Public perceptions of energy consumption and savings

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In a national online survey, 505 participants reported their perceptions of energy consumption and savings for a variety of household, transportation, and recycling activities. When asked for the most effective strategy they could implement to conserve energy, most participants mentioned curtailment (e.g., turning off lights, driving less) rather than efficiency improvements (e.g., installing more efficient light bulbs and appliances), in contrast to experts' recommendations. For a sample of 15 activities, participants underestimated energy use and savings by a factor of 2.8 on average, with small overestimates for low-energy activities and large underestimates for high-energy activities. Additional estimation and ranking tasks also yielded relatively flat functions for perceived energy use and savings. Across several tasks, participants with higher numeracy scores and stronger proenvironmental attitudes had more accurate perceptions. The serious deficiencies highlighted by these results suggest that well-designed efforts to improve the public's understanding of energy use and savings could pay large dividends.

climate change | decision making | judgment | environmental behavior | anchoring

Anthropogenic CO_2 emissions are contributing to global climate change (1) and could negatively impact our way of life if serious action is further delayed. The United States produces 21% of the world's CO_2 emissions, with 98% of US emissions attributed to energy consumption (2).

According to Pacala and Socolow (3), increasing energy efficiency and curtailing activities that consume energy may be our cheapest options for stabilizing atmospheric CO_2 concentrations below a doubling of preindustrial concentrations. Following the analogy of *stabilization wedges* (3), Dietz et al. (4) devised a potential *behavioral wedge*, recommending specific behavioral changes, such as weatherization investments, to be adopted by US households to decrease their emissions. Vandenbergh et al. (5) identified seven actions, such as reducing automobile idling and substituting compact fluorescent light bulbs (CFLs) for incandescent bulbs, that have the potential to achieve large emission reductions at a low cost to the government and with a net savings for individuals. In related work, Gardner and Stern (6) identified a *short list* of the most effective actions US households could take to decrease their contributions to climate change. They argued that by changing the selection and use of household and motor vehicle technologies, households could reduce their energy consumption by nearly 30%—without waiting for new technologies, making major economic sacrifices, or losing a sense of well-being. If households effectively implemented all of Gardner and Stern's recommended changes, US energy consumption would be reduced by approximately 11%. Similarly, Dietz et al. (4) estimated that behavioral interventions could reasonably achieve a 20% reduction in CO_2 emissions from household energy use (a 7.4% reduction in total US emissions) within 10 y.

Gardner and Stern (6) also speculated that people harbor misconceptions about the effectiveness of their actions. For example, "turning out lights when leaving the room" is often suggested as a way to save energy, but it actually saves very little (7). Although Gardner and Stern did not examine people's perceptions of the behaviors on their short list, other research indicates that members of the general public have a poor understanding of the mechanisms

involved in climate change (8, 9) and of the energy consumption associated with familiar activities, even though the public may believe that climate change is real (10). For example, Larrick and Soll (11) reported that people in the United States mistakenly believe that gasoline consumption decreases linearly rather than nonlinearly as an automobile's gas mileage (in miles per gallon) increases. Describing vehicles' fuel efficiency in terms of "gallons per 100 miles" corrected this misperception and led to more fuel-efficient choices. The authors therefore recommended that the United States switch to the latter metric.

Demand-side policy responses to climate change, such as encouraging consumers to adopt more efficient technologies, would benefit from a better understanding of how much individuals know about energy consumption in situations in which they have some direct control. In this study, we investigated public perceptions of energy use and potential energy savings associated with a variety of activities, devices, and technologies, many of which were drawn from Gardner and Stern's (6) short list.

For a key portion of our study, we used the classic risk-perception research of Lichtenstein et al. (12) as a guiding analogy. Those authors asked people to estimate the number of annual deaths in the United States from 30 causes (e.g., heart disease, tornadoes). Although participants' estimated fatality rates were positively correlated with actual fatality rates, the slope of the relationship was relatively flat, with overestimates for low risks and underestimates for high risks. The availability heuristic (13–15), a judgment process in which the frequency of an event is estimated according to the ease with which specific instances come to mind, provides one explanation for this result. Judging by availability can result in estimates that are generally accurate but with systematic overestimates for frequencies of vivid low-probability events (13, 15). A second explanation is provided by the anchoring-and-adjustment heuristic (14, 16), in which a person generates a numerical judgment by first adopting a salient reference point as a starting value and then adjusting his or her judgment in the desired direction. Adjustment is typically insufficient, leading to relative insensitivity to the magnitudes of true differences in frequency estimation tasks. Hertwig et al. (17) replicated Lichtenstein et al.'s (12) results using German fatality rates but argued that the primary pattern could be explained either by the availability heuristic or by direct frequency encoding (learning the true frequencies through experience) combined with regression toward the mean. Because similar judgment processes are likely to affect estimates of energy use and savings, we anticipated that the re-

lationship between participants' estimates and the actual values would be relatively flat. In addition, we expected that some individual differences, such as education, numeracy, and pro-environmental attitudes and behaviors, would be associated with more accurate perceptions of energy consumption and savings.

Results

Perceptions of the "Most Effective Thing." The study began with an open-ended survey question that asked participants to indicate the most effective thing they could do to conserve energy. Two judges identified 17 mutually exclusive categories of responses in an initial set of 40 surveys (Table 1) and then independently coded the remaining responses. Interrater agreement was "almost perfect," with $\kappa = 0.82$ (18). We further classified these categories as curtailment actions (e.g., *Turn off lights*) or efficiency actions (e.g., *Use efficient light bulbs*), although some ambiguous responses (e.g., *Conserve energy*, *Recycle*) could not be classified in this manner. Despite Gardner and Stern's (6) conclusion that efficiency-improving actions generally save more energy than curtailing the use of inefficient equipment, only 11.7% of participants mentioned efficiency improvements, whereas 55.2% mentioned curtailment as a strategy for conserving energy.

Perceptions of Energy Used and Saved. Each participant estimated the energy used by nine devices and appliances and the energy saved by six household activities, with the energy used by a 100-W incandescent light bulb in 1 h provided as a reference point. For each participant, we assessed the correlation between these perceptions and actual energy use and savings (as determined from the literature), after transforming both distributions with base-10 logarithms to reduce positive skew. The mean correlation between log10*Perception* and log10*Actual* was $r = 0.51$ [$t(488) = 36.34, P < 0.0001, \eta^2 = 0.70$], indicating that participants had significant (but imperfect) knowledge of which devices and activities were associated with greater energy use and savings.

To examine this relationship in more detail, we used the multilevel regression model (18, 19) in Eq. **1** to predict participants' perceptions of energy use and savings as a function of actual energy use and savings.

$$\log10Perception_{ij} = \beta_{0j} + \beta_{1j}\log10Actual_i + \beta_{2j}(\log10Actual_i)^2 + r_{ij} \quad [1]$$

In this equation, i indicates the device or activity and j indicates the participant. We modeled variation among participants by letting β_{0j} and β_{1j} vary about their average values, thereby allowing each participant to have his or her own regression equation (i.e., participant j's intercept and slope differed from the average intercept and slope). In contrast, we treated the quadratic effect as fixed, so β_{2j} was the same for all participants (see *SI Text*). The functional form in Eq. **1** is the same as that used in studies of risk perception (12, 17), but we centered the values of log10*Perception* and log10*Actual* relative to the original mean of log10*Actual*, so that the coefficients would be more interpretable. The intercept β_{0j} indicates over- or underestimation, the slope β_{1j} indicates the general relationship between perceptions and actual values, and the coefficient for the quadratic term β_{2j} indicates the curvature in that relationship. This specification allows for a detailed assessment of the accuracy of participants' perceptions; for perfectly accurate perceptions, $\beta_{0j} = 0$, $\beta_{1j} = 1$, and $\beta_{2j} = 0$.

The two predictors in Eq. **1** accounted for 40% of the within-participant variation in energy perceptions (see *SI Text*). Results for the average parameter estimates are shown in Fig. 1, along with mean perceptions for the 15 devices and activities (Fig. 1 *Inset*, which highlights variation across participants, is discussed in the next section). The average intercept, which gives the average elevation of perceptions at the mean of log10*Actual*, was significantly negative [$M(\beta_{0j}) = -0.44, t(492) = -18.03, P < 0.0001$]. On average, participants underestimated energy use and savings by a factor of $10^{0.44} = 2.8$.

The average slope, evaluated at the mean of log10*Actual*, was significantly greater than zero [$M(\beta_{1j}) = 0.28, t(6824) = 26.91, P < 0.0001$] but significantly less than 1 [$t(6824) = -69.70, P < 0.0001$]. This gradual slope reflects two features of the data. First, it reflects the imperfect correlation between perceived and actual values. This regression toward the mean occurs whenever variables are imperfectly correlated, but it does not "explain" why the correlation is imperfect (21). Second, participants' perceptions of energy use and savings were much less variable than actual energy use and savings: The mean SD of log10*Perception*, 0.44, was approximately half that of log10*Actual*, 0.82. On average, participants demonstrated only slight sensitivity to the size of actual energy differences. For example, participants correctly reported that desktop computers consume more energy than laptop computers, but they greatly underestimated the magnitude of this difference (a perceived ratio of 1.2 rather than 2.9). This compression bias (22) is consistent with participants using the 100-Wh reference point as an anchor from which they adjusted insufficiently (15, 16).

The quadratic effect was significant and negative [$M(\beta_{2j}) = -0.19, t(6824) = -18.56, P < 0.0001$], yielding a function that is essentially flat when actual consumption and savings are high. Indeed, participants did not make accurate distinctions among large

Table 1. Categorized responses to an open-ended question about the single most effective thing that participants could do to conserve energy in their lives

Behavior category	Curtailment (C) or efficiency (E)	Percentage of participants
Turn off lights	C	19.6
Conserve energy		15.0
Drive less/bike/use public transportation	C	12.9
Change the setting on the thermostat	C	6.3
Change my lifestyle/not have children	C	5.9
Unplug appliances	C	5.7
Shut off appliances/use appliances less	C	4.9
Recycle		4.2
Other (for behaviors only mentioned once)		4.0
Education/think about my actions		3.8
Use efficient light bulbs	E	3.6
Use efficient appliances	E	3.2
Use efficient cars/hybrids	E	2.8
Sleep more/relax more		2.8
Buy green energy/solar energy/alternative energy		2.6
Insulate my home	E	2.1
There is no way/I don't know		0.8

Some behaviors could not be unambiguously classified as curtailment or efficiency.
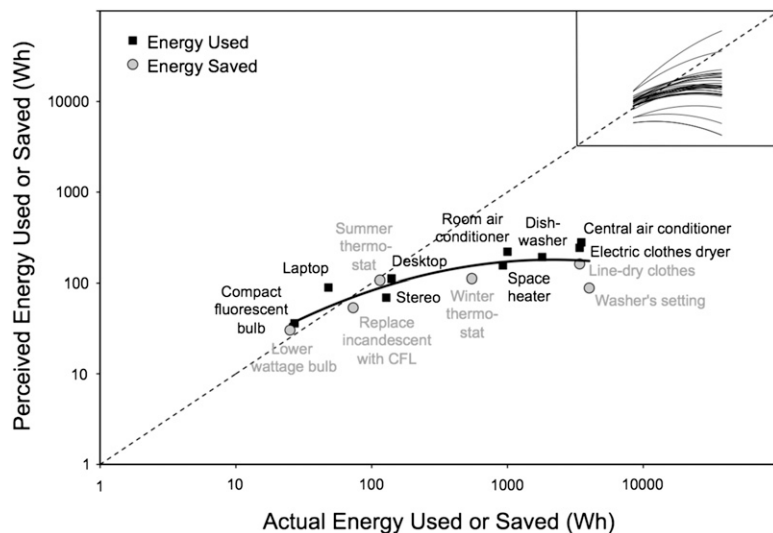
Fig. 1. Mean perceptions of energy used or saved as a function of actual energy used or saved for 15 devices and activities. Error bars for 95% confidence intervals are omitted because they are typically no taller than the symbols themselves. The diagonal dashed line represents perfect accuracy. *Inset:* Individual regression curves for 30 randomly selected participants.

appliances, despite a 10-fold difference in actual energy use. For example, participants estimated that line-drying clothes saves more energy than changing the washer's settings (the reverse is true) and estimated that a central air conditioner uses only 1.3 times the energy of a room air conditioner (in fact, it uses about 3.5 times as much). Respondents were relatively more accurate for behaviors in the middle and lower end of the range (e.g., using a desktop computer, changing their summer thermostat, replacing an incandescent bulb with a CFL, replacing a 100-W bulb with a 75-W bulb). Overall, the combination of mean underestimation and a gradual slope that is flatter for high-energy values reflects very minor overestimates when actual energy use and savings are low and large underestimates when actual use and savings are high (Fig. 1).

We conducted similar multilevel regressions (but without the quadratic term) for (*i*) estimates of the energy saved by three automobile-related activities, (*ii*) rankings of the energy used by different modes of transportation, and (*iii*) rankings of the energy used to make aluminum and glass beverage containers from virgin and recycled materials (see *SI Text*). Average results for these analyses appear in Fig. 2. In all three instances, the average slope was substantially less than the correct slope.

As shown in Fig. 2*A*, the average elevation of perceived gasoline savings was very close to the average of actual savings [$M(\beta_{0j}) = -0.016, t(475) = -0.70, P = 0.49$], indicating that participants did not underestimate or overestimate energy savings for these three behaviors, at least on average. Although the actual and perceived energy savings (in Wh) are much greater than those in Fig. 1, the average slope for gasoline savings was very similar, at 0.23, indicating a relatively flat relationship. For example, the energy saved by reducing one's highway speed from 70 to 60 miles per hour on a 60-mile trip was overestimated, consistent with the relatively small amount of energy saved (0.4 gallons of gasoline). For consistency with the survey, we frequently use US rather than metric units in the text and figures.

As shown in Fig. 2*B*, participants correctly reported that transporting goods via airplanes consumes more energy than using other modes of transportation, and that the energy difference between trains and ships is small. However, they incorrectly reported that trucks consume approximately as much energy as trains and ships, even though trucks actually consume 10 times more energy per ton-mile. Apparently, recent advertising touting the much greater fuel efficiency of trains relative to trucks has been ineffective, at least among this sample of the general public.

As shown in Fig. 2*C*, participants correctly reported that making a can or bottle from virgin aluminum or glass requires more energy than making the same container from recycled materials. However, they incorrectly reported that making a glass bottle requires less energy than making an aluminum can. In fact, the reverse is true: A glass bottle requires 1.4 times as much energy as an alu-

minum can when virgin materials are used and 20 times as much energy when recycled materials are used. In part because glass is so heavy, making a recycled glass bottle actually requires more energy than making a virgin aluminum can.

Individual Differences in the Accuracy of Perceptions. The Fig. 1 *Inset*, which shows the results of Eq. **1** for 30 randomly selected participants, indicates substantial variation in elevations and slopes. Although not shown in Fig. 2, there was also substantial variation around the average elevation and slope in Fig. 2*A* and around the average slopes in Fig. 2 *B* and *C* (but not around the average elevations in Fig. 2 *B* and *C*, because the average ranks were constrained to be 2.5). In a series of exploratory analyses, we attempted to account for this variation by adding 16 centered individual-difference variables (e.g., numeracy, proenvironmental attitudes) as predictors in our multilevel regression models. For example, we allowed the intercept β_{0j} and slope β_{1j} in Eq. **1** to depend on these additional variables (*SI Text*). The effects on β_{0j} are the main effects of the new variables, whereas the effects on β_{1j} are the interactions between these variables and log10*Actual*. We used similar models to assess the effects of the individual-difference variables on the slopes in the three panels of Fig. 2 (*SI Text*).

Results for these augmented models appear in Table 2, with the results for household devices and activities split over two columns. The average elevation in Fig. 1 was negative (indicating underestimation), and the four average slopes in Figs. 1 and 2 were all substantially less than the correct slopes. As a result, positive coefficients for the individual-difference variables imply more accurate perceptions of energy use and savings (less underestimation or steeper slopes) in all five columns of Table 2. Thus, the easiest way to understand these results is to look for variables with consistent significant effects across regressions (i.e., by row rather than by column).

The coefficient for numeracy (23) was positive in all five tests and significant in four, indicating that participants with a better understanding of numerical concepts had more accurate perceptions of energy consumption and savings. The coefficient for the New Ecological Paradigm (NEP) score (24) was positive and significant in four of the five tests, indicating that participants with more proenvironmental attitudes had more accurate perceptions. These two effects were substantial. For the 115 participants with above-average numeracy and NEP scores (numeracy >1.5 and NEP >3.7), the average elevation for predictions of energy use and savings for the devices and activities in Fig. 1 was −0.25 (instead of −0.44 for the whole sample), and the average slope was 0.38 (instead of 0.28).

Surprisingly, participants' self-reported environmental behaviors scale always had a negative coefficient and was significant in three of the five tests, indicating that participants who reported
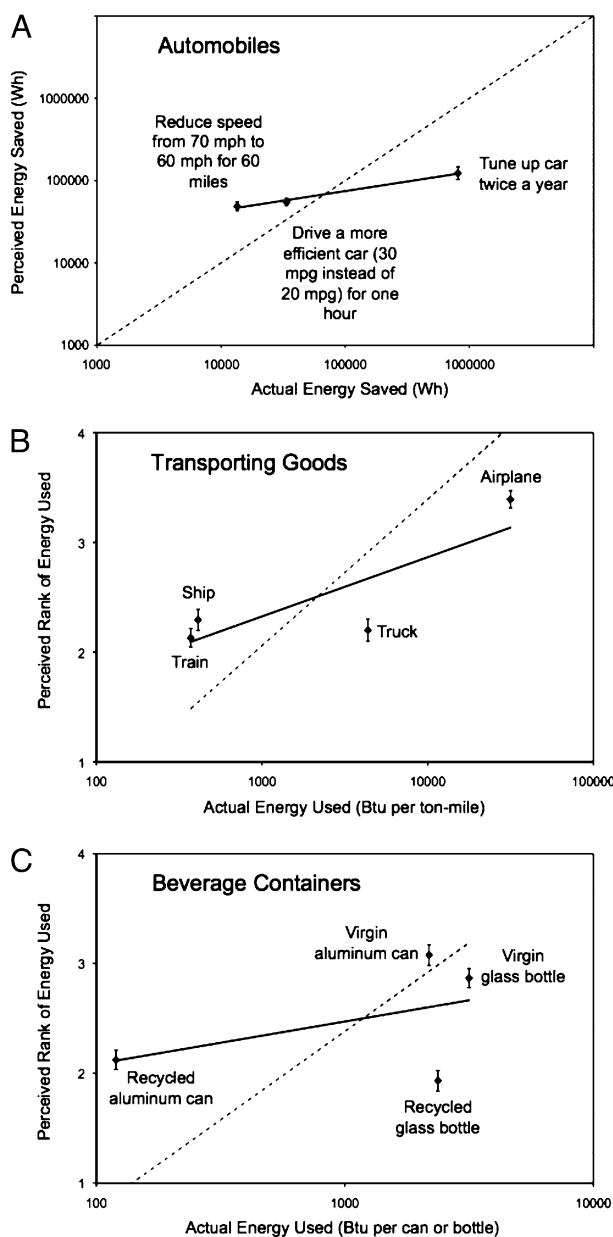
A

B

C

Fig. 2. Mean perceptions of energy used or saved as functions of actual energy used or saved for automobile-related activities (*A*), modes of transporting goods (*B*), and methods of manufacturing beverage containers (*C*). Error bars indicate 95% confidence intervals for mean perceptions. Diagonal dashed lines represent accurate responses. In *B* and *C*, the dashed lines were derived by regressing the correct ranks onto actual energy use.

engaging in a greater number of proenvironmental energy-related behaviors had less accurate perceptions.

Finally, several variables that one might expect to be related to accuracy (e.g., climate-change attitude, home ownership, age, income, education) were not reliable predictors in these regressions. Overall, the percentages of variation in elevations and slopes explained by the individual-difference variables were small to modest (*SI Text*).

Discussion

Notwithstanding a few bright spots (e.g., knowing roughly how much energy is saved by a CFL), participants in this study exhibited relatively little knowledge regarding the comparative energy use and potential savings related to different behaviors. Relative to

experts' recommendations, participants were overly focused on curtailment rather than efficiency, possibly because efficiency improvements almost always involve research, effort, and out-of-pocket costs (e.g., buying a new energy-efficient appliance), whereas curtailment may be easier to imagine and incorporate into one's daily behaviors without any upfront costs.

Participants were also poorly attuned to large energy differences across devices and activities and unaware of differences for some large-scale economic activities (transporting goods by train vs. truck) and everyday items (aluminum vs. glass beverage containers). Knowing these relative magnitudes would allow individuals to make more informed choices regarding energy-saving behaviors.

The observed correlations between judged and actual energy values, although positive, may be too small to support sound decision making. In their studies of risk perception, Lichtenstein et al. (12) noted that positive correlations between perceived and actual fatality rates are almost guaranteed when the actual rates span several orders of magnitude: "Subjects who could make only the roughest discriminations, for example, knowing that death from botulism or lightning is less likely than death from all cancer or all accidents, would show high correlations" (pp 566–567). Similarly, participants in our tasks may have needed only basic knowledge to obtain significant positive slopes. It may not require much insight to realize that a major appliance (of any variety) uses more energy than a single light bulb (be it incandescent or fluorescent) or that tuning one's car saves more energy in a *year* than reducing one's highway speed saves in an *hour*. Despite displaying some sensitivity to these and other differences, participants severely underestimated their magnitudes. In addition, the non-linearity in Fig. 1 indicates that participants were least accurate when energy use and savings were high (e.g., for large appliances). In other words, people's understanding may be worse where the potential for CO_2 reductions is large, although other considerations such as how often a device is used over the course of a year are also relevant.

As in previous research on judgment and decision making, participants with higher numeracy scores had more accurate perceptions (25). Participants with stronger proenvironmental attitudes were also more accurate. Even so, participants who scored high on both measures still had relatively flat slopes. Unexpectedly, participants who engaged more in energy-conserving behaviors had less accurate perceptions of energy use and savings, possibly reflecting unrealistic optimism about the effectiveness of their personal energy-saving strategies compared with alternative ones (26). Alternatively, people may focus primarily on the behaviors they have already adopted, leading to inaccuracies in judging how much energy other behaviors use or save (13).

This study, like others, has limitations. First, we did not offer incentives for accuracy, and we did not assess perceptions in real-world settings that might foster greater accuracy (e.g., among consumers shopping for new appliances). We doubt that financial incentives would have improved participants' accuracy, however, because they are typically ineffective for reducing anchoring effects (16) or improving calibration (17). Second, our Internet sample, although diverse, was not completely representative of the adult US population. Even so, the regression results in Table 2 indicate that most demographic variables were not predictive of accuracy. Third, we do not know whether the reported misperceptions affect actual energy-related behavior.

Given our results, the key question is why most people have difficulty judging energy use and savings. In sorting through the possibilities, it is helpful to note that the simple slope of the relationship between perceived and actual values is just the product of the Pearson correlation and the ratio of the two SDs: $b = r(s_Y/s_X)$. In our primary analysis, these two components contributed roughly equally to the flat slope, with mean values of 0.51 for r and 0.53 for s_Y/s_X. Considering the ratio of SDs, participants' estimates of energy use and savings were greatly compressed relative to the actual values. This compression almost certainly resulted from an anchoring bias (14, 16, 22) in which the reference point provided in the task served as an anchor for participants' estimates, causing those estimates to be too similar to the reference point. The underestimation of energy use and savings in Fig. 1 is consistent with

Table 2. Results of multilevel regressions for predicting individuals' perceptions of energy use and savings

Parameter	Household activities (Fig. 1) Elevation, slope, and main effects (effects on elevation)	Interactions (effects on slope)	Automobiles (Fig. 2A) (elevation, slope, and interactions)	Transporting goods (Fig. 2B) (slope and interactions)	Beverage containers (Fig. 2C) (slope and interactions)
Intercept (elevation)	−0.44*	—	−0.010	—	—
Within-participant (level-1) predictors					
Actual energy use or savings, log10*Actual*	0.28*	—	0.24*	0.54*	0.39*
Quadratic term, (log10*Actual*)^2	−0.19*	—	—	—	—
Between-participant (level-2) predictors					
Numeracy (0–3, $\alpha = 0.59$)	0.076*	0.063*	0.056†	0.078‡	0.017
NEP (0–6, $\alpha = 0.81$)	0.12†	0.086*	−0.003	0.12‡	0.21‡
Climate-change attitude (0–6, $\alpha = 0.79$)	−0.001	−0.027‡	0.060‡	0.037	−0.016
Environmental behaviors (0–9, $\alpha = 0.65$)	−0.033†	−0.008	−0.021	−0.063*	−0.12*
Uses more energy than average	−0.005	−0.026	−0.005	−0.048	−0.12‡
Owns car	−0.030	0.047	−0.13	0.065	0.10
Owns home	0.045	0.015	0.048	0.10	0.24‡
Voted Democrat	−0.14‡	−0.037	0.006	−0.11	0.049
Voted Republican	−0.13‡	−0.029	0.042	−0.19	0.11
Chose not to vote	−0.25†	−0.085‡	0.040	−0.33‡	0.058
Could not vote	−0.32†	−0.10‡	−0.068	−0.051	−0.42
Political views (1–7)	0.018	0.001	0.021	0.015	0.014
Male	0.043	0.006	0.002	−0.027	−0.040
Age	−0.003	0.002	−0.001	0.006	−0.004
Income (1–8)	0.023	0.008	0.005	−0.045	−0.026
Education (1–6)	0.005	0.004	0.045‡	0.050	−0.003

Elevation and slope are reported at the relevant mean of log10*Actual*, the *x* axis variable in Figs. 1 and 2. When elevation varied, it was tested against the relevant mean of actual energy use or savings. Elevation did not vary for transporting goods (Fig. 2B) or beverage containers (Fig. 2C) because the ranking task required each participant's mean elevation to be 2.5. For automobiles (Fig. 2A), the main effects are omitted for brevity. All slopes were tested against the correct slopes (1, 1, 1.33, and 1.61 for the four regressions, respectively). For political categories (e.g., Voted Democrat, Could not vote), the excluded category was "Do not want to divulge." The components of the environmental behaviors scale were: owns CFLs, considers efficiency for large appliances, considers efficiency for small appliances, conducted an energy audit of home, weatherized home, installed double-pane windows, bought renewable energy, wrote a letter about energy, and considers oneself an environmentalist.
*$P < 0.001$.
†$P < 0.01$.
‡$P < 0.05$.

the relatively low reference point provided in our primary task (a 100-W light bulb used for 1 h). We selected the light-bulb reference point because it was the most understandable to participants in our pilot tests. If, as we suspect, incandescent light bulbs serve as natural reference points for judgments about energy, then the observed underestimation of household energy use and savings should generalize beyond our survey procedures.

Turning to the imperfect correlation between perceived and actual values, there are several plausible reasons (in addition to random error in reported perceptions) for *r* to be less than 1. For example, participants may have imagined specific examples of devices or appliances whose energy consumption differed from the *Actual* values we used, or they may have failed to consider important factors related to actual energy consumption and savings (e.g., the volume of air cooled by a central air conditioner usually far exceeds that cooled by a room air conditioner). A more general explanation is that people usually make energy comparisons within rather than across categories of devices (e.g., they compare different models of air conditioners rather than comparing air conditioners to clothes dryers), in part because energy-efficiency labels generally highlight within-category comparisons. For a more thorough discussion of potential explanations for the flat slopes in Figs. 1 and 2, see *SI Text*.

Many people's concerns about energy are simply not strong enough, relative to their other concerns, to warrant learning about energy conservation (27). Although it may be appropriate to criticize the media for not presenting the case for climate change more strongly and for not presenting the implications of individual behavior more clearly (28), scientists share at least some of the responsibility for the current state of affairs. For example, Fischhoff (29) recently argued that scientists may have failed the public by not providing information in a credible and comprehensible manner to facilitate better climate-related decisions. In addition to improved communication efforts, increasing fossil fuel prices to reflect the true environmental costs of CO_2 emissions would also provide strong incentives for learning and behavior change.

Research has demonstrated that successful risk communication requires an understanding of people's knowledge gaps and misconceptions (30), and the same is likely to be true for communications about energy. The results of this study imply that well-designed efforts to increase the public's knowledge of energy use and savings could be quite beneficial, although we hasten to add that providing appropriate information is only one component of a successful intervention strategy (4, 31, 32) and that other barriers to individual emissions reductions must also be addressed (33, 34). Recent research indicates that investments in non–price-based behavioral interventions can be effective in decreasing energy use (27). However, many campaigns have focused on behaviors that save relatively small amounts of energy, such as unplugging one's cell phone charger, whereas other more effective behaviors have

been neglected. So long as people lack easy access to accurate information about relative effectiveness, they may continue to believe they are doing their part to reduce energy use when they engage in low-effort, low-impact actions instead of focusing on changes that would make a bigger difference. If people are un-informed, the substantial potential of behavioral interventions to reduce energy consumption (5–8) may go unrealized. It is therefore vital that public communications about climate change also address misconceptions about energy consumption and savings, so that people can make better decisions for their pocketbooks and the planet.

Methods

Participants. We recruited 505 participants through Craigslist in seven US metropolitan areas: New York, Philadelphia, Washington DC, Houston, Dallas, Denver, and Los Angeles. The sample represented 427 ZIP codes in 34 states (plus Washington DC). The online survey was conducted from 9:00 AM to 3:00 PM on Wednesday, February 11, 2009. Each participant received a $10 gift certificate to Amazon.com.

On the basis of 471 participants who provided demographic data, the median age was 31 y, compared with 36.4 y in the US [US Census Bureau (2007) 2005–2007 American Community Survey 3-year estimates]; 35% of participants were male (49% in the US); and 63% owned their homes (67% in the US). The median family income was $50,000–$79,999 ($60,400 in the US). All participants who were aged 25 y or older held high school diplomas (84% in the US), and 41% held bachelors' degrees (27% in the US). Forty-seven percent self-identified as liberals (score = 1–3), 31% as moderates (score = 4), and 22% as conservatives (score = 5–7). Thirty-seven percent considered themselves environmentalists. These figures may indicate some selection bias or response bias.

Survey Materials. The complete survey and tables of actual energy values are presented in the SI Appendix and SI Text, respectively.

At the beginning of the survey, participants answered an open-ended question about the most effective thing they could do to conserve energy in their life. Next, participants estimated the number of energy units typically used in 1 h by nine devices and appliances (e.g., a stereo, a dishwasher, a CFL that is as bright as a 100-W incandescent bulb). They also estimated the number of energy units that would be saved by six activities (e.g., changing washer temperature settings from "hot wash, warm rinse" to "warm wash, cold rinse" for one load of laundry). To help participants make these com-

parisons, both questions provided a reference point indicating that a 100-W incandescent bulb uses 100 units of energy in 1 h—chosen after pilot tests suggested that this reference point improved understanding.

Participants then indicated how many energy units they thought three automobile-related activities would save (e.g., reducing speed from 70 to 60 miles per hour when driving a 20-miles-per-gallon car for 60 miles). Here, the reference point stated that a "20-miles-per-gallon car going 60 miles per hour uses 100 units of energy in one hour." Thus, 100 units equaled 3 gallons of gasoline, or approximately 101 kWh.

Subsequently, participants ranked the amount of energy needed to transport 1 ton of goods for 1 mile by truck, train, ship, and airplane. They also ranked the energy used to make a can from virgin aluminum, a can from recycled aluminum, a bottle from virgin glass, and a bottle from recycled glass.

Participants then completed the Revised NEP scale (23), a 15-item instrument for assessing proenvironmental attitudes. We coded the original responses (0 = *completely disagree*, 6 = *completely agree*) in the proenvironmental direction and averaged them to yield an overall NEP score for each participant. They also rated four statements regarding personal efficacy and belief in climate change (e.g., "I believe that I need to change my lifestyle to address global warming and climate change"), which we used to calculate an overall *climate-change attitude* score. In addition, participants completed Schwartz et al.'s (22) *numeracy* assessment, which consists of three open-ended questions. For example, "In the BIG BUCKS LOTTERY, the chance of winning a $10 prize is 1%. What is your best guess about how many people would win a $10 prize if 1000 people each buy a single ticket to BIG BUCKS?"

Near the end of the survey, participants answered eight questions regarding their own energy-related actions (e.g., whether they had weatherized their home, whether they thought of energy efficiency when buying large household appliances). Responses were combined with an additional item (considering oneself an environmentalist) to yield a nine-item *environmental behaviors* scale (a count of Yes responses). Demographic questions concluded the survey.

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