CHAPTER FOUR

Increased Wisdom From the Ashes of Ignorance and Surprise: Numerically-Driven Inferencing, Global Warming, and Other Exemplar Realms

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Abstract

What one *knows*, what one does *not* know, and what one *wants*—as well as the dynamics among them—play major roles in psychology. We herein discuss such dynamics—namely, learning—as a desire-driven, generative process that increases knowledge and wisdom through cycles in which incoming information (a) exposes new areas of ignorance, (b) changes one's preferences, and (c) creates an appetite for more knowledge. Evidence is presented that shows that when salient feedback along two described dimensions—numerical and/or mechanistic—conflicts with one's estimates, predictions, or explanations, it can trigger surprise, which in turn produces wisdom-enhancing conceptual change. Highlighting ignorance's importance in increasing wisdom, we describe (1) interventions utilizing surprising information (for instance, from our Numerically Driven Inferencing paradigm), and (2) a specific focus on global warming as a touchstone for increasing wisdom, which includes (3) a direct-to-the-public website for fostering conceptual changes regarding that central phenomenon of climate change (www.HowGlobalWarmingWorks.org).

1. LEARNING, WISDOM, AND IGNORANCE

A central dynamic throughout human psychology is that of learning. General discussions of learning abound, but this chapter focuses on a *subset* of learning phenomena: a collection of changes in beliefs, preferences, or goals that are triggered by modest, but critical information that illuminates one's "knowledge voids." We highlight cases in which a new awareness of one's incomplete knowledge produces normatively desirable attitudes, yet we recognize that people sometimes underweight new evidence—such as when the evidence increases cognitive dissonance (for instance, Festinger & Carlsmith, 1959), challenges strongly held positions (for instance, Lord, Ross, & Lepper, 1979), or reduces the coherence among beliefs (for instance, Ranney & Schank, 1998; Ranney & Thagard, 1988; Thagard, 1989). This chapter also focuses on studies that use content topics about which people *care*[1]; however, our learning participants are neither selected for, nor is there a fictive manipulation to produce, an emotional commitment to any specific set of beliefs. We particularly address Gestalt-like learning (for instance, Wertheimer, 1945) that yields enhanced wisdom from the "irritation" of becoming aware of one's (partial) ignorance, rather like an oyster forming a pearl around an irritant. In the vast majority of

[1] Even predicting a ballistic trajectory is ego involving when feedback is anticipated (Ranney & Thagard, 1988).

these cases, as explored in the following sections, people *accept* surprising information—revising their beliefs and/or goals accordingly.

Wisdom is commonly defined with respect to knowledge, experience, understanding, and judgment: essentially, a multidimensional index of these difficult-to-define, confounded constructs. This chapter emphasizes the knowledge and judgment components, as much of "wisdom" seems represented by the combination of accessible information and one's ability to make choices that match one's values (cf. the "wisdom deficit" mentioned by Clark, Ranney, & Felipe, 2013). We discuss learning as an increase in one's wisdom (beyond just accepting one's ignorance in a domain)—such as (1) desirable knowledge gains and (2) similarly desirable changes in what one wants (for instance, goals, preferences, or priorities among one's goals/preferences). Complications abound, of course. We conceive of the components of wisdom, in interaction with each other and with motivation, to include the part of judgment that involves preferences, goals, and goal management. Goal-infused motivations often spawn knowledge gains, and new knowledge often cyclically changes one's goals and motivations. For instance, consider a child whose goal is to visit another spiral galaxy, which motivates her to learn that the closest, Andromeda, is 2.5 million light-years away, and the unfortunately related "news" that one cannot exceed light's speed. Hopefully, her awareness of a new knowledge void produces curiosity that she is now motivated to fill. She may realize her goal's impossibility, lower its priority, and turn to other endeavors. Alternatively, she might generate and prioritize new goals, like "improve telescope technology to better understand Andromeda," or even "explore teleportation possibilities." We might say that although the child has sacrificed one goal, she seems wiser for having done so. In many of the studies discussed in the following sections, we observe people similarly changing both their preferences and how much they care about issues—which reflect priority changes among the many goals individuals hold.

Related to wisdom is rationality, which Ranney (1996) suggested measuring as the relative fidelity to which one's actions reflect one's goals. It is difficult to ascertain that one is acting *irrationally*, but an indicator occurs when one's actions do not optimize the attainment of one's professed, weighted, goals (Ranney, 1996). Toward an extreme, if self-preservation were one's only goal (or subsumed more than half of all available goal weightings), it would be irrational to throw oneself onto a bomb. But risking one's life could be rational if one's goals include "saving others"; indeed, as human lives have increased in complexity and possibilities, and given our limited temporal and processing resources (Hoadley, Ranney, & Schank, 1994; Ranney & Schank, 1998), finding even satisficing strategies represents a major challenge for many of us. For instance, many mathematically sophisticated people "never get around to" analyzing their financial investments, but without knowing their competing goals, resources, constraints, and satisfaction thresholds, we hesitate to suggest that the seeming procrastination is irrational. Thus, another perspective on wisdom is that it clearly manifests itself when one's beliefs lead to behaviors/actions that optimally satisfy one's most important goals.

We might think of knowledge voids and wisdom voids as cognitive-emotional blind spots that may remain unnoticed without effort.[2] Consider ignorance as a void that can generate wisdom, once discovered—often when accompanied by surprise. Ignorance is primarily defined as a lack of knowledge or information. Ignorance—as a state of being uninformed—generally has a poor reputation. However, none of us knows everything.[3] An appropriately charitable view portrays ignorance as the complementary silence that gives beauty to the musical notes of "wisdom"—knowledge, experience, understanding, and good judgment. Imagine life without ignorance: Would we experience the joys of awe—or mystery novels? Do scientists not appreciate newly exposed ignorance (perhaps gleefully—for instance, in discovering our expanding universe) when saying, "This information raises more questions than it answers"? New information—particularly with participant "buy-in"—sometimes opens delightful new arenas of ignorance.[4] Once discerned, such "generative ignorance" can thus cyclically trigger the reduction of a knowledge void and/or the discovery of previously unimaginable voids. One might call this clearer metacognitive perspective of one's knowledge-likelihood (perhaps due to one's surprising errors) *epistemic humility*—highlighting how ignorance awareness can generate enhanced wisdom.

Ignorance, from this perspective, forms a crucial "ground" for wisdom's "figure" (cf. Wertheimer, 1945). Novelty seems impossible without partial

[2] Even humans' *visual* receptive voids remained undocumented until 1660.

[3] Knowing *everything* about a domain is usually unimpressive: consider an adult who masters tic-tac-toe. However, chess, chemistry, or psychology mastery—even in relief to much remaining ignorance—is noteworthy. This chapter never invokes "ignorance" in a "stupid" or "backward" sense; we focus strictly on ignorance's "lacking information" sense. One of us has even hypothesized that "*human* ignorance was bliss" may prove true for most of Earth's nonhuman species (Ranney, 2009).

[4] A more recent example is the "growth of new ignorance" following the recent discovery of thousands of hominid bones in a cave.

ignorance; furthermore, novelty's intricate dance with familiarity is fundamental to our happiness and its delicate balance between the banal and the overstimulative that ends up privileging surmountable challenges. Our relationship with ignorance is complex: By turns, we wish to eradicate *and* to protect knowledge voids.[5] Ignorance may be blissful for some, yet many wish they could *forget* some knowledge. However, most people value wisdom at critical moments—such as whether or when to consult a physician. Quantifying knowledge, that mainstay of wisdom, is difficult; what one could know seems virtually and practically infinite. Further, we all have areas of ignorance—perhaps thankfully, regarding awe, art, and new stories. We differ primarily in the kinds or extents of ignorance.

Our use of "*generative* ignorance" is meant, in part, to invoke Gestalt problem-solving phenomena and analyses, in the trans-sum spirit of Wertheimer's (1945) notion of productive thinking.[6] In such situations, noticing a "gap" is usually key in initiating problem solving, and commonly that gap includes a knowledge void. En route to a solution, "often the first step is in recognizing that you have a problem," using common parlance. Realizing one's ignorance, especially while feeling surprised, is what unifies this chapter's central phenomena. However, we take no particular theoretical stance on what kind of conceptual restructuring takes place in these instances. The conceptual changes we detail have characteristics of Gestalt recentering (Wertheimer, 1945), analogical productivity (Holyoak & Thagard, 1996), and Piagetian accommodation (as opposed to assimilation; Piaget, 1977). Some of these information-triggered cognitive reorganizations seem to follow stepwise inferencing; others seem more instantaneous and insightful. The belief revisions we discuss later are diverse, yet unified by the provision of disequilibrating information that yields nontrivial downstream changes in cognition.

Returning to the ignorance-wisdom dialectic, our jobs as academics implicitly include enhancing both our own and others' wisdom—partly by reducing knowledge voids in semantic and/or procedural (for instance, action-directing) knowledge. Often we increase others' wisdom by crafting interventions, activities, and curricula that motivate and support learning. Part of that motivation stems from *not* knowing something; as experimental

[5] Another aspect of this complexity is that discomfort with ignorance can sometimes spawn denial.
[6] "Generative ignorance" is also related to analogical/metaphorical processing, given that ignorance also produces the search for a promising analog that might rapidly spawn a cluster of (hopefully apt) generative inferences.

scientists, our ignorance helps *generate* our hypothesis testing. Again, processes of motivation and learning are tightly connected—and connected to the yin-yang phenomena of ignorance and wisdom. We have found that facilitating the perception of a knowledge void, especially when it is attended by surprise, spawns considerable cognitive change.

2. GAUGING ONE'S *NUMERICAL* KNOWLEDGE/ IGNORANCE BOUNDARIES

To quickly make knowledge voids salient—an intended effect of most of our methods—one need only quiz oneself about quantities that seem societally important. For a phenomenal sense of this, we suggest that the reader now quickly hide the numerical values on the right edge of Table 1 by covering them for a bit. If you are like our Berkeley journalism graduate students to whom we provided some numeracy training, you will be surprised at how few of the quantities you feel comfortable estimating, in spite of their importance to American or international society. To help people gauge their own knowledge-ignorance contour, we and colleagues (Ranney et al., 2008) utilized Table 1's "Top 40" numbers (as of fall, 2006 when the experiment was conducted; Appendix A displays the 2006 items' sources). See Appendix B for a 2015 update of the list and the items' sources.[7] We employed this list of quantities that "one should know (but many don't)" with the graduate journalism students—as both estimation practice and benchmarks to enhance number sense regarding social policies. The list's topics span wide societal swaths, including natural resource use/misuse and global warming ("GW"), which was a curricular content emphasis (see items 35–40). As discussed in the following sections, we find that people can gain considerable purchase about a societal issue by seeking or receiving a few critical, germane statistics—or just one critical, germane statistic. For instance, to determine whether a nation has inequality problems, one might initially request the interquartile range of its household income distribution. Likewise, in explaining the shocking item four on legal, surgical abortions, we often find that people better understand it by offering two to four ancillary statistics regarding contraception's failure rates, pregnancy's rarity in a woman's life, the odds that a pregnancy is unplanned, and the odds that an unplanned pregnancy results in an abortion.

[7] We especially thank Liam Gan, and Emily Yan, for their major roles in the updating.

Table 1 Michael Ranney's (2006 version) top 40 numbers one should know (but many don't)[a]. Values are approximations based on the data available on 9/14/06 except where noted; the 40 numbers are grouped by topic and not ranked. (See Appendix B for updated values.)

1.	World population	6.5 billion
2.	US population	300 million
3.	Annual number of live births per 1000 US residents	14
4.	Annual number of abortions per 1000 live births in United States	315
5.	Annual number of legal immigrants per 1000 US residents	4
6.	Average annual legal immigrants per 1000 Americans over the past 150 years	5
7.	Percentage of US residents who are foreign born	12%
8.	Percentage of US residents who are non-Hispanic whites	67%
9.	Number of US households	113 million
10.	Median US household income	$46,250
11.	Percentage of US earnings earned by the top 1% of earners	17%
12.	Percentage of US individual income tax revenue from the top 1% of earners	35%
13.	The annualized total return for the S&P 500 from 1926 to the present	10.4%
14.	Percentage of US heads of household who own their home	69%
15.	Percentage of US residents who are over 65	12%
16.	Percentage of Americans over 25 with a bachelor's degree or higher	28%
17.	Number of US residents incarcerated (in jail or prison) per 1000 US residents	7
18.	Ratio of murders committed to prisoners executed in the United States	274 to 1
19.	US Gross National Income (GNI)	$13 trillion
20.	US GNI as a percentage of world GNI	29%
21.	US military spending as a percentage of world military spending	48%
22.	Percentage of the world population living on less than ~$1 per person per day	17%
23.	Percentage of the population in Sub-Saharan Africa living with HIV	6%
24.	2006 US federal budget	$2.7 trillion
25.	2006 Department of Defense budget as a percentage of the total 2006 US federal budget (excluding emergency funding, such as for conflicts in Iraq and Afghanistan, and so on)	15%

(*Continued*)

Table 1 Michael Ranney's (2006 version) top 40 numbers one should know (but many don't)[a]. Values are approximations based on the data available on 9/14/06 except where noted; the 40 numbers are grouped by topic and not ranked. (See Appendix B for updated values.)—cont'd

26.	US national debt	$8.5 trillion
27.	Percentage of US residents of age 16 or above employed either part or full time	66%
28.	US unemployment rate	4.7%
29.	Number of jobs that must be created each month to match US workforce growth	138,000
30.	Annualized total inflation over the past 50 years in the US	4.2%
31.	Percent change in annual average oil price, 1981 to 2005, adjusted for inflation	−19%
32.	Percentage of Americans who agree that "God created human beings pretty much in their present form at one time within the last 10,000 years or so"	46%; MoE = ±3%
33.	Lifetime odds of dying in a motor vehicle accident in the United States	1 in 78
34.	Lifetime odds of being murdered in the United States	1 in 211
35.	Percentage of the world's carbon dioxide emissions produced by the US	25%
36.	Percent change in the amount of carbon dioxide in the atmosphere since 1750	+31%
37.	Amount global average surface temperature rose during the 20th century	1.1°F
38.	Number of the 10 hottest years since 1880 in the last 10 years	8
39.	Average size of a US household today, compared to 1950	0.77 times as large
40.	Average size (sq. ft.) of new single-family home, compared to 1950	2.5 times as large

[a]With help from many—especially Luke Rinne, Ed Munnich, Tom Johnson, Patti Schank, Louise Yarnall, and the UC-Berkeley Reasoning Group.

Some of the top-40 list's items might seem pedestrian, but even the US population (item two) yields undergraduate estimates ranging roughly from the quadrillions to only 100,000! For the items involving abortions and legal immigration (items 4–5), we have shown that only about 20% of people capture the true values within their "non-surprise intervals"—an interval outside of which one indicates that one would be surprised (for instance, Garcia de Osuna, Ranney, & Nelson, 2004; Munnich, Ranney, & Song, 2007). Alone or with other items, students who first estimated the quantities and then received the true values as feedback gained an enhanced sense of the related topic/issue (for instance, items 39–40: that Americans are non-ecologically building single-family homes with well over thrice the square footage, per person, of 1950-built homes). Magnitudes truly matter, even when one may be unaware when a magnitude indeed matters—which is related to the earlier rationality discussion. For instance, estimating the annualized return on S&P 500 stocks (item 13) at 2% may cause one to avoid such equities due to a perception of modest reward relative to risk, especially given inflation (item 30); however, the mean total (that is, with dividends) return of roughly 10% per year—the *actual* value—makes the risk less disconcerting for long-term investors. Learning the 40 numbers directly increases knowledge, and likely also increases wisdom, in terms of better-informed goal setting, goal deleting, and/or goal weighting.

3. GAUGING ONE'S *MECHANISTIC* KNOWLEDGE/ IGNORANCE BOUNDARIES

In the discussion of our journalism curriculum study, we focused on assessing and enhancing numeracy, hence its salient quantitative focus. Of course, statistical information is not the only form of knowledge, even though a single statistic might represent much cognitive richness about base rates, correlations, and/or even possible causality (for instance, the high correlation between the duration an object fell and its falling distance). Therefore, having noted the contour between knowledge and ignorance for a *numerical* dimension, let us consider a *mechanistic* dimension, given that much of our research also concerns the qualitative, phenomenal, causal, and form-based contour between knowledge and ignorance.

People may generally believe themselves rather knowledgeable of how things work, but that belief is occasionally rocked (for instance, Rozenbilt & Keil, 2002). For instance, please answer the following: Why is the

Earth (essentially) spherical? Why is it not another shape, such as tetrahedral, cubic, or cylindrical? The first author asked this of a number of university denizens and many report never before being asked about the mechanism that has produced a spherical Earth. The vast majority have certainly not considered the question for many years—and they struggle to find an answer. Many initially claim to not know the mechanism and most fail in providing an explanation that fully satisfies them; most attempts, if ventured, are tentative or hypothetical, lacking finality and certainty.

This widespread ignorance about Earth's geophysical development contrasts with the wise certainty people evidence when simply answering about its shape: "It's spherical/round!" Young children learn this centuries-old touchstone of science, yet attempted explanations largely lack mechanistic warrant. Why do people not *know* that warrant, rather than trying to induce, deduce, and/or abduce (and so on) the causality on the fly? We seem to know so much more about hands-on mechanisms (for instance, how single-gear bicycles work). When people realize such ignorance, confidence in their own knowledge often requires reequilibration, and perhaps a new set-point, as the "illusion of explanatory depth" literature explores (for instance, Fernbach, Rogers, Fox, & Sloman, 2013; Fernbach, Sloman, St. Louis, & Shube, 2013; Rozenbilt & Keil, 2002). Ignorance becomes more palpable when turning from the "easy" phenomenon of Earth's shape to explaining projectiles' trajectories (for instance, Ranney, 1994a, 1994b, 1996; Ranney & Thagard, 1988), the mechanism of GW (for instance, Ranney & Clark, 2016), electricity's nature (for instance, Clement & Steinberg, 2002; and Gutwill, Frederiksen, & Ranney, 1996), Earth's having roughly *two* high tides per day, or myriad other phenomena about which people may know facts[8], but understand little about causality. Again, ignorance is rarely far from us, and our veneer of expertise is often thin. Here, hindsight bias and self-charitableness foster the overestimation of our knowledge relative to our ignorance. Instead of asking respondents why Earth is round, imagine simply *providing* a brief explanation—as we typically do in the classroom—such as "Massive celestial objects such as Earth (for instance, bigger than most asteroids) have gravities strong enough to force their matter toward the most compact 3D form,[9] namely a sphere." Hindsight would likely cause people

[8] What a "fact" is turns out to be rather complicated, for instance, regarding evidence (for instance, Ranney, Schank, Hoadley, & Neff, 1996).

[9] Earth's fluids speed its sphericalness, aiding erosion's compaction; Mt. Everest is but a 0.07% aberration on our wet "cue ball."

to believe that their knowledge before receiving the explanation was greater than it truly was, exhibiting a lack of awareness of the ignorance that facilitates achieving wisdom.[10]

Consider a mechanistic-ignorance example that our laboratory studies much more extensively, as reified in responses to two questions: "How is global warming believed to be happening? That is, what are the physical or chemical processes by which Earth's average temperature is believed to be increasing[11]"? Virtually no one, we find—apparently less than 1% of people (Ranney, Clark, Reinholz, & Cohen, 2012a)—can answer this question at even a basic, 35-word level (Ranney & Clark, 2016). At the bottom of Appendix C, we provide such a set of 35 words. In fact, the first author captures much of the mechanism's core in this 13-word haiku (and sentence):

Global Warming's Mechanism
Earth turns sunlight to
IR light that's sponged by folks'
Greenhouse gases glut.

As Ranney and Clark (2016, pp. 51–52) explicated, mechanistic information can "break ties" between competing claims and/or competing evidential corpora. This partly explains why more people do not worry (or are even aware) that they do not know why Earth is spherical. As humanity's slow acceptance of heliocentrism, of evolution, or of tobacco smoke as a carcinogen show (for instance, Ranney, 2012), (1) people are generally unconcerned with mechanistic information unless an "other side" denies a phenomenon or relationship (for instance, some federal representatives denying anthropogenic GW; Edx.org/understanding-climate-denial, 2015), but (2) once people understand a controversial scientific realm's mechanism, they are more likely to accept it, whether it is gravity, tar/free-radicals in tobacco smoke, or the energy-exchange asymmetry of GW.[12,13]

We later return to discuss GW and mechanism explanations that increase participants' acceptance. Now that we have provided at least a skeletal

[10] Hindsight processes are more subtle than the current treatment allows. For more nuance, see Rinne (2010).

[11] Earth's last complete year at this writing, 2015, was yet another "hottest on record" (that is, since 1880), shattering the prior record (2014's) by 0.23°F—and 1.62°F higher than the 20th century mean—according to NOAA and NASA's GISTEMP Team.

[12] We particularly focus on explaining disputed *climate change* aspects, as they are potentially levers for enhancing the acceptance of normative science.

[13] Not understanding a mechanism, as for vaccines, may cause new doubts (but see effective disease-risk materials in Horne, Powell, Hummel, & Holyoak, 2015).

description of the phenomena involved, let us take stock of the numerical and mechanistic arenas (as stimuli and in reasoning)—and how they relate to conceptual change.

4. (ESPECIALLY SURPRISING) NUMERICAL AND MECHANISTIC INFORMATION CAN CHANGE MINDS

Integrating the prior sections' information, this chapter's reasoning phenomena plausibly fall on a two-dimensional space regarding a person's form of reasoning, as Fig. 1 suggests: (1) a horizontal *mechanistic* dimension (from little mechanistic reasoning to a highly articulated/engaged mechanistic mental image or simulation) and (2) a vertical *numerical* dimension (from little numerical reasoning to highly statistical reasoning). Fig. 1 provides a kind of map regarding how 18 of our laboratory's studies or study-clusters,[14] as we continue discussing them, play out in terms of the dimensions. Perhaps not surprisingly, all of our research discussed herein embodies either numerical or mechanistic reasoning, or both. In Fig. 1, the verticality/slope of a ray formed from the origin to a study's location-centrix *roughly* indicates the ratio to which that study's participants' engaged in numerical reasoning relative to mechanistic reasoning—but the locations are not highly precise.[15] Fig. 1 further represents an additional dimension regarding which studies involved overwhelmingly numerical stimuli/input (in plain font), overwhelmingly mechanistic stimuli/input (**bold** font), or a combination of both (<u>underlined</u> font). Thus, Fig. 1 represents *three* dimensions: two (planar) unipolar dimensions regarding reasoning and one (font-wise) bipolar/trichotomous dimension regarding stimuli/input.

For either (numerical or mechanistic) arena, we have found that one's conceptual change is enhanced by our provided information if the person first generates a model-based "read-out"—for instance, in the form of (1) an estimate (as with the journalists), (2) a prediction (for instance, a particular ballistic trajectory, as noted in the next section) and/or (3) an explanation (as discussed earlier and later). Across many studies, we have found that conceptual change

[14] Of course, Fig. 1 could display many other labs' studies. Such placements, beyond being unwieldy, require a level of qualitative understanding regarding participants' processing that is difficult to glean from others' published work. (We virtually always collect qualitative data—for instance, Garcia de Osuna et al., 2004—but do not always publish them.) Having gained insight into our studies, though, from reflecting on where they would fall on this graph, we invite you to do likewise regarding your most familiar research.

[15] Placements are thus meant illustratively, as we lack precise measures for the involved dimensions.

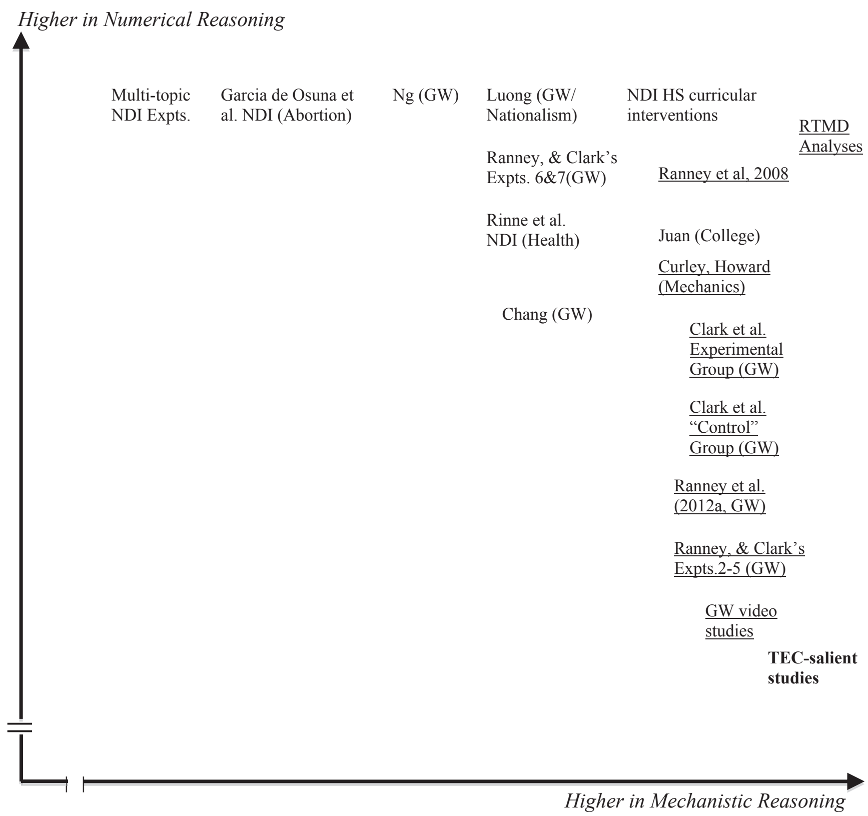

Figure 1 Some of our laboratory's studies discussed in this chapter are here approximately/illustratively represented on the *output*-activity dimensions of Numerical (y-axis) and Mechanistic (x-axis) Reasoning. Regarding *input* activity, regular-font studies involved only numeric stimuli, **bolded** (only the TEC-salient) studies involved only mechanistic stimuli, and underlined studies involved both numeric and mechanistic stimuli. Note: (1) "TEC-salient studies" include Hoadley et al. (1994), Ranney and Schank (1998), Ranney, Schank, Mosmann and Montoya (1993), Ranney and Thagard (1988), and so on. (2) "NDI HS curricular interventions" include High School curricula (that is, Ganpule, 2005; and Munnich et al., 2004), and so on. (3) "Multi-topic NDI Expts." include Clark and Ranney (2010), McGlothlen (2003), Munnich et al. (2003, 2007), Ranney et al. (2001, 2005), and so on. (4) GW = Global warming. (5) GW video studies include Arnold et al. (2014) and Ranney et al. (2015). (6) RTMD Analyses include Ranney (2012) and Ranney and Thanukos (2011), and so on.

(such as when reflected in one's abortion policy; for instance, Garcia de Osuna et al., 2004)—and nonepisodic semantic restructuring (Clark & Ranney, 2010)—often correlate with the degree to which participants find feedback surprising. Without prior read-outs in which people "put their cards on the table," they are less likely to be surprised (a phenomenon likely related to hindsight bias, as noted earlier), and thus less likely to experience a conceptual change (as shown by Rinne, Ranney, & Lurie, 2006).

How much do mechanistic and numerical reasoning dimensions interact? Although we elaborate on this more later, research relating judgment under uncertainty to Bayesian norms offers useful examples. For instance, Tversky and Kahneman (1980) asked participants to indicate how likely an accident involved a blue (vs. a green) cab based on color base rate and suboptimal (for instance, 80% accurate) eyewitness evidence; they found base rate neglect, but argued that triggering a causality heuristic (for instance, the *accident* proportion green cabs caused) brought people closer to normative Bayesian responding. Krynski and Tenenbaum (2007) offered similar findings, but rather than invoking a causality heuristic, they explained base rate neglect in their results within a normative Causal Bayesian model (see Pearl, 2000) that builds in participants' causal scenario models (that is, the purported neglect may be normative given a particular causal model). Space prohibits debating Bayesian normality here, but both of these studies illustrate the potential synergy of mechanistic *and* numerical reasoning dimensions, as participants use numerical information differently depending on their mechanistic understanding—in this case, their causal models of events. Going a step further, evidence from our laboratory shows that surprising numerical evidence alone can bootstrap changes in one's mechanistic understanding that affects one's preferences. Note that, in the research discussed later, we present base rate *frequencies* (for instance, "new legal immigrants per 1000 current US residents" rather than "the immigration rate as a percentage"), following Gigerenzer and Hoffrage's (1995) notion that participants more easily interpret frequencies than probabilities, and we wish to understand participants' quantitative beliefs most directly. However, frequencies are functionally equivalent to probabilities so this has no effect on the analysis-types that can be deployed. Having articulated the numerical and mechanistic dimensions, let us consider them more explicitly with respect to the role of surprise.

5. EXPLANATORY COHERENCE AND NUMERICALLY DRIVEN INFERENCING

Surprise often triggers belief revision. Regarding the numerical arena, if a domain can be expressed meaningfully in terms of quantities, mental models can make quantitative predictions that may draw our attention to our blind spots. Much research has followed from the Theory of

Explanatory Coherence (TEC; Ranney & Schank, 1998; Ranney & Thagard, 1988; Thagard, 1989; and so on), which describes change as spawned by incoherence and competition among ideas, such that people try to revise their beliefs to increase coherence. Such incoherence-spurred revision can occur when people discover conflicting thoughts and attempt to modify their conceptualizations to better approximate maximal coherence, as Clement and Steinberg (2002) found regarding electrical circuits, for which presenting discrepant events can yield improved understandings. Ranney and Thagard (1988) illustrated one aspect of TEC's belief revision account with the typical/composite participant, "Hal," who initially (1) believed that a pendulum bob released at a swing's apex would fall with a lateral (outward) motion, partly because he (2) believed that a child on a playground swing would laterally "fly off" the swing at its apex. Ranney and Thagard modeled Hal's initial belief network as relatively coherent with the generated trajectory prediction (1). Because (1) was incorrect, and the bob was later seen to fall purely vertically, Hal quickly restructured his beliefs—including seriously and appropriately (also as modeled) doubting (2)'s veracity. To illustrate how ego-involving such surprises are, here is a transcript the first author recorded from a participant receiving the dynamic vertical-feedback from the swing's end/apex (E):

> *[Gasp] Nuh-uh! [Pause] Why does it do that? Wow! That's interesting … I guess because E's the endpoint and it. . . It doesn't actually stop there, but it's like an endpoint. It* sort of *stops … It, it slows down so that it can begin to go the other direction. So I guess, for a* split second, *it would stop. And if it were to break there, it would make a fall straight down. Oh wow!*

TEC gained further experimental support from several subsequent experiments. For instance, 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 they revised their beliefs as they incrementally received information (for instance, regarding the Berlin airlift, the Yalta agreement's segmentation, Berlin's location within united Germany, and northern and southern extremes of the border) that tended to disconfirm the "on-the-border" hypothesis. Successive pieces of evidence moved participants toward a more accurate view of Berlin's location relative to the border, consistent with belief networks being modified to maintain coherence with the new information.

According to TEC's data priority principle, evidence that is critical, germane, repeatable, and credible carries maximal weight in our belief systems, so numerical information can carry notable weight and lead to accommodative belief revision. In a series of studies within the Numerically Driven Inferencing paradigm (NDI; introduced by Ranney, Cheng, Nelson, & Garcia de Osuna, 2001), we assessed this and thereby also examined the intersection between mechanistic and numerical reasoning dimensions. NDI usually involves estimation, preference, feedback, and preference-reevaluation but we discuss preferences a bit later; for now, let us focus on feedback on one's estimate and how even a single number can drive a cascade of inferences, as the acronym's title suggests.

For this more basic phenomenal sense of how NDI works, please now answer this question: What percentage of Germans were Jewish in 1932, just before Hitler became Germany's leader? Now, please answer this: How high—and how low—would the percentage have to be to surprise you? Following your three answers, please check the parenthetical at this paragraph's end for the true value, and note whether this value fell outside your "non-surprise interval"—that is, above your upper boundary or below your lower boundary (either of which you projected would result in your surprise). The first author has found that only 20% of University of California, Berkeley, undergraduates specified a non-surprise interval that included the true value; thus, participants were "technically surprised" *four-fifths* of the time. Even people personally familiar with the Holocaust are usually surprised by the true value, perhaps because many people are aware that more than 6 million Jews were killed in the Holocaust. However, the Jewish victims' nationality-distribution is less well-known—for example, at least 3 million Jewish victims were Polish. Although statistics regarding the victims' nationality do not lessen the genocide's horror, the number drives many to various inferences (hence "numerically driven inferencing")—for instance, about the degree to which Jews were scapegoated within Germany, the difficulty/effectiveness of even more widespread Jewish resistance, and so on. Again, this is a realm in which a number impacts one's mechanistic understanding (for instance, of the Holocaust). (The answer to this paragraph's first question is: About 0.9% [9 per 1000] of Germany's population was Jewish in 1932.)

The Jews-in-Germany question is not unique. Our Reasoning Research Group has found other similarly surprising numbers—for instance, both the US legal immigration rate and the US legal abortion rate mentioned earlier (ie., Table 1's items 4–5). High school students' median estimate for the annual legal US immigration rate (relative to the current US population) was found to be about 60 times higher than its true rate of about 0.3%

(at the time; Munnich, Ranney, & Appel, 2004). To reinforce the hardly rare nature of statistical ignorance, recall Table 1's aforementioned top-40 list that was developed for the journalism graduate students' numeracy curriculum. Note that many of these values are critical for policy makers and informed voters. For instance, the United States' large incarcerated population-segment (Table 1's item 17), compared to almost all other nations, might inform "three-strike" and "victimless crime" legislation and voting. That the United States accounts for nearly half of Earth's military spending (item 21) is also surprising to many—as are the odds (relative and absolute) that an American will die by either murder or motor vehicle accident (items 33 and 34). The unfamiliarity with the magnitudes of many items on the list offers much fodder for those who muse that people may be more ignorant than wise.

Beyond assessing individuals' reactions to feedback on their estimates, NDI also explicitly examines how understandings—and *changed* understandings—of relevant base rate information affect people's attitudes on public policy issues, as reified in queries such as this: "Given your [initial or post-feedback] understanding of the immigration rate, what would you prefer that rate to be?" Many people are unfamiliar with even generating a prefeedback preference for quantities (for instance, a dean candidate once admitted to never having thought about what percentage of Americans *ought* hold bachelor's degrees). In interviews (Ranney, Cheng, Nelson, & Garcia de Osuna, 2001), participants often surprisingly say: "I've never thought about it, but I think immigration should be unlimited." But in spite of such apparent magnitude-insensitivity, when asked if they "would mind if five billion people moved to your nation[/town] tomorrow," they quickly agree, realizing that they *do* have a preference—albeit one still being calibrated.[16] (Similarly, the dean candidate admitted that a 100% baccalaureate rate might disadvantage America's economy.)

Ranney et al. (2001) also observed that people considering themselves to be "on different sides of an issue" often lack relevant numerical information, and might find some common ground with their "opposition" if starting with agreed-upon quantitative evidence. For example, many who assert favoring reducing immigration (for instance, estimating a base rate of 10%, but preferring 5%) have more in common than they realize with many claiming

[16] Recent European attitude changes on immigration show how experience/feedback may alter idealism.

to favor *increasing* immigration (for instance, believing the rate is 1%, but sharing a preference for 5%); indeed, many of our "anti-immigration" participants have a much higher numerical immigration-rate preference than many "pro-immigration" participants (which we call "weird reversals"). NDI studies consider the extent to which mechanistic theorizing that drives attitudes have meaningful—albeit not necessarily direct—relationships with relevant quantities. By focusing on quantitative evidence, NDI sheds light on how such evidence interacts with people's initial attitudes, and the extent to which learning true numerical values shapes subsequent attitudes. Thus, NDI provided useful answers to research questions such as these: Do we maintain preferences for the same absolute rates, or for the same proportions relative to actual rates? How much do we shift our policy stances after surprising feedback (Munnich, Ranney, Nelson, Garcia de Osuna, & Brazil, 2003)?

The prototypical NDI method centers on variants of the EPIC (Estimate, state Preference, Incorporate-feedback, Change-preference; Ranney et al., 2001) procedure's four main steps. (1) In EPIC itself, participants first *estimate* a base rate quantity. We usually choose rates/statistics related to familiar issues, but for which people hardly know exact values. Participants must thus activate a network of facts, set relationships, and causal beliefs about the issue to generate an estimate. We often also solicit the aforementioned non-surprise intervals—as well as confidence ratings that the true rate would fall in one's interval. (2) Participants then state their numerical *preferences* for the rate, which rely on the belief networks activated by their estimates, along with their affect and, likely, behaviors relevant to the issue (cf. "inconvenient truths" regarding GW). The ratio of one's preference to one's understanding (initially, one's estimate), is what we call one's *policy* (Munnich et al., 2003). For example, one might find the current abortion rate acceptable and simply offer one's estimate *as* a preference (that is, a status quo policy). Alternatively, one might prefer a reduction or an increase in the abortion rate (the latter is less common, but has been stated by participants concerned that many women lack access to abortion clinics; see Garcia de Osuna et al., 2004). (3) Subsequently, we provide feedback (for instance, the true abortion rate) that participants *incorporate* into their belief system, and we ask participants to rate their surprise on a Likert scale. (4) Finally, we again ask for preferences and note any *change* from one's prefeedback preference and policy. If one is shocked (as is common by the true US abortion rate), it often challenges one's sense of reality (for instance, "Friends don't tell me about unplanned pregnancies?"), and we see preference and/or policy changes.

We hypothesized that the participants' cognitive conflict, upon receiving feedback, would be reflected by their NDI surprise ratings and through their non-surprise intervals (for instance, that a person who was most confident that his estimate would fall within his interval would be the most surprised if it did not). Indeed, we found that the two measurement methods correlated with each other (Munnich et al., 2007) *and*—as predicted—with preference changes (Munnich et al., 2003). Ranney et al. (2001) found that the most surprised participants showed the most qualitatively changed postfeedback preferences. For instance, the true US immigration rate only fell inside of participants' non-surprise intervals 21% of the time—3.5 times less often than the participants' predicted likelihood of capturing the true rate—and those who did not capture the true rate changed their positions *four times* as often as those who captured the rate in their intervals! Moreover, participants indicated visceral surprise or shock in their written and oral comments (see Garcia de Osuna et al., 2004).

Ranney et al. (2001) and Munnich et al. (2003) employed many item-realms, ranging from capital punishment to college admissions criteria, and found that when participants' numerical estimates were far from the true numbers, their policies on issues shifted—akin to Piagetian *accommodation*, in which new, striking pieces of information trigger belief reorganizations. In contrast, when estimates were proximal to true numbers, polices were largely unchanged, akin to Piagetian *assimilation*, in which one's belief network remains essentially intact even with new information (for instance, Piaget, 1977).

An illustrative example from Munnich et al. (2003) involved a between-groups contrast, with undergraduates, of two variants of the abortion item:

A. What is your best estimate of the current number of legal abortions, per 1,000,000 live births in the United States? ____abortions.

B. What is your best estimate of the number of legal abortions performed, per 1,000,000 *fertile* US women (aged 15–44) for a single year? ____ abortions.

Everyone ($n = 28$) who received variant A underestimated the true value, and were notably surprised by it: The median estimate was 10,000 abortions per million live births—33.5[17] times lower than the value at the time: 335,000. By contrast, there was much less underestimation and

[17] With a larger sample, Ranney et al. (2001) reported a median student estimate of 5000 for this query—that is, incorrect by a factor of 67!

surprise among participants receiving B ($n = 53$); the median estimate was (coincidentally also) 10,000 abortions per million fertile women, while the actuality was 20,000. Thus, by subtly altering the question, we observed dramatic changes in estimate accuracies (cf. Schwarz, 1999). Notably, as one would expect from Piagetian-type accommodations, the benefits due to estimating surprising quantities are long term (Munnich et al., 2007) and they transfer beyond the proximal estimation domains (see discussions of our curricular interventions in the following sections regarding Munnich et al., 2004; Ranney et al., 2008).

Preferences across the abortion item's variants also diverged. As implied earlier, we operationalized assimilation as maintaining a similar ratio of (as mentioned earlier) preferred-to-understood values—that is, a policy shift close to zero—and accommodation as either a noteworthy negative or positive policy shift (that is, respectively yielding a significantly more reductive or expansive postfeedback policy). The live-birth-variant estimators showed accommodative policy shifts, with those participants calling for a 64% more reductive abortion policy than they initially indicated—whereas the fertile-women-variant estimators showed more assimilative shifts, roughly maintaining the proportional reduction indicated by their initial policy. Garcia de Osuna et al. (2004) analyzed participants' policy justifications, which echoed the quantitative shifts. For example, of the 32 live-births estimators who initially held status quo policies, 21 (66%) preferred a decrease in abortions postfeedback. Overall, participants continued to assert that abortions should be available, but also that contraception should receive more societal emphasis. Together, these findings suggest that one's numerical understanding, even when involving the same underlying quantity, can trigger the kinds of changes that Tversky and Kahneman (1980) and Krynski and Tenenbaum (2007) noted when they primed different causal models.

Such (for instance, abortion) policy shifts are hardly merely "cool cognition" processes that lack emotion. The abortion feedback commonly profoundly affects people, as their written responses to the statistic show (for instance, "Wow! I can't believe that it's so high."). In contrast to our immigration feedback value, which causes people to care, on average, significantly less about that topic, the abortion number causes people to care significantly *more* about abortion (Garcia de Osuna et al., 2004). Indeed, use of this item is partly because at least one of the authors experienced an unsettling mental animation of a growing mound of 335,000 fetuses—which is not rare for participants from either side of the political spectrum.

6. NUMERICAL AND MECHANISTIC CO-INFLUENCES: GRAPHS AND STATISTICS IMPLYING CAUSALITY

As the NDI abortion (and other) evidence shows, our mechanistic and numerical reasoning dimensions (recalling Fig. 1) are idealizations and can clearly influence each other in application. Once one has left one's highest level of mathematical education, one rarely engages in numerical cognition that is divorced from mechanism (for instance, "pure mathematics").[18] Likewise, many or most mechanistic cognition episodes have quantitative aspects marbled in—for example, the differential force-magnitude implied by "slamming," as opposed to "closing," a door. Consider the acts of extrapolating, and making inferences about, a graph. Inspired by Lewandowsky's (2011) work, Chang (2015) of our laboratory provided about 700 participants graphs of both Earth's mean surface temperature and the Dow Jones Industrial Average (adjusted for inflation: DJIA-a) and requested that they (1) extrapolate the (variably averaged) data into the future and (2) (re)assess their acceptance of GW (as happening, anthropogenic, and so on). Fig. 2 exhibits some of the graphs, from about 1880 through 2014—with both annual span/simple averages (panels A and B, which all participants received) and 16-year (panels C and D) span/simple averages, along with 64-year moving averages (panels E and F, which only a minority of conditions received). This "Bex" experiment's interventions introduced an unbiased alien-robot, Bex, who decides to understand Earth's phenomenal (for instance, temperature and finance) trends after accidentally landing here.

Bex knows that a good strategy for noisy data is to plot them and use averaging techniques if a trend is at all unclear. Bex's graphs generally become more informative when each averaged datum subsumes longer temporal periods. Fig. 2's 64-year moving-average graphs (panels E and F) are particularly compelling because they virtually monotonically increase throughout the functions (thus making it difficult to deny Earth's rising temperature). Even casual viewers of the 16-year-average graphs perceive increasing functions (with "Duh" a common comment)—leading to multiple routes to infer that temperatures are increasing. Of course, many people infer the rising trend after merely viewing the annual temperature data of Fig. 2's panel A.

[18] Truly, few Americans ever again engage anything close to their highest level of math knowledge; most never again factor a quadratic, let alone use a cosecant or employ integration by parts. Some such learning reflects societal gatekeeping (for instance, assessing performance/aptitude with greater precision than essay-writing affords).

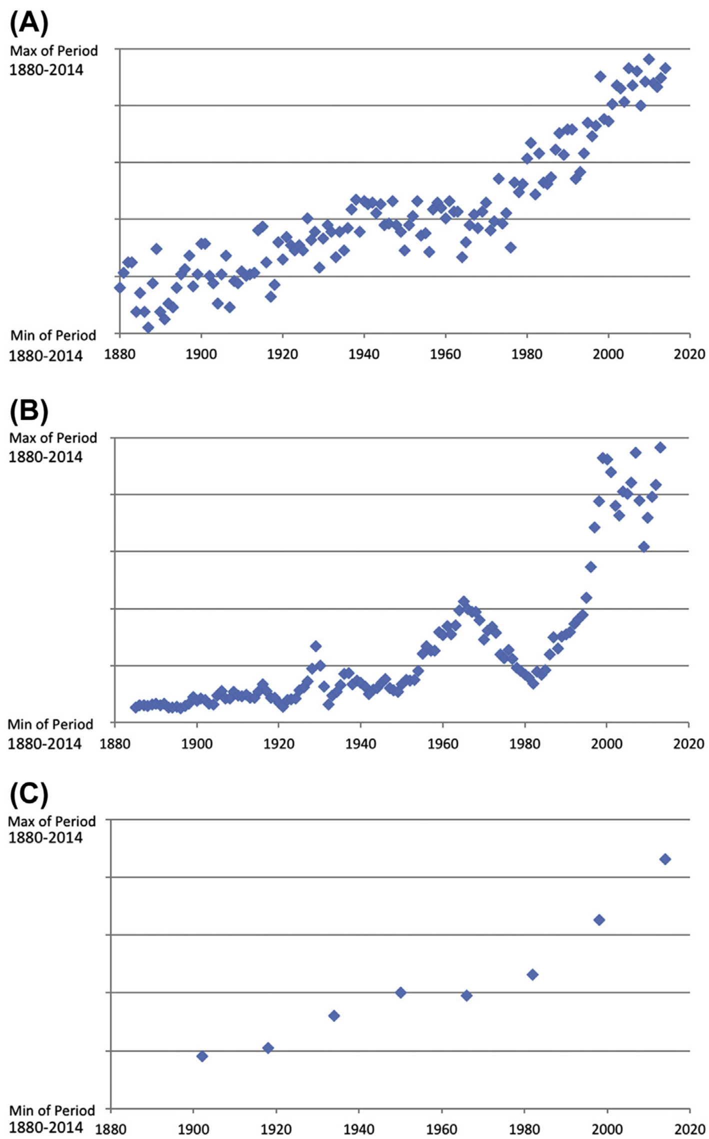

Figure 2 Six graphs that were used in an averaging study (Chang, 2015) are presented. Panels A and B display annual span-averages for, respectively, Earth's surface temperature and the Dow Jones Industrial Average, adjusted for inflation. Panels C and D display those respective data as 16-year span averages. Panels E and F display those respective data as 64-year *moving* averages. *Temperature data are from 1880 to 2014; equities data are from 1885 to 2014.*

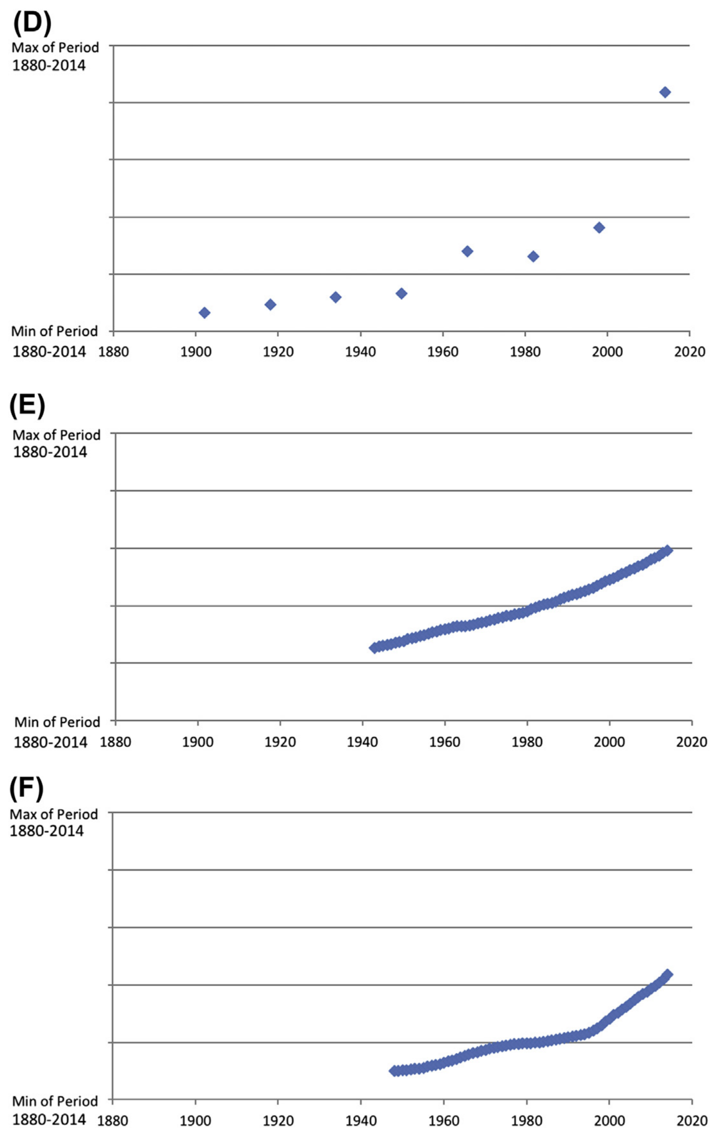

Figure 2 (*continued*).

We have found that, without labeling the y-axes, even faculty and graduate students at an elite business school only randomly discriminated which of Fig. 2's 16-year-average graphs (with nine data points per graph) represents temperatures as opposed to DJIA-a values. (We have since replicated this "chance" finding with a more representative sample; the business participants actually chose nonsignificantly below chance.) Using 10 intervention-variants involving the temperature and equities graphs, we found that each of the 10 markedly increased GW acceptance, and that this increase was maintained 9 days later. Further, 98% of the Amazon Mechanical Turk ("MTurk") participants assessed the temperature 16-year span-average function as increasing. (The other 2% did not think it was decreasing.) Virtually all participants also predicted that Earth's temperature (and the DJIA-a) would continue to rise through 2035—with 2035 being the last of our temporal probes. Further, if one cannot discriminate the (for instance, 16-year) graphs, and if one believes that the DJIA-a has been increasing, *yet another* route appears by which one may infer that Earth's temperature has been increasing.

Were Bex-experiment participants, using its graph-based averaging representations, engaging in numerical or mechanistic reasoning? We believe that both dimensions were engaged, and to degrees that likely varied by individual. Participants extrapolating the graphs clearly virtually unanimously projected magnitude trends such that numerical cognition was engaged in a somewhat meta-statistical way, given that each statistic is a graph-point. Extrapolators were furthermore aware that a graph represented either temperature or stock market data, and their knowledge of climate and finance mechanisms interacted with their extrapolative predictions. Some knew more about stocks, and others about GW; likewise, some may have thought deeply about the amount of data averaged into each graph-point, whereas others may have entertained nonlinear trends for one or more graphs.

The preceding discussions of preference changes and attitude changes, triggered by (sometimes even single) surprising statistics, contrast with those who suggest that effecting such changes is quite difficult. Many researchers underestimate people's abilities to counter their top-down thinking and recognize disconfirming information (Ranney & Clark, 2016). Humans certainly have predilections and favored hypotheses, but we also have bottom-up capacities to assess them; do we repeatedly return to a restaurant after we have seen it has closed forever? In the climate change realm, Kahan and colleagues (for instance, Kahan et al., 2012) suggested that scientific information (which statistics often represent) are ineffective in altering GW beliefs. However, Ranney and Clark (2016) disconfirmed this "stasis theory" with six experiments that successfully used short interventions that each changed participants' GW acceptance (also see Clark et al., 2013; Ranney et al., 2012a). Others have also garnered evidence counter to stasis theory (see a partial review in Ranney & Clark, 2016, pp. 54—55; also see Lombardi, Sinatra, & Nussbaum, 2013; Otto & Kaiser, 2014). The six experiments' interventions included Appendix C's 400-word textual mechanistic explanation, a

45-min high-school curriculum, and two sets of numbers (that is, seven and eight statistics, respectively), which respectively confirm or question GW's occurrence. Likewise, Arnold et al. (2014), demonstrated that a 4-min German video based on the 400 English words likewise increases participants' GW acceptance.

Most recently, our laboratory has expanded upon these stasis-disconfirming experiments, showing all 10 Bex graphs (that is, meta-statistical) interventions to be successful—thus replicating the gains found involving mechanistic texts and video, along with the aforementioned two sets of statistics; further, two laboratory members, Teicheira (2015) and Luong (2015), found that decreasing Americans' nationalism (and often *over*nationalism) increases their GW acceptance. We discuss these GW studies collectively later when addressing such interventions' longevities. All such studies again follow the theme that, when confronted with a disequilibrium regarding the contour between one's knowledge and one's ignorance, one will perform considerable intellectual work to accommodate and restructure one's wisdom's bases. To reach a new homeostatic balance, beliefs—and/or preferences and intentions—then change.

7. USING NDI CURRICULA TO IMPROVE PEOPLE'S ANALYTIC ABILITIES

The NDI abortion findings presented earlier raised a troubling prospect: If statistical variants markedly impact people's policies, then citizens might be readily misled by the mathematical framings of some politicians, media outlets, and so on. Research suggests that improved estimation accuracies result from recruiting category information (for instance, Huttenlocher, Hedges, & Prohaska, 1988), receiving data in frequency formats (Gigerenzer & Hoffrage, 1995), or using "seed" numbers (for instance, Brown & Siegler, 2001), but we wondered whether learning to deploy a range of scientific reasoning strategies during numerical reasoning might transfer to a set of unrelated issues. Results from a series of curricular interventions indicated that coherent, domain-independent, numerical reasoning seems to be a skill that can be efficiently learned.

7.1 Improving *Precollege Students'* Numeric-Analytic Abilities

Our laboratory started with small-scale curricula, as Curley (2003) and Howard (2003) worked with fifth-grade science camp students regarding automobiles' stopping distances, assessing subsequent reasoning about related quantities such as alcohol-related automobile accidents as opposed to unrelated quantities such as US household income. Juan's (2003) group of eighth-grade Algebra students practiced (1) graphing quantities and (2) debates that highlighted alternative perspectives one could take in estimating and forming preferences related to college, versus high-school, graduates' earnings. In each study, both experimental and control groups received content area instruction (in physics or math, as appropriate), and the most striking result was that both groups showed significant pretest-to-posttest improvement in Curley and Howard's studies, and marginally significant improvement in Juan's study; furthermore, a control group's effect seemingly resulted from a practice effect due to estimating the pretest items in an NDI-type format. McGlothlen (2003) interviewed high-school students as they produced estimates and numerical preferences regarding many issues; those who relied on analytic processes containing relevant numerical information and constraints produced reliably more accurate estimates than those not exhibiting such strategies. This cohered with the idea that Curley's, Howard's, and Juan's students' limited NDI practice prompted increased analytic thinking.

Appel (2004) and Munnich et al. (2004) explicitly emphasized analytic processes in an NDI high-school geometry curriculum. To foster students' analytic processes, they were prompted to provide initial estimates and preferences, and then consider both alternative perspectives and constraints perhaps not initially considered—in small-group and class-wide discussions. The intervention's target quantities involved students' career choices and societal issues about which they had opinions (for instance, poverty and oil imports), with our logical argumentation process presented as an introduction to geometric proof. The Experimental class, unlike the Control class, showed estimation-accuracy improvement between pre- and posttests of counterbalanced sets of quantities to which participants were naïve. (See Munnich et al., 2004, for the intervention's items and pre-/posttests.) Analyses revealed both (1) near transfer from the intervention's items (for instance, a US-population item likely improved posttest accuracy on a California-population item) and (2) far transfer to items with no obvious relationship with intervention items (for instance, average hours sleeping). Cumulatively, these findings indicated that 10–15 min per day in class and an equivalent amount of homework, over six weeks, yielded the internalization of analytic strategies for considering important societal issues—and became a model for subsequent efforts, particularly the following one targeting journalists.

7.2 Improving *Journalists'* Numeric-Analytic Abilities

Ambitiously, we hoped our findings might generalize to much more sophisticated participants: journalism graduate students. Journalists can, thankfully, help educate citizens, but their quantitative/analytic skills are often modest (see Yarnall, Johnson, Rinne, & Ranney, 2008). Our pilot experiments showed that both budding and working journalists often resist estimating socially relevant quantities, despite our finding that providing them critical, germane quantities subsequently shifted their own policies (for instance, Ranney, Munnich, Lurie, & Rinne, 2005).

We designed an intervention for students at a prestigious journalism graduate school (Ranney et al., 2008) to (1) extend methods to improve analytic thinking, and (2) suggest routes to address concerns that journalists cannot or will not adequately present the kinds of numerical evidence that would optimally inform the general public (cf. Yarnall et al., 2008). In consultation with other researchers and the students' instructors, the first author presented a curriculum across five graduate news-reporting course sections that consisted of over 4.5 h of classroom sessions and 20 h of out-of-class homework assignments and tests—for which feedback and critiques were provided. Curricular emphases included estimation practice and strategies, such as disconfirmation, benchmarking, decomposition, coherence-building, "whole pie" contextualizations, data-foraging tactics, practice with detecting misleading statistics, and employing the "rule of 72" to address problems involving change.[19] Examples of superior and inferior statistics-use in reporting were also provided. (For more on the activities, including class time deployed for each, see Ranney et al., 2008.) In written activities, students were encouraged not to merely infuse their writing with more numbers, but rather to (1) incorporate the most crucial, contextualized, memorable, and veridical statistics, and (2) use quantitative analysis to understand story topics better.

To assess the intervention's benefits and their longevities, and to ultimately provide all students with the curricular module (as their program requested), we staggered its appearance among the groups: Two class sections received it early (the Experimental Group), and three (smaller, on average) sections received it weeks later (the "Control" Group). We

[19] The rule of 72 "linearizes" exponential growth without more sophisticatedly tackling its $ln(2)$ doubling basis. To address compound interest, for instance, one can divide 72 by the years (for instance, nine) an amount took to double to estimate the annual growth rate percentage (for instance, 72/(9 years) = 8% annual growth).

compared the groups at Pretest, then after experimental participants received the intervention (the Mid-test), and finally after "control" participants received it (this latter Final-test also assessing experimental participants' long-term retention). Counterbalancing ensured that participants only saw items once.

Despite the relatively brief intervention, experimental participants improved markedly on basic math items (for instance, percentage/word problems, and interpreting tables/graphs), and the exponential/rule-of-72 problems. Furthermore, their estimation error decreased over 66 test items varying in topic and difficulty. Gains across estimation and exponential growth items were not correlated with basic mathematical accuracy, indicating that even those with weak math backgrounds learned skills/heuristics providing insight into issue-critical quantities. We also observed significant changes in preference for numerical information (PNI; Viswanathan, 1993), albeit not uniformly positively: Most participants' PNI scores increased, but some decreased (perhaps partially due to a ceiling effect; Ranney et al., 2008).

Evidence discussed so far supports TEC's data-priority principle, because numerical evidence triggered accommodative belief revision. However, privileging numerical data is most helpful when the data are reliable and accurate, and media sources risk misinforming people with incorrect or unrepresentative data when not critically vetted. To assess the journalism students' skepticism about numerical information and to teach framing numerically driven "conclusions" as working hypotheses, we presented scenarios in which a fictional colleague, "Pat," offered alleged statistics (for instance, that 20% of America's energy comes from nuclear power), one-third of which were correct (for instance, the 20% number), while two-thirds were actually higher or lower than the true values. These Pat results were mixed, but students across both groups increased the number of disconfirming reasons they provided over the curriculum's semester. Pinpointing this source's change should enhance future curricula that promote appropriately scientific skepticism.

The preceding NDI curricular interventions' evidence shows that the numerical reasoning in NDI tasks transfers to one's policies and issue articulations. Might there be even broader transfer? NDI estimations are like "Fermi problems," such as "How many piano tuners are in Chicago?" Few, if any, can *exactly* recall correct Fermi answers, but through successive approximations and related, known quantities, one can approach them. Potential employers often assume that one's Fermi answering indicates general analytic ability and/or problem solving creativity, but the literature indicates little general problem-solving-skill transfer across divergent domains (for instance, Singley & Anderson, 1989). However, Wong, Galinsky, and Kray (2009) found transfer to a variety of tasks from tasks that induce different kinds of (for instance, additive/creative vs. subtractive/analytical) counterfactual mind-sets. Thus, if we carefully specify, for instance, the kind of counterfactual reasoning that an NDI curriculum fosters, we may observe transfer well beyond the types of questions NDI tasks pose.

8. LONG-TERM CONCEPTUAL CHANGE AS A HOLY GRAIL

Of course, interventions rarely yield perfect fidelity decades on, but transient improvements in the knowledge–ignorance contour have little utility. Besides the delayed posttest results discussed earlier for journalism students, a deeper look at whether an intervention promotes lasting wisdom came from interviews with high-school geometry students who had received our curriculum (that is, Appel, 2004; Munnich et al., 2004). Five months postintervention, interviews conducted by a researcher who was blind to participants' condition revealed persistent advantages in strategic richness among those who received the module (Ganpule, 2005). Such curricula satisfy the longevity or "half-life" criterion for interventions discussed by Ranney (2008).

In 2015, our laboratory (Ng, 2015) replicated and extended, by adding a delayed posttest, the finding (Experiment 6 of Ranney & Clark, 2016) that a small set of representative statistics relating to GW significantly increases Americans' GW acceptance with little decay. One way to measure such changes is relative to the "room to improve." For instance, we found that nine representative statistics (see Table 2; Ng, 2015) reduced the gap between participants' initial acceptance and extreme acceptance (for instance, "9" on a nine-point scale) by 20% ($p < 0.0001$). Further, after a 9-day delay, participants exhibited no effect decay, as their mean gain nonsignificantly edged down to a 19% gain of the room-to-gain in GW acceptance; in other words, the observed gains were essentially rock-solid 9 days later ($p < 0.0001$), indicating remarkable learning-fidelity.[20] Related to the NDI paradigm discussed earlier, this experimental method included an assessment relating to "preferences"—attitudes and beliefs in this case—before and after the

[20] Note that, upon post hoc analyses, Table 2's items three and four regarding ocean ice and CO_2 seemed least surprising—so they might be omitted by researchers seeking to study the phenomenon more efficiently.

Table 2 Representative numerical information used regarding global warming, with "*" next to the textual description to indicate a reversed-score item (Ng, 2015)

Textual description	Format/value
A 2010 article examined the 908 active researchers with at least 20 climate publications on Google Scholar. What percentage of them have stated that it is "very likely" that human-caused emissions are responsible for "most" of the "unequivocal" warming of the Earth in the second half of the 20th century?	"Percentage of active researchers"/97.5% of researchers
Global surface temperatures have been recorded since 1880. According to the US Government's National Climatic Data Center, how many of the years between 1995 and 2014 (a 20-year period) were among the *hottest* 20 years recorded?	"Number of years (out of 20)"/19 years
* The Intergovernmental Panel on Climate Change provides us with data about the world's ocean ice. What is the change in the world's ocean ice cover, in percentage, since the 1960s?	"% increase (in ocean ice)" or "% decrease (in ocean ice)"/40% decrease
Mauna Loa Observatory in Hawaii provides us with data about CO_2 (carbon dioxide) in the atmosphere. What is the percent change in atmospheric CO_2 levels from 1959, when observation began, to 2014?	"% increase (in CO_2)" or "% decrease (in CO_2)"/26.1% increase
* The US Geological Survey provides us with data about the glaciers in Glacier National Park. In 1850 there were approximately 150 glaciers present in Glacier National Park. How many are present today?	"Number of glaciers"/25 glaciers
* The European Environmental Agency provides us with data about volume of glaciers in the European Alps. From 1850 to 2013, what was the percent change of volume of glaciers in the European Alps?	"% increase in glacier volume" or "% decrease in glacier volume"/65% decrease

The Intergovernmental Panel on Climate Change provides us with data about the atmosphere's level of methane. What has been the change in the amount of atmospheric methane (a greenhouse gas) since 1750?	"% increase (in methane)" or "% decrease (in methane)"/151% increase
January of 2015 was above Earth's 20th-century average monthly temperature, according to the NCDC (National Climatic Data Center). According to the NCDC, including January of 2015, how many of the last 358 months have been above that 20th-century average?	"Number of months"/358 months
The federal National Oceanic and Atmospheric Administration (NOAA) observes temperatures at almost 2000 US locations. According to a published 2009 study using 9 years of NOAA data, how many record temperature highs were observed in the United States for every 100 record temperature lows?	"Number of record temperature highs for every 100 record temperature lows"/204 record temperature highs

estimates-feedback intervention occurred (using a procedure related to an EPIC variant introduced by Rinne et al., 2006, that yielded similarly significant conceptual change in a health-care domain). Participants were also assessed nine days later for the longevity of these changes.

The prior study's attitude changes mirrored participants' increased understanding of GW's statistical basis, employing stimuli that highlight the numerical aspects of Fig. 1's multidimensional space. However, Ranney and Clark (2016) similarly point out that increased GW acceptance based upon *mechanistic* interventions reflects participants' dramatic increases, upon posttesting, of their mechanistic knowledge. Indeed, one sample initially knew so little of GW's mechanism that a 17-fold gain was observed upon posttesting (Ranney et al., 2012a); participants' gains were robust, even upon a 34-day delayed posttest. Most striking in these knowledge gains is participants' understanding of the crucial role of infrared light (see Appendix C) in the asymmetric energy dynamics that underlie GW's mechanism (and that GW is effectively an *extra*, anthropogenic, greenhouse effect).

Relating to long-term retention, pilot participants occasionally remarked thus: "I read your 400 compelling words a couple of months ago, but now I've forgotten the particulars of global warming's mechanism." This does not dramatically concern us, in that the mechanism's details led them more firmly to the scientifically normative position that climate change is occurring and anthropogenic. By analogy, many people have seen a proof of Pythagoras's theorem, and many people have been required to generate the proof themselves. When one examines a proof, the theorem's obviousness often becomes so clear that the result (that is, $a^2 + b^2 = c^2$) is retained even when the proof's particulars, or perhaps even the ability to (re-)generate the proof, have long faded. We suggest much the same regarding GW's mechanism. For instance, a sixth year environmental sciences graduate student who had specialized toward taxonomy confessed to not being able to recall that mechanism. Such instances are hardly ideal, but permanently retaining a mechanism may not be among science education's realistic aims. Imperfect retention may be acceptable as long as understanding the mechanism or its derivation at some point produced a normative belief about ontology and causality (in GW's case, that it exists and is anthropogenic). It is like a person acceptably saying, "I can't derive Pythagoras's theorem anymore, but I saw the proof decades ago, and I believe that it is still sound." Recalling the example about Earth's spherical shape, once a person is convinced of it, one does not doubt it simply because one cannot immediately explain it.[21] For any impressive delayed posttest change, climate change communicators should tactically ask themselves: "How long is 'long enough' to warrant a particular intervention?" Certainly, a gold standard for strong longevity might be akin to the certainty people apply to Pythagoras's Theorem or the Earth's spherical shape.

9. DIRECT TO THE PUBLIC: CONCEPTUAL CHANGE ABOUT GLOBAL WARMING (GW)

Our desire to facilitate people's science-normative GW understandings led our Reasoning Research Group (Ranney et al., 2013) to generate a website—HowGlobalWarmingWorks.org—which we here abbreviate as "HGWW" (Ranney & Lamprey, 2013). This "citizen education" venture (Ranney, Lamprey, Le, & Ranney, 2013; and so on) represents a repository of information that we have shown, through experimental vetting, to increase site-visitors' understanding and acceptance of GW.[22] Initially, HGWW focused on the mechanistic explanation, but we have now added numeric and graphic elements to it. HGWW is meant to directly explain GW's most central elements to the public, given (1) the dearth of that knowledge in our populace, and (2) our results showing that a small amount of instruction can yield dramatic changes (that is, a large bang-per-buck). Notably, we do not include projections about GW's future because we believe that (1) the extant scientific evidence is already compelling, and (2) projections often turn out to be significantly inaccurate, and we did not want to stake our information's objectivity and accuracy upon subsets of physical scientists' predictions.[23] For now, we also avoid specific prescriptions for action; greenhouse gases are the central problem, but there are myriad ways to reduce them if/when people and governments act to do so.

Our 400-word text, and the 35-word short summary subsumed by the 400 words, appears on HGWW. We responded to common suggestions by

[21] Few people deny Earth's sphericalness today, whereas not all yet accept the ontology/causality of GW.

[22] Essentially, HGWW represents our reaction to a "regret" that academics often raise about how they wish that their research had impact beyond the colleagues in their subfield who read their publications.

[23] HGWW visitors generally and readily make appropriate extrapolations about data-trends to date; however, we leave providing even a single state-of-the-art projected "spaghetti plot" function to other websites for now, given the potential danger to objectivity and accuracy—and because we are not formally trained climatologists.

adapting the text into a 4.7-min video for HGWW—with simple graphics tightly connected to the narration (Ranney, Lamprey, Reinholz, et al., 2013); its script, increased to 596 words based on viewer feedback, also appears on HGWW. The video is a straightforward explanation of the mechanism of climate change mirroring the 400-word text that was effective in the laboratory, in classes, and online. Based on viewer feedback, we edited this longest video into four shorter ones, yielding a suite of five (of 0.9, 1.2, 2.9, 3.6, and 4.7 min), appropriate for different purposes. For example, an Earth Sciences teacher might want to use the longest video to show to her class within a curriculum, or to use as course background-preparation; from the 400 words, it includes a "value-added" explanation of what defines a greenhouse gas molecule.[24] At the other end of the spectrum, one might send a link for one of the two shorter videos to a friend or relative with a modest, "cute-animal-video" attention span. More medially, an undergraduate might find the 2.9 min video worthy of sharing with her climatology professor.

Gratifyingly, HGWW has already experienced some viral success, with over 200,000 direct page-views from 200 countries—and over 1 million page views when one includes journalistic pieces that have specifically and particularly focused on our site/video(s). A randomized experiment by Ranney, Lamprey, & Shonman (2015) shows that almost all of the five videos, especially the three longer videos, both markedly and significantly help (further) convince dubious Americans that climate change is occurring and/or anthropogenic—even after a 9-day delay, and with *no* significant loss of any immediate acceptance gains after the 9 days.[25] These results are consistent with research reviewed above on the impact of understanding GW's mechanism. Individuals' mechanistic understandings can also help people—in pubs, town halls, and so on—to better convince fellow citizens.

Having the set of HGWW's videos has also provided for a naturalistic experiment, which we have been assessing alongside the randomized controlled experimentation. By releasing a variety of versions, we "let the market" help us consider which of the video-lengths is most efficacious

[24] That a greenhouse gas molecule must be at least temporarily electrically asymmetrical is something exceedingly few people know—and is even uncommonly known among (and/or is inaccurately communicated by) climate change communicators with little physical-chemical background.

[25] An analysis by Fricke et al. (2016) shows that the 596-word textual *script* of the 4.7-min video also significantly yielded GW acceptance gains and was among the most compelling of all our interventions. Further, although the shortest videos (0.9 and 1.2 min) yielded such gains when the two conditions are combined—even after the 9-day delay—their separate results were less robust.

by tracking their "hits." But the site's early popularity inhibited the diagnosticity of the naturalistic study as most journalists and bloggers who initially informed others about HGWW embedded or promoted links to the shortest two (and least compelling) videos thinking that they would be more likely to be viewed/shared than the longer videos. This introduced a chaos-effect sort of bias into the naturalistic experiment. For instance, a single NPR.org posting that focused on HGWW and our research, and which received over 100,000 page-views on its own, embedded our penultimately briefest video. Similarly, a popular piece by Austria's Der Standard focused on our shortest video, seeding a brief-video bias in Europe, as well. A result of the naturalistic experiment, though, is that we have been able to analyze many comments (over 1000 analyzed so far) that appear on various websites that have introduced HGWW—and they have been both largely gratifying and quite helpful in further shaping both our experiments and HGWW.[26]

Of course, English speakers represent a human minority. Therefore, we have translated some of HGWW's videos, pages, and texts into Mandarin and Cantonese, among other languages. We are trying to popularize HGWW within China, which is the greatest emitter of total, but not per capita, greenhouse gases. Some ventures raised unique challenges; for instance, we placed our videos on Youku so that they are viewable in China (which blocks YouTube, Twitter, Facebook, and so on). As previously mentioned, with Oliver Arnold and others (for instance Arnold et al., 2014), we translated the texts and videos into German, which also appear on HGWW—and results show considerable utility for the videos, particularly the longer ones. A Japanese transcript of the 4.7-min video is also available, and YouTube provides Google Translate captioning in 75 languages (although most, naturally, are suboptimal).

10. FIVE WAYS TO INCREASE GW ACCEPTANCE NUMERICALLY AND/OR MECHANISTICALLY

The Reasoning Group at Berkeley has found about five ways to increase GW acceptance, depending upon how one counts them (Ranney et al., 2016). Collectively, they cover a significant portion of the numerical × mechanistic space described earlier (and in Fig. 1). Each of these five ways seeks to help people move the contour between knowledge and

[26] We particularly thank Matthew Shonman, and Liam Gan, for their comment-analysis efforts.

ignorance to increase the former, such that people can act wisely, and hopefully near-optimally, when facing climate-related choices:

First, like the NDI findings discussed earlier regarding a medley of topics, simply eliciting estimates regarding the focal topic of GW, followed by the provision of numerical feedback for the queried numerical values, yields an increase in GW acceptance. First observed by Ranney and Clark (2016, Experiment 6), our laboratory has recently replicated the finding (Ng, 2015) with 129 MTurk participants, with results mentioned earlier and regarding Table 2's statistics that are representative of GW. In this replication, the 20% gap-reduction from initial to perfect GW acceptance observed on the *immediate* posttest yielded a solid gap reduction of 19% *after 9 days* (for the 90 MTurk participants who returned for a delayed posttest)—which was statistically equivalent to the immediate 20% effect; thus, no significant decay was observed. (This 20% of the "room to gain" measure on the immediate posttest was even larger—22%—when one includes the 39 participants who did not return after the delay.) Furthermore, we observed no polarization[27], as both economic and social conservatives exhibited increased GW acceptance, even after a 9-day delay. This brief intervention is quite efficient in terms of acceptance change per instructional minute. (For more methodological detail, see Clark, 2013, and Ranney & Clark, 2016.)

Second, we have a similar demonstration involving numerical reasoning, but using statistics that indirectly, rather than directly, impact a target variable. Ranney's (2012) Reinforced Theistic Manifest Destiny (RTMD) theory implicitly predicted that reducing one's level of nationalism would cause an increase in one's GW acceptance.[28] This followed from the negative nationalism–GW correlation that Ranney predicted (for instance, Ranney & Thanukos, 2011) and that Ranney and colleagues have now observed many times (Ranney, 2012; Ranney et al., 2012a; and so on) in every US study that has measured the two constructs. (Indeed, our evidence suggests that this

[27] As per Ranney and Clark (2016), we use "polarization" in its high-threshold meaning (similar to Lord et al., 1979): it represents instances in which provided information that would change neutral people's position in direction A moves a biased person in the opposite manner.

[28] RTMD theory (for instance, Ranney, 2012) predicts the relationships among the acceptance-levels of six main constructs that are subdivided into two competing sets: afterlife, deity, creationism, and nationalism on the one hand (which should correlate with each other), and evolution and GW on the other (which should correlate with each other but anticorrelate with the other four constructs). A host of studies now show these predicted relationships, which are significant under reasonable power conditions (for instance, Chang, 2015; Luong, 2015; Ng, 2015; Ranney, 2012; Ranney et al., 2012a). Our lab has never found a significant (US) correlation in a direction opposite of what RTMD predicts, when looking at the 15 relevant correlations.

anticorrelation is growing larger in America;[29] however, none of our interventions have yielded polarization, as our conservative participants changed their GW acceptance in the same direction as our liberal participants.) With Tina Luong and Justin Teicheira (for instance, Luong, 2015), we found that MTurk participants ($n = 35$, excluding control groups) receiving supra-nationalist statistics increased their GW acceptance by 11% of the room available to gain[30]—as participants' level of surveyed nationalism dipped by 10% of the room available to decrease. (As with our other studies, this experiment observed no polarization; the 10 conservative participants—including four at the extremely conservative endpoint of the scale—yielded a mean GW acceptance gain.) By "supra-nationalist," we mean information that contextualizes America in the community of nations in contrast to what is usually portrayed in the United States. For instance, many members of the US Congress repeatedly refer to America's health care system as "the best in the world," yet the system (although not itself a topic in our studies) is the world's most expensive while it underperforms relative to similar countries' systems—for instance, being last of 11 comparable nations according to Davis, Stremikis, Squires, and Schoen (2014). Table 3 shows the supra-nationalist numbers representing the feedback that participants received regarding their estimates.

The third way in which our laboratory has increased GW understanding blends the numerical and the mechanistic, as mentioned earlier regarding the Bex studies in which participants are asked to consider trends in temperature and the stock market (with six of our 10 stimulus-graphs appearing in Fig. 2; we also employed 4-year and 8-year averagings for some conditions; Chang, 2015). The 10 Bex conditions ($N = 663$ MTurk participants) we deployed varied on five manipulation-dimensions (for instance, the amount/resolution of averaging employed—or whether we used span/simple-averaging vs. moving-averaging, or both). Even our most minimal interventions yielded marked gains that were robustly significant after 9-day delays. Over all 10 conditions, the experiment's immediate posttest's gain was 23% of the available room to improve, and it was a similar 20% after 9

[29] Our data suggest that the correlation between nationalism and GW acceptance may be becoming increasingly negative/predictive as climate mitigations become increasingly associated with antinationalistic rhetoric (for instance, "un-American job-killers").

[30] This gain is roughly half that of the *direct* intervention on one's numeric understanding of GW, which was mentioned in the prior paragraph. Naturally, affecting a target variable (GW) indirectly through its associate (nationalism) should be less effective.

Table 3 Supra-nationalist statistics (and their sources)

1.	At $17.3 trillion, the United States ranks **1st** in national debt in the world, which is 66% more than the second-most in-debt nation (which is the United Kingdom) (Central Intelligence Agency).
2.	The United States ranks **21st** of the 34 countries of the Organization for Economic Cooperation and Development (OECD) for the percentage of residents graduating from high school (Organization for Economic Cooperation and Development).
3.	At 69.2%, the United States ranks **1st** of the 34 countries of the Organization for Economic Cooperation and Development (OECD) for the percentage of residents who are technically overweight (BMI over 25) (The World Health Organization).
4.	The United States ranks **3rd** of the 34 countries of the Organization for Economic Cooperation and Development (OECD) in the number of intentional homicides per 1 million people (United Nations Office on Drugs and Crime).
5.	Compared to 42 Peer Nations, the United States ranks **29th** for national math scores. (Program for International Student Assessment).
6.	The United States Ranks **1st** of 42 Peer Nations for percentage of births that are to teen mothers (15–19 years old). (Innocenti Research Centre).
7.	Of the 34 countries of the Organization for Economic Cooperation and Development (OECD), the United States ranks **21st** in median internet speed. (Organization for Economic Cooperation and Development).
8.	The United States ranks **35th** of 38 Peer Nations reporting data for the percentage of college graduates who are in science and engineering fields. (Global Innovation Index).
9.	The Soviet Union was the first country to perform a spacewalk and to launch the following into Earth orbit: a satellite, a living animal, a man, and a woman. (United States National Archives).

days' delay; furthermore, as with the Ng (2015) study, we observed no polarization, as both economic and social conservatives exhibited increased GW acceptance, even after the 9 days. The Bex results show that the most complete interventions (with more kinds/resolutions of averaging provided) yielded the gains with the greatest longevities—although the longest intervention *required* only 4.5 min—and there were modestly diminishing returns beyond 5 min of participants' median consumed intervention time.

The textual mechanistic descriptions described earlier represent the fourth way we have increased participants' GW acceptance.[31] At least six experiments to date have shown that textual descriptions of the GW mechanism facilitate participants' increased acceptance, including four from Ranney and Clark (2016) and one we have just completed. As we have documented these text-based effects more than some other effects, we will not elaborate further on this research vein.

Fifth and finally, the aforementioned five videos viewable on HGWW are also largely mechanistic in nature. One could argue that they are even more mechanistic than the text representing their scripts, in that animation provides additional mechanistic elements, such as when our longest video animates (1) that always-symmetric molecules do not appreciably absorb infrared light or (2) how some infrared light-energy may be passed among many greenhouse gas molecules before escaping Earth. As Arnold et al. (2014) have already shown with a 4-min German video (which excluded the asymmetric-molecule aspect), our videos—like the prior kinds of interventions—also increase participants' GW acceptance.

These five kinds of interventions do not reduce the "room to improve" by a majority of what is possible, meaning that participants' gains are less than half the effect that would result from a "perfect intervention" (which would yield ratings of "9" on *every* one-to-nine-rated acceptance item). However,

[31] Strictly speaking, our 400-word description mentions two numbers—percent changes in atmospheric CO_2 and methane—which support the mechanism with causal evidence about Earth's changes since the industrial age's start. We have sought to disentangle this convolution; for instance, as noted earlier, Fricke et al. (2016) found utility for HGWW's two shorter mechanism-explaining videos although they offer no statistics. Further, note that text-mechanistic participants to date were never asked to *estimate* the quantities—and only one of the two quantities is notably surprising—which suggests that our GW acceptance gains are largely driven by the mechanism itself. Finally, by contrast, Experiment 5 of Ranney and Clark (2016; also see Clark et al., 2013; and Felipe, 2012) controlled for the introduction of six germane statistics that included the significantly effective estimate-and-feedback aspect (the "mechanism-plus" condition)—compared to just providing mechanistic information (the "mechanism-only" condition)—and found a benefit for the mechanistic intervention even without the numerical intervention's additional benefit.

given how brief the interventions are, they represent potent demonstrations that can be built upon with longer interventions/curricula. Even as is, though, imagine the number of policy makers who would be satisfied with interventions that take mere minutes to change minds—given how close some policy votes are among our representatives—particularly interventions that might move such a large number of people when one considers the overall population (or even regarding policy polling).

11. A RISING TIDE OF GERMANE, NONDECEITFUL, INFORMATION "LIFTS ALL WISDOMS"

A crucial reason that these five intervention-types are all successful may be that we explicitly indicate to our participants that the information we provide them is accurate to the best of our knowledge, that they can share the information with their families that very night, and that the experiments involve no deception. This stands in contrast to the many studies involving deception by generating not-fully-accurate persuasive prose, skewed vignettes, and so on. Many psychological participants take such information as "conditionally true," knowing that their debriefing may recant it. This seems especially true for participants in pools such as MTurk or housed in academic units (such as psychology and business).

As alluded to earlier, researchers have occasionally reported that information that seems contrary to a closely held belief is discounted to the point of enhancing that prior belief. We have *not* found such instances of purported "polarization" in our experiments, in concert with Ranney and Clark's (2016) experiments. More recently, Ng (2015) found that our representative statistics increased the average rating for GW acceptance for both economic conservatives and social conservatives at each level of conservatism (that is, at 6, 7, 8, and 9 of our 1—9 conservatism scale). Furthermore, Chang (2015) found the same increases for both of those measures of conservatism (and at virtually each of nine levels of conservatism) following our Bex curricula that juxtaposed financial and temperature graphs with varying averaging resolutions and averaging types. Finally (as noted earlier), Luong (2015) also found increased GW acceptance among conservatives who received supra-nationalistic statistics—and thus, again, no polarization.

Among their seven studies, Ranney and Clark (2016) noted that two quite different forms of scientific-information interventions—statistical/evidential or mechanistic—can yield GW understandings that are more consistent with the scientific consensus without yielding polarization effects (cf. Kahan et al., 2012). In the first intervention form, the largely surprised participants reported feeling less knowledgeable, following *numerical* feedback; when participants' estimates were distal from the true values, they obviously gained knowledge—but they often lost confidence in realizing the ignorance that they had just evidenced. By contrast, in Ranney and Clark's second form of intervention, participants received *mechanistic explanations* and generally did *not* show this confidence-loss. These two intervention-forms show that one's reaction to appreciating one's prior ignorance seems influenced by what the new information tells one about how much more ignorance one might have. Surprising statistics are less comforting in that they leave the causal situation more ambiguous, relative to mechanistic explanations that give one more a sense of "the full story." (See Gutwill et al., 1996, on electrical causality.) It might be said that the statistic-based surprises might heighten our sense of epistemic humility, and being quite distal from the mark in one's estimate might result in a more dramatic recalibration of one's knowledge-to-ignorance ratio (which is, over all topics, below 1:1 for everyone).

11.1 Future Directions With GW as a Touchstone

Regarding GW efforts, our research group is currently analyzing a large study ($N \sim 1100$) in which we are contrasting the utility of our (direct) statistics, along with a number of our texts and videos.[32] Our aim is to gain more understanding about our interventions' relative effectiveness, a la *Consumer Reports*' concerns, and about which kinds of participants experience the greatest increase in GW acceptance gain per second—as well as what they thought of the intervention. To aid in this venture, we are collecting a wide host of demographic variables that should be telling. For instance, given that people generally like something the more they know about it, one might imagine that some people who believe themselves to be quite knowledgeable about climate change would prefer the longest video available; however, some such people might prefer the shortest if they assume they already know what would be in the video. With Oliver Arnold, we are also exploring which video people will select (or switch to), given that they are in a *longest* (of five) video default condition versus a *no-video* default condition.

[32] This effort has been particularly spearheaded with Matthew Shonman, Kyle Fricke, Tina Luong, and ourselves.

Another vein of attractive research would be to combine different interventions—particularly combinations of the five types enumerated in the prior full section—to determine their joint utilities (for instance, GW's mechanism juxtaposed with compelling statistics and useful graphs). Further, we hope to combine representative statistics *with* misleading information to see whether participants can discriminate among them; citizens would be well served by better discriminative skills that can indicate whether a quantity they will receive is representative or not, even before they see the number that "fills in the blank" (for instance, as quantities: Earth's water temperature change vs. just a single country's water temperature change).

Regarding HGWW, future directions might involve introducing a longer (for instance, 7-min) video, as occasionally our 4.7-min offering leads more sophisticated readers to request more information (for instance, "Why/how do asymmetrical molecules absorb infrared light?"). Another reason for more information, unfortunately, stems from some otherwise sophisticated viewers (for instance, oceanography professors, science educators, and climate change communicators) having some misconceptions that we might help improve. For instance, some video commenters (who are usually helpful and supportive, but occasionally misguided) believe that the Earth and the cosmos are in an *instantaneously* interactive equilibrium, without hystereses/lags. Although planets are *generally* in such homeostasis, they can have periods of disequilibrium—which is why Earth (both naturally and anthropogenically) and Venus (nonanthropogenically) have experienced increased atmospheric temperatures. (Earth has had greenhouse effects of varying degrees virtually since it had an atmosphere; again, GW is an *extra*, anthropogenic, greenhouse effect.)

HGWW might also address other misconceptions, some of which seem triggered by analogies that produce too many inferences—and sometimes dangerously incorrect inferences. For instance, one misconception is that light reflects (or "bounces") off the earth and somehow gets trapped on its way out by a "blanket"—in contrast to the correct conception that visible light is absorbed by the earth, then *transformed* into infrared light that is later absorbed by greenhouse gases, thus generating a more accurate notion of something rather like a slightly leaky one-way energy valve. The blanket metaphor is poor in multiple ways—for instance, suggesting that the initial energy source is terrestrial (cf. a person under a blanket), rather than sunlight. We intend to eventually produce FAQ pages (and perhaps more videos) that target specific misconceptions.

Yet another future direction involves expanding our translations. Given that climate change is an international "tragedy of the commons" problem, it requires international agreements. The need for translations is highlighted by considering that only 6% of people are native English speakers (cf. Mandarin's 14%). A notable success is that, comparing cities worldwide, Viennese residents currently represent the second highest number of HGWW page-views (due to the widely read *Der Standard* article). With more precisely translated (rather than Google-translated) materials, we hope that HGWW can further increase grass-roots GW acceptance across the globe, and add pressure to governments to more quickly adopt binding agreements to reduce greenhouse gas emissions.

11.2 Conclusions

In general, we have found that small amounts of crucial information can yield considerable conceptual changes—even changes in preferences, attitudes, and acceptance regarding normative science, such as GW. Within such paradigms, subjects typically predict a phenomenon or statistic and later receive veridical feedback; they "put their cards on the table" prior to that feedback. In the studies discussed earlier, we have presented a variety of interventions that fall along multiple dimensions (as in Fig. 1): (1) the degree to which interventions involve more numerical reasoning, and (2) the degree to which interventions involve more mechanistic reasoning.[33] At the extreme, even a single statistic that is devoid of mechanistic information can transform one's thinking (for instance, the US abortion rate; Garcia de Osuna et al., 2004); likewise, a compelling causal/mechanistic account can similarly yield marked conceptual change (for instance, explaining GW's mechanism; see Ranney & Clark, 2016, and related work).

These dimensions suggest that consumers of information would be wise to employ techniques to defend against misleading information (see Experiment 7 of Ranney & Clark, 2016). Regarding misleading statistics, one should be tuned to better detect nonrepresentative aspects, such as quantities lacking temporal breadth or recency (for instance, a cherry-picked range of "1940–1975" regarding Earth's mean temperature, even though we have

[33] As noted earlier, Fig. 1 represents three dimensions: two unipolar and one bipolar. However, the unipolar dimensions of numerical and mechanistic *reasoning* could be, with seemingly little violence, projected into its own bipolar dimension based upon the aforementioned slopes between the origin and the studies' rough placements. Along with the bipolar dimension regarding stimuli/input, the result would be two bipolar dimensions (regarding reasoning and stimuli), each with a "numerical" and a "mechanistic" pole.

reliable data from at least 1850 and obviously past 1975; cf. Jastrow, Nierenberg, & Seitz, 1991)—or quantities lacking in authority, measurement precision, and/or reasonable spatial extent (for instance, Antarctica's sea ice vs. Earth's total ice; also see Oreskes & Conway, 2010). Regarding misleading mechanisms, one should be better tuned to pseudocausality and explanatory coherence (for instance, Ranney & Schank, 1998; Thagard, 1989): For instance, those denying anthropogenic GW sometimes attribute our warming to volcanoes or plate tectonics, while they neglect to explain why such elements might warm our planet more now than in the past even as its crust should be cooling; in contrast, our 400 words not only explain the warming but what is perturbed in the system—namely that humans are contributing massive amounts of heat-trapping greenhouse gases into our atmosphere.

In sum, we hope that we have articulated some of the underappreciated aspects of *lacking* knowledge—a void that manifests itself across many domains and in several (for instance, numerical and/or mechanistic) incarnations. One might think that turning a light on participants' ignorance amounts to "making people feel stupid,"[34] but our focus on imperfections in one's knowledge and wisdom was borne from bemusements of our own flawed information. One rarely wants to be less knowledgeable than one's peers, of course. However, especially when fertilized by the motivational focusing power of surprise, it is often *ignorance* that spurs the phoenix of new wisdom to rise from the ashes of a flawed estimate, prediction, or explanation. We ought not shrink from gaps in our information. Why not *embrace* ignorance and its generative potential? That seems wise.

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[34] Over the years, some friends have caricatured pieces of our research as doing this—as is also sometimes ascribed to some judgment and decision-making researchers (for instance, regarding the conjunction fallacy). However, such friends often delight in subsequently getting colleagues, acquaintances, and family to estimate/explain some of our stimuli.

APPENDICES

Appendix A: Sources for Table 1, "Michael Ranney's Picks for the Top 40 Numbers One Should Know (But Many Don't)" (Based on the Most Recent Data Available as of 9/14/06)

(Institutional source for the number or the raw data from which the number was calculated)

1. US Census Bureau
2. US Census Bureau
3. US Census Bureau
4. Guttmacher Institute
5. US Census Bureau
6. Center for Immigration Studies
7. US Census Bureau
8. US Census Bureau
9. US Census Bureau
10. Economic Policy Institute
11. Congressional Budget Office
12. Economic Policy Institute
13. Standard & Poor's
14. US Census Bureau
15. US Census Bureau
16. US Census Bureau
17. Bureau of Justice Statistics
18. Bureau of Justice Statistics
19. Bureau of Economic Analysis
20. World Bank
21. Stockholm International Peace Research Institute
22. United Nations
23. United Nations
24. Office of Management and Budget
25. Office of Management and Budget
26. Bureau of the Public Debt
27. US Census Bureau
28. Bureau of Labor Statistics
29. Bureau of Labor Statistics
30. Bureau of Labor Statistics

31. Energy Information Administration
32. Gallup Poll
33. National Safety Council
34. National Safety Council
35. Energy Information Administration
36. Intergovernmental Panel on Climate Change
37. Intergovernmental Panel on Climate Change
38. World Meteorological Organization
39. US Census Bureau
40. US Census Bureau

Appendix B: Michael Ranney's Picks, With Sources, for the "Top 40 Numbers One Should Know (But Many Don't)[a]," Updated With 2015 Statistics (When Available)

(Quantities refer to the current state of affairs except where noted; values are approximations based on the most recent data available as of 12/31/15; the 40 numbers are grouped by topic and *not* ranked 1−40)

	Description	Amount
1.	World population	7.29 billion
2.	US Population	322 million
3.	Annual number of live births per 1000 US residents	12.4
4.	Annual number of abortions per 1000 live births in the United States	268
5.	Annual number of legal immigrants per 1000 US residents	3
6.	Average annual number of legal immigrants per 1000 Americans over the past 150 years[35]	5
7.	Percentage of US Residents who are foreign-born	13.1%
8.	Percentage of US Residents who are non-Hispanic whites	62.1%
9.	Number of US households	116 million
10.	Median US household income	$53,482
11.	Percentage of US Earnings earned by the top 1% of earners	17%
12.	Percentage of US Federal individual income tax revenue that comes from the top 1% of the earners	38.1%
13.	The annualized total return for the S&P 500 from 1926 to the present	10%

	Description	Amount
14.	Percentage of US heads of household who own their home	63.7%
15.	Percentage of US residents over 65	14.5%
16.	Percentage of Americans over 25 with a bachelor's degree or higher	29.3%
17.	Number of US residents incarcerated per 1000 US Residents	7
18.	Ratio of murders committed to prisoners executed in the United States	340 to 1
19.	US Gross National Income (GNI)	$17.6 trillion
20.	US GNI as a percentage of world GNI	22.5%
21.	US Military spending as a percentage of world military spending	34%
22.	Percentage of the world's population living on less than $1.90 per person per day (the UN's 2015 international poverty line)	10%
23.	Percentage of the population in Sub-Saharan Africa (age 15–49) living with HIV	4.5%
24.	2015 US federal budget	3.69 trillion
25.	2015 Department of Defense budget as a percentage of total 2015 US federal budget[36]	13%
26.	US national debt	$18 trillion
27.	Percentage of US residents of age 16 or above who are employed either part or full time	59.3%
28.	US unemployment rate	5.0%
29.	Number of jobs that must be created each month to keep pace with growth in the US workforce	187,000 ± 44,000
30.	Annualized total inflation over the past 50 years in the United States	4.1%
31.	Percentage change in the price of oil from its peak in June 2008 to December 2015, adjusted for inflation	−74%
32.	Percentage of Americans who agree that "God created human beings pretty much in their present form at one time within the last 10,000 years or so"	46%; MoE = ±4%
33.	Lifetime odds of dying in a motor vehicle accident in the United States	1 in 112
34.	Lifetime odds of being murdered in the United States[37]	N/A (not available)[38]
35.	Percentage of the world's carbon dioxide emissions produced by the United States	16.3%

(*Continued*)

	Description	Amount
36.	Percentage change in the amount of carbon dioxide in the atmosphere since 1750	+43%
37.	Amount by which the global average surface temperature rose during the 20th century	1.1°F
38.	Number of the 10 hottest years since 1880 that have occurred in the last 10 years	7
39.	Average size of a US household today, compared to the 1950 average	0.75 times as large
40.	Average size (sq. ft.) of a newly built single-family home, compared to the 1950 average	2.75 times as large

[a] With help from many—especially Luke Rinne, Tom Johnson, Patti Schank, Louise Yarnall, Wenjie Gan, Emily Yan, and the UC-Berkeley Reasoning Group.

Sources:

1. US Census Bureau
2. US Census Bureau
3. Center for Disease Control and Prevention—National Center for Health Statistics
4. Guttmacher Institute and Center for Disease Control and Prevention—National Center for Health Statistics
5. US Department of Homeland Security
6. Center for Immigration Studies
7. US Census Bureau
8. US Census Bureau
9. US Census Bureau
10. US Census Bureau
11. Congressional Budget Office
12. Internal Revenue Service
13. Standard & Poor's
14. US Census Bureau
15. US Census Bureau
16. US Census Bureau

[35] We found no more recent data since our 2006 list for this item.
[36] This is for discretionary defense funding only, excluding nondiscretionary defense funding.
[37] We found no more recent data since our 2006 list for this item.
[38] A related 2015 statistic is that the lifetime odds of an American being assaulted with a firearm is 1 in 358.

17. Bureau of Justice Statistics
18. Bureau of Justice Statistics/FBI/Death Penalty Information Center
19. World Bank
20. World Bank
21. Stockholm International Peace Research Institute
22. World Bank
23. World Bank/AIDS.gov
24. Office of Management and Budget
25. Office of Management and Budget/US Department of Defense
26. US Department of the Treasury
27. Bureau of Labor Statistics
28. Bureau of Labor Statistics
29. Bureau of Labor Statistics/Time Magazine
30. Bureau of Labor Statistics
31. Energy Information Administration
32. Gallup Poll
33. National Safety Council
34. N/A (not available)
35. Energy Information Administration
36. National Oceanic and Atmospheric Administration
37. Intergovernmental Panel on Climate Change
38. National Centers for Environmental Information
39. US Census Bureau
40. US Census Bureau/National Association of Home Builders

Appendix C: 400-Word Text Explaining the Mechanism of Global Warming (From Ranney, Clark, Reinholz, & Cohen, 2012b)

How does climate change ("global warming") work? The mechanism of the greenhouse effect

[Or: "Why do some gases concern scientists—like carbon dioxide (CO_2)—but not others, like oxygen"]

Scientists tell us that human activities are changing Earth's atmosphere and increasing Earth's average temperature. What causes these climate changes?

First, let's understand Earth's "normal" temperature: When Earth absorbs sunlight, which is mostly visible light, it heats up. Like the sun, Earth emits energy—but because it is cooler than the sun, Earth emits lower-energy infrared wavelengths. Greenhouse gases in the atmosphere (methane, carbon dioxide, etc.) let visible light pass through, but absorb infrared light—causing the atmosphere to heat up. The warmer atmosphere emits more infrared light, which tends to be re-absorbed–perhaps many times—before the energy eventually returns to space. The extra time this energy hangs around has helped keep Earth warm enough to support life as we know it. (In contrast, the moon has no atmosphere, and it is colder than Earth, on average.)

Since the industrial age began around the year 1750, atmospheric carbon dioxide has increased by 40% and methane has increased by 150%. Such increases cause *extra* infrared light absorption, further heating Earth above its typical temperature range (even as energy from the sun stays basically the same). In other words, energy that gets to Earth has an even *harder* time leaving it, causing Earth's average temperature to increase—producing global climate change.

[In molecular detail, greenhouse gases absorb infrared light because their molecules can vibrate to produce asymmetric distributions of electric charge, which match the energy levels of various infrared wavelengths. In contrast, non-greenhouse gases (such as oxygen and nitrogen—that is, O_2 and N_2) don't absorb infrared light, because they have symmetric charge distributions even when vibrating.]

Summary: (1) Earth absorbs most of the sunlight it receives; (2) Earth then emits the absorbed light's energy as infrared light; (3) greenhouse gases absorb a lot of the infrared light before it can leave our atmosphere; (4) being absorbed slows the rate at which energy escapes to space; and (5) the slower passage of energy heats up the atmosphere, water, and ground. By increasing the amount of greenhouse gases in the atmosphere, humans are increasing the atmosphere's absorption of infrared light, thereby warming Earth and disrupting global climate patterns.

Shorter summary: Earth transforms sunlight's visible light energy into infrared light energy, which leaves Earth slowly because it is absorbed by greenhouse gases. When people produce greenhouse gases, energy leaves Earth even more slowly—raising Earth's temperature.

REFERENCES

Appel, D. (2004). *A new curriculum improving estimates of real-world quantities: Developing general estimation strategies*. Unpublished Master's Project. Berkeley, CA: University of California, Berkeley.

Arnold, O., Teschke, M., Walther, J., Lenz, H., Ranney, M. A., & Kaiser, F. G. (2014). *Relationships among environmental attitudes and global warming knowledge, learning, and interventions* (Unpublished data).

Brown, N., & Siegler, R. (2001). Seeds aren't anchors. *Memory & Cognition, 49*, 405–412.

Chang, C. (2015). *Bex and the magic of averaging regarding global warming*. Master's project, Graduate School of Education. University of California, Berkeley.

Clark, D. J. (2013). *Climate change and conceptual change* (Doctoral dissertation, University of California, Berkeley.) Retrieved from https://github.com/davclark/UCB_thesis/releases.

Clark, D., & Ranney, M. A. (2010). Known knowns and unknown knowns: multiple memory routes to improved numerical estimation. In K. Gomez, L. Lyons, & J. Radinsky (Eds.), *Learning in the disciplines: Proceedings of the 9th International Conference of the Learning Sciences* (Vol. 1, pp. 460–467). International Society of the Learning Sciences, Inc.

Clark, D., Ranney, M. A., & Felipe, J. (2013). Knowledge helps: mechanistic information and numeric evidence as cognitive levers to overcome stasis and build public consensus on climate change. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics; Proceedings of the 35th Annual Meeting of the Cognitive Science Society* (pp. 2070–2075). Austin, TX: Cognitive Science Society.

Clement, J., & Steinberg, M. (2002). Step-wise evolution of mental models of electric circuits: a "learning-aloud" case study. *Journal of the Learning Sciences, 11*(4), 389–452.

Curley, M. (2003). *An EPIC curriculum: An examination of a curriculum to promote reasoning for conceptual change*. Unpublished Master's Project. University of California, Berkeley.

Davis, K., Stremikis, K., Squires, D., & Schoen, C. (June 2014). *Mirror, mirror, on the wall: How the performance of the U.S. health care system compares internationally*. New York: The Commonwealth Fund. Retrieved from: http://www.commonwealthfund.org/~/media/files/publications/fund-report/2014/jun/1755_davis_mirror_mirror_2014.pdf.

Edx.org/understanding-climate-denial. (June 2015). *UQx Denial 101x 6.7.4.1 full interview with Michael Ranney*. Retrieved from https://youtu.be/ElRSUgRo4dU.

Felipe, J. (2012). *Numerical reasoning, knowledge, and environmental behavior regarding climate change*. Master's project. Berkeley: Graduate School of Education, University of California.

Fernbach, P. M., Rogers, T., Fox, C. R., & Sloman, S. A. (2013). Political extremism is supported by an illusion of understanding. *Psychological Science, 24*, 939–946.

Fernbach, P. M., Sloman, S. A., St. Louis, R., & Shube, J. N. (2013). Explanation friends and foes: how mechanistic detail undermines understanding and preference. *Journal of Consumer Research, 39*, 1115–1131.

Festinger, L., & Carlsmith, J. M. (1959). Cognitive consequences of forced compliance. *Journal of Abnormal and Social Psychology, 58*(2), 203–210.

Fricke, K., Lamprey, L. N., Shonman, M., Luong, T., Zhang, L., & Ranney, M. A. (2016, February). *Reducing Doubts About Global Warming Using Five Independent Methods*. Paper presented at the 16th Annual Education Research Day, Berkeley, CA.

Ganpule, S. (2005). *Strategy use in numerical estimation: Investigating the effects of an EPIC curriculum*. Unpublished Master's Project. Berkeley, CA: University of California, Berkeley.

Garcia de Osuna, J., Ranney, M., & Nelson, J. (2004). Qualitative and quantitative effects of surprise: (mis)estimates, rationales, and feedback-induced preference changes while considering abortion. In K. Forbus, D. Gentner, & T. Regier (Eds.), *Proceedings of the Twenty-sixth Annual Conference of the Cognitive Science Society* (pp. 422–427). Mahwah, NJ: Erlbaum.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: frequency formats. *Psychological Review, 102*, 684–704.

Gutwill, J., Frederiksen, J., & Ranney, M. (1996). Seeking the causal connection in electricity: shifting among mechanistic perspectives. *International Journal of Science Education, 18*, 143–162.

Hoadley, C. M., Ranney, M., & Schank, P. (1994). WanderECHO: a connectionist simulation of limited coherence. In A. Ram, & K. Eiselt (Eds.), *Proceedings of the Sixteenth Annual Conference of the Cognitive Science Society* (pp. 421–426). Hillsdale, NJ: Erlbaum.

Holyoak, K. J., & Thagard, P. (1996). *Mental leaps: Analogy in creative thought*. Cambridge, MA: MIT Press.

Horne, Z., Powell, D., Hummel, J. E., & Holyoak, K. J. (2015). Countering antivaccination attitudes. *Proceedings of the National Academy of Sciences of the United States of America, 112*, 10321–10324.

Howard, C. (2003). *An EPIC quest for justification: The effects of a numerically-based intervention on students' estimates and their justifications*. Unpublished Master's Project. University of California, Berkeley.

Huttenlocher, J., Hedges, L., & Prohaska, V. (1988). Hierarchical organization in ordered domains: estimating the dates of events. *Psychological Review, 95*, 471–488.

Jastrow, R., Nierenberg, W., & Seitz, F. (1991). Global warming: what does the science tell us? *Energy, 16*(11–12), 1331–1345. http://dx.doi.org/10.1016/0360-5442(91)90006-8.
Juan, J. (2003). *An EPIC curriculum with attitude: The extension of a novel curriculum involving estimations and attitudes about higher education*. Unpublished Master's Project. Berkeley: University of California.
Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature Climate Change, 2*, 732–735.
Keysar, B. (1990). *East meets west at the Berlin wall: Mental maps and the changing world order* (Unpublished data).
Krynski, T. R., & Tenenbaum, J. B. (2007). The role of causality in judgment under uncertainty. *Journal of Experimental Psychology: General, 136*(3), 430–450. http://dx.doi.org/10.1037/0096-3445.136.3.430.
Lewandowsky, S. (2011). Popular consensus: climate change is set to continue. *Psychological Science, 22*, 460–463.
Lombardi, D., Sinatra, G. M., & Nussbaum, E. M. (2013). Plausibility reappraisals and shifts in middle school students' climate change conceptions. *Learning and Instruction, 27*, 50–62. http://dx.doi.org/10.1016/j.learninstruc.2013.03.001.
Lord, C. G., Ross, L., & Lepper, M. R. (1979). Biased assimilation and attitude polarization: the effects of prior theories on subsequently considered evidence. *Journal of Personality and Social Psychology, 37*, 2098–2109.
Luong, T. (2015). *Changing Americans' global warming acceptance with supra-nationalist statistics*. Master's project. Graduate School of Education, University of California, Berkeley.
McGlothlen, L. (2003). *High school students reasoning with numbers: Interviews using the estimate, predict, incorporate, and change (EPIC) method*. Unpublished Master's Project. University of California, Berkeley.
Munnich, E., Ranney, M., & Appel, D. (2004). Numerically-driven inferencing in instruction: the relatively broad transfer of estimation skills. In *Proceedings of the Twenty-sixth Annual Meeting of the Cognitive Science Society* (pp. 987–992). Mahwah, NJ: Lawrence Erlbaum and Assoc.
Munnich, E., Ranney, M., Nelson, J., Garcia de Osuna, J., & Brazil, N. (2003). Policy shift through numerically-driven inferencing: an EPIC experiment about when base rates matter. In *Proceedings of the Twenty-fifth Annual Conference of the Cognitive Science Society* (pp. 834–839). Mahwah, NJ: Erlbaum.
Munnich, E. L., Ranney, M. A., & Song, M. (2007). Surprise, surprise: the role of surprising numerical feedback in belief change. In D. S. McNamara, & G. Trafton (Eds.), *Proceedings of the Twenty-ninth Annual Conference of the Cognitive Science Society* (pp. 503–508). Mahwah, NJ: Erlbaum.
Ng, T. K. W. (2015). *The relationship between global warming and (fixed vs. growth) mindset regarding numerical reasoning and estimation*. Berkeley: Master's project. Graduate School of Education, University of California.
Oreskes, N., & Conway, E. M. (2010). *Merchants of doubt: How a handful of scientists obscured the truth on issues from tobacco smoke to global warming*. New York: Bloomsbury Publishing.
Otto, S., & Kaiser, F. G. (2014). Ecological behavior across the lifespan: why environmentalism increases as people grow older. *Journal of Environmental Psychology, 40*, 331–338.
Pearl, J. (2000). *Causality*. New York: Cambridge University Press.
Piaget, J. (1977). *The development of thought: Equilibration of cognitive structures* (A. Rosin, Trans.). New York: Viking (Original work published 1975).
Ranney, M. (1994a). Assessing and contrasting formal and informal/experiential understandings of trajectories. In G. H. Marks (Ed.), *Proceedings of the 1994 International Symposium on Mathematics/Science Education and Technology* (pp. 142–146). Charlottesville, VA: AACE.
Ranney, M. (1994b). Relative consistency and subjects' "theories" in domains such as naive physics: Common research difficulties illustrated by Cooke and Breedin. *Memory & Cognition, 22*, 494–502.

Ranney, M. (1996). Individual-centered vs. model-centered approaches to consistency: a dimension for considering human rationality. *Vivek, A Quarterly in Artificial Intelligence, 9*(2), 35–43 (Also in the Proceedings of the Second International Symposium on Cognition and Education: A Multidisciplinary Perspective.).

Ranney, M. (2008). Studies in historical replication in psychology VII: the relative utility of "ancestor analysis" from scientific and educational vantages. *Science & Education, 17*(5), 547–558.

Ranney, M. (2009, April). *Are Representational Systems Such as Language and Mathematics Bad? A Modest Hypothesis on the Downsides of Technology-Yielding Cultural Abilities*. Paper presented at the 9th Annual Education Research Day, Berkeley, CA.

Ranney, M. A. (2012). Why don't Americans accept evolution as much as people in peer nations do? A theory (Reinforced Theistic Manifest Destiny) and some pertinent evidence. In K. S. Rosengren, S. Brem, E. Evans, & G. M. Sinatra (Eds.), *Evolution challenges: Integrating research and practice in teaching and learning about evolution* (pp. 233–269). Oxford: Oxford University Press.

Ranney, M., Chang, C., Ng., T., Teicheira, J., Luong, T., & Gierth, L. (2016, April). *Four or So Ultra-Brief Interventions That Increase Public Acceptance Regarding Global Warming*. Paper presented at the annual meeting of the American Educational Research Association, Washington, DC.

Ranney, M., Cheng, F., Nelson, J., & Garcia de Osuna, J. (2001, November). *Numerically driven inferencing: A new paradigm for examining judgments, decisions, and policies involving base rates*. Paper presented at the Annual Meeting of the Society for Judgment & Decision Making, Orlando, FL.

Ranney, M. A., & Clark, D. (2016). Climate change conceptual change: scientific information can transform attitudes. *Topics in Cognitive Science, 8*, 49–75. http://dx.doi.org/10.1111/tops.12187.

Ranney, M. A., Clark, D., Reinholz, D., & Cohen, S. (2012a). Changing global warming beliefs with scientific information: knowledge, attitudes, and RTMD (Reinforced Theistic Manifest Destiny theory). In N. Miyake, D. Peebles, & R. P. Cooper (Eds.), *Proceedings of the 34th Annual Meeting of the Cognitive Science Society* (pp. 2228–2233). Austin, TX: Cognitive Science Society.

Ranney, M. A., Clark, D., Reinholz, D., & Cohen, S. (2012b). Improving Americans' modest global warming knowledge in the light of RTMD (Reinforced Theistic Manifest Destiny) theory. In J. van Aalst, K. Thompson, M. M. Jacobson, & P. Reimann (Eds.), *The future of learning: Proceedings of the Tenth International Conference of the Learning Sciences* (pp. 2-481–2-482). International Society of the Learning Sciences, Inc.

Ranney, M. A., & Lamprey, L. N. (Eds.). (2013). *How global warming works*. [Website]. Available at http://www.HowGlobalWarmingWorks.org Accessed 13.12.13.

Ranney, M. A., Lamprey, L. N., Le, K., & Ranney, R. M. (2013). Climate change cognition: direct to the public [Abstract]. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics; Proceedings of the 35th Annual Conference of the Cognitive Science Society*. Austin, TX: Cognitive Science Society. http://cognitivesciencesociety.org/uploads/cogsci13_errata.pdf.

Ranney, M. A., Lamprey, L. N., Reinholz, D., Le, K., Ranney, R. M., & Goldwasser, L. (2013). How global warming works: climate change's mechanism explained (in under five minutes) [video file]. In M. A. Ranney, & L. N. Lamprey (Eds.), *How global warming works*. Available at http://www.HowGlobalWarmingWorks.org/in-under-5-minutes.html Accessed 13.12.13.

Ranney, M. A., Lamprey, L. N., & Shonman, M. (2015, July). *Climate Change Illuminations with Statistics, Graphs, and Mechanisms*. Invited talk at 37th Annual Conference of the Cognitive Science Society, Pasadena, CA.

Ranney, M., Munnich, E., Lurie, N., & Rinne, L. (2005, May). *Talk is Often Cheap, But Self-Explanations Can Aid Learning: Discourse and Dialogue in Numerically Driven Inferencing*. Poster presented at the Talk and Dialogue: How Discourse Patterns Support Learning conference, Pittsburgh.

Ranney, M. A., Rinne, L. F., Yarnall, L., Munnich, E., Miratrix, L., & Schank, P. (2008). Designing and assessing numeracy training for journalists: toward improving quantitative reasoning among media consumers. In P. A. Kirschner, F. Prins, V. Jonker, & G. Kanselaar (Eds.), *International perspectives in the learning Sciences: Proceedings of the 8th International Conference for the Learning Sciences* (pp. 2-246—2-253). International Society of the Learning Sciences, Inc.
Ranney, M., & Schank, P. (1998). Toward an integration of the social and the scientific: observing, modeling, and promoting the explanatory coherence of reasoning. In S. Read, & L. Miller (Eds.), *Connectionist models of social reasoning and social behavior* (pp. 245—274). Mahwah, NJ: Lawrence Erlbaum.
Ranney, M., Schank, P., Hoadley, C., & Neff, J. (1996). "I know one when I see one": how (much) do hypotheses differ from evidence? In R. Fidel, B. H. Kwasnik, C. Beghtol, & P. J. Smith (Eds.), *ASIS monograph series: Vol. 5. Advances in classification research*. Medford, NJ: Learned Information. pp. 141—158, etc.
Ranney, M., Schank, P., Mosmann, A., & Montoya, G. (1993). Dynamic explanatory coherence with competing beliefs: Locally coherent reasoning and a proposed treatment. In T.-W. Chan (Ed.), *Proceedings of the International Conference on Computers in Education: Applications of Intelligent Computer Technologies* (pp. 101—106).
Ranney, M., & Thagard, P. (1988). Explanatory coherence and belief revision in naive physics. In *Proceedings of the Tenth Annual Conference of the Cognitive Science Society* (pp. 426—432). Hillsdale, NJ: Erlbaum.
Ranney, M. A., & Thanukos, A. (2011). Accepting evolution or creation in people, critters, plants, and classrooms: the maelstrom of American cognition about biological change. In R. S. Taylor, & M. Ferrari (Eds.), *Epistemology and science education: Understanding the evolution vs. intelligent design controversy* (pp. 143—172). New York: Routledge.
Rinne, L. F. (2010). *Cognitive and representational cues for assigning weight to numerical information in decision-making*. Unpublished doctoral dissertation. University of California, Berkeley.
Rinne, L., Ranney, M. A., & Lurie, N. (2006). Estimation as a catalyst for numeracy: micro-interventions that increase the use of numerical information in decision-making. In S. A. Barab, K. E. Hay, & D. T. Hickey (Eds.), *Proceedings of the 7th International Conference on Learning Sciences* (pp. 571—577). Mahwah, NJ: Erlbaum.
Rozenbilt, L., & Keil, F. (2002). The misunderstood limits of folk science: an illusion of explanatory depth. *Cognitive Science, 26*, 521—562.
Schwarz, N. (1999). How the questions shape the answers. *American Psychologist, 54*, 93—105.
Singley, M., & Anderson, J. (1989). *Transfer of cognitive skill*. Cambridge, MA: Harvard University Press.
Teicheira, J. (2015). *Increasing global warming acceptance through statistically driven interventions*. Master's project. Graduate School of Education, University of California, Berkeley.
Thagard, P. (1989). Explanatory coherence. *Behavioral and Brain Sciences, 12*, 435—502.
Tversky, A., & Kahneman, D. (1980). Causal schemas in judgments under uncertainty. In M. Fishbein (Ed.), *Progress in social psychology* (pp. 49—72). Hillsdale, NJ: Erlbaum.
Viswanathan, M. (1993). Measurement of individual differences in preference for numerical information. *Journal of Applied Psychology, 78*(5), 741—752.
Wertheimer, M. (1945). *Productive thinking*. Oxford, UK: Harper.
Wong, E. M., Galinsky, A. D., & Kray, L. J. (2009). The counterfactual mind-set: a decade of research. In K. D. Markman, W. P. Klein, J. A. Suhr, K. D. Markman, W. P. Klein, & J. A. Suhr (Eds.), *Handbook of imagination and mental simulation* (pp. 161—174). New York, NY, US: Psychology Press.
Yarnall, L., Johnson, J. T., Rinne, L., & Ranney, M. A. (2008). How postsecondary journalism educators teach advanced CAR data analysis skills in the digital age. *Journalism & Mass Communication Educator, 63*(2), 146—164.