the feedback. This leads to the **Improved Item Numeracy Hypothesis:** After receiving feedback, participants may recall numbers that differ from their initial estimates, and show movement in the direction of the feedback.

Policy Shift Persistence To capture the contingency of preference on one's numerical beliefs at a given time, we represent policy as a ratio between one's numerical preference and what one believes the base rate to be at that time (e.g., Munnich et al., 2003; Ranney et al., 2001). Specific policy formulas are summarized as follows:

Initial Policy = Initial Preference / Estimate

Feedback-Present Policy =
Preference at Time of Feedback / Actual Number

Delayed Policy = Preference at Recall / Recalled Number

In order to determine whether one's policy shifted, we compute *policy ratios.* Such a ratio is the degree to which a policy changed between two points (e.g., between the start and feedback; between feedback and recall; or overall):

A Policy Ratio = A Later Policy / An Earlier Policy

Note that proportionally rescaling one's preference yields a policy ratio of one; for instance, consistently preferring halving a value entails a policy ratio of 0.5/0.5=1. *Policy shifts* are thus signaled by policy ratios that are significantly greater or less than one (e.g., preferring no change initially, then later preferring a doubling: 2/1=2).

In the present work we sought to elicit policy shifts like those observed in earlier studies, and then observe whether they persisted over time. As with the recall of the numbers themselves, if people were never given feedback any subsequent policies they indicated would be expected to cluster randomly around their original policies. This result would also be expected if participants reverted to their initial policies some time following the receipt of feedback, either because (a) they forgot the feedback that had prompted them to adopt new policies in the first place—and it no longer had an effect, or (b) as they had time to digest the feedback, they no longer believed that the base rate warranted a policy shift. In both such cases, although people may indicate policy shifts at the time of feedback, they would be the products of a momentary surprise, and would not constitute lasting revisions of policy beliefs.

In contrast to these scenarios, if delayed policies move away from the set of original policies, and toward the policies formed at the time of feedback, it would suggest that policy shifts persist beyond the point of feedback. This leads to our second hypothesis, the **Persistent Policy Shift Hypothesis**: Policy shifts that occur during the EPIC procedure are long-lasting (i.e., endure one or more weeks), as evidenced by the movement of delayed policies toward the policies people formed when feedback was present, relative to the set of initial policies. To the extent that policy shifts persist beyond the point of feedback, it indicates that feedback produced a relatively permanent change in people's belief networks, such that future policy-making will be affected by the shift that took place when feedback was given.

Table 1. EPIC-RP procedure steps for one item.

Estimate
Out of 1,000 U.S. Citizens between the ages of 18 and 24, estimate the number of people who were **registered** to vote in the presidential election in the year 2000. ____________ out of every 1,000 U.S. citizens were registered to vote in the 2000 presidential election.
Indicate Preference
Imagine you had the power to change this amount. Give your ***preference*** for the number of registered voters between the ages of 18 and 24. ___________ out of every 1,000 U.S. citizens would have been **registered** to vote in the 2000 presidential election.
Incorporate feedback
According to the U.S. Census Bureau, 507 out of every 1,000 U.S. citizens between the ages of 18 and 24 were **registered** to vote in the 2000 presidential election.
Change?
(Identical to Preference above)
Retention interval: 8 days/12 weeks
Recall Feedback
Out of 1,000 U.S. Citizens between the ages of 18 and 24, try your best to remember the number of people who were **registered** to vote in the presidential election in the year 2000. ____________ out of every 1,000 U.S. citizens were registered to vote in the 2000 presidential election.
Change?
(Identical to Preference above)

Method

This study's participants were 95 eighth-grade Algebra I students from three consecutive class periods at a San Francisco Bay Area middle school. All students received four "common" items (Voter Registration, Immigration, Incarceration, Athlete's Salary), and four of 12 other items that were each given to one-third of the students.

Two items in the EPIC format were presented each day over a four-day period. (See Table 1 for format, and Table 2 for a complete list of items.) For each item, students first estimated a quantity. Next, they indicated their preferences for the estimated quantity. Participants then received feedback (the true value) to incorporate, and had the opportunity to revise their preferences in light of feedback.

Beginning eight days after the first EPIC items were presented, an "RP" extension of EPIC was administered—in which students were asked to *recall* the numbers they received on the first day and again to indicate their *preferences*. The following (tenth) day, participants were asked to recall, and give preferences for, the numbers they had received on the second EPIC day. Eleven weeks later, participants were asked to recall the feedback for, and give preferences for, the remaining four items (over two days). Thus, four EPIC-RP item sequences were completed after eight days' delay, and four more after 84 days.

Results

Improved Item Numeracy Hypothesis

We first considered whether recalled numbers moved in the direction of the feedback numbers that participants received (indicating that feedback influenced people's recall). Overall, participants' delayed recall showed a tendency towards the feedback values, relative to their initial estimates: After eight days, 201 of the 271 (74%) applicable responses moved towards the feedback value; after 12 weeks, 148 out of 218 (68%) did so. We tallied the proportions of students for each question whose recall value moved in the direction of the feedback (including those who overshot it) and found that, after both eight days and 12 weeks, majorities of students on *all eight* questions recalled a number that moved in the direction of the feedback (Binomial $p<.01$). Thus, we observed a reliable pattern of movement in the direction of the feedback value among a majority of participants—and over both time delays, supporting the Improved Item Numeracy Hypothesis. Table 2 summarizes estimates, true values (feedback), and recall-values by question, but we urge caution in interpreting its medians.[1]

Persistent Policy Shift Hypothesis

Having examined participants' recall after eight days and 12 weeks, we determined whether feedback-driven policy shifts endured. If the feedback-present policies did *not* persist over a delay, we would expect the delayed policies to be indistinguishable from the initial policies (i.e., people would have returned to their original policies). In contrast, policy shifts should be seen as persistent if the delayed policies move toward feedback-present policies, relative to students' initial policies. Overall, participants' delayed policies showed movement towards feedback-present values: After eight days, 183 of the 271 (68%) of the applicable responses moved towards the feedback-present value; after 12 weeks, 126 out of 218 (58%) did so. Correspondingly, the proportions of students whose delayed policies moved in the direction of their feedback-present policies show that the majority demonstrated this pattern for all eight questions after eight days (Binomial $p<.01$), and for seven out of eight questions (Binomial $p<.05$) after 12 weeks. Paralleling item numeracy findings, we saw reliable movement in the direction of the feedback-present policy among a majority of participants over both delays, which supports the Persistent Policy Shift Hypothesis. Table 2 summarizes initial, feedback-present, and delayed policies, by question, but we again urge caution in interpreting its medians.[2]

Discussion

Preferences are central to human cognition, and many propositions inform our social preferences (e.g., Ranney & Schank, 1998). In particular, *numerical* policies offer cognitive scientists compact, useful, sources of evidence regarding individuals' conceptual changes. Moreover, voters and candidates may form preferences that conflict with what they would otherwise prefer if they ignored base rates.

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[1] That is, another, inferior, way of testing for movement in the direction of feedback is to consider whether the medians move in the direction of the true value. For the numbers recalled eight days after feedback, median recall values diverged from estimates in the direction of the true value, for seven out of eight questions (Binomial $p<.05$). For numbers recalled 12 weeks after feedback, though, median-based analyses are not sufficiently sensitive—and even misleading—as median recall values diverged from estimates in the direction of the true value for only three out of the five items that showed medial movement (of the eight items; *ns*). However, closer examination of the patterns of recall by individual participants reveals that it was quite common for, say, two people to give estimates that straddled the feedback value; if each moved toward the feedback value at the recall stage, but one moved more than the other, their median recall might actually *diverge* from the feedback value, relative to the median estimate! Since an analysis of medians potentially indicates divergence from feedback numbers for cases like this—in which both participants actually approached the feedback—we consider the analyses reported in the main text to be of greater value.

[2] Similarly to our analysis of delayed recall, we considered what happened with median delayed policies For the policies elicited eight days after feedback, median delayed policies diverged from initial policies, moving in the direction of the feedback-present policies, for seven out of eight questions (Binomial $p<.05$). For policies elicited 12 weeks after feedback, though, median delayed policies moved in the direction of the feedback-present policies for only five out of seven items for which the median policy changed (of the eight items; *ns*). As with assessing the prior hypothesis, considering median policies obscures underlying patterns by offsetting effects of participants who actually gave delayed policies that moved asymmetrically in the direction of the feedback-present policies. In concert with the item numeracy results, we, therefore, consider the analyses reported in the main text to be the most informative.

Table 2. Summary of *medians*[1,2] for estimates, true values, recall values, and corresponding policies; 100% = status quo policy.

Question	Estimate	Initial Policy	True Value	Feedback-Pres. Policy	Recall Value	Delayed Policy
Recall and Policies 8 days after feedback						
US Voter Registration per 1000 Young Adults	600	137%	507	177%	500	167%
US Legal Immigration[3] per 1000 Residents	460	125%	3	19999%	7	931%
College Degrees per 1000 Adults	418	222%	275	364%	300	300%
US Sleep per Night	8 Hrs	125%	6.9 Hrs.	130%	6.9 Hrs.	133%
Public University Cost	$19K	35%	$18K	54%	$18.6K	51%
Toyota Camry Price	$20K	50%	$19,560	77%	$19,500	71%
US One-Way Commute	30	33%	25.5	39%	25	30%
Households with TV(s) per 1000 US Households	899	111%	980	101%	800	104%
Recall and Policies 12 weeks after feedback						
US Male Athlete Salary	$1 Mil.	73%	$2.5 Mil.	81%	$1 Mil.	85%
US Incarceration per 1000 Residents	450	80%	7	100%	300	67%
Female Teachers per 1000 Teachers	600	100%	833	60%	600	95%
Garbage Production per day per US resident	25 lbs.	35%	4.5 lbs.	67%	16 lbs.	30%
Inflation: 1962 vs. 2002	$2750	49%	$5785	39%	$2750	28%
US Computers per 1000 Households	647	125%	510	181%	750	130%
US Cars per 1000 Drivers	1,075	85%	1,183	85%	900	69%
Non-diet Soda Calories	135	56%	150	37%	140	47%

NDI theory proposes that estimates and numerical preferences are outputs of our belief systems—the tips of a "reasoning iceberg" (Ranney et al., 2001). Underlying the estimates and preferences, one's understanding of an issue may be thought of as a network of ideas connected by personal experiences, media, religion, etc. When asked to estimate, say, the incarceration rate, few can simply recall it. Instead one usually activates various propositions about crime rates and law enforcement that shape the estimate. Likewise, numerical policy for a given item/topic is, metaphorically, an output from an extensive belief network that lies below the surface of overt response. For example, one might believe one's incarceration estimate to be acceptable and simply reiterate it as one's preference (a status quo policy). However, if later surprised by the true incarceration rate, one's sense of reality is challenged, and one might decide that the prior reasoning was incorrect or incomplete. In this conception, the iceberg's hidden "bulk"—the belief network from which estimates and numerical preferences emerge—may be transformed by the feedback's impact. To extend the metaphor, imagine an object hitting an iceberg, causing much of the ice to fall off: The new contours thus created are analogous to the post-feedback numerical concepts and policies that result when one encounters surprising numbers. In like fashion, NDI can offer rich findings to cognitive scientists interested in the dynamics of belief networks.

The present study demonstrated that numerical feedback was memorable, and that it had lasting effects on policies. As might be expected, effects were perhaps more prominent after eight days than after 12 weeks. However, even at 12 weeks, students recalled whether they had initially over- or underestimated, as indicated by movement in the correct direction over both delays. Similarly, even after 12 weeks, students' policies moved in the direction of the policies they formed while looking at the feedback numbers. (Space prohibits a detailed discussion here, but our results also showed correlations between feedback recall and policy-shift maintenance, and that, while one may be slightly more likely to retain the feedback than one's new policy, a change in one's policy may be more likely to remind one of the feedback than vice versa.)

Skeptics would be correct to point out that few participants maintained the exact policy they formed at the time of feedback, and that few recalled the exact feedback numbers. Does this diminish the importance of the present

[3] Extremely high feedback-present policies suggest that students either misinterpreted this question or had a grossly distorted impression of the U.S. immigration rate. Analyses were carried out with and without this item, but there was no difference in significance.

findings? We think not, for the following reasons: First, it is important to note that these eighth-graders were exposed to the true value for each item for less than five minutes, and the fact that they showed effects of this brief exposure 12 weeks later would delight most parents and teachers. Second, in the parallel case of Ranney et al. (1993), it is notable that many students reached a veridical understanding of the location of Berlin only as the result of the cumulative effect of several facts they were given. If we were to give multiple pieces of numerical feedback in follow-up studies, we expect that each piece of information would increase the odds of a broader restructuring of people's belief networks. Incorporation of each new datum might be likened to a minor impact for the metaphorical iceberg, leading to a slight change in its mass distribution; although the effect of any single event might be minor, a succession of such events may cause a dramatic shift, yielding new features or exposing previously hidden ones.

Prior to the present work, a variety of experiments from our laboratory had shown that a single number can lead to striking shifts in numerical policy preferences. This stood in contrast to work suggesting that conceptual shifts were relatively rare (see Chinn & Brewer, 1993, among others). Until now, though, it was unclear how long such new orientations would last—that is, whether they represented belief revisions or fleeting adjustments that would fade shortly after the experiment. The present findings of persistent numerical concepts and policy shifts indicate that a transformative belief revision can be sparked by a single number.

Acknowledgements

We thank Jake Disston and his students, Dan Appel, Luke Rinne, Christine Diehl, Sujata Ganpule, Janek Nelson, Patti Schank, Michelle Million, Jed Stamas, Daniel Wolf-Root, Kelvin Chan, Sasha Raskin and rest of the UCB Reasoning Group for their helpful comments. This work was funded by a UCB faculty research grant and an AERA/IES Postdoctoral Fellowship.

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