

Supporting Information

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SI Text

SI Methods. Data sources and values of actual energy consumption and savings. The data sources for actual energy use are shown in Tables S1-S4. The data reflect the best available information at the time of analysis. When multiple values were available, we used the arithmetic mean. Multilevel regression models. In each domain (e.g., household devices and activities), we fit two primary models. Model 1 was used to investigate the basic relationship between perceived and actual energy use and savings. Model 2 was used to explore which individual-difference variables (e.g., numeracy, proenvironmental attitudes) account for differences in the accuracy of participants’ perceptions. All models were fit using the restricted maximum likelihood method in SAS PROC MIXED, with unstructured covariance matrices and with empirical (robust) SEs for *t* tests of fixed effects.

Household devices and activities. For household devices and activities, Model 1 was as follows:

$$\begin{aligned} \log 10 \text{ Perception}_{ij} = & (\gamma_{00} + u_{0j}) + (\gamma_{10} + u_{1j}) \log 10 \text{ Actual}_i \\ & + \gamma_{20} (\log 10 \text{ Actual}_i)^2 + r_{ij} \end{aligned}$$

This model is the same as that in Eq. 1 of the main text, with the following substitutions:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + u_{0j} \\ \beta_{1j} &= \gamma_{10} + u_{1j} \\ \beta_{2j} &= \gamma_{20}. \end{aligned}$$

In these equations, γ_{00} and γ_{10} are the average intercept (elevation) and slope, respectively, u_{0j} is the random deviation of participant *j*’s intercept from the average intercept, u_{1j} is the random deviation of participant *j*’s slope from the average slope, and r_{ij} is the level- 1 error. In contrast to β_{0j} and β_{1j} , the coefficient β_{2j} for the quadratic term was treated as fixed rather than random, because its estimated variance was not significantly different from zero in model 1 and because its estimated variance was zero in model 2 . In the main text, the reported means $M(\beta_{0j})$, $M(\beta_{1j})$, and $M(\beta_{2j})$ refer to the estimated values of the average coefficients $\hat{\gamma}_{00}$, $\hat{\gamma}_{10}$, and $\hat{\gamma}_{20}$, respectively.

Model 2 for household devices and activities incorporated the effects of the 16 individual-difference variables on the intercept and slope as follows:

$$\begin{aligned} \log 10 \text{ Perception}_{ij} = & \left(\gamma_{00} + \sum_{k=1}^{16} \gamma_{0k} z_{kj} + u_{0j} \right) \\ & + \left(\gamma_{10} + \sum_{k=1}^{16} \gamma_{1k} z_{kj} + u_{1j} \right) \log 10 A'_{\text{ctual}} \\ & i \end{aligned}$$

In this equation, the z_k s are the individual-difference variables, with each participant *j* having his or her own value on each variable. Again, this model is the same as that in Eq. 1 of the main text, but with the following substitutions:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \sum_{k=1}^{16} \gamma_{0k} z_{kj} + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \sum_{k=1}^{16} \gamma_{1k} z_{kj} + u_{1j} \\ \beta_{2j} &= \gamma_{20} \end{aligned}$$

Thus, the first summation in Eq. S2 represents the main effects of the individual-difference variables on the elevation (intercept), whereas the second summation represents the effects of these variables on the log 10 Actual slope (i.e., the interactions between the z_k s and log 10 Actual). Because the z_k s were centered, they do not affect the average values of β_{0j} and β_{1j} :

Automobiles. For automobile-related activities, we recentered log 10 Actual and omitted the quadratic term. The resulting models 1 and 2 were as follows:

$$\log 10 \text{ Perception}_{ij} = (\gamma_{00} + u_{0j}) + (\gamma_{10} + u_{1j}) \log 10 \text{ Actual}_i + r_{ij}$$

$$\begin{aligned} \log 10 \text{ Perception}_{ij} = & \left(\gamma_{00} + \sum_{k=1}^{16} \gamma_{0k} z_{kj} + u_{0j} \right) \\ & + \left(\gamma_{10} + \sum_{k=1}^{16} \gamma_{1k} z_{kj} + u_{1j} \right) \log 10 \text{ Actual}_i + r_{ij} \end{aligned}$$

Transportation modes and beverage containers. For the transportation of goods, participants provided ranks rather than quantitative estimates. Because the average rank was necessarily 2.5 (the mean of 1, 2, 3, and 4), we did not estimate the intercept or the main effects of the individual-difference variables. We recentered log 10 Actual and omitted the quadratic term. The models for beverage containers were identical to those for transportation modes, except that we again recentered log 10 Actual. Here are models 1 and 2 for the ranking tasks:

$$\text{PerceptionRank}_{ij} = 2.5 + (\gamma_{10} + u_{1j}) \log 10 \text{ Actual}_{li} + r_{ij}$$

$$\text{PerceptionRank}_{ij} = 2.5 + \left(\gamma_{10} + \sum_{k=1}^{16} \gamma_{1k} z_{kj} + u_{1j} \right) \log 10 \text{ Actual}_i + r_{ij}.$$

Distributions of elevations and slopes. In multilevel modeling, the predicted value of each participant’s intercept or slope is a weighted average of the intercept or slope from the appropriate model (e.g., S1-S6) and the intercept or slope from that participant’s own ordinary least squares regression. The Inset in Fig. 1 in the main text shows the predicted regression curves for perceived energy use and savings for household devices and activities (based on model 1 in Eq. S1) for 30 randomly selected participants. These curves indicate substantial variability in both elevations (intercepts) and slopes, and also suggest that some participants had particularly high or low elevations or slopes. Model 2 was intended to explain some of this variability by incorporating individual differences.

For each of our four tasks, descriptive statistics for the distributions of predicted elevations and slopes for model 2 appear in

Table S5. These predicted values of β_{0j} and β_{1j} reflect the effects of the individual-difference variables in Eqs. S2, S4, and S6. The descriptive statistics indicate substantial variability across participants, as well as the presence of at least some outliers (participants with particularly high or low elevations or slopes). Even so, the vast majority of participants had elevations that were too low in the analysis of household devices and activities and slopes that were too low in all four analyses.

Distributions of random effects and level-1 errors. Statistical tests in multilevel models assume that the random intercept deviations u_{0j} , the random slope deviations u_{1j} , and the level- 1 errors r_{ij} are normally distributed. For household devices and activities and for automobiles, histograms and normal probability plots indicated that these distributions had somewhat thick tails, with occasional outliers. Thick tails were not a problem in models of participants’ ranks for transportation modes and beverage containers.

We investigated the effects of outliers and nonnormality on our results in several ways. First, deleting participants with extreme estimates for u_{0j} , extreme estimates for u_{1j} , or high Cook’s D values had no effect on statistical tests related to our primary conclusions (i.e., tests of intercepts, Log10Actual and its square, numeracy, NEP, and environmental behaviors). However, some minor results did change. For example, removing four participants with high Cook’s D values in model 2 for household devices and activities yielded a significant main effect of age ($P = 0.036$ rather than 0.099), a significant effect of “Uses more energy than average” on slope ($P = 0.002$ rather than 0.075), and a nonsignificant effect of “Could not vote” on slope ($P = 0.084$ rather than 0.048). Second, using model-based SEs rather than empirical (robust) SEs also had very minor effects, with tests of “Voted Republican,” “Chose not to vote,” and “Could not vote” changing from barely significant to not quite significant. (Robust SEs, which we used in our primary analyses, are preferred when normality is a concern.) Finally, a nonlinear transformation designed to bring in the tails of the log10Perception distribution (the signed square root of the absolute deviation from the mean of log 10 Perception) resolved the normality issues while leaving our key results unchanged, although again there were a few changes for borderline results. We investigated our other models using similar methods. Overall, the results indicate that our primary conclusions are not sensitive to outliers or to violations of normality assumptions. Modeled variance. It would be useful to know how much of the within-participant and between-participant variation in perceptions of energy use and savings is explained by the predictor variables in Eqs. S1-S6. However, issues regarding explained variance in multilevel models are complicated by the fact that the estimated variance components do not map nicely onto the traditional distinction between within-participant and betweenparticipant variation (1, 2).

We took two approaches to modeling explained variance. In the first approach, we estimated the proportions of the variances of the random intercept term u_{0j} , the random slope term u_{1j} , and the level-1 error r_{ij} that were accounted for by the predictor variables (2). These variances are τ_{00} , τ_{11} , and σ^2 , respectively. Estimating the proportions of τ_{00} and σ^2 explained required that we also fit a null model with no predictors (model 0). The proportion of level- 1 error variance explained by model 1 relative to model 0 (for example) is given by the following expression:

$$(\sigma_{\text{Model0}}^2 - \sigma_{\text{Model1}}^2) / \sigma_{\text{Model0}}^2$$

Results for the comparisons of interest appear in Table S6. The row for σ^2 indicates that the inclusion of Log10Actual (and its square, if present) in model 1 reduced the estimated level- 1 error variance by a modest amount, although the reduction for beverage containers was rather small. The two entries in the τ_{00} row indicate that including the individual-difference variables as predictors in model 2 did little to reduce variation in participants’ elevations. The entries in the τ_{11} row are somewhat higher, although still modest, indicating that the individualdifference variables did a better job of accounting for variation in participants’ Log10Actual slopes. In our second approach, we used Snijders and Bosker’s (1) method to calculate an R^2 value for each level of model 2, omitting the random component of the Log10Actual slope, as suggested by those authors:

$$R_{\text{Level1}}^2 = \frac{(\sigma^2 + \tau_{00})_{\text{Model0}} - (\sigma^2 + \tau_{00})_{\text{Model2}}}{(\sigma^2 + \tau_{00})_{\text{Model0}}}$$

$$R_{\text{Level2}}^2 = \frac{((\sigma^2/n) + \tau_{00})_{\text{Model0}} - ((\sigma^2/n) + \tau_{00})_{\text{Model2}}}{((\sigma^2/n) + \tau_{00})_{\text{Model0}}}$$

For household devices and activities and for automobiles, both R^2 values are relatively low because the individual-difference variables did a poor job of reducing τ_{00} (Table S6). For transporting goods and for beverage containers, the level-1 and level- 2 R^2 s are equal because $\tau_{00} = 0$. We find the results of our first approach more interpretable. Although it is possible that other individual-difference variables might improve predictions, we suspect that much of the unexplained variation in participants’ perceptions reflects idiosyncratic factors (e.g., familiarity or experience with different devices) and random error. SI Discussion. Expanded discussion of flat slopes. This section provides a more extensive discussion of the possible reasons for the flat slopes in Figs. 1 and 2 (main text) As noted in the main text, it is helpful to recall that (ignoring any quadratic relationship) the simple slope of the relationship between log 10 Perception and log10 Actual is equal to 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 first, participants’ estimates of energy use and savings were greatly compressed relative to the actual values. This compression almost certainly resulted from an anchoring bias (3-5) 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. Substantial research (reviewed in ref. 4) indicates that such effects occur because the anchor preferentially activates anchor-consistent information in memory. Anchoring is unrelated to regression toward the mean, which is reflected in the imperfect correlation. Because we used a relatively low reference point in our primary task (a 100-W light bulb used for 1 h), anchoring would be expected to lead to underestimation of energy use and savings on average. We observed exactly this result. Although it would be possible to eliminate this underestimation (or even generate overestimation) by using a higher reference point, we selected the light-bulb reference point because it was the most understandable to participants in our pilot tests. Indeed, the ease with which people recall information about the energy used by incandescent light bulbs suggests that these bulbs may serve as natural reference points when people make judgments about household energy use and savings in the real world. If this inference is correct, then the observed underestimation of household energy use and savings should generalize beyond our survey procedures. We also used an easily understood reference point for the automobile-related activities in Fig. 2A (main text), but because that reference point was near the center of the range, anchoring effects (although present) did not lead to under- or overestimation on average. Finally, anchoring effects play no role in Fig. 2B and C (main text) because reference points were not provided and because the ranking tasks ensured that s_Y/s_X equaled the correct value for each participant (i.e., participants could not compress their ranks).

Additional evidence for anchoring also comes from Fig. 2A (main text). We noted in the main text that 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). However, had an activity in Fig. 1 (main text) used or saved that much energy (13,480 Wh), we would have expected an underestimate rather than an overestimate. We attribute this difference to the fact that the reference points in the two tasks differed by a factor of 1,000 (the reference activity for the automobile questions used 3 gallons of gas, or approximately 101 kWh , compared with 100 Wh for the electricity questions). These results are consistent with an anchoring explanation for the compression of energy perceptions (35) and with the results of Lichtenstein et al. (6), who noted that quantitative fatality estimates were higher, but still relatively flat, when a larger reference point was used.

Turning to the imperfect correlation between log 10 Perception and log 10 Actual, 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, such as their own air conditioners, whose energy consumption in fact differed from our Actual values. Such idiosyncrasies would degrade individuals’ correlations even if our actual values were accurate for the average participant. Alternatively, participants may have failed to consider some factors that are 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).

Perceptions may also have been affected by systematic biases that mimic random error when they are not modeled. One intriguing possibility is that perceptions of energy use differ from

1. Snijders T, Bosker R (1999) Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling (Sage Publications, Thousand Oaks, CA).

2. Raudenbush S, Bryk A (2002) Hierarchical Linear Models: Applications and Data Analysis Methods (Sage Publications, Thousand Oaks, CA), 2nd Ed.

3. Poulton EC (1994) Behavioral Decision Theory: A New Approach (Cambridge Univ Press, New York).

4. Chapman G, Johnson E (2002) Incorporating the irrelevant: Anchors in judgments of belief and value. *Heuristics and Biases: The Psychology of Intuitive Judgment*, eds Gilovich T, Griffin D, Kahneman D (Cambridge Univ Press, New York), pp 120-138. perceptions of energy savings. To test this possibility, we augmented the model in Eq. S1 by adding a contrast code that differentiated energy use and energy savings, along with the interaction between this code and log 10 Actual. The average coefficients for the two new predictors were both positive, indicating greater elevation and slope for energy use than for energy savings (i.e., more accurate perceptions for energy use), both $t\text{ s} \geq 8.99$, both $P\text{ s} < 0.0001$. Although it is tempting to interpret these results as a framing effect (7,8), we are hesitant to do so because the use and savings activities were not matched. In the most closely matched comparison, the perceived energy used by an electric dryer ($M = 242$ Wh) exceeded the perceived energy saved by linedrying clothes ($M = 160$ Wh) [$t(482) = 8.16, P < 0.0001, \eta^2 = 0.12$]. A more general explanation for the imperfect relationship is that, to the extent that people make energy comparisons at all, they may do so within rather than across categories of devices (e.g., they compare different models of air conditioners rather than comparing air conditioners to computers). Consumers have not routinely been provided with cross-category information like that in Gardner and Stern’s (9) short list. Indeed, energy-efficiency labels on products from washing machines to automobiles highlight within-category rather than cross-category comparisons. As a result, some facts about relative energy consumption (e.g., that a dishwasher uses much more energy than a typical room air conditioner in 1 h) can be surprising. Of course, people do sometimes make choices across categories, at least implicitly (e.g., deciding to replace an old furnace with a more efficient one rather than installing a programmable thermostat or adding additional insulation in the attic). Similarly, consumers sometimes choose between air and ground shipping for small items, although they do not typically decide whether goods should be shipped by train or truck. However, consumers with the relevant knowledge might react favorably to a shipping company that advertises that they transport goods by rail rather than by truck.

5. Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. *Science* 185:1124-1131.

6. Lichtenstein S, Slovic P, Fischhoff B, Layman M, Combs B (1978) Judged frequency of lethal events. *J Exp Psychol Hum Learn* 4:551-578.

7. Kahneman D, Tversky A (1984) Choices, values, and frames. *Am Psychol* 39:341-350.

8. Dunning D, Parpal M (1989) Mental addition versus subtraction in counterfactual reasoning: On assessing the impact of personal actions and life events. *J Pers Soc Psychol* 57:5-15.

9. Gardner G, Stern P (2008) The short list: The most effective actions U.S. households can take to curb climate change. *Environment Magazine* 50:12-24.

Table S1. Data sources and values for energy use of household devices and appliances (in W)

Device or appliance	Reference				Mean
	AltE (1)		DOE (2)		Navigant (3)
Stereo	10	30	70	400	128
Compact fluorescent light bulb (with equal brightness to a 100 – W incandescent light bulb)		30			23
Laptop computer	20	75	50		48
Desktop computer	80	200			140
Room air conditioner		1,000			1,000
Central air conditioner	2,000	5,000			3,500
An electric clothes dryer			1,800	5,000	3,400
Dish washer			1,200	2,400	1,800
Portable heater			750	1,100	925

“Drying one load of laundry on a clothes line instead of using an electric dryer” had mean savings of 3,400 W (equivalent to not using the electric dryer).

1. Alternative Energy Store. (2008) Power ratings (typical) for common appliances. Available at <http://www.altestore.com/howto/Tools-Calculators-Reference/Reference-Materials/Power-Ratings-typical-for-Common-Appliances/a21/>. Accessed October 26, 2008.

2. U.S. Energy Information Administration (1992) Measuring Energy Efficiency in the United States Economy. Available at: [http://www.eia.doe.gov/emeu/efficiency/eefig_ch5.h](http://www.eia.doe.gov/emeu/efficiency/eefig_ch5.htm) Accessed October 26, 2008.

3. Navigant Consulting Inc (2002) U.S. Lighting Market Characterization (National Lighting Inventory and Energy Consumption Estimate), Vol I (US Department of Energy, Washington, DC). Available at http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl//mc_vol1_final.pdf. Accessed October 26, 2008.

Table S2. Information sources and values for energy saved by household and transportation activities

Activity	Gallons of gasoline	Mean savings (Wh)	Reference
Setting the thermostat on your air conditioner 5°F higher for 1 h in the summer		115	(1)
Setting the thermostat on your heater 5°F lower for 1 h in the winter		546	(2)
Changing washer temperature settings from “hot wash, warm rinse” to “warm wash, cold rinse” for one load of laundry		4,000	(3)
Driving a more fuel efficient car (30 vs. 20 miles per gallon) at 60 miles per hour for 1 h	1	33,700	Calculated
Tuning up a car twice per year	24	808,800	(4)
Cutting highway speed from 70 miles per hour to 60 miles per hour, while driving a 20-miles-per-gallon car for 60 miles	0.4	13,480	(4)

1. Armstrong M (2009) Thermostat Setbacks-Do They Really Work? Available at http://www.homeenergy.org/article_full.php?id=566&article_title=Thermostat_Setbacks_94Do_They_Really_Work. Accessed March 7, 2009.
2. Northeast Utilities (2009) Top Ten Energy-Saving Tips. Available at: <http://www.psnh.com/Residential/StartSaving/tips.asp>. Accessed March 7, 2009.
3. Rocky Mountain Institute (2009) Home Energy Brief: Cleaning Appliances. Available at: http://www.rmi.org/images/PDFs/HEBs/E04-16_HEB6_CleanApps.pdf. Accessed March 7, 2009.
4. DOE (2009) A Consumer’s Guide to Energy Efficiency and Renewable Energy. Available at: http://apps1.eere.energy.gov/consumer/your_home/appliances/index.cfm/mytopic=11877. Accessed March 7, 2009.
5. EPA (2009) Emission Facts: Greenhouse Gas Emissions from a Typical Passenger Vehicle. Available at: <http://www.epa.gov/OMS/climate/420f05004.htm>. Accessed March 7, 2009.

Table S3. Information sources and values for energy consumption related to transportation modes

	Train	Ship	Truck	Airplane	Reference
Btu per ton-mile	371	411	4,360	31,600	(1)
Rank	1	2	3	4	

¹Table S4. Information sources and values for energy consumption related to manufacturing beverage containers

	Recycled aluminum can	Virgin aluminum can	Recycled glass bottle	Virgin glass bottle	Reference
Btu per gram of material	10	182	6	8	(1)
Btu per can or bottle	120	2,180	2,370	3,160	Calculated
Rank	1	2	3	4	

1. Imhoff D (2005) Paper or Plastic: Searching for Solutions to an Overpackaged World (Sierra Club, San Francisco, CA).

Table S5. Descriptive statistics for predicted elevations and slopes from model 2

	Household activities (Fig. 1; main text)		Automobiles (Fig. 2A; main text)		Transporting goods (Fig. 2B; main text) (slope)	Beverage containers (Fig. 2C; main text) (slope)
	Elevation	Slope	Elevation	Slope		
Perfect accuracy	0	1	0	1	1.33	1.61
Mean	-0.44	0.28	-0.01	0.24	0.54	0.40
SD	0.41	0.18	0.44	0.31	0.28	0.34
Maximum	1.01	1.08	1.90	2.51	1.15	1.18
Q3	-0.18	0.40	0.22	0.36	0.73	0.63
Median	-0.43	0.27	-0.04	0.15	0.59	0.46
Q1	-0.66	0.17	-0.31	0.06	0.37	0.19

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1. Imhoff D (2005) Paper or Plastic: Searching for Solutions to an Overpackaged World (Sierra Club, San Francisco, CA).

	Household activities (Fig. 1; main text)		Automobiles (Fig. 2A; main text)		Transporting goods (Fig. 2B; main text) (slope)	Beverage containers (Fig. 2C; main text) (slope)
Minimum	-2.20	-0.33	-1.45	-0.27	-0.48	-0.96

All results are from models for the 460 participants with complete data for the individual-difference variables. For transporting goods and for beverage containers, the slopes for perfect accuracy were derived by regressing the correct ranks onto actual energy use.

Table S6. Proportions of variation explained in multilevel regressions for predicting individuals’ perceptions of energy use and savings

	Model comparison	Household activities (Fig. 1; main text)	Automobiles (Fig. 2A; main text)	Transporting goods (Fig. 2B; main text)	Beverage containers (Fig. 2C; main text)
Variance component					
Level-1 residual, σ^2	1 vs. 0	0.40	0.58	0.23	0.09
Intercept, τ_{00}	2 vs. 1	0.11	0.01	-	-
Slope for log 10 Actual, τ_{11}	2 vs. 1	0.20	0.06	0.23	0.47
R^2					
Level 1	2 vs. 0	0.22	0.09	0.17	0.06
Level 2	2 vs. 0	0.11	0.01	0.17	0.06

In each analysis, model 0 is the null model with no predictors. Models 1 and 2 are given by Eqs. S1-S6. All calculations are based on models for the 460 participants with complete data.

Other Supporting Information Files

SI Appendix (PDF)