Supporting Information

Khaw et al. 10.1073/pnas.1715293114

SI Results

Permutation Tests of Postadaptation Bid Data. To avoid specific distributional assumptions in testing the significance of the bid data, we also examined postadaptation bids using permutation tests. The primary analyses in the main text (Fig. 2) examined the difference between post-*Hi* and post-*Lo* bids in an example subject and across the subject population. Here, we test the significance of these results against shuffled versions of the data in which the block identities are permuted independently for each good. Following permutation, the mean difference between permuted post-*Hi* and post-*Lo* bids were quantified; this permutation was repeated for $n = 10{,}000$ iterations. As shown in Fig. S1, the observed difference in bids between adaptation conditions is significantly larger than all permutation differences ($P < 0.0001$) for both the example subject and the entire population.

Adaptation-Induced Changes in Rating Trials. In addition to willingness-to-pay measures quantified during bid trials, we examined whether adaptation also influenced pleasantness ratings quantified during *Adapt* block rating trials. In the experimental design, the primary function of rating trials was to induce adaptation by creating a local value context (low or high), enabling examination of adaptation-driven changes in subsequent *Test* block bid trials. As discussed in the main text, these bid trials presented the identical set of all 30 items in different value environments, allowing a comparison across different adaptation conditions. In contrast, the different *Adapt* block rating trials presented different goods: the 10 lowest-valued items and the 10 highest-valued items in the low and high conditions, respectively. Because different goods were rated in low versus high rating trials, we focused our analysis on rating changes within rather than between *Adapt* blocks.

If adaptation affects ratings in an analogous manner to valuations, we hypothesized that ratings would change in a value-dependent manner within *Adapt* blocks; specifically, continued exposure to low- or high-value items would increase or decrease ratings, respectively, over the course of an *Adapt* block. Fig. S2*A* plots example subject rating data for each of 10 items in *Lo-Adapt* and 10 items in *Hi-Adapt* blocks. As evident in the example data, there is considerable heterogeneity in rating dynamics across subjects, adaptation conditions, and individual items. However, population average pleasantness ratings showed a significant linear decrease across *Hi-Adapt* blocks (Fig. S2*B*; $P = 0.018$); furthermore, the distribution of individual-specific *Hi-Adapt* regression weights was also significantly negative across the subject population (Fig. S2*C*; $P = 0.017$, t test). In contrast, the pleasantness ratings across the *Lo-Adapt* block showed no significant trend in either analysis ($P > 0.05$). Note that for these regression analyses, due to a small number of subjects (9/43) with *Adapt* blocks of 260 instead of 300 trials, data were examined for trials 1–260. For both population average and individual subject analyses, similar results were obtained using exponential rather than linear decay functions. We note that the difference in within-block dynamics between high and low rating trials may be related to the asymmetric changes in postadaptation valuations observed in bid trials, which we postulate may be driven by stronger high value adaptation conditions in the experimental environment (see section below).

Although these data suggest that pleasantness ratings also exhibit some aspects of history dependence, precise comparison between this phenomenon and adaptation in item valuations will require further research. The current study was designed to examine adaptation in valuations during bid trials, and we note several caveats for interpreting adaptation in pleasantness ratings. First, pleasantness ratings did not correlate strongly with valuations. As evident in example rating data (Fig. S2), low- and high-value items—which by definition differed in their bid trial valuations—exhibited overlapping pleasantness ratings in some subjects. In total, pleasantness distributions in *Lo Adapt* and *Hi Adapt* blocks overlapped in 23/43 subjects. Across all subjects, item valuations (initial block average bid) and initial ratings were only moderately correlated (*Lo-value* items: mean $r = 0.48$; *Hi-value* items: mean $r = 0.45$). Thus, the *Adapt* block conditions, which were designed to implement low- or high-value environments, did not necessarily correspond to distinct pleasantness environments. Second, because the current experiment was not designed to test rating adaptation, rating data were only obtained for items that were also used to induce adaptation. The use of identical items in test and adaptation introduces two issues for interpretation: (*i*) items for which rating adaptation was quantified were presented many times, leaving open the possibility that ratings may change due to repetition alone; (*ii*) different items were presented in the different adaptation conditions. In the primary value adaptation experiment, postadaptation valuations were quantified for all items, enabling us to quantify both low- and high-value adaptation in an independent set of items (goods never presented in *Adapt* blocks). Finally, unlike valuations elicited in bid trials, pleasantness ratings were not elicited in an incentive-compatible manner. In summary, a proper test of pleasantness rating adaptation would require an experimental design incorporating adaptation conditions explicitly varying pleasantness, identical test items across adaptation conditions, and an incentive compatible rating elicitation.

Asymmetry in Postadaptation Bid Changes. In the primary results, postadaptation changes in valuation exhibit an asymmetry, with larger magnitude bid deviations following high vs. low adaptation (Fig. 3). This difference mirrors similar differences observed in successive contrast effects in a number of species. Successive contrast effects describe experiments in which behavior—typically running speed or reward consummatory behavior—depends on previous reward conditions. It is a general consensus in the literature that negative contrast effects (elicited by decreases in the reward environment, and evident as decreases in speed/consummation) are stronger and more prevalent that positive contrast effects (elicited by increases in the reward environment, and evident as increases in speed/consummation). Our observed differences in value adaptation are consistent with these previous effects: stronger bid changes in post-*Hi* effects reflect a stronger negative contrast effect in subjective valuation. In fact, we believe that asymmetry in value adaptation, as demonstrated here, offers a potential explanation for the relative abundance of negative over positive contrast effects in the behavioral literature.

In addition, an examination of the adaptation conditions faced by the subjects in our task offers a second potential explanation for the asymmetry between high- and low-value adaptation (Fig. S3). In the task design, low- and high-value adapters were selected for individual subjects as the items with the 10 lowest and 10 highest average initial bids, respectively. However, typical subjects did not exhibit a uniform distribution of average values across the 30 tested items (Fig. S3*A*); instead, most individual subject value distributions showed positive skew (mean skewness = 0.62), with a concentration of relatively low-valued items and a smaller tail of relatively high-valued items. This asymmetry is also evident in the distributions of *Lo-value* and *Hi-value* items across the subject population (Fig. S3*B*). As a result, *Lo-value* and *Hi-value* items were related in different ways to the *Test* bid items (Fig. S3*A*): compared with *Lo-value* items, the value of the average *Hi-value* item exhibited a larger difference from that of the average *Test* item (all 30 items). To examine this difference in individual subjects, we quantified the strengths of the *Lo* and *Hi* adapter sets, with adapter strength defined as the difference between the mean adapter value and the mean test item value. Across the population, the adapter strength of *Hi-value* items was significantly larger than that of *Lo-value* items ($P = 3.94 \times 10^{-5}$, paired t test; Fig. S3*C*). This difference in adapter set strengths offers a potential explanation for the observed asymmetry in bid adaptation, with larger magnitude bid deviations in post-*Hi* vs. post-*Lo* bids. Consistent with this idea, effect size (defined as the average bid deviation) varied as a similar function of adapter strength in both low- and high-value adaptation (Fig. S3*D*).

SI Methods

Adaptive Valuation Model. To examine whether the observed postadaptation bid effects could be explained by a normalization process, we fit a value normalization model (*Results*) to individual subject bid data using nonlinear least-squares regression. For each subject, a single normalization model was fit to the combined data from post-*Lo* and post-*Hi Test* block bids. The dependent variables in the normalization model were the value of the item in the current trial and the average value of items presented in the previous 60 trials (from either rating or bid trials). For a given item, value was calculated as the average bid for that item across all nine bids in the session. Analysis of model-predicted bid, bid deviation, and bid deviation dynamics data were implemented in the same manner as the analysis of observed subject bids.

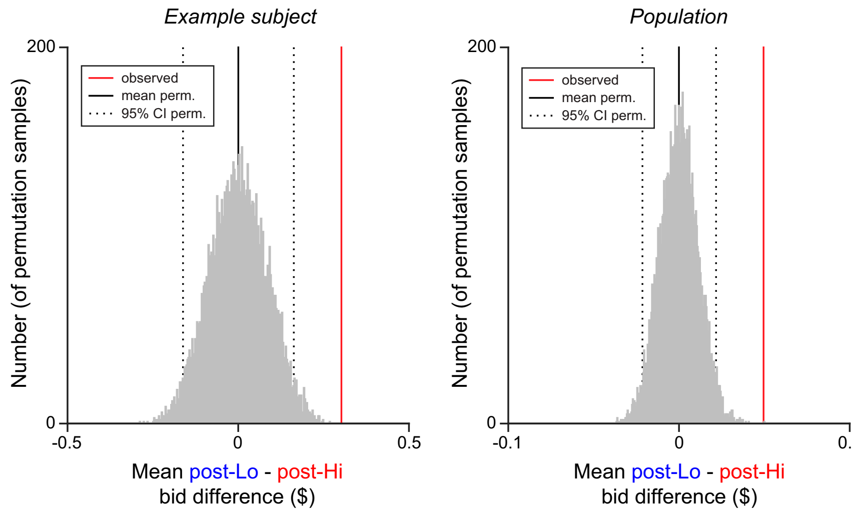

Fig. S1. Permutation test of postadaptation bid differences. (*Left*) Distribution of permutation results for example subject shown in Fig. 2*B*. (*Right*) Distribution of permutation results across the population. The histograms show the distribution of mean bid differences (post-*Lo* − post-*Hi*) across 10,000 permutation iterations. Solid and dotted black lines indicate the mean and 95% confidence interval values of the permutation bid differences. The red line indicates the experimentally observed mean bid difference in the example subject data (*Left*) and across the population (*Right*). In both analyses, the observed mean bid difference is larger than all permutation bid differences ($P < 0.0001$).

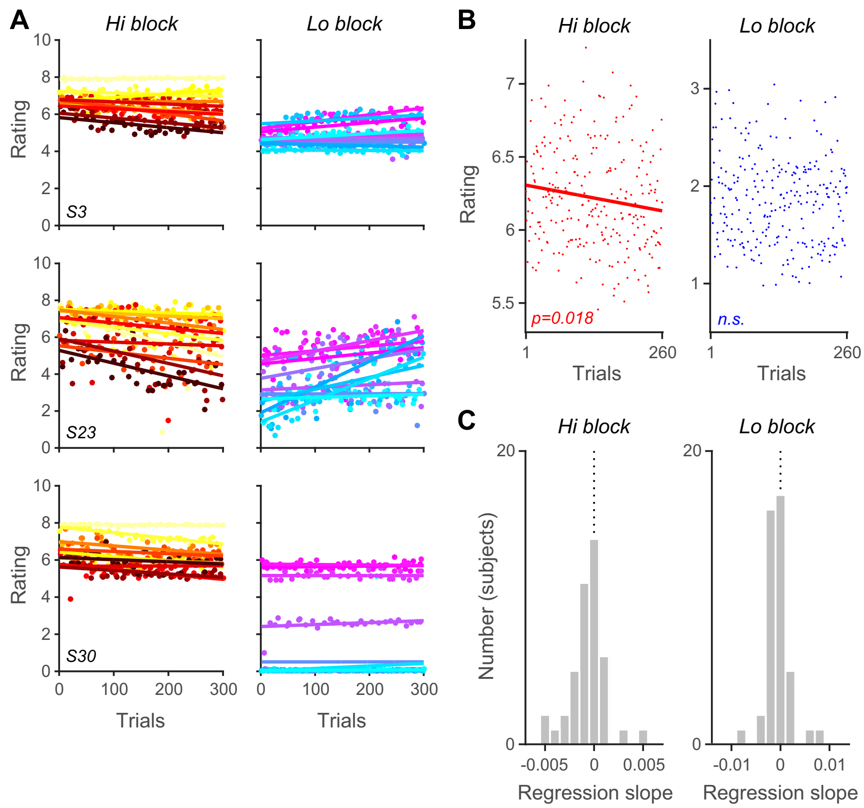

Fig. S2. Dynamic changes in rating data within adaptation blocks. (*A*) Heterogeneous dynamics of within-block pleasantness ratings in example subjects. Each pair of panels plots the pleasantness ratings for the 10 presented goods in the *Hi-Adapt* (*Left*) and *Lo-Adapt* (*Right*) blocks. Lines show the linear regression fits for each good as a function of trial number. Colors denote different good items. (*B*) Average pleasantness ratings across *Hi-Adapt* and *Lo-Adapt* blocks. Population average ratings show a significant linear decrease across *Hi-Adapt* blocks ($P = 0.018$) but no significant change across *Lo-Adapt* blocks ($P > 0.05$). (*C*) Regression analysis of individual subject dynamics. Consistent with the average population rating dynamics, regression analyses examining pleasantness rating changes in individual subjects show a significant decrease in *Hi-Adapt* block ratings ($P = 0.017$, *t* test) but no significant change in *Lo-Adapt* ratings ($P > 0.05$, *t* test).

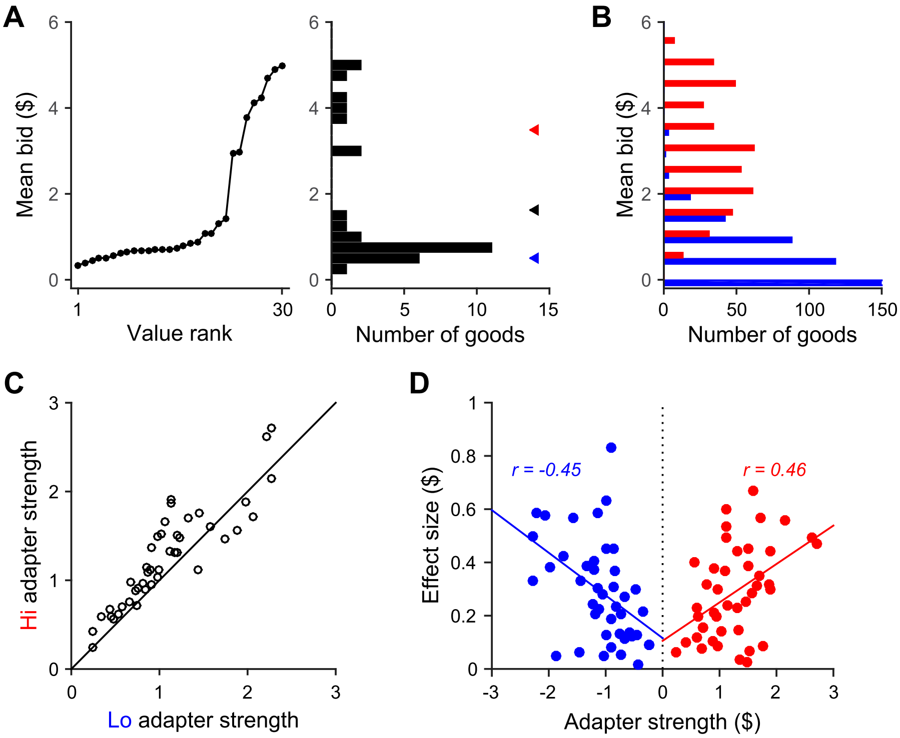

Fig. S3. Asymmetric bid change magnitudes may reflect asymmetric adaptation condition strengths. (*A*) Asymmetry in example subject bid distribution. (*Left*) Items ranked by mean initial bid value. (*Right*) Value distribution. Due to the right skew in the distribution, the difference between the mean value of all items (black triangle) and the mean value of high adapter items (red) is greater than that between all items and low-adapter items (blue). (*B*) Low (blue) and high (red) adapter value distributions across the population. (*C*) Comparison of *Hi Adapt* and *Lo Adapt* adapter strengths. Points represent individual subjects. Across the population, high-adapter strengths are significantly greater than low-adapter strengths ($P = 3.94 \times 10^{-5}$, paired *t* test). (*D*) Effect size as a function of adapter strength in *Lo-Adapt* (blue) and *Hi-Adapt* (red) conditions.